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ISBN

9798197828828

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Publication Date

2026-07-02

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UNIVERSITY OF CALIFORNIA,
IRVINE

Community Colleges in the Online Learning Era:
Student Decision-Making, Labor-Education Tradeoffs, and Pedagogical Innovation

DISSERTATION

submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in Education

by

Gala Merari Ledezma

Dissertation Committee:
Professor Di Xu, Chair
Professor Richard Arum
Associate Professor Rachel Baker

DEDICATION

This level of education is unprecedented in my family—
yet it is only possible because of those who came before me.

To my mother—
forbidden from learning beyond primary school,
one of many women denied the right to choose her own path,
taught that the highest aspiration was to be a man's wife—
and yet, relentless,
she carved a path out of limitation,
leaving her country by any means necessary,
arriving in a place that greeted her with poverty and prejudice,
cleaning houses to exhaustion,
carrying the quiet hope
that her daughters might live differently.

To my father—
whose first glimpse of the “American dream”
was found in the fields of Imperial Valley,
in back-breaking labor beneath an unforgiving sun,
in years of long days and longer nights,
in multiple jobs and little rest—
and still, he urged his daughters forward,
toward lives not only of survival, but of fulfillment,
finding his reward not in wealth,
but in the moment his daughter would rise
and claim her PhD.

To my sister—
who went first,
who showed me that this path was possible,
who turned rivalry into fuel,
and example into direction—
who now gives what she once sought,
guiding countless students
as she once guided me.

Your sacrifices made this possible.
I share this achievement with you.

*En mi familia, nadie había llegado a este nivel de estudios—
y aun así, estoy aquí gracias a quienes vinieron antes que yo.*

*A mi mamá—
a quien no le permitieron estudiar más allá de la primaria,
una de tantas mujeres a las que no les dieron la oportunidad de elegir su propio camino,
a quien le enseñaron que lo más importante era ser la esposa de un hombre—
y aun así, sin rendirse,
se abrió camino con lo que tenía,
dejando su país como pudo,
llegando a un lugar que la recibió con pobreza y prejuicio,
trabajando limpiando casas hasta el cansancio,
guardando en silencio la esperanza
de que sus hijas pudieran vivir diferente.*

*A mi papá—
que conoció el “sueño americano” por primera vez
en los campos del Valle Imperial,
en el trabajo duro bajo un sol que no perdona,
en años de días largos y noches más largas,
en varios trabajos y casi sin descanso—
y aun así, siempre empujó a sus hijas hacia adelante,
hacia una vida no solo de sobrevivir, sino de salir adelante,
encontrando su recompensa no en la riqueza,
sino en el momento en que su hija pudiera levantarse
y lograr su doctorado.*

*A mi hermana—
la que fue primero,
la que me enseñó que este camino sí era posible,
la que convirtió la rivalidad en impulso
y el ejemplo en dirección—
y que ahora da a otros lo que antes buscaba,
guiando a tantos estudiantes
como alguna vez me guió a mí.*

*Sus sacrificios hicieron todo esto posible.
Este logro también es suyo.*

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ACKNOWLEDGMENTS

I am deeply grateful to my committee for their guidance throughout this dissertation and for their support along the PhD journey.

To Di—your mentorship has been a defining part of this process. You have truly transformed how I think about research methods. You are a brilliant researcher, and you bring a level of precision that pushed me to engage more deeply with my work. Your sharp questions, especially the ones that cut straight to identification and measurement, have reshaped how I evaluate research. I’ve learned to approach research with a more critical and disciplined lens because of you. I find myself thinking, “what would Di say?” whenever I read a study. I am especially grateful for your investment in my development and for the high expectations that pushed me to grow into a stronger scholar.

To Richard—your curiosity and critical perspective consistently pushed me to think beyond the surface in all the work I do. You have taught me how to become a better storyteller with my data. Your love of theory is contagious, and you’ve shown me how theory can be a powerful tool for understanding the world and making sense of data. You have also been an incredible thought partner. Every conversation with you left me inspired and full of new ideas. Thank you for your generosity with your time, for welcoming me into your office to talk through research questions, and for your endless stream of literature recommendations.

To Rachel—my “unofficial” advisor—when you left UCI for Penn, you promised that your mentorship would not change. As I complete this program, I can say with certainty that you kept that promise. Working with you on the RCT across every stage—from implementation to data collection, analysis, and communication—has been one of the most formative experiences of my doctoral training. I deeply admire your ability to cut through the noise of academia with honesty and humor. Beyond your intellectual mentorship, I am grateful for your wit and authenticity, both of which have made this journey so special.

Thank you all for the valuable lessons you have provided through this dissertation and beyond. I am grateful for your guidance and for the relationships we have built, which I know will continue well past this program.

Finally, I would like to thank my partner. I can’t fully reflect on this journey without acknowledging your role in all of it.

To Gabe—you’ve been my steady ground through all of this. Thank you for your patience through the emotional ups and downs, for listening to me vent, for being attentive to my well-being, and a champion for my mental health. You’ve been my confidant, my support system, and my biggest hype-man, believing in me even when I felt like an imposter. Thank you for nerding out with me, listening to my research with excitement, and genuinely engaging with the work I care so deeply about. Thank you for bringing so much happiness, laughter, and light into my life. Your support has meant more than I can put into words.

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- Organized and facilitated outreach sessions at partner colleges; designed Qualtrics surveys to track participants
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ABSTRACT OF THE DISSERTATION

Community Colleges in the Online Learning Era:
Student Decision-Making, Labor-Education Tradeoffs, and Pedagogical Innovation

By

Gala Merari Ledezma

Doctor of Philosophy in Education

University of California, Irvine, 2026

Professor Di Xu, Chair

Community colleges are designed to expand access to higher education, serving students who might otherwise be excluded from traditional four-year pathways. In the post-COVID era, online learning has endured as a central feature of higher education, further expanding access for time-constrained and place-bound students. Simultaneously, it has created less structured environments that can place greater responsibility on students to manage their own learning. This dissertation examines a central paradox: how does inequality persist even as access expands?

The first chapter opens the black box of transfer decision-making by examining how students form intentions, expectations, and strategies under uncertainty. While aspirations and confidence are consistently high, access to transfer-related knowledge and communication networks varies systematically based on students' social and economic positionality. The second chapter positions asynchronous learning as a labor-education tradeoff. It shows that students use asynchronous course formats to balance work and school, but this flexibility is associated with

lower academic performance compared to synchronous and face-to-face formats. The third chapter demonstrates that pedagogy can serve as a lever for equity. It provides evidence that humanizing, student-centered teaching practices can improve outcomes in online courses, showing that training faculty to design more supportive online environments can mitigate some of the costs associated with online learning.

INTRODUCTION

Community colleges are integral to higher education access in the United States. As open-access institutions, they serve a diverse student population, including first-generation, low-income, and working students who might otherwise be excluded from four-year pathways. At the same time, the institutional structure of community colleges presents unique challenges. When open-access institutions present no filtering barriers for applicants, the result is heterogeneity in student preparation and resources; transfer pathways are often complex and uncertain and institutional structures tend to, albeit inadvertently, place a greater burden on students to navigate their own academic trajectories. As a result, students must actively make decisions about their educational pathways, often under conditions of limited information and uncertainty, shaped by their broader social and economic positionality.

In recent years, these dynamics have been further transformed by the rapid expansion of online learning. Prior to the COVID-19 pandemic, distance education was already used to expand access for working adults, nontraditional students, and individuals seeking flexible pathways to complete credentials or advance their careers. Online learning provided opportunities for students balancing employment, caregiving responsibilities, and other time constraints to engage in higher education at their own pace. In particular, asynchronous formats, courses that do not require real-time interaction, offer flexibility that enables students to participate in ways that were previously not possible. While many community colleges had begun investing in online learning prior to the pandemic, the COVID-19 crisis accelerated this shift, forcing institutions to adopt online modalities at scale. Regardless of their level of preparedness, colleges were required to shift instruction online as in-person participation became

infeasible. This transition affected a broad range of students, from traditional college-aged individuals to working adults, and required both institutions and instructors to adapt quickly. Faculty were tasked with redesigning courses for online delivery, often with varying levels of support and success. At the same time, the pandemic revealed some of the benefits of online learning, particularly its capacity to expand access. In the post-pandemic period, online learning has endured as a core feature of the higher education landscape, driven by student demand for flexible learning options. Online instruction moved from an alternative option to an expected modality, which has altered the accessibility of higher education forever.

Online learning is more than just a mode of course delivery; it has fundamentally reshaped the relationship between access and success. On one hand, it expands who can participate in higher education by reducing constraints related to time and location. On the other hand, it changes how learning occurs. Online courses, especially asynchronous ones, often involve less structure, reduced interaction, and greater reliance on self-regulation. Consequently, the responsibility for managing time, work, and learning shifts increasingly onto students. In this way, online access redistributes responsibility from institutions to individuals.

This transformation introduces a central tension. Although access to higher education has expanded through both open-access institutions and flexible online learning, student outcomes remain inequitable. Course success varies widely, transfer rates remain limited, and persistent inequities continue across student groups throughout the degree pipeline. These patterns raise an important question: how does expanded access actually operate in practice, and under what conditions does it translate into equitable opportunity? This dissertation contributes to answering this question in three key ways.

The first chapter, “How Transfer Decisions Take Shape,” contributes to the literature on transfer by shifting attention from outcomes to the processes that precede them. Transfer is a central mechanism through which community college students access bachelor’s degree pathways, yet relatively few students successfully make this transition. As a result, transfer outcomes represent a key site of inequality within higher education. While prior research has extensively documented stratification in transfer rates, this study opens the “black box” of decision-making by examining how students form transfer intentions, expectations, and strategies. Community college students must make decisions under conditions of uncertainty, particularly when navigating complex and often opaque transfer systems. This involves interpreting institutional requirements, forming expectations about future opportunities, and maintaining confidence in their ability to succeed. Historically, many of the disparities in transfer are framed through a student deficit lens. This study challenges this framing by demonstrating that inequality emerges from differences in informational access and sensemaking processes, rather than from differences in student motivation or ability. The findings show that all students report high aspirations and confidence. However, access to transfer-related knowledge and communication networks varies systematically across groups. These findings demonstrate how inequity can emerge prior to observable outcomes.

The second chapter, “Flexibility as a Cost?” contributes to research on online learning in community colleges by reframing asynchronous instruction as a labor-education tradeoff rather than simply a mode of course delivery. This study shows that students sort into asynchronous courses based on time and financial constraints, using flexibility to balance school with work and other responsibilities. At the same time, it provides evidence of a clear tradeoff: while asynchronous courses expand access by enabling participation, they are associated with lower

academic performance. Importantly, these academic costs are broadly shared and are not substantially reduced for the students most likely to select into these courses. These findings highlight a recurring theme in this dissertation: the same features that expand access may also introduce new forms of inequality.

Third, Chapter 3, “Humanizing Pedagogy for Online STEM Courses,” contributes to the literature on pedagogy and equity in online learning by demonstrating that instructional practices can meaningfully shape student outcomes. Not all online learning is experienced the same: students encounter variation in learning environments, particularly in course design and instructional practices. Through an evaluation of a professional development intervention, this study shows that humanizing, student-centered teaching practices can improve engagement and narrow racial equity gaps in online STEM courses. By linking changes in instructor beliefs and practices to student-level outcomes, the chapter provides evidence that pedagogy can mitigate some of the inequities associated with less structured online environments. At the same time, the findings highlight the limits of instructional interventions, showing that their effects are context-dependent and do not fully eliminate broader structural disparities.

In sum, community colleges in the online learning era therefore represent an interesting intersection for understanding how access is navigated, constrained, and reshaped. This dissertation posits that access is not simply provided by institutions, but actively navigated by students as they make decisions under uncertainty, balance competing demands, and engage with different learning environments. A consistent pattern emerges across the chapters that follow: the same features that expand access can also introduce new constraints and reproduce inequality. The dissertation concludes by reflecting on these findings and discussing their implications for policy and future research.

STUDY 1

How Transfer Decisions Take Shape:

Sensemaking, Navigation, and Aspiration among Community College Students

Abstract

Research on transfer frequently documents stratification in outcomes. However, far less attention has been paid to the informational and perceptual processes through which students form transfer decisions. This study offers a window into the pre-transfer decision-making process by examining community college students' transfer knowledge, navigation strategies, and aspirations for four-year institutions.

Using survey data from 1,400 students, we analyze communication networks, confidence, and transfer expectations across racial/ethnic and first-generation groups. Findings reveal a paradoxical pattern: although students report high self-efficacy and strong transfer aspirations, access to transfer-related knowledge and navigation resources varies systematically across groups. These patterns suggest that stratification emerges not only in eventual transfer outcomes but also in the informational, relational, and behavioral processes that precede them.

Background

Educational systems in the United States are structured by race and socioeconomic status, with disparities in access and mobility across levels of schooling (Reardon, 2011; Jackson, 2013; Torche, 2011). Although more students now attend college, they do not enroll in the same institutions or follow the same pathways. Students are unevenly distributed across institutional sectors, levels of selectivity, academic programs, and degree outcomes (DiPrete & Eirich, 2006; Hout, 2012). As access to education becomes more widespread, inequality does not disappear but instead manifests in different ways (Lucas, 2001). Advantaged families secure positions in more selective institutions, more rigorous programs, and more advantageous academic pathways, maintaining an advantage even in contexts of mass access. Community colleges are an important site to examine how stratification operates within open-access systems. By design, they expand access to postsecondary education. However, precisely because they serve as the entry point for large numbers of students, they also become sites where differentiation occurs.

Democratization vs. Stratification

Community colleges occupy a contradictory position within higher education. On the one hand, they are praised as engines of democratization that provide affordable and accessible entry into postsecondary education. On the other hand, they have been characterized as sorting mechanisms that reproduce inequality within the broader higher education system (Brint & Karabel, 1989; Dougherty, 1987, 1994, 2001). Historically, community colleges have redirected many working-class and racially minoritized students away from bachelor's degree pathways by channeling them into vocational or terminal programs (Brint & Karabel, 1989).

Understanding this stratification requires attention to the organizational processes that govern students' experiences. Community colleges and transfer systems are not neutral providers of opportunity (Ray, 2019; Bonilla-Silva, 1997). They are organizational sites in which stratification is produced and maintained. Within community colleges, students occupy positions that shape their access to time, institutional knowledge, and guidance (Lovell, 2014; Perna & Odle, 2020). Organizational structures distribute financial aid, transfer supports, and academic information unevenly, privileging students from more advantaged racial and socioeconomic backgrounds while constraining opportunities for historically marginalized groups (Casanova & Alonso Blanco, 2025; Graves, 2024; Hunter, 2024; Levine & Ritter, 2023). These processes reflect broader patterns of stratification within higher education, where alignment with dominant institutional norms operates as a form of credentialing (Chin, 2024; Corces-Zimmerman, 2018). Students whose behaviors, communication styles, and educational expectations align more closely with these norms are more likely to receive access to institutional support. At the same time, organizational decoupling—the gap between formal commitments and everyday practice—can obscure how these advantages are produced (Meyer & Rowan, 1977). Colleges may publicly commit to access and inclusion, yet advising systems, funding structures, and informational infrastructures often continue to privilege students who are already positioned closer to institutional norms (Aguilar-Smith, 2021; Bush, 2025; Harper & Thiry, 2022). Through these mechanisms, democratization and stratification coexist: although access expands, organizational processes shape how students navigate the institution and the opportunities available to them.

The Structure of California Higher Education

These dynamics are particularly salient in California, where institutional hierarchy is formally embedded within the structure of higher education. The 1960 Master Plan established a three-tiered system in which the University of California (UC) admitted the top one-eighth of high school graduates, the California State University (CSU) admitted the top one-third, and community colleges remained open access (Master Plan Survey Team, 1960). While framed as expanding access, this structure institutionalized vertical differentiation across sectors (Anderson, 2015; Baum & Kurose, 2013; Clark, 1960, 1980; Dowd, 2003).

Scholars argue that the Master Plan has functioned as a mechanism of racialized and class-based sorting, channeling working-class and racially minoritized students into community colleges while preserving elite access for more advantaged groups (Higgins, 2023; Goldrick-Rab & Kinsley, 2013). Community colleges disproportionately enroll low-income and racially minoritized students, yet they often operate with fewer resources, lower per-student funding, and higher student-to-staff ratios (Goldrick-Rab & Kinsley, 2013; McCambly et al., 2023).

Degree attainment patterns reflect these structural inequalities. Among California-born young adults, 58 percent of Asian Americans and 41 percent of Whites hold a bachelor's degree, compared to only 20 percent of Latinxs and 25 percent of Black Americans (Baldassare, 2018; Cook, 2024b). Latinx students constitute the largest group within the CCC and CSU systems, which generally reflect the state's high school demographics (Cook, 2024b). Specifically, 50 percent of CCC students and 46 percent of CSU students are Latinx, whereas the more selective UC system overrepresents Asian students and underrepresents Latinx students (Cook, 2024b).

One of the most consequential mechanisms through which this sorting occurs is the vertical transfer process. Ultimately, while community colleges are formally positioned as gateways to four-year institutions, the pathway to a bachelor's degree is neither automatic nor equally accessible. In a tiered system such as California's, transfer serves as a critical mechanism linking open-access institutions to more selective sectors.

Transfer Pathways

While community college students often aspire to transfer to four-year institutions, there is a substantial gap between intentions and outcomes. Approximately three-quarters of community college students report that transferring is their goal, yet only about 21 percent successfully transfer within four years (Cook, 2025). Part of this gap reflects the differentiated academic trajectories students experience within community colleges. Placement into remediation, variation in course-taking sequences, and differences in early academic momentum contribute to stratified pathways through these institutions (Bahr, 2012, 2013). Early attainment of credit milestones is strongly associated with persistence and transfer likelihood (Scott-Clayton, 2011; Cuellar Mejia & Johnson, 2025). However, access to structured program pathways and opportunities for early credit accumulation remains uneven (Lin et al., 2020; Cuellar Mejia & Johnson, 2025). Thus, students approach the point of transfer from noticeably different academic positions shaped by institutional sorting.

Beyond internal differentiation, the transfer process itself is structurally complex. Students frequently encounter credit loss, broken articulation systems, and fragmented institutional coordination (Fink et al., 2018; U.S. Government Accountability Office, 2017; Tichenor et al., 2025). Even when credits transfer between institutions, they may not apply

toward degree requirements, leading students to accumulate excess credits and extend time to completion (Fink et al., 2018; Tichenor et al., 2025). These inefficiencies disproportionately affect community college students and exacerbate existing inequities.

Navigating transfer requires interpreting institutional policies, cross-referencing online resources, and consulting advisors and peers to assess requirements and timelines (Metzer et al., 2003). Yet institutional information is frequently difficult to access or understand. Many college websites fall below accessibility standards, and a large share of articulation agreements are written at levels exceeding students' reading ability (Schudde et al., 2019; Taylor, 2017). Advising resources are also unevenly distributed. Students who receive sustained and proactive advising are more likely to remain engaged and successfully progress, but advising intensity varies considerably across institutions and student groups (Community College Research Center, 2018). Limited access to counselors, misalignment between community colleges and four-year institutions, and geographic and financial constraints further complicate transfer pathways. These barriers contribute to extended timelines; for example, only 8 percent of bachelor's degree graduates who began at a community college followed the intended 2+2 pattern (Jenkins & Fink, 2016). Ultimately, transfer is structured by power asymmetries in which universities define rules, timelines, and standards, while community college students must navigate fragmented and poorly aligned systems (Schudde et al., 2020). These structural arrangements contribute to persistent disparities in transfer outcomes, even as aspirations remain high. Although many community college students intend to transfer, institutional complexity, uneven advising, and misaligned policies constrain their ability to do so.

Importantly, these disparities are often attributed to individual deficits rather than the systemic conditions that shape transfer pathways. While existing research documents these structural barriers, far less is known about how students interpret these systems, access information, and construct their own strategies in response to them. Understanding these pre-transfer processes is critical for identifying how stratification unfolds before formal transfer decisions are made.

Foundations of Decision-Making

Transfer decisions represent a critical decision in students' educational trajectories. Research on educational decision-making suggests that choices about continuation are shaped by perceptions of risk, expected returns, and access to information (Breen & Goldthorpe, 1997; Wickersham, 2020). When institutional pathways are complex and outcomes uncertain, differences in knowledge and perceived feasibility can structure how students evaluate their options. Decisions are therefore influenced by access to advising, social networks, and confidence in one's ability to navigate institutional requirements. These informational and relational processes influence aspirations and perceived feasibility long before formal transfer applications are submitted. The pre-transfer decision-making stage is thus an important space where educational trajectories are shaped. Rather than focusing solely on whether students ultimately transfer, this study extends existing research by examining how transfer decisions take shape prior to formal application.

Research Questions

This study examines sensemaking, navigation, and aspiration among community college students. Using race/ethnicity and first-generation status as axes of stratification, we assess whether these items differ systematically across student groups.

Specifically, we ask:

1. How do students communicate about transfer, and from whom do they seek information?
2. To what extent do students differ in their confidence in navigating transfer requirements and understanding institutional processes?
3. How do students' transfer intentions and perceived likelihood of admission vary across groups?

Data

We developed a survey and distributed to a random sample of 9,000 transfer-directed¹ community college students across three California colleges and obtained 2,084 responses (23% response rate). After removing ineligible cases and those with missing demographic information necessary for our analyses, the final analytic sample included 1,411 students (see Appendix Section 1). Table 1 shows the demographic breakdown of our sample. The sample was slightly more women (56%) than men. The largest racial groups were White (33%), followed by Latinx (29%), followed by Asian (22%)². This reflects the general student body of the campuses we

¹ Transfer directed students refer to those who have completed a college-level transferrable English course and Math course. Through course-taking records, these students demonstrate transfer intent.

² The community colleges in this study primarily serve as transfer pipelines to nearby CSU and UC campuses, whose racial compositions differ across sectors. In general, CSU campuses in the region enroll majority-

sampled from (Appendix A, Table 1). The level of parental education is also spread, with half of our sample being first generation colleges students (neither parent has a bachelor's degree).

In our analyses, we focus on White, Asian, and Latinx students, as these groups represent the largest racial categories in both our sample and the three community colleges included in this study. We refrain from making inferences about smaller groups, specifically Black, Native Hawaiian or Pacific Islander, and American Indian or Alaska Native students, given that a very small share of students in our analytic sample identify with these categories. Although the representation of these students reflects their overall proportions on the participating campuses, the small sample sizes limit our ability to draw reliable conclusions. This represents an important limitation of our study, and we urge future research to intentionally center and amplify the experiences of these student groups.

Our analyses are further constrained by the race and ethnicity categories available in the administrative data, which reflect federally defined census categories and do not fully capture the complexity and diversity of racial identities. We use these categories as proxies to explore how community college students' experiences differ, while recognizing their limitations. In particular, we recognize the growing body of scholarship calling for the disaggregation of Asian student data, as national-origin subgroups have distinct migration histories, socioeconomic profiles, and experiences of marginalization in the United States (Nguyen et al., 2018; Teranishi, 2013). Aggregating these groups into a single category can obscure important within-group inequities. While our data do not permit full disaggregation, we partially address this limitation by

Latinx student bodies, while UC campuses enroll comparatively higher proportions of Asian and White students (see Appendix B, Section 1 for detailed institutional demographics).

examining patterns across race in conjunction with first-generation college status. Using first-generation status as an additional axis of stratification allows us to capture variation in educational background and potential differences in access to institutional knowledge that may not be visible through race alone.

Methods

To examine differences across racial and generational groups, we test whether there are statistically significant differences by race, first-generation status, and the interaction between race and first-generation status. Race is categorized as White, Asian, and Latinx, and first-generation status is coded as a binary indicator. For each survey area, we test whether: (1) there are overall differences across racial groups, (2) first-generation students differ from continuing-generation students, and (3) racial differences vary by first-generation status. These tests allow us to determine whether observed differences in group means are statistically significant. When racial differences are statistically significant, we conduct pairwise comparisons across racial groups to identify which specific groups differ from one another.

Survey areas

We organize the analysis around three domains aligned with our research questions. Communication network measures capture how frequently students discuss transfer with different sources (Table 2, Panel A), how often they seek transfer-related information online (Table 2, Panel B), and familiarity with transfer process (Table 2, Panel C). These outcomes reflect students' access to transfer-related information and their engagement with multiple sources of information. Confidence measures assess students' perceived ability to understand transfer requirements and navigate the transfer process (Table 3, Panel A), as well as expected

four-year experiences (Table 3, Panel B). Aspiration measures include students' reported likelihood of applying to transfer to different institution types (Table 4, Panel A) as well as their perceived probability of admission (Table 4, Panel B).

Communication and confidence measures are presented primarily to describe patterns of informational access and perceived readiness across groups. Transfer aspirations and perceived admission likelihood serve as the primary outcomes of interest, as they most directly reflect how students position themselves within transfer pathways.

Results

Communication

Sources of information

We first examine the frequency of students' transfer-related conversations across different sources (Table 2, Panel A). Responses were measured on a Likert scale ranging from 0 ("I have not") to 4 ("more than five times"). Across the full sample, students most frequently engaged with family ($M = 2.65$), followed by friends ($M = 2.26$), peers or classmates ($M = 2.00$), counselors ($M = 1.87$), faculty ($M = 1.42$), and staff ($M = 1.27$). There were no statistically significant differences by race or first-generation status in the frequency of transfer conversations with community college faculty or staff. However, racial differences emerged in conversations with counselors. Race was significantly associated with transfer talk frequency with counselors ($p = 0.022$), with Asian students reporting the highest levels of counselor engagement ($M = 2.09$), compared to Latinx students ($M = 1.87$) and White students ($M = 1.77$). Pairwise comparisons show that Asian students reported significantly more frequent transfer discussions with counselors than both White students ($+0.32$, $p = 0.001$) and Latinx students ($+0.22$

difference between Asian and Latinx, $p = 0.044$). There were no significant differences between Latinx and White students. These findings suggest racial variation in counselor engagement, independent of first-generation status.

Patterns were similar in peer-based communication. Race was significantly associated with transfer discussions with friends ($p = 0.001$), while first-generation status was not. Asian students reported higher levels of transfer conversations with friends ($M = 2.54$) compared to both White ($M = 2.19$; $+0.35$, $p = 0.002$) and Latinx students ($M = 2.21$; $+0.33$, $p = 0.006$). A similar pattern emerged for general peer transfer discussions ($p < 0.001$), with Asian students ($M = 2.31$) reporting significantly more peer engagement than White ($M = 1.88$; $+0.43$, $p < 0.001$) and Latinx students ($M = 1.90$; $+0.41$, $p < 0.001$). No significant first-generation differences were detected in these peer communication measures. There were also no statistically significant differences by race or first-generation status in transfer conversations with family members. Taken together, the communication findings indicate that racial differences are most pronounced in counselor and peer-based transfer discussions.

Online Information-Seeking Behaviors

We next examine students' online information-seeking behaviors related to transfer (Table 2, Panel B). Across the full sample, students most frequently consulted their community college website ($M = 2.40$) and four-year university websites ($M = 2.23$), followed by Assist.org ($M = 1.83$), a platform that provides course articulation information. Racial differences were evident across several online sources. Use of the community college website differed significantly by race ($p = 0.012$), though not by first-generation status. Asian students reported more frequent use than both White students ($+0.23$, $p = 0.028$) and Latinx students ($+0.40$, $p <$

0.001). Similarly, use of four-year university websites differed by race ($p = 0.001$), with Asian students again reporting significantly higher engagement than White (+0.23, $p = 0.033$) and Latinx students (+0.41, $p = 0.001$).

The largest racial disparities emerged in use of Assist.org ($p < 0.001$). Asian students reported substantially higher levels of assistance-seeking through this platform ($M = 2.38$) compared to White ($M = 1.68$; +0.70, $p < 0.001$) and Latinx students ($M = 1.43$; +0.95, $p < 0.001$). Latinx students were marginally lower than White students in Assist use ($p = 0.056$). No significant differences were found for other online sources.

Overall, these results indicate systematic racial differences in online transfer information-seeking behaviors, with Asian students consistently reporting higher levels of engagement across institutional web platforms.

Knowledge of Transfer Terminology

We also assess students' familiarity with common transfer-related terminology (Table 2, Panel C). Across the full sample, fewer than half of students reported familiarity with many key transfer terms, indicating that transfer-related jargon may function as an informational barrier.

First-generation status was modestly associated with knowledge of lower-division requirements ($p = 0.037$), while race was not statistically significant for this measure. However, substantial racial differences emerged for specific transfer frameworks. Knowledge of the Intersegmental General Education Transfer Curriculum (IGETC) requirements differed significantly by race ($p < 0.001$), with predicted probabilities indicating higher familiarity among Asian students (0.490) compared to White (0.382; +0.11, $p = 0.004$) and Latinx students (0.335; +0.15, $p < 0.001$).

A similar pattern appeared for Transfer Admission Guarantee (TAG) knowledge ($p = 0.001$), which is the guaranteed admissions program for the UC system. Asian students (0.608) were significantly more likely to report familiarity than White students (0.472; $+0.14, p < 0.001$) and Latinx students (0.391; $+0.22, p < 0.001$). Latinx students also reported lower familiarity with TAG compared to White students ($-0.08, p = 0.041$). Other terminology measures (e.g., ADT, upper division, etc.) did not show statistically significant racial differences.

Confidence

Transfer Self-Efficacy

We next examine students' confidence in navigating the transfer process. Transfer self-efficacy captures students' perceived ability to understand transfer requirements and procedures (Table 3, Panel A). Responses were measured on a Likert scale ranging from 0 ("Cannot do this") to 4 ("Can do this"). Across the full sample, students reported generally high levels of confidence in their ability to understand the transfer process, with minimal variation across groups. There were no statistically significant differences by race, first-generation status, or their interaction (all $p > .25$). Similarly, measures of advising knowledge such as knowing who to speak with about transfer, where to seek advising, and how to access online advising resources, did not differ systematically across racial or generational groups.

Expected Experiences at a Four-Year Institution

Students were also asked about their anticipated academic experiences at a four-year institution (Table 3, Panel B). Responses were measured on a Likert scale ranging from 0 (“Almost never true”) to 4 (“Almost always true”). Overall, students expressed positive expectations. On average, they anticipated that classes would be interesting ($M = 3.07$) and that learning support resources would be available ($M = 3.05$), with little variation across racial or first-generation groups. Most measures of anticipated challenges, including concerns about classwork difficulty, navigating web-based information, accessing technical support, interacting in class, using learning support resources, feeling comfortable in class, receiving support from friends, and managing credit requirements did not show statistically significant differences by race or first-generation status.

One notable exception emerged for anticipated help-seeking from professors. Race was significantly associated with this measure ($p < 0.001$), and a significant interaction was detected ($p = 0.040$). Among continuing-generation students, Asian students reported higher expectations of seeking professor help compared to White students ($+0.24$, $p = 0.005$) and Latinx students ($+0.46$, $p < 0.001$). However, among first-generation students, there were no significant racial differences (all $p > 0.61$).

This pattern suggests that racial differences in anticipated faculty engagement are concentrated among continuing-generation students, whereas first-generation students report similar expectations across racial groups.

Aspirations

Application Intentions

We first examine students' transfer intentions, specifically their reported likelihood of applying to different types of four-year institutions from 0 to 100 (Table 4, Panel A). Across the full sample, aspirations were high: approximately 80% of students reported that they were likely to apply to at least one four-year institution. These results were left-skewed (see Appendix C), with most students reporting high levels of confidence. Notably, however, there were students who reported a zero likelihood of applying to transfer, despite being transfer directed. This self-reported measure of transfer likelihood reveals uncertainty in community college students' transfer intentions. Although all of these students initially indicated on their applications that their educational goal was to transfer, when given a chance to respond beyond a binary through a spectrum of likelihood, many students indicate uncertainty. This nuance may reflect changes in their knowledge, experiences in higher education, perceptions of academic preparation, or evolving goals.

When disaggregated by sector, 68% indicated they were likely to apply to a CSU campus, 63% to a UC, and 36% to a private or out-of-state institution. Perceived admission likelihood followed a similar pattern (Table 4, Panel B). Students reported the highest perceived probability of being admitted to a CSU campus (74%), followed by UC (61%), and private or out-of-state institutions (53%). These descriptive patterns suggest that students view CSU campuses as the most accessible transfer option, with UC perceived as more selective. There were no racial or first-generation differences in students' self-reported CSU application likelihood.³ Taken

³ Results are largely consistent across alternative definitions of first-generation status (see Appendix E for results under alternative specifications of first-generation status).

together, perceived CSU application expectations appear broadly similar across racial and generational groups.

In contrast, perceived probability of applying to UC campuses shows clear stratification. Race is a strong and statistically significant predictor. Asian students report substantially higher perceived probability of applying to UC compared to White students (+12.96 percentage points, $p < .001$). Latinx students do not significantly differ from White students. First-generation status is also strongly associated with perceived UC application probability. Among White students, first-generation students report significantly lower perceived probability of applying to UC (-9.20 percentage points, $p = .014$). These findings indicate that UC application expectations are stratified along both racial and generational lines, with Asian students reporting higher expectations and first-generation students reporting significantly lower expectations of applying.

Perceived Admission Likelihood

We also look at students' perceived likelihood of admission (Table 4, Panel B). There is consistent evidence of a first-generation confidence gap. First-generation students report significantly lower perceived probability of being admitted to CSU (approximately 8 p.p., $p = .033$). This suggests that generational status shapes admission confidence even in the context of institutions perceived as broadly accessible. Overall, CSU admission expectations show clearer stratification by first-generation status than by race.

Similarly, for perceived probability of being admitted to UC, racial differences are minimal. Race coefficients are small and statistically non-significant in both interaction and GPA-adjusted models (Table 6). However, there is moderate evidence of a first-generation confidence gap. In models without GPA controls, first-generation students report approximately

5-6 percentage points lower perceived probability of admission (marginally significant). After adjusting for GPA, the gap remains around five percentage points and remains marginally significant. Importantly, GPA is a strong predictor of perceived admission probability, suggesting that academic self-assessment plays a central role in shaping UC admission expectations. Overall, UC admission expectations reveal modest generational stratification but little evidence of racial differentiation.

Conditional results

Comparing non-conditional and conditional estimates reveals important differences in how group disparities emerge across outcomes (Appendix D). For CSU application intentions, results are highly consistent across specifications. Racial differences, first-generation status, and their interaction remain statistically insignificant in both the full sample and the conditional sample restricted to non-zero probabilities. This suggests that intentions to apply to CSU are broadly similar across groups, regardless of whether students report any initial likelihood of applying. In contrast, results for UC application intentions differ meaningfully across specifications. In the non-conditional estimates, both racial and first-generation differences are present. However, when restricting the sample to students reporting non-zero probabilities, these differences attenuate, indicating that disparities are largely driven by whether students consider applying at all rather than differences in intensity among those who do.

For perceived admission likelihood to CSU, findings again remain stable across specifications, with no significant differences by race, first-generation status, or their interaction. This reinforces the conclusion that perceptions of CSU accessibility are relatively uniform across groups. However, for perceived admission likelihood to UC, patterns diverge. First-generation

differences remain statistically significant even in the conditional sample, and racial differences become more pronounced. This suggests that, among students who perceive a non-zero chance of admission, disparities in perceived likelihood persist particularly along racial lines.

Discussion

Across communication, online information-seeking, and knowledge of transfer terminology, racial differences are more pronounced than differences by first-generation status. Asian students consistently report higher levels of counselor engagement, peer discussions, use of institutional web resources, and familiarity with formal transfer frameworks such as IGETC and TAG. These findings suggest that stratification is visible in the informational and relational foundations of transfer well before formal applications are submitted.

Perhaps most strikingly, fewer than half of students in the full sample reported familiarity with key transfer-related terminology. Such low levels of familiarity across the board point to institutional shortcomings rather than individual failures, reflecting informational asymmetries that hinder community college students' ability to access and interpret critical transfer requirements (Grote et al., 2023). While transfer is challenging for all students, its obstacles disproportionately affect racially minoritized groups (Martin, 2014; Ray, 2019; Ray, Herd, & Moynihan, 2023). These findings mirror broader evidence documenting structural and administrative barriers, including unclear articulation agreements, inconsistent advising, and the complexity of transfer pathways (Taylor, 2017; Tichenor et al., 2025; Schudde et al., 2019; Schudde et al., 2020). Students' limited knowledge and uneven familiarity with transfer processes are thus not reflections of ability, but consequences of institutional design.

In contrast to the pronounced racial differences observed in communication and information-seeking behaviors, confidence measures show far fewer stratified patterns. Across racial and generational groups, students report generally high levels of transfer self-efficacy and positive expectations about their academic experiences at four-year institutions. Students anticipate engaging coursework and the availability of learning support resources, reflecting the aspirational capital they bring to the transfer process (Yosso, 2005). This finding challenges deficit-oriented narratives that portray community college students as lacking motivation or ability. Instead, students clearly believe in their capacity to succeed. The limited variation in confidence suggests that disparities in transfer pathways may stem less from differences in self-belief and more from differences in access to information, communication networks, and familiarity with institutional processes.

Patterns of aspiration further this theme. Application expectations for CSU campuses are broadly similar across groups, reinforcing CSU's perception as accessible. In contrast, perceived probability of applying to UC campuses is strongly stratified by both race and first-generation status. Asian students report substantially higher expectations of applying to UC compared to White students, while first-generation students report significantly lower expectations than their continuing-generation peers. These findings indicate that UC application expectations are stratified along both racial and generational lines.

Several factors may contribute to these patterns, including perceived selectivity, cost considerations, proximity to home, institutional missions, and historical feeder patterns (Black et al., 2020; Cuellar Mejia & Johnson, 2025). Students of color may internalize narratives about institutional legitimacy, viewing selective or flagship campuses as spaces where they may not belong. Latinx students, for example, are less likely than White students to apply to flagship

universities even when controlling for preparation and school quality (Black et al., 2020). In contrast, CSU campuses, most of which are designated Hispanic-Serving Institutions, have established outreach and support infrastructures that may foster greater familiarity and confidence among Latinx students (California State University, 2025; Excelencia in Education, n.d.). These sectoral differences suggest that transfer aspirations could be shaped by institutional histories and perceived pathways of belonging. Finally, across both CSU and UC admission expectations, there is consistent evidence of a first-generation confidence gap. Even after controlling for GPA, first-generation students report lower perceived probabilities of admission.

Collectively, these findings reveal a tension between students' confidence and their structural positioning within California's transfer system. Community college students express strong self-efficacy and ambitious transfer intentions, yet their uneven knowledge of transfer mechanisms and the stratified patterns of application expectations suggest that institutional complexity and resource disparities shape their sensemaking. In this way, stratification is evident not only in ultimate transfer outcomes but in the processes through which students interpret and navigate institutional pathways.

Conclusion

By examining communication networks, confidence, and aspirations across racial and first-generation groups, this study provides insight into how transfer decisions take shape before applications are submitted. A consistent pattern emerges: community college students demonstrate high levels of motivation, optimism, and belief in their ability to succeed, yet institutional barriers structure access to information, advising, and opportunity. These findings reinforce that transfer inequalities should not be attributed to student deficits. Rather, they reflect

the uneven distribution of institutional knowledge, support, and recognition within a stratified higher education system. Addressing these disparities requires moving beyond symbolic commitments to equity. Surface-level interventions such as isolated workshops or short-term advising initiatives are insufficient. Meaningful reform requires attention to both institutional culture and resource allocation, including staffing, policy design, and budgeting (McCamby et al., 2023). Aligning structural supports with students' demonstrated aspirations and self-efficacy is essential for creating transfer pathways that are equitable in practice.

References

- Anderson, G. M., Barone, R. P., Sun, J. C., & Bowlby, N. (2015). The new stratification: Differentiating opportunity by race and class at community colleges in America. In A. M. Martinez Aleman, B. Pusser, & E. M. Bensimon (Eds.), *Critical approaches to the study of higher education: A practical introduction* (pp. 241-256). Johns Hopkins University Press.
- Aguilar-Smith, S. (2021). *Seeking to serve or \$erve? Hispanic-serving institutions' race-evasive pursuit of racialized funding*. *AERA Open*, 7(1), 1–15.
- Bahr, P. R. (2012). Deconstructing remediation in community colleges: Exploring associations between course-taking patterns, academic preparation, and socioeconomic status. *Educational Evaluation and Policy Analysis*, 34(4), 463–485.
<https://doi.org/10.3102/0162373712448951>
- Bahr, P. R. (2013). The labor of learning: Educational pathways and community college outcomes. *Educational Evaluation and Policy Analysis*, 35(4), 431–458.
<https://doi.org/10.3102/0162373713497929>
- Baldassare, M., Bonner, D., Lopes, L., & Dykman, A. (2018). *PPIC Statewide Survey: Californians and higher education, November 2018*. Public Policy Institute of California.
<https://www.ppic.org/publication/ppic-statewide-survey-californians-and-higher-education-november-2018/>
- Baum, S., & Kurose, C. (2013). *Community colleges in context: Exploring financing of two- and four-year institutions*. In The Century Foundation Task Force on Preventing Community

- Colleges from Becoming Separate and Unequal (Eds.), *Bridging the higher education divide: Strengthening community colleges and restoring the American dream* (pp. 73-108). The Century Foundation Press.
- Bonilla-Silva, E. (1997). *Rethinking racism: Toward a structural interpretation*. *American Sociological Review*, 62(3), 465–480.
- Breen, R., & Goldthorpe, J. H. (1997). Explaining educational differentials: Towards a formal rational action theory. *Rationality and Society*, 9(3), 275–305.
<https://doi.org/10.1177/104346397009003002>
- Brint, S., & Karabel, J. (1989). *The diverted dream: Community colleges and the promise of educational opportunity in America, 1900–1985*. Oxford University Press.
- Bush, M. (2025). *Vertical transfer for Black and Latinx community college students: The prevalence and perpetuation of color-evasive racism within advising and counseling departments*. University of Michigan.
- Casanova, S., & Alonso Blanco, V. J. (2025). “Transfers tend to be an afterthought”: The role of institutional support for staff in creating a receptive culture for transfer students of color. *Journal of Diversity in Higher Education*, 18(4), 557–569.
- California State Polytechnic University, Pomona Institutional Research and Planning. (n.d.). Fall term student characteristics [Data dashboard]. California State Polytechnic University, Pomona. Retrieved February 25, 2026, from <https://www.cpp.edu/data/dashboards/fall-term-characteristics.shtml>

California State University. (n.d.). *Latino communities*. In *Impact of the CSU*.

<https://www.calstate.edu/impact-of-the-csu/community/Pages/latino-communities.aspx>

California State University. (2025). *Hispanic-Serving Institutions (HSI) fact sheet*. California State University.

California State University, Fullerton Office of Institutional Effectiveness and Planning.

(n.d.). Headcount and FTES by college and student level. California State University, Fullerton. Retrieved February 25, 2026,

from <https://www.fullerton.edu/data/institutionalresearch/student/enrollments/headcounts-ftesbycollegeandstudentlevel.php>.

California State University, Long Beach Institutional Research & Analytics. (n.d.). Enrollment at a glance [Data dashboard]. California State University, Long Beach. Retrieved February 25, 2026, from <https://tableau.ir.csulb.edu/t/BeachPublic/views/EnrollmentAt-a-Glance/EnrollmentAtaGlance>.

California State University, Los Angeles Diversity, Equity, Inclusion, and Belonging.

(n.d.). Student demographics [Web page]. California State University, Los Angeles. Retrieved February 25, 2026, from <https://www.calstatela.edu/diversity/student-demographics>

Chin, L. G. (2024). How the Visibility of “Whiteness as a Credential” Creates Trade-offs for the Fit and Belonging of Minoritized Students at College. *Sociology of Race and Ethnicity*, 10(4), 472-488.

- Clark, B. R. (1960). The 'cooling-out' function in higher education. *American Journal of Sociology*, 65, 569-576.
- Cook, K. (2024a). *California's higher education system*.
<https://www.ppic.org/publication/californias-higher-education-system/>
- Cook, K. (2024b). *Higher education in California: Increasing equity and diversity*. Public Policy Institute of California. <https://www.ppic.org/publication/higher-education-in-california-increasing-equity-and-diversity/>
- Cook, K. (2025). *California's higher education system* (Fact sheet). Public Policy Institute of California.
- Corces-Zimmerman, C. (2018). *Normalizing whiteness on college campuses. Understanding & Dismantling Privilege*, 8(2), 90–108.
- Cuellar Mejia, M., & Johnson, H. (2025). *Improving transfer from community college to the California State University*. Public Policy Institute of California.
- DiPrete, T. A., & Eirich, G. M. (2006). Cumulative advantage as a mechanism for inequality: A review of theoretical and empirical developments. *Annual Review of Sociology*, 32, 271–297. <https://doi.org/10.1146/annurev.soc.32.061604.123127>
- Dougherty, K. J. (1987). The effects of community colleges: Aid or hindrance to socioeconomic attainment? *Sociology of Education*, 60(2), 86–103. <https://doi.org/10.2307/2112584>
- Dougherty, K. J. (1994). *The contradictory college: The conflicting origins, impacts, and futures of the community college*. SUNY Press.

Dougherty, K. J. (2001). *The contradictory college* (Updated edition). SUNY Press.

Dougherty, K. J., & Kienzl, G. S. (2006). It's not enough to get through the open door:

Inequalities by social background in transfer from community colleges to four-year colleges. *Teachers College Record*, 108(3), 452–487. <https://doi.org/10.1111/j.1467-9620.2006.00658.x>

Dowd, A. (2003). From access to outcome equity: Revitalizing the democratic mission of the community college. *The ANNALS of the American Academy of Political and Social Science*, 486, 92-119.

Excelencia in Education. (n.d.). *Seal of Excelencia: Certified institutions*.

Fink, J. (2017). *Visualizing the many routes community college students take to complete a bachelor's degree*. Community College Research Center, Teachers College, Columbia University.

Fink, J., Jenkins, D., & Yanagiura, T. (2018). *What happens to students who transfer?* Community College Research Center.

Graves, D. L. (2024). Financial Aid as Whiteness as Property: Implications for Research and Practice. *The Journal of Higher Education*, 96(6), 936-958.

Goldrick-Rab, S., & Kinsley, P. (2013). *School integration and the open door philosophy: Rethinking the economic and racial composition of community colleges*.

- Grote, D. M., Richardson, A. J., Lee, W. C., Knight, D. B., Hill, K., Glisson, H., & Watford, B. A. (2023). Lost in Translation: Information Asymmetry as a Barrier to Accrual of Transfer Student Capital. *Community College Review*, 52(1), 3-29.
- Harper, R., & Thiry, H. (2022). Advising from Community College to University: What It Takes for Underrepresented Transfer Students in STEM to Succeed. *Community College Journal of Research and Practice*, 47(9), 582–601.
- Higgins, A. S. (2023). *Higher Education for All: Racial Inequality, Cold War Liberalism, and the California Master Plan*. University of North Carolina Press.
- Hout, M. (2012). Social and economic returns to college education in the United States. *Annual Review of Sociology*, 38, 379–400. <https://doi.org/10.1146/annurev.soc.012809.102503>
- Hunter, T. E. (2024). *Empowering transitions: A phenomenological study of black transfer students from community colleges to California state universities*.
- Jain, D., Herrera, A., Bernal, S., & Solorzano, D. (2011). Critical race theory and the transfer function: Introducing a transfer receptive culture. *Community College Journal of Research and Practice*, 35(3), 252–266.
- Jenkins, D., & Fink, J. (2016). *Tracking transfer: New measures of institutional and state effectiveness in helping community college students attain bachelor's degrees*. Community College Research Center, Teachers College, Columbia University.
- Levine, P. B., & Ritter, D. (2023). *The racial wealth gap, financial aid, and college access*. National Bureau of Economic Research

- Lin, Y., Fay, M. P., & Fink, J. (2020). *Stratified trajectories: Charting equity gaps in program pathways among community college students* (CCRC Working Paper No. 126). Community College Research Center, Teachers College, Columbia University.
- Lovell, E. D. (2014). College Students Who are Parents Need Equitable Services for Retention. *Journal of College Student Retention: Research, Theory & Practice*, 16(2), 187-202. <https://doi.org/10.2190/CS.16.2.b>(Original work published 2014)
- Lucas, S. R. (2001). Effectively maintained inequality: Education transitions, track mobility, and social background effects. *American Journal of Sociology*, 106(6), 1642–1690. <https://doi.org/10.1086/321300>
- Martin, L. (2014). *The hidden curriculum exposed: How one outreach program bridges cultural capital and cultural wealth for Latina/o community college transfer students*.
- Master Plan Survey Team. (1960). A master plan for higher education in California: 1960-1975. Sacramento, CA: California State Department of Education. Retrieved December 3, 2022 from <http://www.ucop.edu/acadinit/mastplan/mp.htm>
- McCamby, H. N., Aguilar-Smith, S., Felix, E. R., Hu, X., & Baber, L. D. (2023). Community Colleges as Racialized Organizations: Outlining Opportunities for Equity. *Community College Review*, 51(4), 658-679.
- Meyer, J. W., & Rowan, B. (1977). Institutionalized organizations: Formal structure as myth and ceremony. *American Journal of Sociology*, 83(2), 340–363. <https://doi.org/10.1086/226550>

- Nguyen, M. H., Chan, J., Nguyen, B. M. D., & Teranishi, R. T. (2018). Beyond compositional diversity: Examining the campus climate experiences of Asian American and Pacific Islander students. *Journal of Diversity in Higher Education*, 11(3), 346–363.
- Perna, L. W., & Odle, T. K. (2020). Recognizing *the* Reality of Working College Students. *Academe*, 106(1), 18–22. <https://www.jstor.org/stable/26900051>
- Ray, V. (2019). *A theory of racialized organizations*. *American Sociological Review*, 84(1), 26–53. <https://www.jstor.org/stable/48588888>
- Ray, V., Herd, P., & Moynihan, D. (2023). *Racialized burdens: Applying racialized organization theory to the administrative state*. *Journal of Public Administration Research and Theory*, 33(1), 139–152.
- Reardon, S. F. (2011). The widening academic achievement gap between the rich and the poor. *Educational Leadership*, 70(8), 10–16.
- Schudde, L., Bradley, D., & Absher, C. (2019). Navigating Vertical Transfer Online: Access to and Usefulness of Transfer Information on Community College Websites. *Community College Review*, 48(1), 3-30. <https://doi.org/10.1177/0091552119874500> (Original work published 2020)
- Schudde, L., Jabbar, H., & Hartman, C. (2020). How Political and Ecological Contexts Shape Community College Transfer. *Sociology of Education*, 94(1), 65-83. <https://doi.org/10.1177/0038040720954817> (Original work published 2021)

- Scott-Clayton, J. (2011). *The shapeless river: Does a lack of structure inhibit students' progress at community colleges?* (CCRC Working Paper No. 25, Assessment of Evidence Series). Community College Research Center, Teachers College, Columbia University.
- Taylor, Z. W. (2017). Inarticulate Transfer: Do Community College Students Understand Articulation Agreements? *Community College Journal of Research and Practice*, 43(1), 65–69. <https://doi.org/10.1080/10668926.2017.1382400>
- Taylor, J. L., & Jain, D. (2017). The multiple dimensions of transfer: Examining the transfer function in American higher education. *Community College Review*, 45(4), 273–293. <https://doi.org/10.1177/0091552117725177>
- Teranishi, R. T., Lok, L., & Nguyen, B. M. D. (2013). *iCount: A data quality movement for Asian Americans and Pacific Islanders in higher education*. Educational Testing Service & College Board Advocacy & Policy Center.
- Tichenor, E., Kurzweil, M., & Logue, A. W. (2025). *Transfer credit problems are real*. Inside Higher Ed.
- Torche, F. (2011). Is a college degree still the great equalizer? *American Journal of Sociology*, 117(3), 763–807. <https://doi.org/10.1086/661904>
- University Effectiveness, Planning, and Analytics, California State University, Dominguez Hills. (n.d.). Fall enrollment. California State University, Dominguez Hills. Retrieved February 25, 2026, from <https://www.csudh.edu/uepa/student-data/fall-enrollment>.

University of California, Irvine Institutional Research, Assessment and Planning. (n.d.). Student enrollment [Data dashboard]. University of California, Irvine. Retrieved February 25, 2026, from <https://irap.uci.edu/student-enrollment-1/>

University of California, Los Angeles. (n.d.). Facts and figures [Web page]. University of California, Los Angeles. Retrieved February 25, 2026, from <https://www.ucla.edu/about/facts-and-figures>

U.S. Government Accountability Office. (2017). *Higher education: Students need more information to help reduce challenges in transferring college credits* (GAO-17-574).

Wickersham, K. R. (2020). *Where to go from here? Toward a model of 2-year college students' postsecondary pathway selection*. *Community College Review*, 48(2), 107–132.

Yosso, T. J. (2005). *Whose culture has capital? A critical race theory discussion of community cultural wealth*. *Race Ethnicity and Education*, 8(1), 69–91.

Tables and Figures

Table 1. Sample demographics

	Percent (%)
<i>Gender</i>	
Man	43.8
Woman	56.2
<i>Race</i>	
White	33.1
Latinx	29.2
Asian	26.1
Black	1.8
American Indian/Alaska Native	0.1
Native Hawaiian/Pacific Islander	0.1
Multi-racial	9.5
<i>Parent education</i>	
Less than high school	11.4
High school	14.4
Some college	15.4
Associate degree	8.3
Bachelor degree	28.8
Graduate degree	21.8
Observations	1411

Notes: Values are percentages.

Table 2. Communication networks

	Full sample	Race			First-gen	College Generation			Race (p)	First-gen (p)	Race x first-gen (p)
		White	Asian	Latinx		White first-gen	Asian first-gen	Latinx first-gen			
Panel A. Transfer talk											
CC faculty	1.42	1.44	1.45	1.34	1.40	1.41	1.52	1.33	0.89	0.80	0.69
CC staff	1.27	1.29	1.26	1.20	1.27	1.27	1.37	1.20	0.59	0.78	0.53
CC counselor	1.87	1.77	2.09	1.82	1.84	1.76	2.04	1.79	0.02	0.87	0.89
Family	2.65	2.70	2.75	2.52	2.46	2.52	2.30	2.45	0.08	0.06	0.07
Friends	2.26	2.20	2.57	2.14	2.15	2.16	2.33	2.09	0.00	0.72	0.37
Peer/classmate	2.00	1.91	2.35	1.82	1.83	1.77	2.08	1.76	0.01	0.16	0.60
Panel B. Information seeking online											
CC website	2.40	2.34	2.59	2.24	2.41	2.47	2.64	2.28	0.01	0.19	0.81
4yr website	2.23	2.18	2.46	1.99	2.15	2.29	2.31	1.98	0.00	0.23	0.15
Assist.org	1.81	1.70	2.41	1.42	1.63	1.61	2.23	1.41	0.00	0.43	0.58
Other	0.28	0.30	0.33	0.21	0.23	0.25	0.32	0.18	0.97	0.43	0.78
Panel C. Terminology familiarity											
Lower division	0.39	0.40	0.44	0.33	0.34	0.34	0.39	0.33	0.09	0.04	0.44
Upper division	0.32	0.37	0.33	0.25	0.28	0.33	0.30	0.24	0.20	0.20	0.97
IGETC	0.40	0.39	0.51	0.33	0.34	0.35	0.40	0.33	0.00	0.20	0.08
TAG	0.47	0.48	0.62	0.34	0.39	0.43	0.55	0.30	0.00	0.12	0.47
ADT	0.47	0.48	0.42	0.48	0.47	0.50	0.40	0.48	0.86	0.48	0.57
Impacted									0.05	0.50	0.98
Major	0.32	0.32	0.40	0.26	0.29	0.30	0.37	0.25			
Observations	1411	456	359	403	698	157	138	308			

Notes: Panels (a) and (b): values are Likert scores where 0 is “I have not” and 4 is “more than 5 times.” Panel (c) Values are proportions of students who reported they could explain this term to a friend.

Table 3. Confidence and expectations

	Full sample	Race			College generation						
		White	Asian	Latinx	First-gen	White first-gen	Asian first-gen	Latinx first-gen	Race (p)	First-gen (p)	Race x first-gen (p)
Panel A. Self efficacy											
Who to ask in college	3.26	3.28	3.26	3.23	3.26	3.29	3.28	3.20	0.72	0.84	0.50
Know req. after counselor	3.24	3.23	3.26	3.23	3.23	3.23	3.22	3.22	0.76	0.99	0.88
Where to find info online	3.24	3.23	3.21	3.22	3.24	3.26	3.15	3.20	0.73	0.58	0.49
Know req. after online search	3.26	3.26	3.25	3.22	3.23	3.27	3.12	3.19	0.65	0.91	0.25
Panel B. Expected four-year experiences											
Class will be a lot of work	2.81	2.87	2.87	2.70	2.75	2.88	2.75	2.69	0.30	0.90	0.33
Difficult to get help from prof.	1.68	1.68	1.83	1.55	1.60	1.61	1.62	1.57	0.00	0.26	0.04
Find enrollment info on school's website	2.85	2.87	2.83	2.87	2.87	2.93	2.83	2.87	0.88	0.26	0.63
Tech support is available	2.89	2.92	2.78	2.93	2.90	2.90	2.76	2.93	0.21	0.77	0.98
Classes will be interesting	3.07	3.13	2.96	3.13	3.07	3.11	2.89	3.12	0.15	0.75	0.82
Will have learning support resources	3.05	3.08	2.99	3.05	3.04	3.09	2.95	3.03	0.61	0.82	0.82
Feel comfortable taking classes	3.04	3.14	2.90	3.07	3.01	3.12	2.77	3.04	0.08	0.74	0.52
Will make friends	2.74	2.81	2.74	2.68	2.63	2.75	2.54	2.60	0.75	0.35	0.30
Know how to transfer CC credits	2.40	2.52	2.42	2.25	2.27	2.41	2.26	2.18	0.75	0.15	0.74
Observations	1339	432	341	384	666	151	129	294			

Notes: Panel A: Values are Likert scores where 0 is “I cannot do this” and 4 is “I can do this.” Panel B: Values are Likert scores where 0 is “Almost never true” and 4 is “Almost always true.”

Table 4. Aspirations

		Race			College generation						
	Full sample	White	Asian	Latinx	First-gen	White first-gen	Asian first-gen	Latinx first-gen	Race (p)	First-gen (p)	Race x first-gen (p)
Panel A. Application intentions											
Apply to transfer in next 5 yrs	80.20	79.35	83.12	78.12	78.23	77.33	79.91	78.22	0.11	0.32	0.49
Apply to transfer to CSU	68.31	65.51	65.27	74.17	71.22	67.67	68.87	74.92	0.13	0.36	0.88
Apply to transfer to UC	63.48	60.29	73.36	58.59	58.94	54.32	68.30	57.37	0.00	0.01	0.77
Apply to transfer to private	35.53	36.62	35.66	30.80	32.13	28.67	32.50	29.36	0.38	0.00	0.36
Panel B. Perceived admission likelihood											
Admitted to CSU	74.00	75.33	73.86	72.00	71.66	74.33	70.91	70.45	0.92	0.58	0.53
Admitted to UC	61.03	62.33	63.32	56.53	56.55	58.61	58.51	53.90	0.77	0.06	0.50
Admitted to private	53.33	56.70	50.16	50.66	50.07	51.45	47.80	48.89	0.05	0.03	0.71
Observations	1336	432	337	384	664	150	129	293			

Notes: Values are self-reported probability of application from 0-10

Table 5. Application intentions

	(1) Race	(2) Race + Firstgen	(3) Race x Firstgen	(4) Race x Firstgen + GPA
Panel A. Apply to CSU				
Asian	-0.0887 (2.624)	-0.252 (2.623)	-1.120 (3.309)	-0.636 (3.304)
Latinx	8.890*** (2.524)	7.214*** (2.690)	7.458* (4.303)	6.842 (4.314)
First-gen		4.087* (2.284)	3.316 (3.645)	3.036 (3.639)
Asian*First-gen			2.315 (5.437)	2.515 (5.429)
Latinx*First-gen			0.0947 (5.621)	-1.346 (5.642)
GPA				-6.271*** (2.123)
Panel B. Apply to UC				
Asian	13.38*** (2.679)	13.61*** (2.667)	13.44*** (3.357)	12.75*** (3.354)
Latinx	-1.581 (2.611)	1.679 (2.774)	-0.934 (4.494)	-0.824 (4.500)
First-gen		-7.896*** (2.345)	-9.205** (3.716)	-8.877** (3.705)
Asian*First-gen			0.540 (5.536)	1.592 (5.526)
Latinx*First-gen			4.125 (5.821)	5.978 (5.837)
GPA				7.289*** (2.174)
N	1123	1123	1123	1116

Notes: The outcome is a continuous score ranging from 0 to 100. White is the omitted racial category. Continuing-generation college students are the omitted category for parental education status. Standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6. Perception of admission

	(1) Race	(2) Race + Firstgen	(3) Race x Firstgen	(4) Race x Firstgen + GPA
Panel A. Admitted to CSU				
Asian	-1.607 (2.043)	-1.451 (2.040)	-0.334 (2.580)	-0.916 (2.523)
Latinx	-2.984 (1.937)	-1.382 (2.066)	1.192 (3.311)	2.004 (3.251)
First-gen		-3.882** (1.765)	-1.550 (2.825)	-1.046 (2.761)
Asian*First-gen			-3.089 (4.220)	-2.782 (4.122)
Latinx*First-gen			-4.625 (4.318)	-1.823 (4.251)
GPA				11.87*** (1.611)
Panel B. Admitted to UC				
Asian	0.947 (2.199)	1.179 (2.184)	1.832 (2.728)	0.655 (2.656)
Latinx	-5.497** (2.161)	-2.126 (2.301)	1.310 (3.750)	1.973 (3.661)
First-gen		-7.839*** (1.939)	-5.661* (3.096)	-5.100* (3.007)
Asian*First-gen			-1.927 (4.554)	-0.881 (4.423)
Latinx*First-gen			-5.655 (4.850)	-2.316 (4.741)
GPA				13.81*** (1.732)
N	1038	1038	1038	1032

Notes: The outcome is a continuous score ranging from 0 to 100. White is the omitted racial category. Continuing-generation college students are the omitted category for parental education status. Standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix A

Table A1. Enrollment by ethnicity across partner community colleges

<i>A. Campus 1</i>	n	%
American Indian/Alaska Native	27	0.2
Asian	6058	35.1
Black	326	1.9
Filipino	491	2.8
Latinx	3453	20.0
Pacific Islander	32	0.2
Multiracial	782	4.5
White	5470	31.7
Unknown	615	3.6
	17254	100

<i>B. Campus 2</i>	n	%
American Indian/Alaska Native	53	0.2
Asian	5236	23.2
Black	427	1.9
Filipino	409	1.8
Latinx	8038	35.7
Pacific Islander	64	0.3
Multiracial	1159	5.1
White	6542	29.0
Unknown	604	2.7
	22532	100

<i>C. Campus 3</i>	n	%
American Indian/Alaska Native	82	0.3
Asian	4061	12.6
Black	646	2.0
Filipino	726	2.2
Latinx	8550	26.5
Pacific Islander	60	0.2
Multiracial	1511	4.7
White	15102	46.8
Unknown	1532	4.7
	32270	100

Note: Enrollment by ethnicity 2022-23. Sourced from California Community Colleges Chancellor's Office.

Table A2. Sample of survey questions

Category	Statement examples
Communication	In the past year, how often have you talked about transfer with CC faculty? In the past year, how often have you talked about transfer with CC staff? In the past year, how often have you talked about transfer with family?
Information-seeking online	In the past year, how often have you looked online at the course requirement transferring on your community college website? In the past year, how often have you looked online at the course requirement transferring on the website of the four-year university you wish to transfer to?
Ability to understand transfer	Please rate how certain you are about your ability to figure out what the requirements are to transfer to a four-year university after talking to a counselor.
Applying to transfer	How likely are you to apply to transfer to a four-year university in the next 5 years?
Terminology	Please check which terms you are confident in defining or explaining to a peer or friend: - Associate Degree for Transfer (ADT) - Impacted Major - Lower-division
Beliefs about four-year experience	Please rate how true you think each of these statements are: - classes at a four-year university will be a lot of work - there will be learning support resources available

Section 1. Analytical sample

We received survey responses from 2,084 students across three community colleges. Of these, 20 students could not be matched to administrative records. An additional 314 students were filtered out based on a survey question indicating that they had already transferred or were currently four-year students taking courses at a community college. Because our research questions examine racialized structures, we retained only students with complete demographic information. As such, 339 students were missing key demographic variables, either race or parental education. After applying these exclusions, the final dataset includes 1,411 students.

Appendix B

Section 1. Demographic Composition of Nearby CSU and UC Campuses

The community colleges in this study serve as primary transfer pipelines to nearby CSU and UC campuses, whose racial compositions differ in meaningful ways. Among the surrounding CSU campuses, Latinx students represent the largest share of enrollment, though proportions vary by institution. At CSU Dominguez Hills, 66.7% of students identify as Latinx, followed by 13.1% Black, 7.8% Asian, and 5% White; 43% of students are first generation (University Effectiveness, Planning, and Analytics, California State University, Dominguez Hills, n.d.). At CSU Long Beach, 52% of students are Latinx, followed by 18.6% Asian and 14.7% White, and 30% are first generation (California State University, Long Beach Institutional Research & Analytics, n.d.). Similarly, 56% of students at CSU Fullerton are Latinx, followed by 19% Asian and 13% White; 32% are first generation (California State University, Fullerton Office of Institutional Effectiveness and Planning, n.d.). At Cal Poly Pomona, 55% of students are Latinx, 21% are Asian, and 13% are White, and 55% are first generation (California State Polytechnic University, Pomona Institutional Research and Planning, n.d.). At Cal State Los Angeles, 76% of students are Latinx, followed by 10% Asian and 5% White; 55% of students are first generation (California State University, Los Angeles Diversity, Equity, Inclusion, and Belonging, n.d.). In contrast, nearby UC campuses enroll comparatively higher proportions of Asian and White students and lower proportions of Latinx students. At UC Irvine, 38% of students are Asian, 25% Latinx, and 13% White; 36% are first generation (University of California, Irvine Institutional Research, Assessment and Planning, n.d.). At UCLA, 35.1% of students are Asian, 25% White, and 22% Latinx; 29% are first generation (University of California, Los Angeles, n.d.). These sectoral differences reflect the stratified structure of California's higher education system and provide important context for understanding how students form transfer intentions within a tiered institutional landscape.

Appendix C: Distribution of Self-Reported Likelihood

Figure 1. Applying to transfer to a CSU

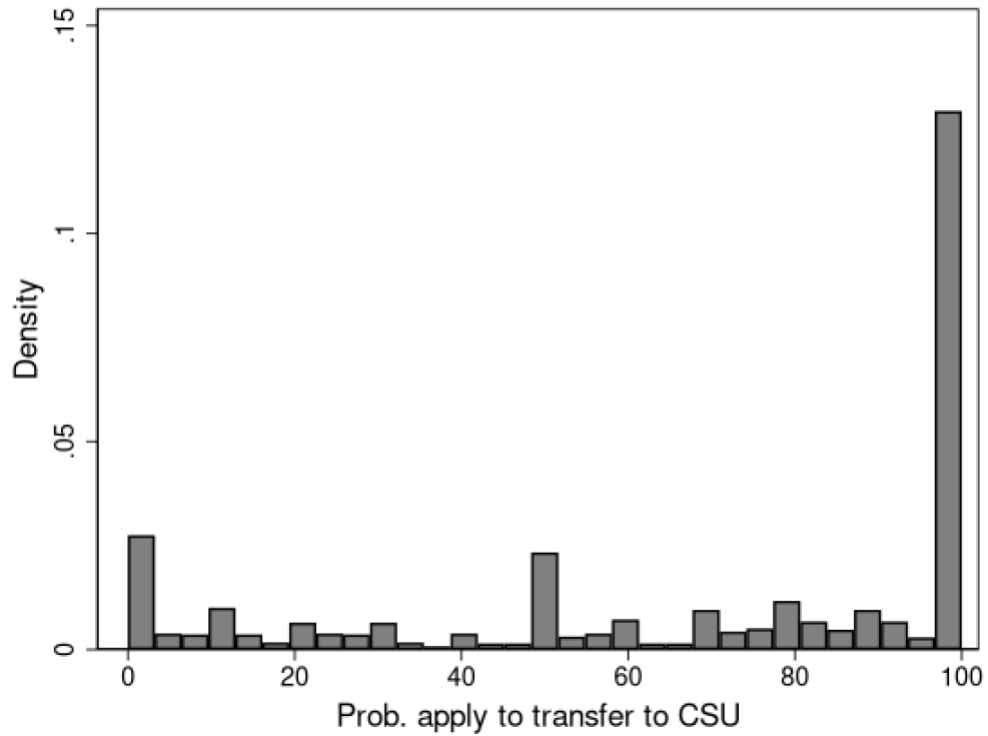


Figure 2. Applying to transfer to a UC

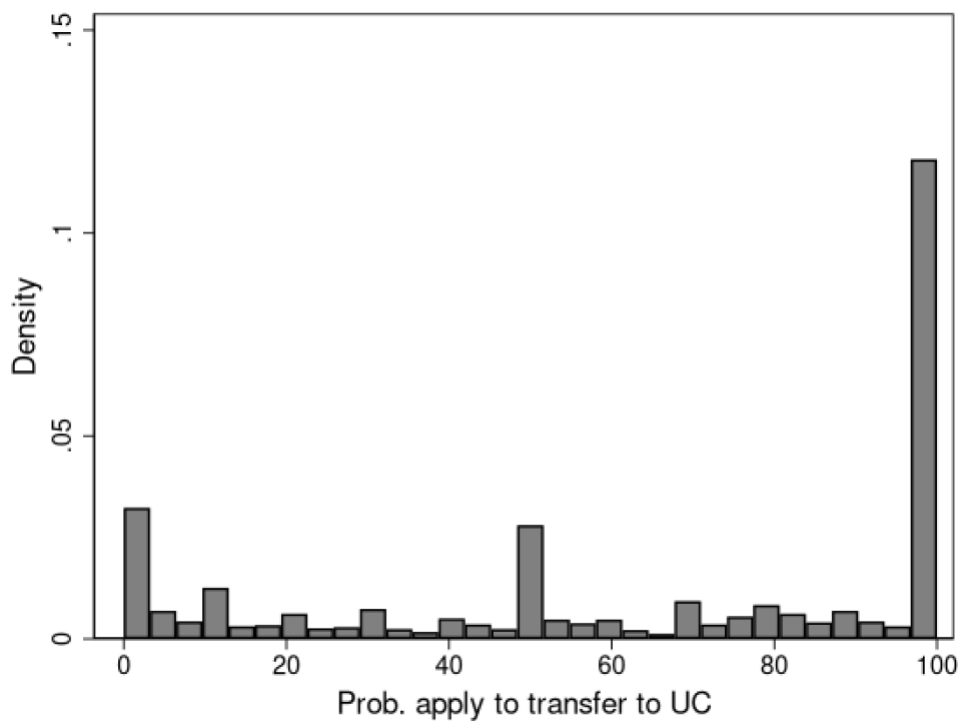


Figure 3. Admitted to a CSU

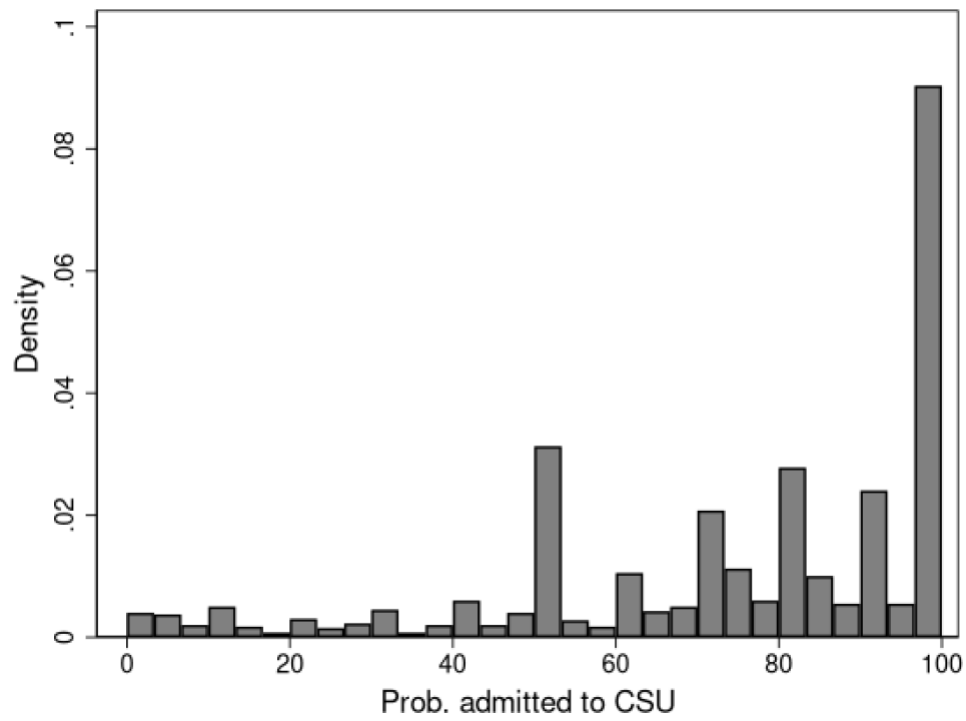
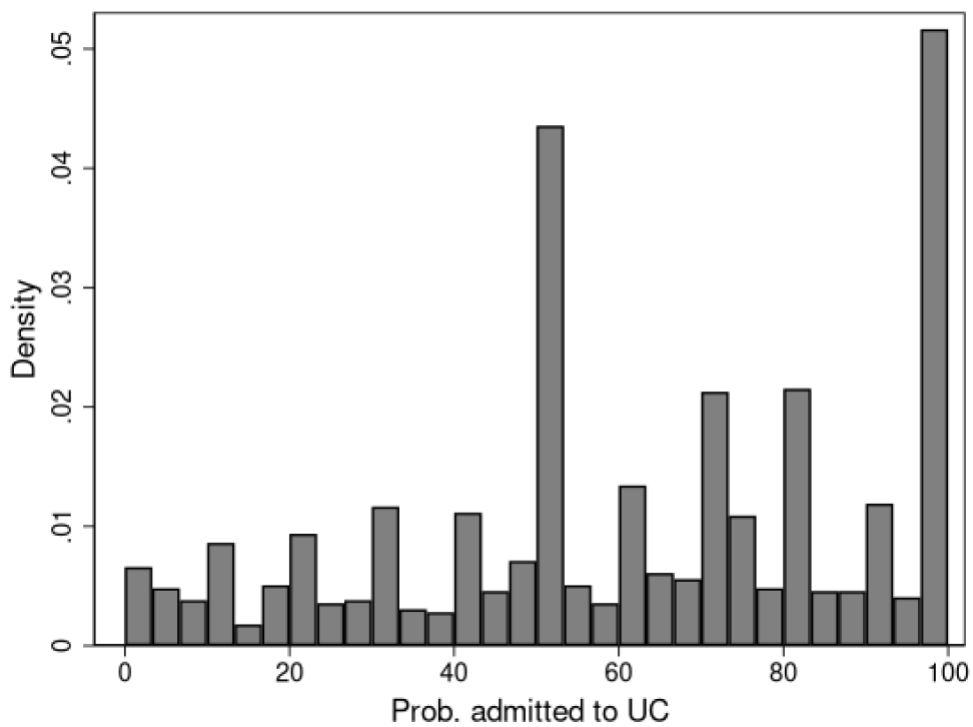


Figure 4. Admitted to a UC



Appendix D. Conditional results

	Full sample	Race			First-gen	College generation			Race (p)	First-gen (p)	Race x first-gen (p)
		White	Asian	Latinx		White first-gen	Asian first-gen	Latinx first-gen			
Panel A. Application intentions											
Apply to CSU	74.57	75.53	74.48	72.75	72.33	74.33	71.52	71.15	0.85	0.50	0.49
Apply to UC	61.58	62.49	64.09	57.52	57.21	59.06	59.02	54.90	0.55	0.08	0.42
Panel B. Perceived admission likelihood											
Admitted to CSU	72.89	70.56	71.31	76.22	74.69	72.65	74.75	76.56	0.31	0.35	0.74
Admitted to UC	68.93	66.39	77.83	63.34	64.04	61.31	73.46	61.43	0.00	0.03	0.97
Observations	1283	416	324	369	640	147	123	281			

Notes: Values are self-reported probability of application. Restricts sample to non-zero probabilities.

Appendix E. Alternative measures of first-generation status

Section 1. Summary

We estimate additional models using alternative definitions of first-generation status based to assess the robustness of our results. While the main analyses define first-generation status students whose parents have less than a bachelor's degree, in this appendix we examine application intentions and perceived admission likelihood for both CSU and UC using more restrictive thresholds: parental education of an associate's degree or less and high school or less.

For CSU application intentions and perceived admission likelihood, findings are stable across all specifications. There are no statistically significant differences by race, first-generation status, or their interaction, regardless of whether first-generation status is defined as lacking a parental bachelor's degree, associate's degree, or high school diploma. This suggests that both aspirations and perceived access to CSU are broadly uniform across student groups and not sensitive to how first-generation status is operationalized. In contrast, results for UC outcomes reveal more nuanced patterns. For application intentions, Asian students consistently report higher likelihoods of applying to UC, with the magnitude of this difference increasing under more restrictive definitions of first-generation status. However, the negative coefficient for first-generation status observed under the baseline definition (parental BA or higher) attenuates and becomes statistically insignificant under stricter definitions.

For perceived admission likelihood to UC, a different pattern emerges. First-generation status is consistently associated with lower perceived probabilities of admission across specifications and remains statistically significant under both the baseline and most restrictive definitions. This suggests that disparities in perceived access to selective institutions persist even when focusing on students from the most educationally disadvantaged family backgrounds.

Table 1A. Associates degree or less: application intentions

	(1) Race	(2) Race + Firstgen	(3) Race x Firstgen	(4) Race x Firstgen + GPA
Panel A. Apply to CSU				
Asian	-0.0887 (2.624)	-0.466 (2.629)	-2.535 (3.128)	-2.037 (3.122)
Latinx	8.890*** (2.524)	7.023*** (2.716)	7.816** (3.798)	7.000* (3.807)
First-gen		4.309* (2.329)	2.103 (4.030)	1.935 (4.020)
Asian*First-gen			6.786 (5.797)	7.011 (5.790)
Latinx*First-gen			0.239 (5.622)	-1.153 (5.634)
GPA				-6.307*** (2.117)
Panel B. Apply to UC				
Asian	13.38*** (2.679)	13.86*** (2.678)	14.23*** (3.185)	13.52*** (3.182)
Latinx	-1.581 (2.611)	1.117 (2.803)	-0.194 (3.958)	0.347 (3.965)
First-gen		-6.232*** (2.395)	-6.645 (4.106)	-6.413 (4.090)
Asian*First-gen			-1.055 (5.914)	0.191 (5.902)
Latinx*First-gen			2.182 (5.799)	3.736 (5.805)
GPA				7.442*** (2.174)
N	1129	1129	1129	1121

Notes: The outcome is a continuous score ranging from 0 to 100. White is the omitted racial category. Continuing-generation college students are the omitted category for parental education status. Standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1B. Associates degree or less: perception of admission

	(1) Race	(2) Race + Firstgen	(3) Race x Firstgen	(4) Race x Firstgen + GPA
Panel A. Admitted to CSU				
Asian	-1.607 (2.043)	-1.284 (2.047)	-0.378 (2.445)	-0.905 (2.389)
Latinx	-2.984 (1.937)	-1.489 (2.088)	0.251 (2.917)	1.711 (2.864)
First-gen		-3.417* (1.795)	-0.866 (3.131)	-0.261 (3.059)
Asian*First-gen			-3.362 (4.499)	-3.284 (4.392)
Latinx*First-gen			-4.175 (4.325)	-2.047 (4.244)
GPA				11.94*** (1.608)
Panel B. Admitted to UC				
Asian	0.947 (2.199)	1.418 (2.194)	1.692 (2.594)	0.649 (2.522)
Latinx	-5.497** (2.161)	-2.653 (2.321)	-1.014 (3.275)	0.665 (3.198)
First-gen		-6.447*** (1.977)	-4.894 (3.426)	-3.899 (3.325)
Asian*First-gen			-1.216 (4.881)	-0.620 (4.735)
Latinx*First-gen			-3.386 (4.813)	-1.322 (4.687)
GPA				14.00*** (1.733)
N	1028	1028	1028	1021

Notes: The outcome is a continuous score ranging from 0 to 100. White is the omitted racial category. Continuing-generation college students are the omitted category for parental education status. Standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2A. High school or less: application intentions

	(1) Race	(2) Race + Firstgen	(3) Race x Firstgen	(4) Race x Firstgen + GPA
Panel A. Apply to CSU				
Asian	-0.0887 (2.624)	-0.520 (2.639)	-2.152 (2.900)	-1.699 (2.894)
Latinx	8.890** (2.524)	7.468** (2.709)	7.498** (3.175)	6.357** (3.197)
First-gen		3.680 (2.553)	-0.767 (5.502)	-0.367 (5.485)
Asian*First-gen			9.389 (7.220)	9.676 (7.214)
Latinx*First-gen			3.385 (6.609)	1.613 (6.620)
GPA				-6.435*** (2.111)
Panel B. Apply to UC				
Asian	13.38*** (2.679)	14.08*** (2.689)	16.14*** (2.947)	15.51*** (2.943)
Latinx	-1.581 (2.611)	0.892 (2.796)	1.840 (3.285)	2.940 (3.306)
First-gen		-6.417** (2.634)	1.252 (5.606)	0.913 (5.583)
Asian*First-gen			-13.02* (7.375)	-11.33 (7.364)
Latinx*First-gen			-7.828 (6.777)	-6.373 (6.781)
GPA				7.405*** (2.166)
N	1129	1129	1129	1121

Notes: The outcome is a continuous score ranging from 0 to 100. White is the omitted racial category. Continuing-generation college students are the omitted category for parental education status. Standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2B. High school or less: perception of admission

	(1) Race	(2) Race + Firstgen	(3) Race x Firstgen	(4) Race x Firstgen + GPA
Panel A. Admitted to CSU				
Asian	-1.607 (2.043)	-1.054 (2.051)	-1.972 (2.259)	-2.565 (2.207)
Latinx	-2.984 (1.937)	-1.117 (2.082)	0.260 (2.446)	2.349 (2.412)
First-gen		-4.705** (1.950)	-4.308 (4.216)	-5.286 (4.118)
Asian*First-gen			3.739 (5.555)	4.879 (5.424)
Latinx*First-gen			-2.994 (5.045)	-0.150 (4.953)
GPA				11.88*** (1.602)
Panel B. Admitted to UC				
Asian	0.947 (2.199)	1.496 (2.201)	0.892 (2.410)	-0.0587 (2.338)
Latinx	-5.497** (2.161)	-3.179 (2.311)	-3.360 (2.730)	-0.800 (2.673)
First-gen		-6.011*** (2.168)	-8.037* (4.565)	-8.118* (4.418)
Asian*First-gen			3.758 (6.057)	4.543 (5.864)
Latinx*First-gen			1.908 (5.541)	4.044 (5.384)
GPA				14.25*** (1.727)
N	1028	1028	1028	1021

Notes: The outcome is a continuous score ranging from 0 to 100. White is the omitted racial category. Continuing-generation college students are the omitted category for parental education status. Standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

STUDY 2

Flexibility at a Cost?

Asynchronous Learning as a Labor Market-Education Tradeoff

Abstract

Community colleges increasingly serve students who must balance college with work, caregiving, and other responsibilities. This study reframes instructional modality as a labor-education tradeoff rather than simply a mode of course delivery. We examine how flexible course formats help students manage competing demands and what academic tradeoffs may accompany that flexibility. Using course enrollment data from the Virginia Community College System from 2015 to 2023, we analyze which students enroll in asynchronous courses and how online course modality (i.e., asynchronous versus synchronous) relates to academic outcomes. Results show that asynchronous enrollment is more common among students facing greater time and financial constraints, including older students, women, Pell-eligible students, and employed students. However, leveraging within-student, within-term variation across courses taken in different instructional formats, we find that asynchronous instruction is linked to lower academic performance, while synchronous online courses perform much more similarly to face-to-face courses. Additional analyses suggest that students may use asynchronous coursework to accommodate labor market participation and other responsibilities—even when this flexibility comes with academic costs. This study highlights how community college students actively negotiate competing demands between education and labor-market participation through their enrollment choices.

Introduction

The college student population has changed substantially over time. In particular, community colleges now serve a large and growing share of students who are balancing academic participation with employment, caregiving, and other responsibilities. These students, often described as “nontraditional,” are no longer a marginal group but a central part of contemporary college enrollment.

A large body of evidence shows that employment during college is widespread, and for many students, it is necessary rather than optional. Perna (2010) documents that nearly half of full-time students and approximately 80 percent of part-time students work while enrolled. Woods and Frogge (2017) find that non-traditional students work significantly more hours than traditional students, often exceeding 30 hours per week. Students work for a variety of reasons, including financial necessity, career development, and identity formation. However, the implications of work for academic participation are similar: students must allocate time across competing demands. These constraints are particularly salient in community colleges, where students are more likely to be older, financially independent, and responsible for supporting themselves or their families (Bound et al., 2010). While students make enrollment and work decisions, such as attending part-time or working long hours, these strategies often increase time-to-degree and reduce the likelihood of completion (King, 2002). Many students face constraints on their time and financial resources. In turn, these constraints shape how they are able to participate in higher education.

The expansion of online education can be understood, in part, as a response to student constraints. Over the past two decades, colleges and universities had increasingly adopted online

instructional formats to accommodate a changing student population, particularly within community colleges (Johnson & Cuellar Mejia, 2014). Many students enrolled in these institutions face barriers to traditional face-to-face attendance, including rigid work schedules, caregiving responsibilities, and geographic limitations. For these students, online courses provide a level of flexibility that allows them to participate in higher education in ways that would otherwise be infeasible (Hrastinski, 2008; Watts, 2016; Xu & Xu, 2019). The COVID-19 pandemic accelerated this trend dramatically. In spring 2020, institutions across the United States rapidly transitioned to remote instruction, making online learning a central modality across higher education (Bird et al., 2022). This shift led to widespread adoption of digital platforms, increased instructor familiarity with online pedagogy, and greater student exposure to virtual learning environments (Hart et al., 2025). At the same time, the rapid expansion of online instruction exposed important disparities in access to technology, variation in course design quality, and differences in student engagement (Tate & Warschauer, 2022). Even as campuses reopened, online instruction endured as an important component of course offerings, reflecting sustained student demand for flexible learning options (Weissman, 2023).

Within the broader category of online learning, asynchronous instruction represents the most flexible format. Unlike face-to-face or synchronous online courses, which require students to attend scheduled class sessions, asynchronous courses allow students to engage with course material on their own time. This flexibility may be particularly valuable for students balancing employment, family responsibilities, and other obligations. In principle, asynchronous formats can reduce scheduling conflicts and enable students to remain enrolled even when their availability is constrained. However, this flexibility comes with important tradeoffs. Compared to face-to-face and synchronous instruction, asynchronous courses typically provide less

structure, fewer opportunities for real-time interaction, and greater reliance on students' ability to manage their own learning. As a result, asynchronous learning environments may place greater demands on self-regulation, time management, and access to support. These differences raise a fundamental question: does the flexibility offered by asynchronous instruction improve students' ability to participate in higher education, or does it come at the cost of reduced academic performance?

Existing research provides mixed evidence. A large empirical literature finds that online courses, on average, are associated with lower grades, lower completion rates, and reduced persistence relative to face-to-face instruction (Hart et al., 2018; Xu & Xu, 2019; Altindag et al., 2024). More recent work suggests that modality differences within online learning are also important. Synchronous courses, which retain structured schedules and real-time interaction, tend to produce outcomes more similar to face-to-face instruction, while asynchronous courses are often associated with larger performance gaps (Hart et al., 2026). At the same time, other research suggests that online learning may support longer-term outcomes, such as persistence and degree completion, particularly for students facing time and location constraints (Johnson & Cuellar Mejia, 2014; Ortagus, 2018). However, much of the existing literature focuses on average differences in outcomes across modalities, without fully considering the role of student constraints in shaping both modality choice and outcomes.

This paper reframes asynchronous instruction as a form of scheduling flexibility and examines how students use this flexibility in the presence of labor market and time constraints. Rather than asking only whether asynchronous courses produce lower academic outcomes, the analysis asks who enrolls in these courses, whether the academic costs differ across student

groups, and whether asynchronous enrollment is associated with outcomes such as employment and course load. In this framework, students allocate time across work, school, and other responsibilities, and instructional modality affects the feasibility of this allocation by relaxing or imposing scheduling constraints. However, greater flexibility may also reduce the structure and support available to students, creating a tradeoff between access and academic performance. In the following section, we review literature on time use and labor supply to illustrate how these constraints shape students' allocation of time and engagement with academic work and to situate the present study within existing empirical work on instructional modality and student outcomes.

Background

Community Colleges and Time-Constrained Students

Unlike traditional college populations, community college students are disproportionately likely to work while enrolled, attend part-time, and balance multiple competing responsibilities. These patterns reflect broader structural changes in both higher education and the labor market. Over time, increases in college enrollment have been concentrated in community colleges and less selective public institutions, which tend to operate with fewer resources per student (Bound, Lovenheim, & Turner, 2010). These institutions enroll a larger share of students from economically disadvantaged backgrounds, many of whom must work while attending school. Bound et al. (2010) argue that this shift in where students enroll has contributed to declining completion rates, in part because these students face greater difficulty balancing academic and employment demands within resource-constrained institutional settings.

Financial considerations play a central role in shaping student behavior. King (2002) shows that a majority of undergraduates work while enrolled, and many attend part-time in order

to manage the cost of college. These decisions are often driven by necessity rather than preference, as students seek to reduce borrowing, support themselves or their families, and accommodate other responsibilities. However, these strategies have important academic consequences. Working long hours and enrolling part-time are associated with longer time-to-degree and increased likelihood of non-completion, suggesting that financial constraints translate directly into differences in educational attainment. More recent work reinforces the idea that employment during college reflects broader financial pressures rather than purely individual choice. Student labor supply has increased over time, driven by rising tuition costs, limited financial aid, and changing student demographics (Scott-Clayton, 2012). Goldrick-Rab (2016) characterizes college affordability as a structural problem, arguing that financial aid systems are often insufficient to cover students' total cost of attendance, including living expenses. As a result, students frequently rely on employment to fill the gap, even when doing so may interfere with their academic progress. Indeed, Park and Scott-Clayton (2018) show that increases in financial aid reduce student labor supply and support full-time enrollment. However, the effects of student employment depend in part on the type and structure of work. Scott-Clayton (2011) and Scott-Clayton and Minaya (2016) find that participation in structured, campus-based employment programs such as federal work-study can improve persistence and degree completion, particularly relative to students engaged in unstructured or high-intensity off-campus work. These findings suggest that not all employment is equal, and that the relationship between work and academic outcomes depends on how employment is integrated with students' educational experiences.

Qualitative and descriptive evidence provides additional insight into how these constraints are experienced by students. Steinhauer and Lovell (2021) find that time constraints

are consistently identified as the primary barrier to academic success among nontraditional community college students. Many students report working full-time while enrolled, limiting the time available for studying and participation in coursework. These students often rely on off-campus support systems, such as family members or employers, and report lower levels of engagement with campus life. Similarly, Perna (2010) emphasizes that working students must juggle multiple roles which creates ongoing time conflicts and emotional strain.

Despite these challenges, students actively adapt to their circumstances. Woods and Frogge (2017) show that non-traditional students often work more hours while also devoting substantial time to studying, suggesting that they attempt to compensate for constraints through increased effort and time management. However, these adaptations do not eliminate the underlying trade-offs. Students continue to make enrollment decisions such as reducing course loads or selecting particular course formats in response to the constraints they face.

Ultimately, community college students operate under binding financial and time constraints. These constraints create demand for flexibility in instructional delivery, as students look for ways to integrate academic participation with work and other obligations. If students are constrained primarily by time and scheduling conflicts, then instructional formats that relax these constraints may enable continued enrollment. Simultaneously, if these formats alter the structure and support of the learning environment, they may also affect academic performance. The next section builds on this framework by examining how time constraints and labor supply shape students' allocation of time and engagement with academic work.

Time Poverty and Labor-Education Tradeoffs

The constraints faced by community college students are not limited to financial resources; they also reflect fundamental limitations on time. Understanding how students allocate time across competing demands is essential for interpreting both their academic behavior and the potential role of flexible instructional formats. In this context, the concept of “time poverty” provides a useful framework for analyzing the tradeoffs students face.

Vickery (1977) argues that poverty should be understood not only in terms of income but also in terms of time availability. Households differ in the amount of time they can allocate to paid and unpaid activities, and those with fewer available hours face greater constraints in meeting both economic and household needs. For students, particularly those in community colleges, these constraints are often severe. Many students must simultaneously manage employment, coursework, commuting, and caregiving responsibilities, leaving limited time for sustained academic engagement. Furthermore, labor markets often reward long, continuous, and inflexible work hours, with nonlinear returns to time that disproportionately benefit workers who can meet rigid scheduling demands (Goldin, 2014). Individuals who require flexibility are often limited in their access to these opportunities. Household structure further intensifies these constraints. Parents respond to increased work demands not by eliminating household responsibilities but by reallocating time through multitasking and reductions in leisure or housework (Bianchi et al., 2006). However, total workloads remain high, especially for women, who continue to bear a disproportionate share of unpaid labor. For community college students who are also parents or caregivers, time scarcity may arise not only from employment but also from the cumulative demands of unpaid household responsibilities.

Empirical research on time use provides further evidence of how employment affects academic engagement. Kalenkoski and Pabilonia (2011) use time-diary data to show that working students spend less time on homework, particularly on days when they are employed. Although their study focuses on high school students, the underlying mechanism is directly relevant for higher education populations. When time is fixed, increases in work hours necessarily reduce the time available for studying and other academic activities. For community college students, who are more likely to face additional responsibilities, these tradeoffs may be even more pronounced. However, not all academic outcomes seem to be affected in the same way. Darolia (2014) shows that increases in work hours are associated with reductions in credit accumulation but not related to declines in performance within individual courses. This suggests that students adjust the quantity of their academic engagement by taking fewer courses or credits, while attempting to maintain performance in the courses they do take.

Students operate under time constraints that require tradeoffs between work, school, and other responsibilities. These tradeoffs are shaped by structural factors such as financial need, household composition, and labor market conditions. As a result, students' academic decisions such as course load, enrollment intensity, and potentially instructional modality can be understood as responses to these constraints. The next section builds on this insight by examining how differences in instructional modality, particularly between synchronous and asynchronous formats, shape the balance between flexibility and structure in online learning environments.

Asynchronous Learning as Flexibility with Reduced Structure

Online learning is often understood as a mechanism for expanding access to higher education, particularly for students who face constraints on their time, location, or availability.

However, the expansion of online instruction does more than simply increase access, it also fundamentally changes the structure of the learning environment. These changes have important implications for how students engage with coursework and for the outcomes they experience. A key distinction within online education is between synchronous and asynchronous instructional formats. Synchronous online courses retain many of the features of traditional face-to-face instruction, including scheduled class meetings, real-time interaction, and opportunities for immediate feedback. In contrast, asynchronous courses allow students to engage with course materials on their own schedules, without required real-time participation (Hrastinski, 2008; Watts, 2016). This flexibility can reduce scheduling conflicts and enable students to participate in coursework despite work or family obligations. Simultaneously, it alters the structure of the learning process by removing externally imposed timelines and reducing opportunities for direct interaction.

Existing research emphasizes the importance of structure in supporting student success in online environments. Well-structured courses, which are characterized by clear organization, aligned assessments, and consistent expectations, are strongly associated with improved student outcomes (Jaggars & Xu, 2016). Similarly, work on asynchronous learning highlights the importance of course design elements such as timely feedback, clear communication, and opportunities for engagement in mitigating the challenges associated with reduced immediacy (Varkey et al., 2022). In the absence of these features, students may struggle to interpret expectations, manage their time effectively, and remain engaged with course material. These challenges are closely tied to the increased reliance on self-regulated learning in asynchronous environments. Without fixed meeting times or regular real-time interaction, students must take greater responsibility for planning, pacing, and monitoring their own progress. Self-regulation

strategies such as goal setting, time management, and strategic planning are strong predictors of success in online courses (Kizilcec et al., 2017). This suggests that the effectiveness of asynchronous instruction depends on students' ability to manage their own learning processes. Students who lack these skills or who face competing demands on their time may find it more difficult to succeed in less structured environments. Qualitative evidence further highlights these challenges. Gartland (2024) finds that nontraditional adult learners in asynchronous courses often report difficulties related to reduced interaction and a lack of connection with instructors and peers. While many students are motivated by clear academic and career goals, the absence of regular engagement can affect motivation and persistence. Similarly, Bork and Rucks-Ahidiana (2013) show that unclear expectations in online courses can create role ambiguity, leaving students uncertain about how to approach assignments and participate effectively.

Asynchronous learning offers clear advantages in terms of flexibility. By allowing students to engage with coursework at times that fit their schedules, asynchronous formats may enable participation for students who would otherwise be unable to attend scheduled classes. In this sense, asynchronous instruction can be understood as a mechanism for relaxing scheduling constraints and expanding access to higher education. However, this flexibility is not without tradeoffs. The same features that make asynchronous learning more accessible, such as lack of fixed schedules, reduced real-time interaction, and greater autonomy, may also reduce the structure and support that facilitate academic success. Equity considerations further complicate this relationship. Tate and Warschauer (2022) argue that success in online learning depends on access to a range of resources, including technology, academic support, and social networks. Less structured environments may place greater demands on these resources, potentially disadvantaging students who have less access to support while benefiting those who require

flexibility to remain enrolled. This suggests that the effects of asynchronous learning may depend not only on individual characteristics but also on how instructional formats interact with students' broader circumstances.

Empirical evidence on online learning outcomes reflects this tension. A large literature finds that online courses are associated with lower academic performance on average, including lower grades, reduced course completion rates, and decreased persistence relative to face-to-face instruction (Hart et al., 2018; Xu & Xu, 2019; Altindag et al., 2024). Within online modalities, synchronous courses tend to produce outcomes closer to face-to-face instruction, while asynchronous courses are often associated with larger performance gaps (Hart et al., 2026). Thus, asynchronous instruction may expand access by allowing students to better align academic participation with work and other responsibilities. However, it may also reduce the structure and support that promote academic success, leading to lower performance in individual courses.

Research Questions

This study examines asynchronous online instruction as a form of scheduling flexibility that may help students manage competing academic and employment responsibilities. The analysis is guided by four research questions:

1. Which students are most likely to enroll in asynchronous online courses?
2. What academic costs are linked with asynchronous enrollment relative to synchronous and face-to-face instruction?
3. Are these academic costs, if any, concentrated among students facing greater time constraints, or are they broadly shared?

4. Is asynchronous enrollment associated with outcomes such as employment and course load?

Together, these questions can help us understand how students use asynchronous instruction and what tradeoffs are associated with this flexibility.

Data

Institutional Context

This study is situated within the Virginia Community College System (VCCS), a large statewide system of 23 associate degree-granting institutions. The system serves students across urban, suburban, and rural regions of Virginia and plays a central role in the state's higher education and workforce development strategy. As open-access institutions, VCCS colleges enroll students with diverse academic preparation, socioeconomic backgrounds, and educational goals, including degree-seeking students, transfer-oriented students, and students pursuing workforce credentials. Over the past decade, the demographic composition of the VCCS student population has also shifted. Between 2014 and 2024, the share of Hispanic students in the system increased by 7 percentage points, rising from 10 percent to 17 percent. Over the same period, the share of white students declined by 8 percentage points, from 58 percent to 50 percent. By 2024, the system's enrollment was composed of approximately 50 percent white students, 18 percent Black students, 17 percent Hispanic students, and 9 percent Asian students. In the 2023-24 academic year, roughly one-third of students were Pell Grant recipients. These patterns reinforce the importance of examining how instructional modality interacts with student constraints and equity-related outcomes.

Data Sources and Time Frame

The analysis uses administrative course enrollment data provided by VCCS. The dataset spans academic years 2015 through 2023. This period captures both the steady expansion of online learning prior to 2020 and the abrupt systemwide transition to remote instruction beginning in spring 2020. Each observation represents a student enrolled in a specific course section in a given academic term. This structure allows for the estimation of modality differences while accounting for variation across students, courses, colleges, and terms. Student-level data include demographic characteristics, such as race/ethnicity, gender, and age; indicators of socioeconomic status, including Pell eligibility; and measures of prior academic preparation (Table 1). Course- and section-level data provide information on subject area, course level, credit hours, and section characteristics. Importantly, the dataset includes administrative indicators of course delivery mode and format, which are used to construct measures of instructional modality. Academic outcomes include final course grades and indicators of successful course completion.

Sample Restrictions

We implement several restrictions to construct the analytic sample. First, we restrict the sample to credit-bearing courses. Second, summer term enrollments are excluded because summer courses often differ from fall and spring courses in length, pacing, and student composition. Third, courses with more than six credit hours are excluded. High-credit courses often represent clinical experiences, practica, or other specialized formats that differ substantively from standard lecture-based courses. At the student level, we restrict the sample to degree-seeking community college students. Dual-enrolled students, defined as high school

students taking college coursework, are excluded. Students without a standard high school credential are also excluded, as are students who already hold a prior postsecondary degree. Students who report academic goals other than transfer or associate degree attainment are excluded. These restrictions focus the analysis on students for whom community college enrollment represents a primary pathway toward postsecondary attainment. Finally, we limit the sample to courses delivered in one of three clearly defined formats: face-to-face, synchronous online, or asynchronous online. Courses coded in alternative or ambiguous delivery formats are excluded.

Operationalizing Modality

Instructional modality is constructed using administrative indicators of course delivery mode and delivery format recorded by VCCS. These indicators reflect systemwide definitions that classify each course section according to how instruction is delivered and how students and instructors interact. Using these fields, we construct a three-category modality variable. Face-to-face instruction is defined as courses in which instruction occurs primarily in person at a physical campus location. Synchronous online instruction is defined as courses delivered online with required real-time meetings. These sections involve scheduled virtual class sessions in which students and instructors interact simultaneously. Asynchronous online instruction is defined as courses delivered fully online without required real-time meetings. Instruction is provided through recorded lectures, learning management systems, discussion boards, assignments, and other time-flexible tools. Hybrid sections are coded as synchronous or asynchronous online depending on whether their online instruction requires real-time participation. This classification is important because the core distinction of interest is not simply whether a course uses online

technology, but whether students are required to participate at scheduled times. In this framework, asynchronous instruction represents the greatest degree of scheduling flexibility, while synchronous instruction retains more structure through scheduled interaction.

Figures 1 and 2 present descriptive trends in instructional modality across the study period. VCCS substantially expanded its online offerings before and after the onset of the COVID-19 pandemic. Online enrollment grew steadily in the years leading up to 2020, suggesting that demand for flexible instructional options was already increasing prior to the pandemic. The most dramatic shift occurred in the 2020-21 academic year, when the pandemic prompted a rapid transition away from face-to-face instruction. In 2020-21, more than 80 percent of total enrollment occurred in online courses. Of this, 43.9 percent of total enrollment was in asynchronous courses and 38.2 percent was in synchronous courses. Synchronous online instruction represented only a small share of enrollment in pre-pandemic years, and its rapid expansion during 2020-21 reflects the system's reliance on real-time virtual instruction as a substitute for in-person classes. In subsequent years, as campuses reopened, face-to-face instruction rebounded. However, online modalities remained a substantial component of total enrollment. By 2023, roughly half of all enrollments were still in online courses. This suggests that the pandemic did not simply produce a temporary shift in instructional delivery, but accelerated a longer-term restructuring of course offerings.

Empirical Strategy

The empirical analysis proceeds in four steps, corresponding to the four research questions. First, we examine which students are more likely to enroll in asynchronous courses. Second, we estimate the relationship between instructional modality and short-term academic

outcomes. Third, we examine whether these academic costs differ across student subgroups. Fourth, we estimate the relationship between asynchronous enrollment and complementary term-level outcomes, including employment and course load.

Sorting into Instructional Modality

To answer the first research question, we estimate a multinomial logit model of student enrollment by instructional modality. This analysis assesses whether students sort into face-to-face, synchronous, and asynchronous courses along observable characteristics. In these models, face-to-face instruction serves as the reference category, and coefficients are reported as relative risk ratios. The model includes student characteristics, including age, gender, first-generation status, Pell eligibility, race/ethnicity, and prior-term employment status. It also includes term and college fixed effects. As students may take courses in multiple modalities within a term, these estimates should be interpreted as associations with enrollment in each modality relative to face-to-face instruction. If asynchronous instruction functions as a flexibility margin, then students facing greater time or financial constraints should be more likely to enroll in asynchronous courses. The results from this model provide evidence on whether asynchronous enrollment is concentrated among students for whom scheduling flexibility is likely to be especially valuable.

Academic Outcomes and Modality

To answer the second research question, we estimate the relationship between instructional modality and course-level academic outcomes. Estimating this relationship presents several identification challenges because students are not randomly assigned to course formats. Students who enroll in asynchronous courses may differ systematically from students who enroll

in synchronous or face-to-face courses. Courses offered asynchronously may also differ from courses offered in other formats. To address these concerns, the preferred specification leverages within-student, within-term variation in modality across courses. Specifically, estimates are identified from differences in outcomes across courses taken by the same student in the same academic term that are offered in different modalities. The estimating equation is:

$$Y_{ijkct} = \beta_1 Asynch_{jkct} + \beta_2 Synch_{jkct} + \sigma Sec_{jkct} + \mu_{it} + \theta_{kct} + \epsilon_{ijkct}$$

where Y_{ijkct} represents the outcome for student i in section j , course k , college c , and term t .

The two primary outcomes are short-term measures of course performance. The first is an indicator for passing a course, defined as earning a final grade of C or higher. Students who receive a D, F, or withdraw from the course are coded as not passing. The second outcome is grade points earned, measured on a 0-4 scale. The coefficients of interest are β_1 and β_2 , which capture the relationship between asynchronous and synchronous instruction, respectively, and academic outcomes relative to face-to-face instruction. Face-to-face instruction serves as the reference category. Student-by-term fixed effects, represented by μ_{it} , allow comparisons across courses taken by the same student in the same term. Course-by-college-by-term fixed effects, represented by θ_{kct} , restrict comparisons to students taking the same course at the same institution in the same term, but in different instructional modalities. The models also include section-level controls, represented by Sec_{jkct} . These controls account for observable section characteristics, including enrollment composition and scheduling features, that may be correlated with both modality and student outcomes.

Heterogeneity in Academic Costs

To answer the third research question, we examine whether the academic costs associated with instructional modality differ across student subgroups. This analysis is motivated by the possibility that asynchronous instruction may be especially beneficial, or less harmful, for students facing greater time constraints. If asynchronous courses provide flexibility that helps employed or low-income students manage competing responsibilities, then the academic penalty associated with asynchronous instruction might be smaller for these groups. To test this possibility, we estimate models that interact instructional modality with student subgroup indicators. The dependent variables are the same course-level academic outcomes used in the main analysis: passing a course and grade points earned. The key coefficients are the interactions between modality and subgroup status. A positive interaction indicates that the negative effect of online instruction is smaller for that subgroup, while a negative interaction indicates a larger penalty. These models include student-by-term fixed effects and course-by-college-by-term fixed effects, so estimates continue to rely on within-student, within-term variation across courses offered in different modalities. The subgroup analysis includes measures of financial need, employment, age, gender, first-generation status, and race/ethnicity.

Complementary Outcomes

To answer the fourth research question, we examine the relationship between asynchronous course-taking and term-level outcomes that capture how students manage work and enrollment over time. These models use student fixed effects and compare the same student across terms in which they take more or fewer asynchronous courses. The key predictors are: (1) the share of courses taken asynchronously in a given term and (2) an indicator for whether the

student took at least one asynchronous course in that term. Outcomes are measured at the term level and include employment, total credits enrolled, and number of courses enrolled.

Importantly, these estimates should be interpreted as within-student associations rather than causal effects. Even with student fixed effects, time-varying shocks such as job changes, family responsibilities, health concerns, or financial strain may influence both asynchronous enrollment and student outcomes. However, this analysis provides exploratory evidence on what students may be gaining in exchange for the academic costs associated with asynchronous instruction.

Results

Sorting into Modalities

The first set of results examines whether students sort into instructional modalities based on observable characteristics (Table 2). This analysis is important because asynchronous instruction may be especially attractive to students facing time and financial constraints. If asynchronous courses function as a flexibility margin, then students who are older, employed, Pell-eligible, or otherwise constrained should be more likely to enroll in them.

The results provide strong evidence of sorting into asynchronous instruction. Student age is positively associated with enrollment in both online formats. Each additional year of age is associated with a 2.3 percent increase in the likelihood of enrolling in synchronous courses and a 2.9 percent increase in the likelihood of enrolling in asynchronous courses relative to face-to-face instruction. The larger association for asynchronous enrollment suggests that older students are especially likely to select into the most flexible modality. Gender differences are also large. Female students are 17.7 percent more likely than male students to enroll in synchronous courses and 32.6 percent more likely to enroll in asynchronous courses relative to face-to-face

instruction. This pattern is consistent with the possibility that women, who may face greater caregiving and household responsibilities, are more likely to choose formats that provide scheduling flexibility. Socioeconomic status is also strongly associated with modality choice. Pell-eligible students are 10.7 percent more likely to enroll in synchronous courses and 19.8 percent more likely to enroll in asynchronous courses relative to face-to-face instruction. This suggests that students with greater financial need are more likely to choose online formats, particularly asynchronous formats, which may allow them to combine school with work or other responsibilities. There are also meaningful differences by race and ethnicity. Hispanic students are 9.1 percent less likely to enroll in synchronous courses and 25.7 percent less likely to enroll in asynchronous courses relative to White students. Asian students are also less likely to enroll in both synchronous and asynchronous courses. These patterns may reflect differences in access, preferences, course-taking patterns, advising, or other factors, including the digital divide identified in prior work (Johnson & Cuellar Mejia, 2014). Black students do not differ substantially from White students in asynchronous enrollment after accounting for model covariates.

Employment status provides direct evidence of the relationship between work and modality choice. While prior-term employment is not significantly associated with synchronous enrollment, students who were employed in the previous term are 8.1 percent more likely to enroll in asynchronous courses in the following term relative to face-to-face courses. This pattern is consistent with the interpretation that asynchronous instruction provides a scheduling advantage for students balancing employment and coursework.

Overall, these results show that students do not enroll in instructional modalities at random. Students who are older, female, Pell-eligible, and previously employed are more likely to enroll in asynchronous courses. These patterns support the interpretation of asynchronous instruction as a flexibility margin that is especially relevant for students facing time and financial constraints.

Academic Costs of Instructional Modality

The next set of results examines whether this flexibility is associated with academic costs. The analysis estimates the relationship between instructional modality and course performance, using face-to-face instruction as the reference category.

Course Pass Rates

Table 3 presents estimates for course pass rates. The models are introduced progressively to show how estimates change as additional controls and fixed effects are incorporated. In the baseline specification, asynchronous enrollments are associated with lower pass rates relative to face-to-face instruction, while synchronous enrollments appear to be associated with slightly higher pass rates. These initial differences likely reflect selection across students, courses, and sections. As fixed effects are introduced, the estimated relationships change. In the preferred specification, which includes student-by-term and course-by-college-by-term fixed effects, both synchronous and asynchronous instruction are associated with lower pass rates relative to face-to-face instruction. However, the magnitude of the association differs substantially across online formats.

The coefficient on synchronous instruction is -0.018, indicating that enrollment in a synchronous online course is associated with a 1.8 percentage point lower probability of passing relative to face-to-face instruction. This estimate is modest in magnitude and suggests that synchronous online instruction performs similarly, though not identically, to in-person instruction in terms of course completion. The coefficient on asynchronous instruction is much larger at -0.078. This indicates that asynchronous enrollment is associated with a 7.8 percentage point lower probability of passing relative to face-to-face instruction. This estimate suggests that the flexibility of asynchronous instruction comes with a sizable academic cost in terms of course completion. The pass rate results show a clear gradient across modalities. Face-to-face instruction is associated with the highest pass rates, synchronous instruction is associated with a modestly lower probability of passing, and asynchronous instruction is associated with the largest decline.

Grade Points Earned

Table 4 presents analogous models using grade points earned as a continuous outcome measured on a 0 to 4 scale. As with pass rates, baseline differences evolve as controls and fixed effects are added. In the preferred specification, the association between synchronous instruction and grades is small and statistically insignificant. The coefficient on synchronous instruction is -0.005, indicating that grades in synchronous courses are statistically indistinguishable from grades in face-to-face courses once student-level and course-level selection are accounted for. This suggests that synchronous online instruction is broadly comparable to face-to-face instruction in terms of average grade performance. In contrast, asynchronous instruction remains negatively associated with grades. The coefficient of -0.191 indicates that asynchronous

enrollment is associated with approximately 0.2 lower grade points relative to face-to-face instruction. This is a meaningful decline on a 0 to 4 scale and reinforces the pattern observed for pass rates.

The pass rate and grade results suggest that asynchronous instruction is consistently linked to lower academic performance, while synchronous instruction is much closer to face-to-face instruction. These findings do not imply that asynchronous instruction lacks value. Rather, they suggest that the scheduling flexibility provided by asynchronous courses may come at the cost of reduced structure and lower course-level performance.

Heterogeneity in Academic Costs

The third set of results examines whether the academic costs associated with asynchronous instruction are concentrated among particular students or are broadly shared. This analysis is important because students facing greater time constraints may be more likely to select into asynchronous courses. If asynchronous formats are especially well matched to their needs, then the academic penalties might be smaller for these students. Alternatively, if reduced structure creates challenges across the student population, then the penalties may be broadly shared.

Pass Rates

Table 5 examines whether the relationship between instructional modality and course passing varies across student subgroups. Consistent with the main results, both synchronous and asynchronous modalities are associated with lower probabilities of passing relative to face-to-face instruction. The magnitude of this difference is substantially larger for asynchronous courses than for synchronous courses.

The most important result is that there is little evidence that employed or Pell-eligible students experience smaller asynchronous penalties. For Pell-eligible students, the interaction terms are small and not statistically significant, and the joint test fails to reject the null of no heterogeneity. This indicates that pass rate penalties in online modalities do not meaningfully differ by financial need. Similarly, employment status does not significantly moderate the relationship between modality and pass rates. The interaction terms between employment and both synchronous and asynchronous instruction are close to zero and statistically insignificant. The joint test also fails to reject the null of no differential effects. This is notable because employed students are more likely to enroll in asynchronous courses, yet they do not appear to experience smaller academic penalties in those courses. In other words, employment shapes modality choice, but it does not appear to protect students from the academic costs associated with asynchronous instruction.

There is stronger evidence of heterogeneity by age. Younger students, particularly those ages 18-24, experience larger declines in pass rates in online courses relative to face-to-face instruction. These negative effects are diminished for older students. Students ages 35-44 and students ages 45 and older experience smaller penalties in online modalities, with the largest attenuation observed for students ages 45 and older in asynchronous courses. This pattern is consistent with the possibility that older students may have stronger self-regulation skills, clearer academic goals, or a better alignment between flexible course formats and their external responsibilities (Kizilcec et al., 2017).

Gender differences are also present. Female students experience smaller reductions in pass probability in both synchronous and asynchronous courses relative to male students. This

may reflect differences in course-taking patterns, academic preparation, time management, or other unobserved factors. Patterns by race and ethnicity are more mixed. Black students experience modality effects that are broadly similar to those of non-Black students. Latinx students experience a larger penalty in asynchronous courses, suggesting that asynchronous formats may be particularly challenging for this group in terms of course completion. In contrast, Asian students experience smaller penalties in both synchronous and asynchronous formats.

Overall, the pass rate heterogeneity results suggest that the academic costs of asynchronous instruction are not concentrated primarily among employed or low-income students. Instead, the penalties are broadly shared, with more meaningful variation by age, gender, and some racial and ethnic groups.

Grade Points Earned

Table 6 examines heterogeneity in grade points earned. As in the main results, synchronous instruction has little effect on grades on average, while asynchronous instruction is consistently associated with lower grades.

The results again provide limited evidence that employment status moderates the relationship between modality and grades. The interactions between employment and both synchronous and asynchronous instruction are small and statistically insignificant. Employed students do not experience significantly different grade penalties from online instruction compared to their non-employed peers. The same general pattern holds for financial need. The interaction between Pell eligibility and asynchronous instruction is small and not statistically

significant, indicating that the negative association between asynchronous enrollment and grades is similar for Pell-eligible and non-Pell students.

Age-related heterogeneity is more limited for grades than for pass rates. Students ages 25-34 experience a slightly larger asynchronous grade penalty, while students ages 45 and older experience a smaller penalty. However, these differences are less systematic than the pass rate patterns. Gender differences are more consistent. Female students experience smaller grade penalties in both synchronous and asynchronous courses. The asynchronous interaction suggests that the negative effect of asynchronous instruction is reduced by approximately 0.045 grade points for female students. There is also some evidence of heterogeneity by first-generation status for synchronous instruction, though the asynchronous interaction is not statistically significant. Patterns by race and ethnicity again vary across groups. White and Black students show little evidence of meaningful heterogeneity. Latinx students experience somewhat more favorable outcomes in synchronous instruction, while Asian students experience substantially smaller penalties in both synchronous and asynchronous formats.

These results suggest that while asynchronous courses appear to attract students facing time and financial constraints, these students do not experience clear academic protection from the challenges of the modality.

Pandemic-era Changes

The COVID-19 pandemic fundamentally altered the scale and normalization of online instruction in higher education. The rapid transition to remote instruction expanded institutional experience with online delivery and increased student exposure to online learning environments.

As a result, the relationship between course modality and academic outcomes may have changed in the post-pandemic period. Improvements in instructional technology, faculty experience, institutional support, and student familiarity with online coursework may have reduced some of the academic disadvantages historically associated with online instruction. At the same time, the expansion of online coursework may also have changed which students enroll in asynchronous courses and the purposes these courses serve within students' academic pathways. We explore these relationships below.

Course Outcomes

Table 7 examines whether the relationship between course modality and academic outcomes changed following the COVID-19 pandemic. Specifically, the analysis compares the impact of online instruction on student performance during the pre-pandemic period (2015-2019) and the post-COVID recovery period (2022-2024) (see Appendix Table 1 for year-by-year estimates). The results show notable differences between asynchronous and synchronous online instruction. Across both time periods, asynchronous courses are associated with lower grades and lower probabilities of course passing relative to face-to-face instruction. Prior to COVID, asynchronous enrollment was associated with a 0.217-point reduction in course grades and an 8.2 percentage point reduction in the probability of passing a course. Although these negative associations decrease somewhat in the post-COVID period, they remain sizable and statistically significant. Between 2022 and 2024, asynchronous coursework is associated with a 0.142-point reduction in grades and a 6.7 percentage point reduction in course passing relative to face-to-face courses. In contrast, synchronous online instruction exhibits considerably smaller associations with academic performance. Before COVID, synchronous courses were not significantly

associated with course grades and were associated with only a modest 1.9 percentage point reduction in passing rates relative to face-to-face instruction. In the post-COVID period, synchronous instruction becomes positively associated with grades, corresponding to a 0.034-point increase in course performance, though synchronous courses continue to exhibit slightly lower pass rates than face-to-face courses.

These findings suggest that the relationship between online instruction and student outcomes changed meaningfully following the pandemic. The negative associations associated with asynchronous instruction became smaller after COVID, potentially reflecting institutional improvements in online course delivery, increased student familiarity with online learning environments, or broader normalization of remote instruction. At the same time, synchronous online instruction appears to more closely resemble face-to-face instruction in terms of academic performance, particularly in the post-pandemic period. However, even after COVID, asynchronous coursework remains associated with substantially worse academic outcomes than either synchronous or face-to-face instruction.

Differential Growth in Asynchronous Course-Taking

Table 8 examines whether the growth in asynchronous course-taking following the COVID-19 pandemic differed across student groups. The results show that the post-pandemic expansion of asynchronous coursework was not uniform across the student population. Increases in asynchronous enrollment were concentrated among certain groups of students, particularly Pell-eligible and employed students. Column (1) shows that Pell-eligible students experienced a 3.2 percentage point larger increase in asynchronous course-taking during the post-COVID period relative to non-Pell students. Given the flexibility associated with asynchronous

instruction, this pattern may reflect increased demand for course formats that better accommodate employment or other financial constraints.

Column (2) shows that employed students also experienced greater growth in asynchronous course-taking following COVID, though the magnitude is smaller. Relative to non-employed students, employed students experienced an additional 0.8 percentage point. This finding reinforces the idea that students may use asynchronous coursework to balance academic enrollment with labor market participation.

Column (3) examines heterogeneity by age. Relative to students ages 18-24, older students experienced smaller post-COVID increases in asynchronous course-taking. Students ages 25-34 experienced a 6.1 percentage point smaller increase in asynchronous enrollment, while students ages 35-44 and 45+ experienced 5.7 and 4.7 percentage point smaller increases, respectively. Although older students have historically been more likely to enroll in online coursework, these results suggest that the post-pandemic growth in asynchronous enrollment was concentrated more heavily among traditional-age students. These findings suggest that the pandemic not only changed the scale of asynchronous instruction, but also altered which students disproportionately relied on these courses. The post-COVID expansion of asynchronous coursework appears to have been especially concentrated among students facing greater economic and employment constraints, while younger students experienced the largest relative increases in asynchronous enrollment.

Complementary Outcomes

The final set of results examines whether online course-taking is associated with other outcomes that may help explain why students enroll in online courses despite their academic costs. This analysis focuses on employment and course load (Table 9). Prior results showed that employed students are more likely to enroll in asynchronous courses and that asynchronous instruction is associated with lower grades and pass rates. The complementary outcomes analysis asks what students may be gaining in exchange for this academic cost.

Using student fixed effects, we estimate two separate specifications that compare students across terms in which they take more or fewer online courses. The first specification is an intensity model, which includes the share of asynchronous courses and the share of synchronous courses taken within a term as predictors (i.e., the “share” model). For example, a student taking two asynchronous courses out of four total courses would have an asynchronous course share of 0.50; if one of those four courses is synchronous, that student would have a synchronous course share of 0.25. Accordingly, coefficients in Column (1) represent the estimated change associated with moving from a share of 0 (no courses in that modality) to 1 (all courses in that modality), relative to face-to-face instruction.

The second specification is a presence model, which includes indicators for whether a student took at least one asynchronous course and whether the student took at least one synchronous course during the term (i.e., the “any” model). Coefficients in Column (2) therefore represent the estimated difference between terms in which students had any exposure to a given online modality and terms in which they had none. Whereas the share specification captures the

intensity of online exposure, the any specification captures whether any online exposure occurred during the term. Students contribute observations only for enrolled terms.

Panel A shows that both asynchronous and synchronous enrollment are positively associated with employment, though the associations are somewhat larger for asynchronous coursework. Moving from no asynchronous courses to a fully asynchronous course load is associated with a 1.9 percentage point increase in the probability of employment, while a fully synchronous schedule is associated with a 1.6 percentage point increase. Similarly, taking at least one asynchronous course is associated with a 0.8 percentage point increase in employment, compared to a 0.4 percentage point increase for synchronous courses. These findings suggest that online modalities, especially asynchronous courses, may help students accommodate labor market participation.

Panel B examines course load and reveals a more nuanced pattern. In the "share" specification (column 1), higher exposure to both asynchronous and synchronous coursework is associated with enrolling in fewer credits and fewer courses. The negative associations are somewhat larger for asynchronous coursework. Moving toward a fully asynchronous course load is associated with enrolling in 2.7 fewer credits and approximately one fewer course during the term, while a fully synchronous schedule is associated with 2.3 fewer credits and 0.8 fewer courses. These findings suggest that terms dominated by online coursework may correspond to periods when students reduce enrollment intensity, potentially due to work, family, or other constraints.

In contrast, the "any" specification shows positive associations between online course-taking and course load (column 2). Students who take at least one asynchronous course enroll in

more credits and courses, and the associations are even larger for synchronous coursework. This pattern suggests that limited exposure to online modalities may help students maintain or expand enrollment within constrained schedules, while heavy reliance on online coursework may signal periods of reduced academic capacity.

Overall, these complementary outcomes suggest that asynchronous courses play a dual role. For some students, taking at least one asynchronous course may expand flexibility and allow them to maintain a larger course load while working. For others, heavy reliance on asynchronous coursework may signal periods of greater constraint, lower enrollment intensity, and elevated risk of stopping out.

Robustness Checks

The opposite-signed coefficients observed in the “share” and “any” specifications raise the possibility that the negative course-load estimates in the share model may be driven by the distribution of the asynchronous share variable. For example, a student taking a single asynchronous course would have an asynchronous share of 1.0, even though they are enrolled in only one class. By contrast, a student taking four courses, two of which are asynchronous, would have an asynchronous share of 0.5 despite carrying a much heavier course load. If fully asynchronous terms are disproportionately composed of students taking only one or two courses, the negative coefficient on asynchronous share could simply reflect differences in enrollment intensity across terms rather than a broader relationship between asynchronous coursework and course-taking behavior.

To assess this possibility, we first examined the distribution of the asynchronous share measure. As shown in Figure A1, the distribution is highly concentrated at the extremes, with large proportions of student-terms containing either no asynchronous courses or entirely asynchronous schedules. This pattern suggests that fully asynchronous terms may exert disproportionate influence on the estimated coefficients. Descriptive analyses provide support for this concern. Student-terms with a fully asynchronous schedule averaged 7.4 credits and 2.5 courses, compared with 10.7 credits and 3.6 courses among all other student-terms (Table A2). More generally, course load varied substantially across asynchronous share categories (Table A3). Terms with limited asynchronous enrollment ($0 < \text{share} < 0.5$) exhibited the highest average course loads (13.4 credits), while fully asynchronous terms exhibited the lowest (7.4 credits). Interestingly, terms with no asynchronous courses showed lower loads relative to mixed-modality terms (9.5 credits). These descriptive results suggest that students relying exclusively on asynchronous coursework tend to enroll less intensively than students with mixed-modality schedules, as well as students with no asynchronous courses.

To determine whether the negative coefficients in the share models were driven primarily by these fully asynchronous terms, we estimated the models under alternative sample restrictions (Table A4). First, we restricted the sample to terms in which students enrolled in at least one online course (column 2). Under this restriction, the negative association between asynchronous course share and course enrollment became much larger. Moving from no asynchronous courses to a fully asynchronous schedule was associated with enrolling in 7.5 fewer credits and 2.8 fewer courses, compared with 2.7 fewer credits and 1.0 fewer courses in the full sample. Similar patterns emerged for synchronous coursework. These results suggest that among students already participating in online education, greater reliance on online modalities is associated with

substantially lower enrollment intensity. We then excluded all fully asynchronous terms from the restricted sample (column 3). Although the coefficients were decreased, they remained negative and statistically significant. For example, the estimated association between asynchronous course share and number of courses declined from -2.82 to -1.35, while the coefficient for credits declined from -7.52 to -2.96. These reductions indicate that fully asynchronous, low course-load terms contribute meaningfully to the negative coefficients observed in the share models. However, the persistence of the relationship after excluding those observations suggests that the findings cannot be explained entirely by the composition of fully asynchronous terms. The employment results were notably stable across all specifications. In the full sample, moving from no asynchronous courses to a fully asynchronous schedule was associated with a 1.9 percentage point increase in the probability of employment. This estimate changed only modestly when restricting the sample to terms with at least one online course (2.2 percentage points) and remained positive after excluding fully asynchronous terms (3.2 percentage points).

The robustness analyses indicate that fully asynchronous terms contribute meaningfully to the negative association between asynchronous course share and enrollment intensity. Students taking some asynchronous coursework often carry relatively large course loads, whereas students enrolled in entirely asynchronous schedules tend to carry substantially lighter course loads. However, the persistence of negative and statistically significant coefficients after excluding fully asynchronous terms indicates that the findings are not solely a compositional artifact. Increasing reliance on asynchronous coursework remains associated with lower enrollment intensity, even among students already participating in online education. These findings suggest that limited online enrollment may expand scheduling flexibility and support

larger course loads, whereas extensive reliance on asynchronous coursework may coincide with periods of greater external constraints and reduced academic engagement.

Discussion

This study examines asynchronous online instruction as a form of scheduling flexibility within a large statewide community college system. The central contribution is to examine how asynchronous courses operate within students' broader labor market and academic constraints. Several findings emerge.

First, students sort into asynchronous courses in ways that are consistent with the flexibility interpretation. Students who are older, female, Pell-eligible, and previously employed are more likely to enroll in asynchronous courses relative to face-to-face instruction. These patterns suggest that asynchronous instruction is especially attractive to students who may face greater time and financial constraints. The fact that prior-term employment predicts asynchronous enrollment, but not synchronous enrollment, is particularly important. It suggests that the distinctive feature of asynchronous instruction is not simply that it is online, but that it removes required meeting times and provides greater scheduling flexibility.

Second, this flexibility is associated with academic costs. Consistent with prior research on online learning (Altindag et al., 2024; Hart et al., 2018, 2026; Xu & Xu, 2019), asynchronous courses are associated with lower pass rates and grades relative to face-to-face instruction. In the preferred specification, asynchronous enrollment is associated with a 7.8 percentage point reduction in the probability of passing and approximately a 0.2 reduction in grade points. Synchronous instruction, by contrast, is much closer to face-to-face instruction. The synchronous

pass rate penalty is smaller, and the grade difference is statistically indistinguishable from zero. This pattern is consistent with the idea that real-time interaction and externally imposed schedules may preserve some of the structure that supports academic performance.

Third, the academic costs of asynchronous instruction are not substantially smaller for the students who are most likely to select into these courses. Employed and Pell-eligible students are more likely to enroll in asynchronous courses, but they do not experience meaningfully smaller penalties in pass rates or grades. This is an important finding because it suggests that the flexibility of asynchronous instruction does not fully offset the challenges created by reduced structure. The academic cost appears to be broadly shared rather than concentrated only among students with fewer resources or greater constraints. At the same time, there is some heterogeneity. Older students experience smaller pass rate penalties, especially in asynchronous courses, which may reflect stronger self-regulation, clearer academic goals, or better alignment between flexible formats and external responsibilities. Female students also experience smaller penalties in online modalities. Patterns by race and ethnicity are mixed: Black students experience similar effects to other students, Latinx students face somewhat larger asynchronous pass rate penalties, and Asian students experience smaller penalties in both online formats. These differences suggest that while the overall academic cost of asynchronous instruction is broad, students' ability to manage reduced structure may vary across groups.

Fourth, the COVID-19 pandemic was associated with changes in both the prevalence of asynchronous instruction and its relationship to student outcomes. Although asynchronous courses remained associated with lower grades and pass rates in the post-pandemic period, these negative associations became smaller relative to the pre-pandemic period. At the same time,

asynchronous enrollment grew disproportionately among Pell-eligible and employed students following COVID. These findings suggest that asynchronous instruction became more normalized and more broadly integrated into students' educational pathways after the pandemic. The shrinking of asynchronous penalties may reflect institutional improvements in online course delivery, increased faculty experience with remote instruction, and greater student familiarity with online learning environments. However, the persistence of sizable academic penalties even after COVID indicates that asynchronous instruction continues to differ meaningfully from face-to-face coursework in ways that affect academic performance.

Fifth, asynchronous enrollment is associated with complementary outcomes that help explain why students may choose these courses despite lower academic performance. Both asynchronous and synchronous enrollment are positively associated with employment, suggesting that online instruction may help students combine college enrollment with labor market participation. These associations are generally larger for asynchronous coursework, consistent with the greater scheduling flexibility offered by asynchronous formats. However, the course load results complicate this interpretation. In the “any” specification, taking at least one asynchronous or synchronous course is associated with enrolling in more credits and more courses, suggesting that limited exposure to online coursework may help students fit additional classes into constrained schedules. In contrast, the “share” specification shows that higher exposure to both asynchronous and synchronous coursework is associated with lower credit loads and fewer courses, with substantially larger negative associations for asynchronous instruction. This suggests that heavy reliance on asynchronous courses may occur during periods of greater constraint, when students are reducing academic intensity or are at higher risk of stopping out.

These findings highlight a central tension in the role of asynchronous instruction in community colleges. On one hand, asynchronous courses may expand access by allowing students to participate in higher education while working or managing other responsibilities. On the other hand, this flexibility is associated with lower academic performance and, in some cases, lower enrollment intensity. Asynchronous instruction may help constrained students remain connected to college, but it may also reinforce disparities if students who need flexibility are disproportionately exposed to course formats with lower success rates. The findings also suggest that flexibility should not be treated as a substitute for support. If asynchronous courses are serving students with substantial time and financial constraints, then course design and institutional support become especially important. Clear pacing, frequent feedback, proactive instructor communication, embedded advising, and structured opportunities for engagement may help reduce the academic costs associated with asynchronous learning. The goal should be to pair flexibility with enough structure to support student success.

Conclusion

The expansion of online instruction has reshaped higher education, particularly in community colleges where many students balance academic enrollment with employment, caregiving, and other responsibilities. This study shows that asynchronous instruction should be understood as a form of scheduling flexibility that students may use to manage competing demands. The findings show that students who are older, female, Pell-eligible, and previously employed are more likely to enroll in asynchronous courses. This pattern is consistent with the idea that asynchronous instruction functions as a flexibility margin for students facing time and financial constraints. However, asynchronous courses are also associated with lower pass rates

and grades relative to face-to-face instruction. Synchronous online courses, which preserve scheduled interaction, are much closer to face-to-face courses in terms of academic performance.

Importantly, the academic costs of asynchronous instruction are not substantially smaller for employed or Pell-eligible students. Although these students are more likely to select into asynchronous courses, they experience similar performance penalties as their peers. This suggests that while asynchronous instruction may expand access, flexibility alone does not eliminate the academic challenges associated with reduced structure and interaction. The complementary outcomes provide additional evidence of the tradeoffs involved. Asynchronous enrollment is positively associated with employment, suggesting that students may use flexible formats to participate in the labor market while enrolled. However, heavier reliance on asynchronous coursework is also associated with lower course loads and lower subsequent enrollment. These patterns suggest that asynchronous courses may serve different functions depending on intensity of use: taking some asynchronous coursework may help students fit college into constrained schedules, while fully or heavily asynchronous terms may reflect periods of greater strain.

From a policy perspective, these findings suggest that institutions should not treat asynchronous instruction as a simple solution to access barriers. Asynchronous courses provide flexibility that may be essential for working and non-traditional students, but they also require stronger supports to compensate for reduced structure. Investments in course design, instructor presence, pacing, feedback, and student support may be necessary to ensure that flexibility does not come at the expense of academic success. Asynchronous learning may expand participation

in higher education, but its benefits depend on whether institutions can provide targeted support that support student success.

References

- Altindag, D. T., Filiz, E. S., & Tekin, E. (2024). Is online education working? *Educational Evaluation and Policy Analysis*, 47(4), 1136–1162. <https://doi.org/10.3102/01623737241274802>
- Bailey, T. R., Jaggars, S. S., & Jenkins, D. (2015). *Redesigning America's community colleges: A clearer path to student success*.
- Bettinger, E. P., Fox, L., Loeb, S., & Taylor, E. S. (2017). Virtual classrooms: How online college courses affect student success. *American Economic Review*, 107(9), 2855–2875.
- Bianchi, S. M., Robinson, J. P., & Milkie, M. A. (2006). *Changing rhythms of American family life*. Russell Sage Foundation.
- Bird, K. A., Castleman, B. L., & Lohner, G. (2022). Negative impacts from the shift to online learning during the COVID-19 crisis: Evidence from a statewide community college system. *AERA Open*, 8, 1–16. <https://doi.org/10.1177/23328584221081220>
- Bound, J., Lovenheim, M. F., & Turner, S. (2010). Why have college completion rates declined? An analysis of changing student preparation and collegiate resources. *American Economic Journal: Applied Economics*, 2(3), 129–157. <https://doi.org/10.1257/app.2.3.129>
- Bork, R. H., & Rucks-Ahidiana, Z. (2013). Role ambiguity in online courses: An analysis of student and instructor expectations.

- Darolia, R. (2014). Working (and studying) day and night: Heterogeneous effects of working on the academic performance of full-time and part-time students. *Economics of Education Review*, 38, 38–50.
- Ebner, C., & Gegenfurtner, A. (2019). Learning and satisfaction in webinar, online, and face-to-face instruction: A meta-analysis. *Frontiers in Education*, 4, Article 92. <https://doi.org/10.3389/feduc.2019.00092>
- Gartland, T. L. (2024). *Asynchronous online learning motivation experiences for community college degree-seeking non-traditional adult learners: A qualitative study* (Doctoral dissertation, Liberty University).
- Garrison, D. R., Anderson, T., & Archer, W. (2000). Critical inquiry in a text-based environment: Computer conferencing in higher education. *The Internet and Higher Education*, 2(2–3), 87–105.
- Ghilay, Y. (2022). Quantitative courses in higher education: A comparison between asynchronous and synchronous distance learning. *Journal of Education and Learning*, 11(5), 93–106.
- Goldin, C. (2014). A grand gender convergence: Its last chapter. *American Economic Review*, 104(4), 1091–1119.
- Goldrick-Rab, S. (2016). *Paying the price: College costs, financial aid, and the betrayal of the American dream*. University of Chicago Press.

- Hart, C. M. D., Baker, R., Hill, M., et al. (2026). Online student performance under synchronous and asynchronous instruction in California community colleges. *Research in Higher Education*, 67, 16. <https://doi.org/10.1007/s11162-025-09873-3>
- Hart, C. M. D., Berger, D., Jacob, B., Loeb, S., & Hill, M. (2019). Online learning, offline outcomes: Online course taking and high school student performance. *AERA Open*, 5(1), 1–17. <https://doi.org/10.1177/2332858419832852>
- Hart, C. M. D., Friedmann, E., & Hill, M. (2018). Online course-taking and student outcomes in California community colleges. *Education Finance and Policy*, 13(1), 42–71. https://doi.org/10.1162/edfp_a_00218
- Hart, C. M., Xu, D., Alonso, E., et al. (2025). COVID-19 in California community colleges: College responses, college resources, and student outcomes. *Research in Higher Education*, 66, 1. <https://doi.org/10.1007/s11162-024-09819-1>
- Hrastinski, S. (2008). Asynchronous and synchronous e-learning. *EDUCAUSE Quarterly*, 31(4), 51–55.
- Jaggars, S. S., & Xu, D. (2016). How do online course design features influence student performance? *Computers & Education*, 95, 270–284.
- Johnson, H., & Cuellar Mejia, M. (2014, May). *Online learning and student outcomes in California's community colleges*. Public Policy Institute of California.

- Kalenkoski, C. M., & Pabilonia, S. W. (2011, October). *Time to work or time to play: The effect of student employment on homework, sleep, and screen time* (Working Paper No. 450).
- Kizilcec, R. F., Pérez-Sanagustín, M., & Maldonado, J. J. (2017). Self-regulated learning strategies predict learner behavior and goal attainment in massive open online courses. *Computers & Education, 104*, 18–33.
- Olson, J. S., & McCracken, F. E. (2015). Is it worth the effort? The impact of incorporating synchronous lectures into an online course. *Online Learning Journal*, Volume(19).
- Ortagus, J. C. (2018). National evidence of the impact of first-year online enrollment on postsecondary students' long-term academic outcomes. *Research in Higher Education, 59*, 1035–1058.
- Park, R. S. E., & Scott-Clayton, J. (2018). The impact of Pell Grant eligibility on community college students' financial aid packages, labor supply, and academic outcomes. *Educational Evaluation and Policy Analysis, 40*(4), 557–585.
<https://doi.org/10.3102/0162373718783868>
- Perna, L. W. (2010). *Understanding the working college student*. Academe.
- Scott-Clayton, J. (2011). The causal effect of federal work-study participation: Quasi-experimental evidence from West Virginia. *Educational Evaluation and Policy Analysis*.
- Scott-Clayton, J. (2012). What explains trends in labor supply among U.S. undergraduates? *National Tax Journal, 65*(1), 181–210.

- Scott-Clayton, J., & Minaya, V. (2016). Should student employment be subsidized? Conditional counterfactuals and the outcomes of work-study participation. *Economics of Education Review*, 52, 1–18. <https://doi.org/10.1016/j.econedurev.2015.06.006>
- Shlomo, A., & Rosenberg-Kima, R. B. (2024). F2F, Zoom, or asynchronous learning? Higher education students' preferences and perceived benefits and pitfalls. *International Journal of Science Education*, Advance online publication. <https://doi.org/10.1080/09500693.2024.2355673>
- Steinhauer, A., & Lovell, E. D. (2021). Non-Traditional Community College Students' Academic Pursuits: Time, Connectedness, Support, Wages and Research. *Community College Journal of Research and Practice*, 45(3), 223–226. <https://doi.org/10.1080/10668926.2019.1666066>
- Tate, T., & Warschauer, M. (2022). Equity in online learning. *Educational Psychologist*, 57(3), 192–206. <https://doi.org/10.1080/00461520.2022.2062597>
- Varkey, T. C., Varkey, J., Ding, J. B., & Varkey, P. K. (2022). *Asynchronous learning: A general review of best practices for the 21st century*. *Journal of Research in Innovative Teaching & Learning*, 16(2), 4–16. <https://doi.org/10.1108/JRIT-06-2022-0036>
- Vickery, C. (1977). The time-poor: A new look at poverty. *The Journal of Human Resources*, 12(1), 27–48.

- Watts, L. (2016). Synchronous and asynchronous communication in distance learning: A review of the literature. *Quarterly Review of Distance Education*, 17(1), 23–32.
<https://doi.org/10.1108/QRDE-06-2016-0003>
- Weissman, S. (2023, July 7). *Online learning still in high demand at community colleges*. Inside Higher Ed.
- Wickersham, K. R. (2020). Where to go from here? Toward a model of 2-year college students' postsecondary pathway selection. *Community College Review*, 48(2), 107–132.
- Woods, K., & Frogge, G. (2017). Preferences and experiences of traditional and nontraditional university students. *The Journal of Continuing Higher Education*, 65(2), 94–105.
<https://doi.org/10.1080/07377363.2017.1318567>
- Xu, D., & Jaggars, S. S. (2011). The effectiveness of distance education across Virginia's community colleges: Evidence from introductory college-level math and English courses. *Educational Evaluation and Policy Analysis*, 33(3), 360–377.
- Xu, D., & Jaggars, S. S. (2013). The impact of online learning on students' course outcomes: Evidence from a large community and technical college system. *Economics of Education Review*.
- Xu, D., & Jaggars, S. S. (2014). Performance gaps between online and face-to-face courses: Differences across types of students and academic subject areas. *The Journal of Higher Education*, 85(5), 633–659. <https://doi.org/10.1080/00221546.2014.11777343>
- Xu, D., & Xu, Y. (2019). The promises and limits of online higher education: Understanding how distance education affects access, cost, and quality. *American Enterprise Institute*.

Zeng, H., & Luo, J. (2024). Effectiveness of synchronous and asynchronous online learning: A meta-analysis. *Interactive Learning Environments*, 32(8), 4297–4313. <https://doi.org/10.1080/10494820.2023.2197953>

Tables and Figures

Figure 1. Course enrollments by modality

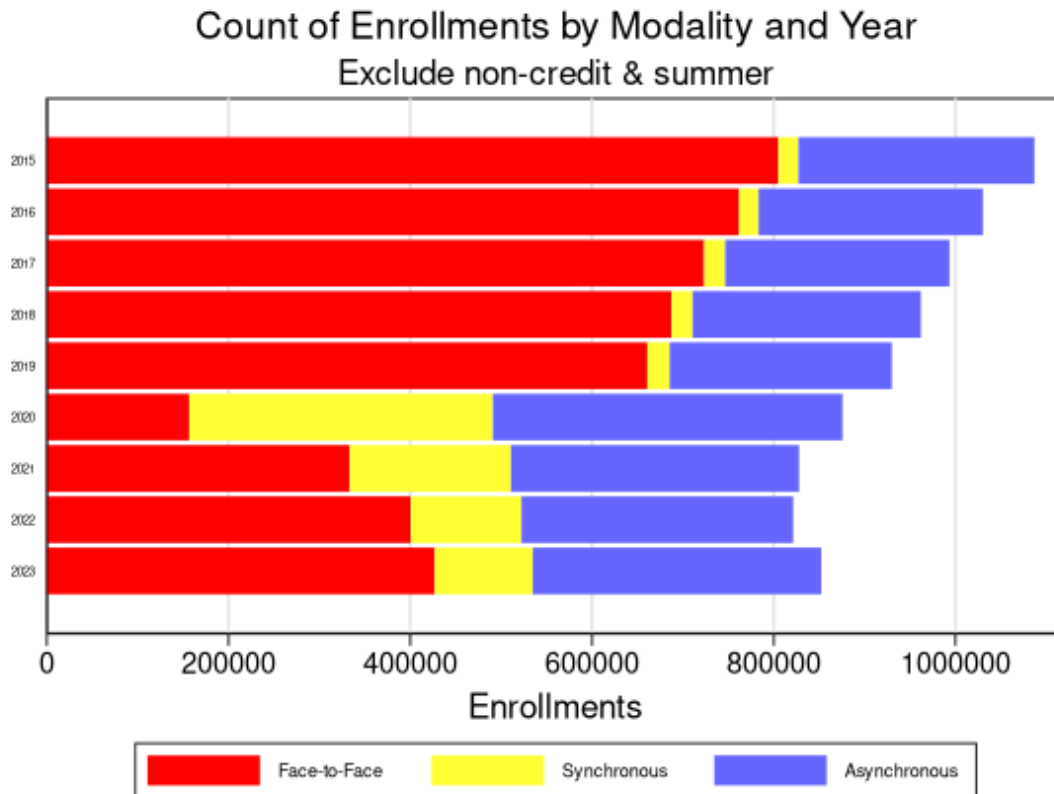


Figure 2. Share of enrollments by modality within year

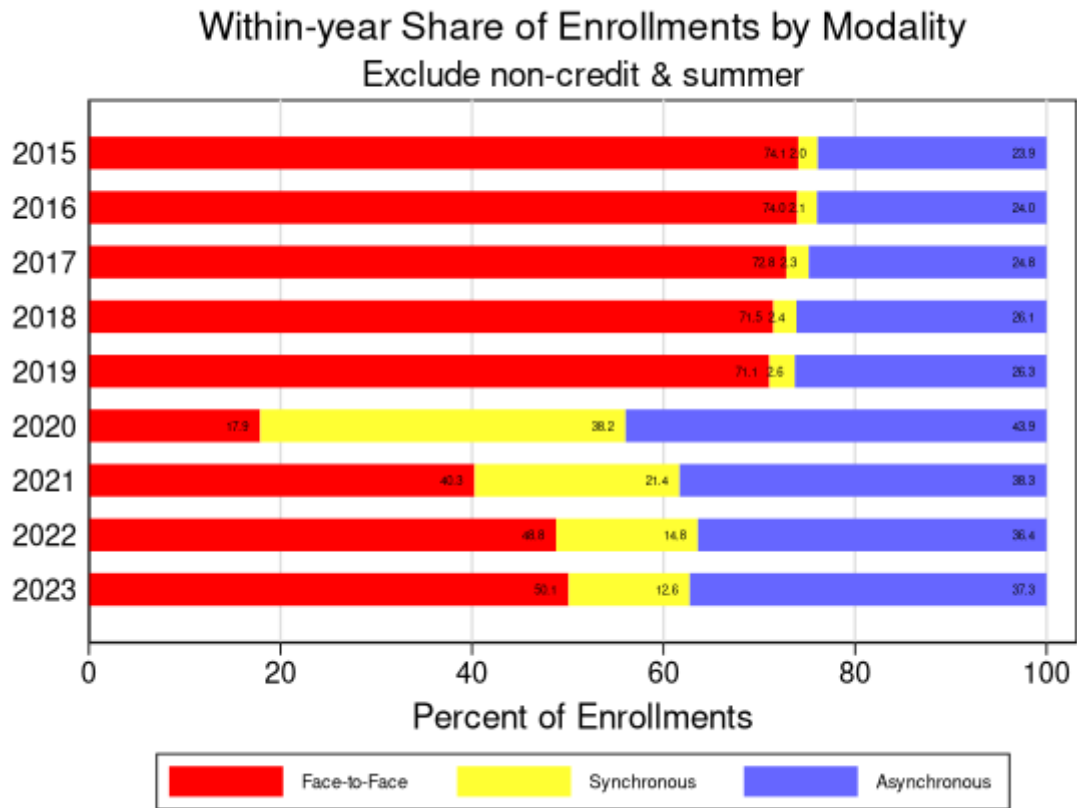


Table 1. Descriptive Statistics of Sample

	(1) All enrollment	(2) Face-to-face	(3) Synchronous	(4) Asynchronous
<i>Gender</i>				
Female	0.56 (0.50)	0.53 (0.50)	0.58 (0.49)	0.63 (0.48)
<i>Race</i>				
White	0.50 (0.50)	0.48 (0.50)	0.47 (0.50)	0.54 (0.50)
Black/African-American	0.19 (0.40)	0.19 (0.39)	0.16 (0.37)	0.22 (0.41)
Latinx	0.15 (0.36)	0.16 (0.37)	0.19 (0.39)	0.12 (0.32)
Asian	0.09 (0.28)	0.10 (0.30)	0.10 (0.30)	0.06 (0.23)
American Indian/Alaskan	0.00 (0.06)	0.00 (0.06)	0.00 (0.06)	0.00 (0.06)
Hawaiian	0.01 (0.08)	0.01 (0.07)	0.01 (0.08)	0.01 (0.08)
Two or more races	0.05 (0.21)	0.05 (0.21)	0.04 (0.21)	0.05 (0.21)
Unknown	0.01 (0.12)	0.01 (0.12)	0.03 (0.16)	0.01 (0.12)
<i>Demographics</i>				
First-generation	0.30 (0.46)	0.30 (0.46)	0.26 (0.44)	0.31 (0.46)
Pell award	0.48 (0.50)	0.45 (0.50)	0.46 (0.50)	0.53 (0.50)
<i>Course Outcomes</i>				
Persisted to the end of the course	0.92 (0.27)	0.93 (0.26)	0.94 (0.24)	0.90 (0.31)
Course grade point	2.78 (1.37)	2.79 (1.34)	2.90 (1.33)	2.74 (1.42)
C pass versus below	0.73 (0.45)	0.73 (0.44)	0.78 (0.42)	0.70 (0.46)
N (Student Enrollments)	4,822,528	3,052,289	280,323	1,489,916

Note: Values represent mean coefficients. Standard deviation listed in parentheses,

Table 2. Sorting into Modality (Multinomial Logit)

	(1) Synchronous	(2) Asynchronous
Lagged employ	-0.007 (0.006)	0.081*** (0.004)
Age (yrs.)	0.023*** (0.000)	0.029*** (0.000)
Female	0.177*** (0.007)	0.326*** (0.004)
First-generation	-0.007 (0.008)	0.008 (0.005)
Pell-eligible	0.107*** (0.007)	0.198*** (0.004)
Black	0.017 (0.010)	0.005 (0.006)
Latinx	-0.091*** (0.010)	-0.257*** (0.007)
Asian	-0.042*** (0.012)	-0.271*** (0.009)
Constant	-4.600*** (0.037)	-0.823*** (0.017)
Observations	6105877	

Notes: Values represent percentage changes in the relative likelihood of enrolling in synchronous or asynchronous courses relative to face-to-face instruction, calculated from multinomial logit relative risk ratios (RRRs). The outcome variable indicates course modality: 1 = face-to-face (FTF, omitted category), 2 = synchronous online, and 3 = asynchronous online. Coefficients represent the relative likelihood of enrolling in synchronous or asynchronous courses compared to FTF. All specifications control for student characteristics, including age, gender, first-generation status, Pell eligibility, race/ethnicity, and prior-term employment status, and include term and college fixed effects. Standard errors are clustered at the student level. As students may take courses in multiple modalities within a term, the estimates should be interpreted as associations with enrollment in each modality relative to FTF rather than as a discrete, mutually exclusive choice. $p < 0.05$, $p < 0.01$, $p < 0.001$.

Table 3. Main Results: Pass

	(1)	(2)	(3)	(4)
Synchronous	0.025*** (0.006)	0.026*** (0.006)	-0.008* (0.003)	-0.018*** (0.003)
Asynchronous	-0.044*** (0.005)	-0.045*** (0.005)	-0.079*** (0.003)	-0.078*** (0.003)
Section controls		X	X	X
Student-term FE			X	X
Student-college-course FE				X
Constant	0.804*** (0.006)	0.774*** (0.010)	0.790*** (0.004)	0.806*** (0.003)
Observations	4335856	4335856	4333914	4151790

Notes: Regressions estimated at the student-section level. The outcome variable is an indicator for earning a grade of C or higher. Face-to-face instruction is the omitted reference category. Models progressively introduce controls and fixed effects. Model (4), the preferred specification, includes student-by-term fixed effects, course-by-college-by-term fixed effects, and section-level controls. Sample size varies across specifications due to the inclusion of high-dimensional fixed effects, which drop singleton observations that do not contribute to within-group variation. Robust standard errors are reported in parentheses and are clustered at the student level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4. Grade point

	(1)	(2)	(3)	(4)
Synchronous	0.111*** (0.016)	0.107*** (0.016)	0.054** (0.018)	-0.005 (0.016)
Asynchronous	-0.048** (0.017)	-0.048** (0.017)	-0.144*** (0.013)	-0.191*** (0.012)
Section controls		X	X	X
Student-term FE			X	X
Student-college-course FE				X
Constant	2.786*** (0.019)	2.852*** (0.039)	2.800*** (0.015)	2.874*** (0.024)
Observations	3599263	3599263	3597311	3367779

Notes: Regressions estimated at the student-section level. The outcome variable is a continuous variable representing course grade in points from 0 to 4. Asynchronous and synchronous course indicators are included, with face-to-face instruction serving as the omitted reference category. Models progressively introduce controls and fixed effects. Model (4), the preferred specification, includes student-by-term fixed effects, course-by-college-by-term fixed effects, and section-level controls. Sample size varies across specifications due to the inclusion of high-dimensional fixed effects, which drop singleton observations that do not contribute to within-group variation. Robust standard errors are reported in parentheses and are clustered at the student level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5. Pass Outcomes: Heterogeneous Effects

	Subgroups											
	Pell	Employed	Age 18-24	Age 25-34	Age 35-44	Age 45+	Female	First-gen	White	Black	Latinx	Asian
Panel A. Regression coefficients												
<i>Interaction terms</i>												
Synch*Subgroup	0.003 (0.002)	0.000 (0.002)	-0.008*** (0.002)	0.005* (0.002)	0.008* (0.003)	0.011* (0.005)	0.008*** (0.002)	0.006** (0.002)	-0.007** (0.002)	-0.000 (0.003)	0.007* (0.003)	0.011** (0.004)
Asynch*Subgroup	0.003 (0.002)	0.000 (0.001)	-0.010*** (0.002)	0.002 (0.002)	0.013*** (0.002)	0.029*** (0.003)	0.012*** (0.002)	0.001 (0.001)	0.005* (0.002)	-0.004 (0.002)	-0.008* (0.003)	0.011*** (0.003)
<i>Main effects</i>												
Synch	-0.018*** (0.002)	-0.017*** (0.002)	-0.010*** (0.002)	-0.017*** (0.003)	-0.017*** (0.003)	-0.017*** (0.003)	-0.021*** (0.003)	-0.018*** (0.002)	-0.014*** (0.003)	-0.016*** (0.002)	-0.018*** (0.002)	-0.018*** (0.002)
Asynch	-0.079*** (0.002)	-0.078*** (0.002)	-0.070*** (0.002)	-0.078*** (0.003)	-0.078*** (0.002)	-0.078*** (0.002)	-0.084*** (0.002)	-0.078*** (0.002)	-0.080*** (0.003)	-0.076*** (0.002)	-0.076*** (0.002)	-0.078*** (0.002)
Constant	0.828*** (0.001)	0.828*** (0.001)	0.828*** (0.001)	0.828*** (0.001)	0.828*** (0.001)	0.828*** (0.001)	0.828*** (0.001)	0.828*** (0.001)	0.828*** (0.001)	0.828*** (0.001)	0.828*** (0.001)	0.828*** (0.001)
Observations	5,187,430	5,187,430	5,187,430	5,187,430	5,187,430	5,187,430	5,187,430	5,187,430	5,187,430	5,187,430	5,187,430	5,187,430
Panel B. F-tests												
i. Subgroup * Modality (F)	1.92	0.07	12.67	3.22	14.24	39.93	22.78	3.48	11.67	1.90	17.32	8.88
p-value	0.15	0.93	0.00	0.04	0.00	0.00	0.00	0.03	0.00	0.15	0.00	0.00
ii. Subgroup * Synch (F)	2.30	0.04	13.88	6.41	6.31	5.88	13.25	6.81	9.03	0.02	6.23	8.48
p-value	0.129	0.85	0.00	0.01	0.01	0.02	0.00	0.01	0.00	0.89	0.13	0.00
iii. Subgroup * Asynch (F)	3.35	0.14	20.11	0.71	27.15	78.07	45.16	1.10	5.50	2.95	5.67	14.27
p-value	0.07	0.71	0.00	0.40	0.00	0.007	0.00	0.29	0.02	0.09	0.02	0.00

Notes: Panel A shows estimates from linear probability models of student-course level outcomes. The dependent variable in this table is an indicator for passing a course (earning a grade of C or higher). Key coefficients are for asynchronous and synchronous instructional modalities, with face-to-face instruction as the reference category. All models include student-by-term fixed effects and course-by-college-by-term fixed effects, such that estimates are identified from within-student, within-term variation across courses offered in different instructional modalities. Models also control for section-level characteristics, including enrollment composition and scheduling features. All subgroup indicators are binary variables equal to one if the student belongs to the specified subgroup. The employed indicator equals one if the student is employed in the given term. Standard errors are clustered at the course level. Panel B shows f-statistics test (i) the joint significance of all modality $\times$ subgroup terms and (ii) the significance of interaction terms for asynchronous and (iii) synchronous modalities separately.

Table 6. Grade Outcomes: Heterogeneous Effects

	Subgroup											
	Pell	Employed	Age 18-24	Age 25-34	Age 35-44	Age 45+	Female	First-gen	White	Black	Latinx	Asian
Panel A. Regression coefficients												
<i>Interaction terms</i>												
Synch*Subgroup	0.013 (0.007)	0.005 (0.007)	-0.006 (0.011)	0.002 (0.010)	0.003 (0.013)	0.014 (0.017)	0.045*** (0.010)	0.022** (0.008)	-0.042*** (0.011)	-0.002 (0.012)	0.036*** (0.011)	0.060*** (0.016)
Asynch*Subgroup	0.003 (0.008)	0.008 (0.005)	0.010 (0.010)	-0.021* (0.009)	-0.005 (0.010)	0.037** (0.012)	0.045*** (0.008)	0.010 (0.007)	-0.019 (0.010)	-0.006 (0.009)	0.007 (0.012)	0.077*** (0.013)
<i>Main effects</i>												
Synch	-0.004 (0.016)	-0.001 (0.014)	0.007 (0.013)	0.002 (0.016)	0.002 (0.016)	0.002 (0.016)	-0.021 (0.017)	-0.003 (0.016)	0.021 (0.017)	0.002 (0.015)	-0.005 (0.015)	-0.004 (0.016)
Asynch	-0.195*** (0.012)	-0.199*** (0.011)	-0.201*** (0.012)	-0.190*** (0.012)	-0.194*** (0.012)	-0.195*** (0.012)	-0.219*** (0.012)	-0.197*** (0.012)	-0.184*** (0.015)	-0.193*** (0.011)	-0.195*** (0.011)	-0.201*** (0.012)
Constant	2.890*** (0.005)	2.890*** (0.005)	2.891*** (0.005)	2.891*** (0.005)	2.891*** (0.005)	2.890*** (0.005)	2.889*** (0.005)	2.890*** (0.005)	2.891*** (0.005)	2.891*** (0.005)	2.891*** (0.005)	2.891*** (0.005)
Observations	4,249,932	4,249,932	4,249,932	4,249,932	4,249,932	4,249,932	4,223,514	4,249,932	4,249,932	4,249,932	4,249,932	4,249,932
Panel B. F-tests												
i. Subgroup * Modality (F)	1.83	1.48	1.06	3.69	0.31	5.13	16.01	3.42	6.59	0.22	6.86	18.37
p-value	0.16	0.23	0.35	0.03	0.73	0.01	0.00	0.03	0.00	0.80	0.00	0.00
ii. Subgroup * Synch (F)	3.13	0.60	0.27	0.04	0.07	0.68	20.61	6.77	13.17	0.03	11.54	14.40
p-value	0.08	0.44	0.61	0.84	0.79	0.41	0.00	0.01	0.00	0.86	0.00	0.00
iii. Subgroup * Asynch (F)	0.15	2.94	0.98	5.50	0.26	9.83	29.39	2.17	3.69	0.41	0.34	35.60
p-value	0.70	0.09	0.32	0.02	0.61	0.00	0.00	0.14	0.06	0.53	0.56	0.00

Notes: Panel A shows estimates from linear probability models of student-course level outcomes. The dependent variable in this table is a continuous variable for course grade on a scale of 0 to 4. Key coefficients are for asynchronous and synchronous instructional modalities, with face-to-face instruction as the reference category. All models include student-by-term fixed effects and course-by-college-by-term fixed effects, such that estimates are identified from within-student, within-term variation across courses offered in different instructional modalities. Models also control for section-level characteristics, including enrollment composition and scheduling features. All subgroup indicators are binary variables equal to one if the student belongs to the specified subgroup. The employed indicator equals one if the student is employed in the given term. Standard errors are clustered at the course level. Panel B shows f-statistics test (i) the joint significance of all modality $\times$ subgroup terms and (ii) the significance of interaction terms for asynchronous and (iii) synchronous modalities separately

Table 7. Course Outcomes Relative to Pandemic

	Pre-Covid		Post-Covid	
	Grade	Pass	Grade	Pass
Synchronous	-0.026 (0.028)	-0.019*** (0.004)	0.034* (0.017)	-0.011*** (0.003)
Asynchronous	-0.217*** (0.014)	-0.082*** (0.003)	-0.142*** (0.016)	-0.067*** (0.004)
Observations	2812603	3544478	1437329	1642952

Notes: Pre-COVID refers to the pre-pandemic period (2015-2019) and post-COVID refers to the recovery period (2022-2024).

Regressions are estimated at the student-section level. The outcome variable in Columns (1) and (3) is course grade measured on a four-point scale. The outcome variable in Columns (2) and (4) is an indicator for course passing, coded as one if the student earned a grade of C or higher. Models include indicators for asynchronous and synchronous online instruction, with face-to-face instruction serving as the omitted reference category. All specifications include student-by-term and course-by-college-by-term fixed effects, as well as controls for section-level characteristics. Sample size varies across specifications due to the inclusion of high-dimensional fixed effects, which drop singleton observations that do not contribute to within-group variation. Robust standard errors clustered at the student level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8. Differential Growth in Asynchronous Course-Taking

	(1) Pell	(2) Employed	(3) Age
Post-covid*Pell	0.032*** (0.002)		
Post-covid*Employed		0.008*** (0.002)	
Post-covid*25-34 yrs			-0.061*** (0.002)
Post-covid*35-44 yrs			-0.057*** (0.004)
Post-covid*45+ years			-0.047*** (0.005)
Observations	6141500	6141500	6126461

Notes: This table reports coefficients on interaction terms between the post-COVID indicator and student subgroup characteristics. The dependent variable is the share of courses taken asynchronously within a term. “Post-COVID” refers to academic years 2022-2024, with pre-COVID years (2015-2019) serving as the reference period. Reported coefficients represent the differential change in asynchronous course-taking when both the post-COVID indicator equals one and the subgroup indicator equals one (e.g., Pell-eligible students in the post-COVID period), relative to the omitted reference group. Column (1) examines Pell eligibility, Column (2) employment status, and Column (3) age categories, with students ages 18-24 serving as the omitted age reference group. All models include student fixed effects; coefficients therefore reflect within-student changes over time. Coefficients should be interpreted as the additional post-COVID change in asynchronous course-taking for students in the specified subgroup relative to the omitted reference group. Standard errors clustered at the student level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9. Online course-taking and student outcomes

	(1) Intensity: “Share” model	(2) Presence: “Any” model
<i>Panel A. Labor Market Participation</i>		
Employment		
Asynchronous	0.019*** (0.001)	0.008*** (0.001)
Synchronous	0.016*** (0.002)	0.004*** (0.001)
<i>Panel B. Course enrollment</i>		
Credits in a term		
Asynchronous	-2.708*** (0.015)	0.744*** (0.011)
Synchronous	-2.338*** (0.027)	1.537*** (0.015)
Courses in a term		
Asynchronous	-1.009*** (0.005)	0.293*** (0.003)
Synchronous	-0.781*** (0.009)	0.554*** (0.005)
Observations	1834830	1834830

Notes: This table reports estimates from two separate model specifications examining the association between online course-taking and student outcomes, a “share” model and an “any” model. Both specifications include student fixed effects; coefficients reflect within-student variation over time. The key predictor variables in model (1) are the share of asynchronous courses and the share of synchronous courses taken in a given term (i.e., the “share” model). The key predictor variables in model (2) are indicators for

whether the student took any asynchronous course in that term, and for whether the student took any synchronous course in that term (i.e., the “any” model). Student outcomes are measured at the term level. Face-to-face is the omitted category. Employment is an indicator for being employed in a given term. Course load is captured by the number of courses and total credits enrolled in a term (both continuous variables). Standard errors are robust and clustered at the student level. The sample includes 1,834,830 student-term observations. * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Appendix

Table A1. Course Outcomes Across Time

	2016		2018		2022		2024	
	<i>Grades</i>	<i>Pass</i>	<i>Grades</i>	<i>Pass</i>	<i>Grades</i>	<i>Pass</i>	<i>Grades</i>	<i>Pass</i>
Synchronous	0.015 (0.036)	-0.006 (0.006)	-0.043 (0.036)	-0.026*** (0.006)	0.004 (0.018)	-0.017*** (0.003)	0.065*** (0.019)	-0.004 (0.003)
Asynchronous	-0.243*** (0.016)	-0.087*** (0.003)	-0.205*** (0.017)	-0.084*** (0.004)	-0.163*** (0.017)	-0.070*** (0.004)	-0.117*** (0.019)	-0.061*** (0.004)
Observations	593024	734812	558182	673666	466226	535915	495109	563496

Notes: Regressions are estimated at the student-section level. Course grade is measured on a four-point scale. Course pass is coded as one if the student earned a grade of C or higher. Models include indicators for asynchronous and synchronous online instruction, with face-to-face instruction serving as the omitted reference category. All specifications include student-by-term and course-by-college-by-term fixed effects, as well as controls for section-level characteristics. Sample size varies across specifications due to the inclusion of high-dimensional fixed effects, which drop singleton observations that do not contribute to within-group variation. Robust standard errors clustered at the student level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A2. Course enrollment by fully asynchronous term

Term Type	Mean Credits	Mean Courses	Student-Terms
Not Fully Asynchronous (Async Share < 1)	10.65	3.63	1,388,705
Fully Asynchronous (Async Share = 1)	7.40	2.47	446,125
Total	9.86	3.35	1,834,830

Table A3. Course Enrollment by Asynchronous Category

Asynchronous Share Category	Mean Credits	Mean Courses	Student-Terms
Share = 0	9.50	3.19	802,120
$0 < \text{Share} < 0.5$	13.38	4.67	302,146
$0.5 \leq \text{Share} < 1$	10.99	3.76	284,439
Share = 1	7.40	2.47	446,125
Total	9.86	3.35	1,834,830

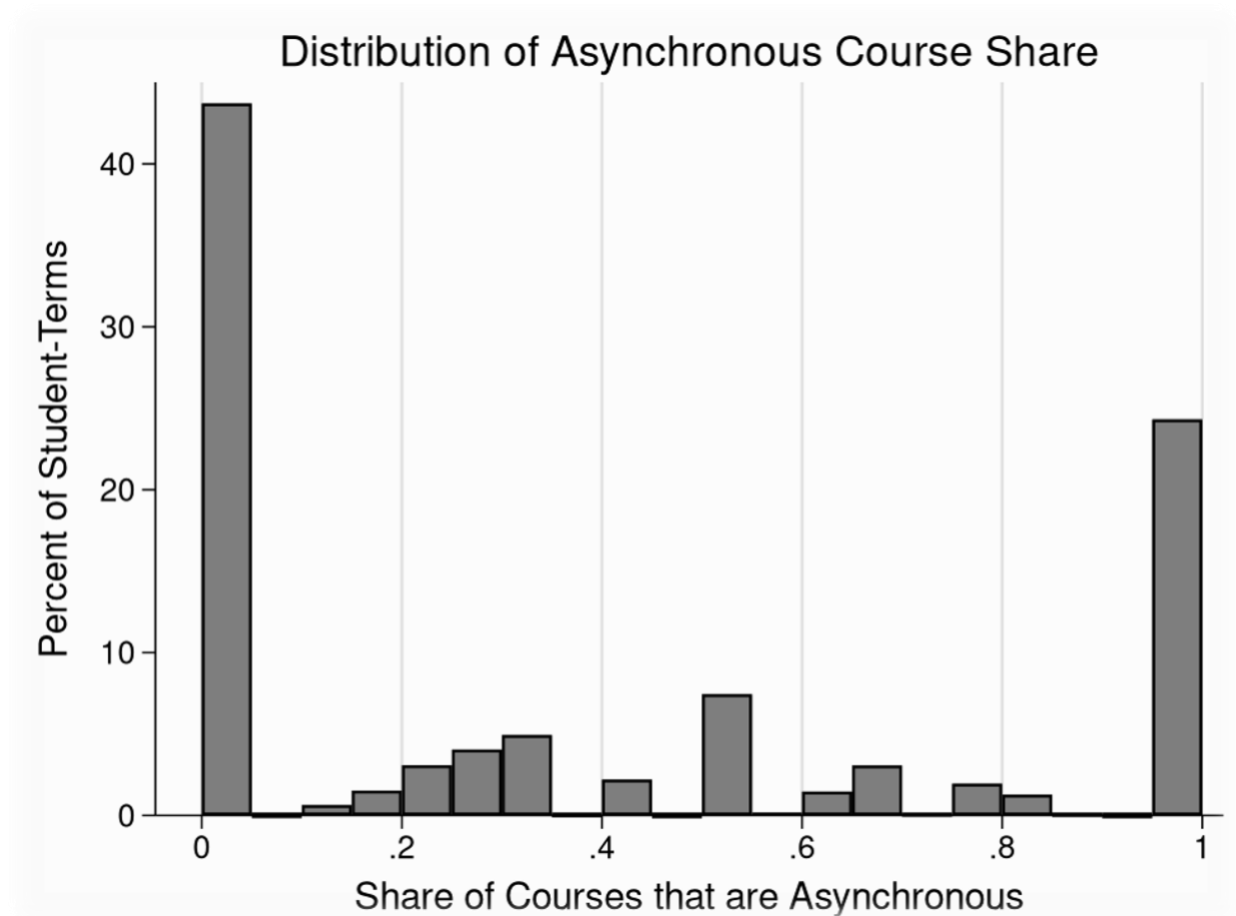
Notes: This table reports descriptive statistics for student-term observations grouped by the share of courses taken asynchronously within a term. Mean credits refers to the average number of credit hours enrolled during the term. Mean courses refers to the average number of courses enrolled during the term. The asynchronous share measure ranges from 0 (no asynchronous courses) to 1 (all courses asynchronous).

Table A4. “Share” Model Across Sample Restrictions

	(1) Full sample	(2) At least one online course	(3) At least one online course + asynch share < 1
<i>Panel A. Labor Market Participation</i>			
Employment			
Asynchronous	0.019*** (0.001)	0.022*** (0.001)	0.032*** (0.003)
Synchronous	0.016*** (0.002)	0.018*** (0.002)	0.019*** (0.003)
<i>Panel B. Course enrollment</i>			
Credits in a term			
Asynchronous	-2.708*** (0.015)	-7.523*** (0.015)	-2.963*** (0.038)
Synchronous	-2.338*** (0.027)	-7.222*** (0.032)	-6.735*** (0.038)
Courses in a term			
Asynchronous	-1.009*** (0.005)	-2.823*** (0.007)	-1.347*** (0.012)
Synchronous	-0.781*** (0.009)	-2.628*** (0.010)	-2.418*** (0.012)
Observations	1834830	1169267	723142

Notes: This table reports student fixed effects estimates from the asynchronous/synchronous course share specification across alternative sample restrictions. Coefficients reflect within-student variation over time. The key independent variables are the share of courses taken asynchronously and the share of courses taken synchronously in a given term; face-to-face courses are the omitted category. Column (1) uses the full sample of student-term observations. Column (2) restricts the sample to terms in which students enrolled in at least one online course (asynchronous or synchronous). Column (3) further excludes terms in which all enrolled courses were asynchronous (asynchronous share = 1). Employment is an indicator for being employed during the term. Course load outcomes include total credits enrolled and total courses enrolled in a term. Standard errors are robust and clustered at the student level. * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Figure A1. Distribution of asynchronous course share



Notes: This figure displays the distribution of the asynchronous course share variable across student-term observations. The measure is calculated as the proportion of courses taken asynchronously within a term and ranges from 0 (no asynchronous courses) to 1 (all courses asynchronous). The sample includes 1,834,830 student-term observations.

STUDY 3

Humanizing Pedagogy for Online STEM Courses

A Professional Development Evaluation

Abstract

This study examines the impact of the Humanizing Online STEM Academy, a professional development program designed to improve online STEM education through inclusive, student-centered teaching strategies. The study explores two primary strands: instructor beliefs, measured through pre- and post-training surveys, and student outcomes, assessed through administrative data analysis of student performance and persistence. Survey results from 52 instructors across five institutions revealed significant improvements in instructors' understanding of equity, increased self-efficacy in designing online courses, and greater use of humanized teaching practices. A difference-in-differences analysis based on over 30,000 course enrollments further shows that the Academy helped narrow racial disparities in course grades and persistence rates. Findings suggest that targeted professional development has the potential to meaningfully advance equity in online STEM instruction at scale.

Background

Inequities in higher education are especially pronounced in STEM fields. Between 1995 and 2001, only 53% of students who initially declared STEM majors persisted, while 47% either switched fields or left college without earning a credential (Chen, 2009). These stop-out rates are not evenly distributed: White and Asian students earn STEM degrees at significantly higher rates than Black and Latinx students (Chen, 2009). Black and Latinx STEM students are more likely than their White peers to switch majors and complete degrees in non-STEM fields—a pattern not observed in non-STEM disciplines such as the humanities (Riegle-Crumb et al., 2019).

Introductory STEM courses, in particular, act as a significant barrier to persistence. Poor performance in these courses disproportionately affects URM students (Chang et al., 2008; Gasiewski et al., 2012; Seymour & Hewitt, 1997). Hatfield et al. (2022) found that a White male student with average preparation and C-level grades in introductory STEM courses had a 48% chance of earning a STEM degree, compared to 35% for an equally prepared URM female student. These challenges are amplified in online learning environments, where performance gaps are wider for men, Black students, and students with lower GPAs (Xu & Jaggars, 2014). Online introductory STEM courses, in particular, have lower retention rates than their non-STEM counterparts (Wladis et al., 2013).

While multiple factors contribute to persistent racial disparities in STEM education, growing evidence points to the role of classroom climate and instructional practices in shaping student success. Stereotype threat, limited instructor engagement, and rigid course structures can undermine student engagement and performance in STEM classes, especially for underrepresented students (Steele & Aronson, 1995; Estrada et al., 2018). These barriers can be amplified in online learning environments, where interpersonal connections are harder to build.

Despite growing evidence on the value of inclusive pedagogy, culturally responsive teaching, and high quality student-instructor interactions (Dewsbury & Brame, 2019; Lin et al., 2019; Jaggars & Xu, 2016), faculty rarely receive training tailored to STEM teaching in online contexts.

This study addresses the gap in the literature by evaluating a professional development intervention designed to mitigate inequities in introductory online STEM courses. The Humanizing Online STEM Academy is a six-week asynchronous professional development program that equips instructors with equity-minded, student-centered teaching strategies for online STEM courses. Through modules on trust-building, inclusive course design, high-impact feedback, and authentic instructor presence, participants learn to create more engaging and supportive learning environments for historically underserved students. Previous qualitative research has found that the Humanizing Online STEM Academy cultivates an equity mindset, culturally responsive teaching, and improved student interactions (Pacansky-Brock et al., 2022; Xu et al., 2025). A key contribution of our study is not only assessing changes in instructor attitudes and perceptions but also examining whether these changes lead to the second stage of impact: improved student outcomes.

Humanizing Online STEM Academy

The Humanizing Online STEM Academy is a research-based online professional development program designed to promote equity in STEM education (Humanizing Online STEM Academy, n.d.). Developed with funding from the California Education Learning Lab, the Academy is informed by equity-minded research and made available under an open license for institutions using the Canvas learning management system. The program is fully asynchronous

and spans six weeks, requiring approximately 10 hours of work per week. Participants engage with weekly modules that include assignments and discussions facilitated within a community of peers and a dedicated facilitator. The focus is on integrating humanizing elements into one of the participants' existing online courses.

The Academy begins by emphasizing the importance of humanizing STEM education. Participants review data illustrating the disproportionate impact of STEM fields on Black, Latinx, Indigenous, and women students and are encouraged to analyze their course design through the lens of minoritized student identities. It then introduces the concept of instructors' imperfect presence as a foundation for building trust. Participants explore ways to authentically present themselves to students, including strategies for pre-course communication. Another focus is on the "warm demander" framework, which involves setting high expectations while providing supportive and wise feedback. Participants identify high-opportunity students and reflect on ways to offer constructive, growth-oriented feedback. Building a learning community is another critical component of the program. Participants are guided on fostering student-student interactions and enhancing overall engagement in their courses. Additionally, the Academy highlights the effective use of media to strengthen teaching presence and support student learning. Participants create welcome videos to introduce themselves and develop short instructional videos, known as "bumper videos," to clarify course content. In the final module, participants reflect on the impact of the Academy and showcase the humanizing elements they have incorporated into their online courses. By equipping instructors with practical strategies and fostering equity-minded teaching practices, the Humanizing Online STEM Academy seeks to address inequities in STEM education and improve outcomes for all students.

Theoretical Framework

The Humanizing Online STEM Academy is grounded in theories of teaching, learning, and equity that explain how instructor practices can shape student experiences and outcomes in online STEM education. The Academy is motivated by persistent inequities in STEM, particularly for historically underserved students, and seeks to address these disparities by transforming how instructors design and facilitate their courses.

Situated Cognition

Humanizing STEM is rooted in situated cognition theory, which posits that learning is inherently shaped by the social and cultural contexts in which it occurs (Brown et al., 1989). According to this perspective, knowledge is not transmitted in isolation but constructed through authentic participation in communities of practice. Learning thus depends on the relationships, interactions, and cultural norms that define the learning environment. In the context of online education, where isolation can inhibit engagement and belonging, this framework emphasizes the importance of designing opportunities for meaningful interaction and social connection. The Academy's design promotes contextualized, socially embedded learning by encouraging instructors to humanize their courses through authentic communication, collaborative activities, and relational trust-building.

Culturally Responsive Teaching

The Academy also draws on culturally responsive teaching (Gay, 2010) and culturally relevant pedagogy (Ladson-Billings, 1995), both of which emphasize the importance of connecting instruction to students' cultural identities, lived experiences, and community contexts. These frameworks argue that equitable learning environments affirm students' identities while promoting academic success and critical consciousness. In alignment with these

ideas, the Academy explicitly asks instructors to examine their courses through the lens of historically minoritized students, making culture and identity central to course design.

One key component of this approach is the “warm demander” stance, which involves maintaining high expectations while providing empathy and emotional support (Delpit, 2012; Kleinfeld, 1975). This approach is particularly important in STEM education, where rigor is often conflated with exclusion or detachment. The Academy trains instructors to balance academic challenge with relational warmth, positioning them as educators who communicate belief in students’ potential while offering the support needed to meet rigorous standards. In doing so, the program operationalizes the “warm demander” framework by encouraging instructors to combine high expectations with relational care to build trust and motivation among students historically marginalized in STEM.

Humanizing Pedagogy

The Academy is further informed by humanizing pedagogy, which emphasizes mutual respect, dialogue, and recognition of students as whole humans with intersecting identities (Freire, 1970; hooks, 1994). Online STEM courses, in particular, risk dehumanizing learning by privileging content mastery and efficiency over connection and care. The Humanizing Online STEM Academy explicitly challenges this paradigm by helping instructors cultivate authenticity, trust, and presence in their courses. Activities such as creating welcome videos, developing “liquid syllabi,” and integrating reflective and inclusive practices embody a commitment to affirming students’ belonging, agency, and humanity. The Academy also challenges deficit-based narratives about underrepresented students in STEM by encouraging instructors to reflect critically on how their own course design and communication practices may reproduce inequities.

As Pacansky-Brock (2020) notes, humanized online teaching is built on recognizing students as capable, resilient individuals who bring diverse perspectives, experiences, and forms of knowledge while also navigating challenges shaped by racism, poverty, and social marginalization. Humanized teaching, as described by Pacansky-Brock (2020), rests on four interwoven principles: trust, presence, awareness, and empathy. Trust involves intentionally cultivating a sense of safety and openness, often through “selective vulnerability,” where instructors share aspects of themselves that portray authenticity and relatability (Hammond, 2014). Presence requires instructors to make themselves visible and real in online spaces, using brief, imperfect videos and personalized communication to signal that they are engaged in the learning journey alongside students (Costa, 2020). Awareness entails learning about students’ circumstances, strengths, and needs to provide appropriate supports. Finally, empathy calls for flexibility and understanding in order to foster an environment where all can succeed.

Together, these frameworks offer a comprehensive understanding of how the Humanizing Online STEM Academy operates. Situated cognition explains how learning and relationship-building occur through authentic, contextualized interactions. Humanizing pedagogy and the warm demander framework describe the specific instructor behaviors, such as care, presence, and high expectations, that foster equity and belonging. Collectively, these theories support the hypothesis that shifts in instructor mindset and relational practices, rather than content delivery alone, can improve equity, engagement, and persistence in online STEM education.

This informs the study’s empirical approach in two important ways. First, it provides a rationale for measuring both instructor-level changes (e.g., equity beliefs and teaching strategies) and student-level outcomes (e.g., grades and persistence). Second, the focus on URM and non-

URM students is theoretically grounded, as the humanizing approach explicitly aims to close equity gaps by fostering inclusive climates that benefit historically underserved populations. To this end, the study investigates whether participation in the Humanizing Online STEM Academy is associated with changes in instructor beliefs and practices, as well as student academic outcomes, with particular attention to equity implications across student groups.

Research Questions

This study is guided by the following research questions, which aim to explore the effects of the Humanizing Online STEM Academy on both instructors and students.

1. How do instructor beliefs, attitudes, and instructional strategies, change as a result of the Academy, if at all?
2. What is the impact of the Academy on student course outcomes? How is this impact different for URM students, if at all?

Data

This study examines the effects of the Humanizing Online STEM Academy through two primary strands: (1) instructor beliefs, attitudes, and behaviors, measured via survey analysis, and (2) student-level outcomes, analyzed using administrative data. The first strand focuses on immediate outcomes, exploring changes in instructors' beliefs, attitudes, and instructional practices following their participation in the Academy. The second strand investigates the Academy's impact on student outcomes, with particular attention to differences observed among URM students. Together, these analyses provide a comprehensive understanding of how the Academy influences both instructors and students in online STEM courses.

Survey data and methodology

The study collected survey data from instructors across two waves: a pre-Academy survey and a post-Academy survey. A total of 65 instructors were invited to participate in the Academy, with 80% (52 instructors) completing both rounds of surveys. The final sample of 52 instructors represented four cohorts, who completed training between spring and summer of 2023.

These instructors were affiliated with five institutions, 4 California Community Colleges and 1 California State University campus. Tables A1 through A5 show the demographic composition of the 5 partner campuses. CCC 1, which enrolls approximately 28,600 students is 68% Latinx, followed by 17% White, and 6% Black. This institution would be categorized as an HSI. CCC 2, which enrolls approximately 6,500 students is 47% Latinx, followed by 33% White, and 9% Black. This institution would be categorized as an HSI. CCC 3, which enrolls approximately 4,400 students is 80% Latinx, followed by 12% White, and 2% multiracial. This institution would be categorized as an HSI. CCC 4, which enrolls approximately 32,300 students is 47% White, followed by 27% Latinx, and 13% Asian. This institution would be categorized as an HSI and an AANAPISI. The CSU, which enrolls approximately 5,400 students is 51% White, followed by 30% Latinx, followed by 3% Asian and 3% Black. This institution would be categorized as an HSI.

Table 1 shows the demographics of Academy participants. The majority of participants are women (58%), and 47% of participants were between 35 and 44 years. A majority of participants were White (60%), followed by Black (14%) and Latinx (12%). Half of participants had master's degree, while 46% had a doctoral degree. Participants had an average of 11.1 years of teaching experience ($SD = 7.5$), including 4.4 years of online teaching experience ($SD = 4.3$).

Additionally, 40% had received some form of professional development training prior to their participation in the Humanizing Online STEM Academy.

We used descriptive analyses to identify patterns across instructor perceptions and attitudes and instructional practices. To evaluate shifts in these concepts before and after Academy participation, we conducted paired t-tests to determine statistically significant differences in pre- and post- responses.

Tables 2 and 3 first captured the reception of humanizing elements taught in the Academy. Table 2 shows the results of how instructors perceived the benefit of particular humanizing elements, on a scale of “not at all beneficial” (1) to “extremely beneficial” (5). Instructors overwhelmingly thought that the elements would be helpful in establishing trust and inclusivity with their students. In particular, the instructors perceived the benefit of warm wise feedback (M=4.6), get-to-know-you survey (M=4.5), microlectures (M=4.5), and liquid syllabus (M=4.4). Table 3 captured the intent of instructors to implement these strategies in their class, with 96% of respondents saying they would implement the humanized homepage, humanized course card, and get-to-know-you survey, while 94% said they would implement bumper videos, and 92% said they would implement the liquid syllabus.

Changes in Instructor Perceptions and Attitudes

Change in instructor equity beliefs. Instructors were asked to rate their agreement with various statements about equity on a 5-point Likert scale, where 1 indicated “Strongly Disagree” and 5 indicated “Strongly Agree.” The analysis of pre- and post-Academy survey data revealed significant shifts in instructors’ beliefs (Table 4, rows 1-6). Specifically, the belief that the instructional environment shapes student emotions and sense of belonging increased by 0.38

points, from a score of 3.90 pre-Academy to 4.28 in the post-Academy. Additionally, the belief in the role of sense of belonging and emotions in STEM success increased by 0.38 points, from a score of 4.09 to 4.47. Another large difference in instructor beliefs was in the notion of students' capability to succeed, which increased by 0.31 points, from 3.60 to 3.91. All of these differences were statistically significant ($p < 0.001$). The strength of belief in the role of teaching and instructor-student relationships in STEM success also increased by 0.17 points, from 4.46 to 4.63, a difference that was statistically significant ($p < 0.01$). These changes reflect the Academy's success in raising instructors' awareness of the emotional factors influencing student success and the critical role instructors assume in influencing student emotions.

Changes in instructor flexibility and self-efficacy. Instructor self-efficacy significantly increased following the Academy (Table 4, rows 7-8). The average self-efficacy score, measured on a 5-point scale from "not at all confident" (1) to "extremely confident" (5), increased by 0.56 points, from 4.02 pre-Academy to 4.58 post-Academy ($p < 0.001$). This score indicated that the Academy made instructors more confident in their ability to design and deliver effective and welcoming online courses. Additionally, instructors showed greater flexibility in their course policies post-Academy. The average score on flexibility with policies such as late submissions and make-up assignments, measured on a 5-point scale (1 = very inflexible to 5 = very flexible), increased by 0.26 points, from 3.71 to 3.97 ($p < 0.05$). This shift reflects a move toward more accommodating and student-centered teaching practices.

Changes in beliefs about instructor responsibilities. There were significant shifts in instructors' cultural responsiveness and inclusivity following the Academy. Instructors were asked to rate their agreement with various statements regarding their teaching responsibilities (Table 4, rows 9-12). The belief that fostering belonging and connection is part of an instructor's

responsibility increased by 0.27 points, from a pre-Academy mean of 4.29 to a post-Academy mean of 4.56 ($p < 0.001$) on a 5-point scale ranging from “strongly disagree” (1) to “strongly agree” (5). There was also an increased agreement that it is instructors’ responsibility to be culturally responsive and use student-centered practices, with a 0.25-point increase ($p < 0.001$), from 4.16 to 4.41. These changes suggest that the Academy effectively encouraged instructors to adopt more inclusive and culturally responsive teaching practices, better aligned with the needs of diverse student populations.

Changes in Instructional Practices

Change in use of teaching strategies. A significant outcome of the Academy was the widespread adoption of humanizing instructional practices among nearly all instructors (Table 5, rows 1-9). For instance, the use of personalized course homepages increased dramatically from 55% pre-Academy to 99% post-Academy; the use of visually oriented videos to demystify difficult concepts increased from 48% to 98%; and the use of surveys to identify high-opportunity students who benefit from high-touch interactions increased from 27% to 96%. Furthermore, the likelihood of implementing microlectures (short video lectures, summaries, or topic introductions) increased by 1.28 points, from 2.83 to 4.11 ($p < 0.001$) on a 5-point Likert scale. Similarly, the likelihood of providing supportive and motivating voice/video feedback increased by 1.24 points, from 2.92 to 4.16 ($p < 0.001$). These changes show a clear shift toward practices that make course materials more accessible and engaging for students.

Changes in instructor-student interaction. Instructor-student interactions, both academic and social, showed significant improvements post-Academy (Table 5, rows 10-12). Academic interactions, including offering office hours, providing feedback on student work, and engaging

with students through synchronous (e.g., Zoom) and asynchronous (e.g., discussion boards) communication tools, increased by 0.39 points from 3.85 to 4.24 ($p < 0.001$) on a 5-point scale (1 = never, 5 = very frequently). Management interactions, such as providing opportunities for student feedback, sharing grading criteria, proactively identifying and supporting struggling students, and responding promptly to logistical questions, increased by 0.52 points from 3.95 to 4.47 ($p < 0.001$). Additionally, the presence of social interaction opportunities, including introducing themselves to students through written, visual, or video communication and sharing a personal video in a non-academic context, increased from 63% pre-Academy to 97% post-Academy ($p < 0.001$). These findings indicate that instructors were increasingly focused on building strong, supportive relationships with their students—a key outcome of humanized online instruction.

Changes in student-student interactions. Instructors also demonstrated a greater focus on providing opportunities to promote student-student interactions (Table 5, rows 13-14). Academic interactions, such as collaborative group assignments, increased by 0.56 points, from 2.96 to 3.52 ($p < 0.01$) on a 5-point scale (1 = never, 5 = very frequently). Similarly, the presence of social interactions, such as icebreaker activities, rose from 62% pre-Academy to 96% post-Academy ($p < 0.001$). These changes reflect an increased emphasis on fostering peer connections and collaborative learning.

Changes in media use. Media use in instruction expanded significantly as a result of the Academy (Table 5, rows 15-16). Instructors reported greater use of audio and video tools across multiple areas (e.g., announcements, feedback beyond grades, etc.), with the use of audio rising by 1.27 points, from 1.10 to 2.37 ($p < 0.001$) on a 5-point scale (1 = never, 5 = very frequently). Similarly, the use of video increased by 1.87 points, from 2.25 to 4.12 ($p < 0.001$) on the same

scale. This shift toward more diverse communication formats demonstrates that instructors became more comfortable using dynamic, interactive methods to engage students and support the cultural communication preferences of diverse students.

The survey results from the Humanizing Online STEM Academy reveal significant improvements in instructors' perceptions, attitudes, and instructional practices. Instructors demonstrated increased confidence in designing effective, welcoming courses and adopted more humanizing instructional practices. There was an increased understanding of their role in promoting cultural responsiveness and inclusivity in the classroom. There was also an increase in positive interactions, with instructors placing greater emphasis on building strong, supportive relationships with students, fostering peer connections, and creating collaborative learning environments. Additionally, instructors embraced diverse communication tools, such as audio and video, to engage students. These findings emphasize the Academy's effectiveness in fostering inclusive and dynamic teaching methods, which contribute to more supportive and engaging online STEM learning environments.

Administrative Data and Methodology

To evaluate the impact of the Humanizing Online STEM Academy on student performance, we conducted an analysis using de-identified student-level data. We obtained administrative data from the five colleges, 4 CCCs and 1 CSU. Institutional analysts de-identified the data, making student IDs and instructor IDs anonymous. The dataset includes student-level transcript information from Spring 2017 to Fall 2023, along with demographic details such as race, gender, major, and first-term admitted, among others. The transcript data contains course-level information for each term, including the grade earned and the instructor

who taught the course. This allows us to track which courses were taught by Academy instructors and those taught by non-participant instructors over time. This also allows us to assess whether the Academy led to measurable improvements, particularly for traditionally underrepresented student groups.

We constructed the analytic sample by restricting to courses that Academy instructors indicated they intended to “humanize” according to their pre-Academy survey. Courses were included in the analysis if they met the following criteria: (1) the instructor identified the course for humanization in the pre-Academy survey; (2) the course was taught by at least one Academy instructor and at least one non-participant instructor in the pre-Academy period; and (3) the course was taught by at least one Academy instructor and at least one non-participant instructor in the post-Academy period. For instance, if an Academy participant at Institution A completed the Academy in Spring 2023 to humanize Math 1A, and subsequently taught the humanized Math 1A course in Fall 2023, any instructor who taught Math 1A both before and during Fall 2023 at institution A would be included in our analytical sample. It is important to note that, because instructors completed the Academy at different times, the post-period for each instructor is relative to the completion of their specific cohort.

To assess the impact of the Academy training, we used a difference-in-differences design. The treatment group consists of instructors who participated in the Academy, and the post-period is defined as any term following their Academy training. For instance, if an instructor completed the Academy in Spring 2023, the first post-period would be Summer 2023. Similarly, if an instructor completed training in Summer 2023, the first post-period would be Fall 2023. Term dates are defined according to the academic calendar of the institution where each instructor teaches, as start dates may vary. This method compares the change in student performance over

time between two groups: students taught by Academy participants (the treatment group) and those taught by non-participants who were teaching the same courses taught by the Academy participants (the control group), both before and after the Academy. The first difference in the model captures how student outcomes changed before and after the Academy. For example, we compared student course persistence rates before and after the Academy's implementation for both Academy and non-Academy instructors. The second difference isolates the unique impact of the Academy by comparing these changes between the two groups. Essentially, the DID model helps us control for external factors that could influence all students in the absence of the Academy (e.g., curriculum changes, institution-wide policies), enabling us to focus on the additional benefits that stem from Academy participation.

We examined three key outcomes: (1) average course grade, (2) course pass rate, and (3) course persistence. Average course grade is calculated according to each institution's guidelines (e.g., some institutions differentiate between an A- and A in grade points, while others treat them the same). Course pass rate is coded as 1 if a student received an A, B, C, D, or P, and 0 if they withdrew or received an F. Course persistence is coded as 1 if the student remained enrolled in the course (i.e., received a final grade), and 0 if they withdrew. Receiving a W is determined based on each institution's final drop deadline.

Descriptive statistics

Table 6 shows that Academy participants come from a variety of fields, with the highest concentration in mathematics (10), followed by engineering (3) and psychology (3). Figures 1 and 2 descriptively compare outcomes between students taught by Academy instructors and non-Academy instructors, segmented by URM and non-URM students. Figure 1 illustrates the changes in average course grades for these groups before and after the Academy training.

Overall, it seems that the Academy training had a differential impact on URM and non-URM students. Specifically, for URM students, both Academy and non-Academy instructors saw slight improvements in average grades over time, but the increase seemed to be noticeably larger for those taught by Academy instructors. In contrast, the trend seemed to be opposite among non-URM students who experienced a decline in average course grades after the Academy training. Figure 2 displays changes in course pass rates and shows similar patterns: URM students taught by Academy instructors seemed to experience a larger improvement in average course pass rates post-Academy, which is not observed among non-URM students.

Regression model

We evaluated the Academy's effect on student performance using a DID methodology. The equation that represents the empirical strategy is:

$$Y_{itcs} = \beta_0 + \beta_1 Academy_{it} + \beta_2 URM_s + \beta_3 (Academy_{it} * URM_s) + \gamma_c + \tau_t + \theta_i + X_{st} + \epsilon_{itcs}$$

where Y is the outcome (e.g., course grade, persistence, or pass rate) for student s in course c during term t taught by instructor i . $Academy_{it}$ is an indicator variable equal to 1 if instructor i participated in the Academy and is teaching in the term t post-training. URM_s is an indicator variable equal to 1 if student s is American Indian/Alaska Native, Black, Latinx, Native Hawaiian/Pacific Islander, or multiracial. $Academy_{it} * URM_s$ is the interaction term of interest, which estimates the differential effect of the Academy on URM students' outcomes relative to non-URM students taught by Academy instructors after the Academy. The term γ_c represents

course-by-college fixed effects, τ_t represents term fixed effects, θ_i represents instructor fixed effects, and X_{st} represents a vector of student-level variables, such as cohort, major, and gender.

Parallel trends

Figure 3 plots the dynamic effects of the humanizing PD intervention on average course grades. The estimated leads are statistically indistinguishable from zero, indicating no detectable differences in trends between treated and comparison courses prior to implementation. Beginning in the term of the PD and persisting thereafter, the coefficients become negative and statistically significant, suggesting that average grades declined following the introduction of humanizing practices. For course persistence, the estimated leads and lags remain near zero and statistically insignificant throughout the period (Figure 4). This pattern suggests that the Academy did not meaningfully alter students' likelihood of remaining enrolled in the course. Figure 5 presents event study estimates for pass rates. The coefficients for leads indicate that courses taught by future Academy instructors exhibited higher pass rates several terms prior to the Academy, but these rates gradually declined as the intervention approached. Specifically, estimates were highest five terms before the PD and decreased steadily in each subsequent term, reaching negative values after the PD. This downward trend suggests that treated courses were already experiencing a decline in pass rates prior to the Academy, which complicates interpretation of the post-treatment effects. The post-PD estimates continue this downward trajectory, implying that the training did not reverse the pre-existing decline. Although the Academy aimed to promote more humanized and supportive learning environments, these changes may not have translated into improvements in pass rates, at least in the short term.

The event study for pass rates shows that the parallel trends assumption does not hold for this outcome, suggesting that the post-treatment estimates should not be interpreted causally. Instead, these results likely reflect pre-existing downward trajectories among instructors who later participated in the Academy. For other outcomes, the event study plots indicate that the parallel trends assumption is more plausibly satisfied. Specifically, course grades and persistence rates show coefficients that are indistinguishable from zero in the pre-treatment period, suggesting that treated and untreated courses followed similar trajectories prior to the Academy. These patterns support the validity of the difference-in-differences estimates for these two outcomes, lending credibility evidence that the observed post-Academy improvements reflect the effects of the professional development rather than pre-existing trends.

Regression results

Results from this regression model are shown in Table 8. The *URM* coefficients show that there were pre-existing gaps between URM (e.g., American Indian/Alaska Native, Black, Latinx, Native Hawaiian/Pacific Islander, or multiracial students) and non-URM (e.g., White or Asian) students before the Academy. Specifically, URM students performed 0.307 grade points lower (i.e., B- vs. B) on average relative to their non-URM counterparts ($p < 0.001$). URM students were 3.1 percentage points ($p < 0.001$) less likely to persist compared to non-URM students, and 6.1 percentage points ($p < 0.001$) less likely to earn a passing grade compared to non-URM students.

To examine at the differential impacts of the Academy on URM students, we turn to the interaction term. Column 1 of Table 8 shows that the Academy raised URM students' grades by 0.315 grade points ($p < 0.05$) more than it raised grades for non-URM students. Column 2

suggests the Academy raised URM students' persistence rates by 11.4 percentage points ($p < 0.05$) more than it raised persistence rates for non-URM students. Column 3 suggests the Academy raised URM students' persistence pass rates by 12.6 percentage points ($p < 0.05$) more than it raised pass rates for non-URM students. In the context of pre-existing gaps, these differential impacts of the Academy on URM students narrowed these gaps. These results suggest that the Academy's humanizing strategies can promote greater equity in online STEM education. The results show that while URM students initially underperformed in grades, persistence, and pass rates, the Academy significantly narrowed these gaps.

Subgroup analysis

We conducted a subgroup analysis on a sample of 7 courses with science content in the following departments: biology, engineering, environmental studies, foods, psychology, and registered nursing (Table 9). We see the same pre-existing gaps between URM and non-URM students. On average, URM students earn grades that are 0.33 points ($p < 0.001$) lower than non-URM students before the Academy. URM students were also 3.0 percentage points ($p < 0.001$) less likely to persist, and 5.7 percentage points less likely to pass ($p < 0.001$) in science courses than non-URM students before the Academy. The interaction term shows that the Academy raised URM students' science course grades by 0.442 grade points ($p < 0.05$) more than it raised grades for non-URM students. The coefficients for course persistence rates and course pass rates did not reach statistical significance. This suggests that the Academy may not be entirely successfully in promoting persistence in certain disciplines. However, conditional on persisting, URM students tend to have higher grades than non-URM students in humanized courses. In the context of existing inequities, the Academy may close the course performance grades, but this may be because lower-performing URM students drop out of the course.

Spillover effects

While the humanizing intervention was designed for instructors to select a specific course to restructure, we also examined an alternative analytic sample that includes all online STEM courses taught by Academy participants after training. This spillover sample includes two types of courses: (1) online STEM courses taught by Academy instructors that were not explicitly humanized as part of the training, and (2) online STEM courses taught by non-Academy instructors during the same period. This approach allows us to explore potential spillover effects, under the assumption that instructors may retain and apply elements of the training even in courses they did not explicitly restructure. Using the same model as in our main analysis, which includes course-by-college fixed effects, term fixed effects, and instructor fixed effects, we find no statistically significant effects of the Academy on course grades, persistence, or pass rates (Table 10). URM students continue to underperform relative to non-URM students, and the interaction terms between Academy participation and URM status are small and not statistically significant. These results suggest that the benefits of the humanizing training are largely confined to courses that were actively restructured, with no evidence of spillover to other courses taught by the same instructors.

Finding no effect in non-humanized courses strengthens the claim that the intervention's impact depends on intentional course redesign rather than just general exposure to the PD. If the PD only improved outcomes in humanized courses, it suggests that specific changes in course structure, assignments, or pedagogy are driving the gains, rather than broad improvements in teaching style or instructor motivation.

Did the Humanizing STEM negatively impact White and Asian students?

In Table 8, we saw that the *Academy* coefficient, which represents the impact of the PD intervention on non-URM students, was negative. Specifically, we pay attention to the decrease in course grade and course persistence.

Before discussing the implications of these findings, we first assess whether humanized courses systematically alter the composition of students who enroll or persist in them. For instance, if humanized courses feature more flexible deadlines, adaptable structures, and supportive instructors, they might attract or retain students who are typically lower-performing. To test this, we collapse the data to the instructor–course level and examine three outcomes that could indicate changes in class composition: overall enrollment, share of URM students, and the average cumulative GPA of incoming students.

Table 11 presents results for course-level enrollment. In the fully saturated model (column 4), we find no evidence of changes in enrollment size. However, because enrollment caps are often fixed and low-enrollment courses may be canceled, this metric may not fully capture composition shifts. Thus, Table 12 examines the demographic composition of courses, where the outcome is the proportion of URM students. The estimated coefficient (column 4) suggests a 4.9 percentage point decrease in URM representation, though this result is not statistically significant. Given that the average class size in our data is 36 students, with approximately 60% identifying as URM, this corresponds to roughly two fewer URM students per course. Finally, Table 13 considers students' academic preparation, measured by cumulative GPA prior to course enrollment in the absence of SAT or high school GPA data. Here, we find a small and statistically insignificant decline, about 0.22 grade points on a 4-point scale, among students entering humanized courses.

Taken together, these results suggest that the humanized intervention does not systematically alter the composition of students enrolled in these courses, either in terms of demographics or prior academic preparation. While there is a small decrease in cumulative GPA, it is imprecisely estimated. Enrollment size and the proportion of URM students remain essentially unchanged, indicating that shifts in who enrolls are unlikely to explain the observed post-intervention outcomes. Therefore, the negative impact observed for non-URM students is more plausibly attributable to changes in the instructional environment itself, rather than changes in the composition of the classroom.

Discussion

The first strand of our project, which focused on survey data, indicated that instructors are adopting more inclusive and dynamic teaching strategies. Participants in the Humanizing Online STEM Academy reported implementing practices designed to make their classrooms more affirming, relational, and student-centered. The second strand of our project, which analyzes administrative data, shows that these practices had differential impacts: while URM students generally benefited from the intervention, non-URM students experienced unexpected declines in outcomes. We also provide evidence against the possibility that these effects were driven by systematic changes in the composition of students enrolled in humanized courses. This contrast raises an important question: why might humanizing practices result in worse outcomes for non-URM (i.e., white and Asian) students?

It is important to note that classroom grades do not necessarily represent mastery of course material in the same way as criterion-referenced standardized tests. Grades are an imperfect and often unreliable indicator of student learning because they can vary across

instructors, within courses, and by assessment format (Schinske & Tanner, 2014). Critics have argued that widespread grade inflation can undermine the meaning of grades and thus their usefulness for evaluating performance (Rojstaczer & Healy, 2012; Schneider & Hutt, 2014). Ultimately, grades are often positional outcomes. In this study, we see them as a reflection of a student's performance relative to peers rather than an absolute measure of achievement. Under this framework, apparent declines among non-URM students may simply reflect shifts in relative standing within the course cohort, rather than reductions in learning. In other words, if humanizing practices elevate URM student outcomes, the corresponding “decline” for non-URM students is a relative, context-dependent effect, mechanically built into a grading system that reflects a distribution. This is an inherent limitation of using grades to evaluate program impacts.

Alternative mechanisms

Suspending the limitations of grades as relative rather than absolute measures of learning, we also consider additional theoretical perspectives that may help explain these patterns. It is possible that humanizing practices require instructors to devote time to relational and affective activities which can create opportunity costs by reducing attention for other tasks or student groups. These trade-offs reflect the longstanding theme that pedagogical innovations compete for finite time and cognitive resources (Cuban, 1993; Tyack & Tobin, 1994). Second, schema disruption and epistemic authority may play a role: students bring expectations about “rigorous” STEM instruction that emphasize objectivity, structure, and instructor authority, while humanizing approaches emphasize flexibility, collaboration, and emotional connection. Deviations from these schemas can generate uncertainty or disengagement (Kruglanski et al., 2005; Zagzebski, 2012). This disruption has been documented in prior research on gender dynamics in classrooms (Boring, Ottoboni, & Stark, 2016; Oreopoulos & Hoffman, 2019;

Solanki & Xu, 2018). Finally, identity and inclusion dynamics may contribute: efforts explicitly supporting historically marginalized students can trigger perceptions of exclusion or identity threat among dominant-group students. Majority-group members may feel devalued or displaced when inclusion initiatives emphasize minority identities (Andriessen et al., 2023; Bell, 1980; Steele et al., 2002; Plaut et al., 2011; Osborn, Sosa, & Rios, 2019; Starck, Sinclair, & Shelton, 2021). Together, these mechanisms suggest that negative outcomes among non-URM students may reflect short-term adjustment costs or misalignment with instructional expectations. Taken together, the limitations of grades as relative measures of learning make interpreting the outcomes of this intervention complex. However, the humanizing professional development still had a measurable impact on grades, which gives us insight into ways we can serve historically underserved students.

Conclusion

This study examines the impact of the Humanizing Online STEM Academy on both instructor practices and student outcomes, offering valuable insights into professional development in online STEM education. By analyzing survey data, the research highlights how the Academy fosters inclusive and dynamic teaching strategies, contributing to more supportive and engaging learning environments. Complementary analysis of administrative data indicate that improvements for URM students corresponded with relative shifts for non-URM students in the grade distribution. Taken together, this shows the Academy's potential to promote greater equity in student outcomes.

The findings have significant policy implications, particularly for institutions seeking to address equity gaps in STEM education. The Academy offers a cost-effective intervention with

an open-access license available through Canvas. This study highlights the effectiveness of the Academy in diverse higher education settings, as it was tested across California Community Colleges and a California State University campus. Given the critical role community colleges and CSUs play in serving URM students—who constitute a substantial proportion of their student populations—this intervention offers a scalable and evidence-based approach to promoting equity in STEM courses.

By fostering inclusive teaching practices and reducing performance gaps for URM students, the Academy can contribute to improving both the retention and success of students in STEM fields. Policymakers and institutional leaders could consider adopting or adapting the Academy as a professional development initiative to support equity goals. These findings have important policy implications, as they demonstrate how professional development can promote inclusive teaching and help address persistent equity gaps in STEM, strengthening the pathways for diverse talent into these critical fields. However, future research should further disentangle the mechanisms through which non-URM students experienced declines in performance to better understand how inclusive practices affect all student groups.

References

- Boring, A., Ottoboni, K., & Stark, P. (2016). Student evaluations of teaching (mostly) do not measure teaching effectiveness. *ScienceOpen Research*.
- California Community Colleges Chancellor's Office. (n.d.). Students by ethnicity. DataVista. Retrieved 01 November 2024, from <https://datavista.cccco.edu>.
- Chang, M. J., Cerna, O., Han, J., & Sáenz, V. (2008). The contradictory roles of institutional status in retaining underrepresented minorities in biomedical and behavioral science majors. *The Review of Higher Education*, 31(4), 433–464.
- Chen, X. (2009). *Students Who study science, technology, engineering, and mathematics (STEM) in postsecondary education*. Stats in Brief. NCES 2009-161. National Center for Education Statistics. <https://nces.ed.gov/pubs2009/2009161.pdf>
- Costa, K. (2020). The value of imperfect videos. *Current Issues in Education*, 21(2, Special Issue).
- Cuban, L. (1993). *How teachers taught: Constancy and change in American classrooms, 1880–1990* (2nd ed.). New York, NY: Teachers College Press.
- Delpit, L. (2012). “*Multiplication is for White people*”: *Raising expectations for other people's children*. The New Press.
- Dewsbury, B., & Brame, C. (2019). Inclusive teaching. *CBE—Life Sciences Education*, 18(2), 1–5. <https://doi.org/10.1187/cbe.19-01-0021>
- Estrada, M., Eroy-Reveles, A., & Matsui, J. (2018). The influence of affirming kindness and community on broadening participation in STEM career pathways. *Social Issues and Policy Review*, 12(1), 258–297. <https://doi.org/10.1111/sipr.12046>
- Freire, P. (1970). *Pedagogy of the oppressed*. Continuum.

- Gasiewski, J. A., Eagan, M. K., Garcia, G. A., Hurtado, S., & Chang, M. J. (2012). From gatekeeping to engagement: A multicontextual, mixed method study of student academic engagement in introductory STEM courses. *Research in higher education*, 53, 229-261.
- Gay, G. (2010). *Culturally responsive teaching: Theory, research, and practice* (2nd ed.). Teachers College Press.
- Gunawardena, C. N. (2014). Supporting diverse online learners. In I. Jung & C. N. Gunawardena (Eds.), *Culture and online learning: Global perspectives and research* (pp. 79–90). Stylus.
- Hammond, Z. (2014). *Culturally responsive teaching and the brain: Promoting authentic engagement and rigor among culturally and linguistically diverse students*. Corwin.
- Hatfield, N., Brown, N., & Topaz, C. M. (2022). Do introductory courses disproportionately drive minoritized students out of STEM pathways? *PNAS Nexus*, 1(4), 167.
<https://doi.org/10.1093/pnasnexus/pgac167>
- Hoffman, F., & Oreopoulos, P. (2009). A professor like me: The influence of instructor gender on university achievement. *Journal of Human Resources*, 44(2), 479–494.
- hooks, b. (1994). *Teaching to transgress: Education as the practice of freedom*. Routledge.
- Humanizing Online STEM Academy. (n.d.). *Humanizing online learning*. Retrieved November 6, 2024, from <https://humanizeol.org>
- Jaggers, S.S., & Xu, D. (2016). How do online course design features influence student performance? *Computers & Education*, 95, 270-284
- Kleinfeld, J. (1975). Effective teachers of Eskimo and Indian students. *The School Review*, 83(2), 301–344.

- Kruglanski, A. W., Pierro, A., Mannetti, L., & De Grada, E. (2005). Groups as epistemic providers: Need for closure and the unfolding of group-centrism. *Psychological Review*, 112(1), 84–100.
- Ladson-Billings, G. (1995). Toward a theory of culturally relevant pedagogy. *American Educational Research Journal*, 32(3), 465–491.
- Lin, L. C., Hung, I., & Chen, N. S. (2019). The impact of student engagement on learning outcomes in a cyber- flipped course. *Educational Technology Research and Development*, 67(6), 1573–1591. <https://doi.org/10.1007/s11423-019-09698-9>
- Osborn, H. J., Sosa, N., & Rios, K. (2020). Perceiving demographic diversity as a threat: Divergent effects of multiculturalism and polyculturalism. *Group Processes & Intergroup Relations*, 23(7), 1014–1031.
- Pacansky-Brock, M. (2017). Best practices for teaching with emerging technologies (2nd ed.). Routledge. <https://doi.org/10.4324/9781315629292>
- Pacansky-Brock, M. (2020). *How to humanize your online class (Version 2.0)* [Infographic]
- Pacansky-Brock, M., Smedshammer, M., & Vincent-Layton, K. (2020). Humanizing online teaching to equitize higher education. *Current Issues in Education*, 21(2), 1–21. <https://cie.asu.edu/ojs/index.php/cieatasu/article/view/1905>
- Peacock, S., Cowan, J., Irvine, L., & Williams, J. (2020). An exploration into the importance of a sense of belonging for online learners. *International Review of Research in Open and Distributed Learning*, 21(2), 18–35. <https://doi.org/10.19173/irrodl.v20i5.4539>
- Plaut, V. C., Garnett, F. G., Buffardi, L. E., & Sanchez-Burks, J. (2011). “What about me?” Perceptions of exclusion and Whites’ reactions to multiculturalism. *Journal of Personality and Social Psychology*, 101(2), 337–353.

- Riegle-Crumb, C., King, B., & Irizarry, Y. (2019). Does STEM stand out? Examining racial/ethnic gaps in persistence across postsecondary fields. *Educational Researcher*, 48(3), 133–144. <https://doi.org/10.3102/0013189X1983100>
- Rojstaczer, S., & Healy, C. (2012). Where A is ordinary: The evolution of American college and university grading, 1940-2009. *Teachers College Record*, 114(7), 1–23.
- Schinske, J. N., & Tanner, K. D. (2014). *Teaching more by grading less (or differently)*. *CB-Life Sciences Education*, 13(2), 159-166.
- Schneider, J., & Hutt, E. (2014). *Making the grade: A history of the A–F marking scheme*. *Journal of Curriculum Studies*, 46(2), 201–224.
- Seymour, E., & Hewitt, N. (1997). *Talking about leaving: Why undergraduates leave the sciences*. Boulder, CO: Westview Press.
- Solanki, S. M., & Xu, D. (2018). Looking beyond academic performance: The influence of instructor gender on student motivation in STEM fields. *American Educational Research Journal*, 55(4), 801–835.
- Starck, J. G., Sinclair, S., & Shelton, J. N. (2021). How university diversity rationales inform student preferences and outcomes. *Proceedings of the National Academy of Sciences of the United States of America*, 118(16), e2013833118.
- Steele, C. M., & Aronson, J. (1995). Stereotype threat and the intellectual test performance of African Americans. *Journal of Personality and Social Psychology*, 69(5), 797–811. <https://doi.org/10.1037/0022-3514.69.5.797>
- Steele, C. M., Spencer, S. J., & Aronson, J. (2002). Contending with group image: The psychology of stereotype and social identity threat. In M. P. Zanna (Ed.), *Advances in experimental social psychology* (Vol. 34, pp. 379–440). Academic Press.

- Tobias, S. (1990). Stemming the science shortfall at college. *They're not dumb, they're different*. Tucson, AZ: Research Corporation.
- Tyack, D., & Tobin, W. (1994). The “grammar” of schooling: Why has it been so hard to change? *American Educational Research Journal*, 31(3), 453–479.
- Wladis, C., Conway, K. M., & Hachey, A. C. (2015). The Online STEM Classroom—Who Succeeds? An Exploration of the Impact of Ethnicity, Gender, and Non-traditional Student Characteristics in the Community College Context. *Community College Review*, 43(2), 142-164. <https://doi.org/10.1177/0091552115571729>
- Wladis, C., Hachey, A. C., & Conway, K. (2013). Are online students in STEM (science, technology, engineering and mathematics) courses at greater risk of non-success?. *American Journal of Educational Studies*, 6(1).
- Xu, D. & Jaggars, S.S. (2014). Performance gaps between online and face-to-face courses: Differences across types of students and academic subject areas. *Journal of Higher Education*, 85, 633-659
- Zagzebski, L. T. (2012). *Epistemic authority: A theory of trust, authority, and autonomy in belief*. Oxford University Press.

Tables and Figures

Table 1. Academy participant demographics

	M
<i>Gender</i>	
Female	0.58
<i>Age</i>	
25-34	0.16
35-44	0.47
45-54	0.16
55 or older	0.20
<i>Race/ethnicity</i>	
Asian	0.06
Black	0.14
Latinx	0.12
Middle Eastern	0.02
White	0.60
Other race	0.06
<i>Education</i>	
Professional degree	0.04
Master's degree	0.50
Doctoral degree	0.46
<i>Professional experience</i>	
Years of teaching experience	11.05 (7.52)
Years of online teaching experience	4.36 (4.33)
Full-time position	0.73
Prior professional development training	0.40

Notes: Based on survey responses from 52 instructors. Years of teaching experience are formatted M(SD). All other variables are proportions.

Table 2. Perceived benefit of humanizing techniques

How beneficial with the following humanizing elements will be in helping you establish trust with your students and helping your students feel included, respected, and engaged in your course?

	M	SD	min	max
Liquid syllabus	4.44	0.87	2	5
Humanized Homepage	4.60	0.69	2	5
Humanized Course Card	3.96	0.99	2	5
Getting to know your survey	4.54	0.58	3	5
Warm wise feedback	4.60	0.72	2	5
Self-affirming icebreaker	4.35	0.81	2	5
Wisdom wall	4.13	0.86	2	5
Bumper video	4.44	0.73	2	5
Microlectures	4.54	0.78	2	5

Notes: Based on survey responses from 52 instructors. *Likert responses are on a 5-item scale from "not at all beneficial" (1) to "extremely beneficial" (5).*

Table 3. Plan to use

Plan to use	M
Liquid syllabus	0.92
Humanized Homepage	0.96
Humanized Course Card	0.96
Getting to know your survey	0.96
Warm wise feedback	0.90
Self-affirming icebreaker	0.87
Wisdom wall	0.63
Bumper video	0.94
Microlectures	0.85

Notes: Based on survey responses from 52 instructors. *Responses are binary (yes or no).*

Table 4. Change in instructor beliefs and perceptions

	Pre-academy		Post-academy		Post-Pre Difference
	M	SD	M	SD	
1. Students' capability to succeed	3.60	0.86	3.90	0.66	0.31***
2. Role of gender and race in STEM success	3.41	1.04	3.39	0.91	-0.02
3. Role of sense of belonging and emotions in STEM success	4.09	0.74	4.47	0.57	0.38***
4. Role of teaching and instructor-student relationships in STEM success	4.46	0.49	4.63	0.35	0.17**
5. Instructor awareness of culture and inclusivity	4.14	0.68	4.28	0.69	0.14
6. Instructional environment shapes student emotions and sense of belonging	3.90	0.59	4.28	0.52	0.38***
7. Flexibility	3.71	1.10	3.97	0.92	0.26*
8. Self-efficacy	4.02	0.63	4.58	0.42	0.56***
9. Culturally responsive and student-centered practices	4.16	0.47	4.41	0.52	0.25***
10. Student affirmation and support	4.67	0.46	4.81	0.33	0.15**
11. Authoritative and competitive approaches	2.81	0.78	3.04	0.75	0.24*
12. Fostering belonging and connection	4.29	0.58	4.56	0.44	0.27***

*Notes: Based on pre-and post- survey responses from 52 instructors. Rows 1-6: 19 survey statements about equity were aggregated using principal-component factor analysis. Likert responses are on a 5-item scale from "Strongly Disagree" (1) to "Strongly Agree" (5). Rows 7-8: Flexibility is average of the following statements' Likert scores: allowing late submissions; providing extra credit opportunities; allowing make-up exams/assignments. Likert responses are on a 5-item scale from "very inflexible" (1) to "very flexible" (5). Self-efficacy is average of the following statements' Likert scores: build an online course; upload course materials; create course assignments; interact with students; create quizzes and exams; record student grades; support the individual needs of students; design a welcoming environment for students. Likert responses from rows 7-8 are on a 5-item scale from "not at all confident" (1) to "extremely confident" (5). Rows 9-12: 25 survey statements about instructor responsibilities were aggregated using principal-component factor analysis. Likert responses are on a 5-item scale from "Strongly Disagree" (1) to "Strongly Agree" (5). Paired t-test for changes in pre- and post- responses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.*

Table 5. Change in use of teaching practices

	Pre-academy		Post-academy		Post-Pre Difference
	M	SD	M	SD	
<i>Teaching strategies</i>					
1. Send public, mobile-friendly link with supportive language/welcome video	0.29	0.46	0.96	0.19	0.67***
2. Have course homepage with video/photo of me and “start here” cue	0.55	0.33	0.99	0.06	0.44***
3. Survey to identify high-opportunity students who benefit from high-touch interactions	0.27	0.45	0.96	0.19	0.69***
4. Give supportive and motivating voice/video feedback	2.92	0.76	4.16	0.56	1.24***
5. Use icebreaker activity that has students share their values with each other	0.51	0.50	0.92	0.27	0.41***
6. Have students share advice with future incoming students	0.33	0.47	0.90	0.30	0.58***
7. Use 2-3 minute, visually-oriented video to demystify a difficult concept	0.48	0.50	0.98	0.14	0.50***
8. Use microlectures: <10 min video lectures, summaries, topic introductions	2.83	1.16	4.11	0.71	1.28***
9. Show care for students while also challenging them	4.15	0.75	4.69	0.51	0.54***
<i>Instructor-student interactions</i>					
10. Academic interactions	3.85	0.59	4.24	0.42	0.39***
11. Social interactions	0.63	0.27	0.97	0.09	0.34***
12. Management interactions	3.95	0.69	4.47	0.41	0.52***
<i>Student-student interactions</i>					
13. Academic interactions	2.96	1.34	3.52	0.90	0.56**
14. Social interactions	0.62	0.34	0.96	0.13	0.35***
<i>Media use</i>					
15. Audio use	1.10	1.32	2.37	1.96	1.27***
16. Video use	2.25	1.25	4.12	1.41	1.87***

Notes: Based on pre-and post- survey responses from 52 instructors. **Rows 1-9:** Statement (4), (8), and (9) are average scores based on 5-item scale. All other statements are binary, where 1 is yes and 0 is no. **Rows 10-12:** Likert responses for Academic interactions and Management

interactions are on a 5-item scale from "Never" (1) to "Very Frequently" (5). Responses for Social interactions are binary (yes/no). Academic interaction includes the following: I provided office hours for students to ask academic related questions or to get additional support; I provided feedback (beyond a grade) on student work; I interacted with students using synchronous communication tools (e.g., Zoom, Skype or other video conference tools); I interacted with students using asynchronous communication tools (e.g., discussion boards, Flip, VoiceThread, etc.); I directly responded to student postings regarding academic content on discussion forums. Social interaction includes the following: I introduced myself to my students via written communications containing text, and/or images, and/or voice, and/or video communications; I shared at least one brief, imperfect video of myself in a non-academic setting (a park, beach, backyard, etc.); I tried to make my personality come through in my communication with students; I shared aspects of my hobbies, interests, pets, and other aspects of my life with my students; I surveyed students in week one to identify high opportunity students who will benefit from high touch interactions the most. Management interaction includes the following: I provided opportunities for students to give feedback about the course; I provided explicit grading criteria (e.g., rubric); I proactively identified students who were struggling (e.g., missing assignments, low grades, low-class participation) and reached out to them; When I recognized struggling students, I offered additional support (e.g., study tips, resources, advice, and encouragement); When a student asked a question about logistics and course requirements, I quickly responded (within 24 hours). **Rows 13-14:** Academic interaction statement is on 5-item scale from "Never" (1) to "Very Frequently" (5): students provided collaborative work (e.g., group assignments, peer review). Social interactions statements are binary and include: students encouraged to get to know each other more than what was required for assignments or tasks; included icebreaker activity in week one that had students share their values. **Rows 15-16:** Instructors' media use in the following areas: (1) announcements or reminders to students about course content and assignments; (2) office hours for students to ask academic related questions or to get additional support; (3) provided feedback (beyond a grade) on student work; (4) communicated synchronously; (5) communicated asynchronously; (6) directly responded to student postings regarding academic content on discussion forums. Paired t-test for changes in pre- and post- responses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 6. Number of instructors by department

	Academy	Non-Academy	Total
Biology	2	19	21
Economics	2	9	11
Engineering	3	3	6
Environmental Science	1	3	4
Foods	1	6	7
Mathematics	10	32	42
Psychology	3	44	47
Nursing	1	3	4

Table 7. Number of instructors by course category

	Academy	Non-Academy	Total
Math	14	75	89
Science	9	44	53

Note: Math category includes 7 unique courses taught in the following departments: mathematics, economics, and psychology. Science category includes 7 unique courses taught in the following departments: biology, engineering, environmental studies, foods, psychology, and registered nursing. Individual classes within a department may fall into either science or math. For example, “Biological Psychology” would be categorized as science content, whereas “Research Methods in Psychology” would be categorized as math content.

Table 8. The impact of the Academy on reducing racial equity gaps

	(1) Course grade	(2) Course persist	(3) Course pass
Academy	-0.295* (0.133)	-0.098* (0.049)	-0.107 (0.054)
URM	-0.307*** (0.022)	-0.031*** (0.006)	-0.061*** (0.007)
Academy*URM	0.315* (0.133)	0.114* (0.045)	0.126* (0.049)
Course FE	X	X	X
Term FE	X	X	X
Instructor FE	X	X	X
Student controls	X	X	X
Constant	15.654*** (3.784)	-3.777*** (0.936)	-1.499 (1.243)
Observations	25788	31526	31526

Note: URM students include American Indian/Alaska Native, Black, Latinx, Native Hawaiian/Pacific Islander, and multiracial students. White and Asian students are the omitted category. Student controls include gender, major, age, cohort, enrollment status (full-time/part-time), and first-time student status. Mean-imputation method used for missing data; missingness indicators included in the regression. Column (1) is a continuous outcome on a 0-4 GPA scale. Columns (2) and (3) are linear probability models of binary outcomes. Standard errors for all models are clustered at the instructor level, shown in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 9. Subgroup: Science courses

	(1) Course grade	(2) Course persist	(3) Course pass
Academy	-0.317* (0.155)	-0.103 (0.061)	-0.131 (0.083)
URM	-0.333*** (0.024)	-0.030*** (0.007)	-0.057*** (0.007)
Academy*URM	0.442* (0.171)	0.086 (0.049)	0.136 (0.068)
Course FE	X	X	X
Term FE	X	X	X
Instructor FE	X	X	X
Student Controls	X	X	X
Constant	16.291** (4.672)	-1.764 (0.988)	0.658 (1.659)
Observations	9599	12840	12840

Note: Sample restricted to 7 courses with science content in the following departments: biology, engineering, environmental studies, foods, psychology, and registered nursing. URM students include American Indian/Alaska Native, Black, Latinx, Native Hawaiian/Pacific Islander, and multiracial students. White and Asian students are the omitted category. Student controls include gender, major, age, cohort, enrollment status (full-time/part-time), and first-time student status. Mean-imputation method used for missing data; missingness indicators included in the regression. Column (1) is a continuous outcome on a 0-4 GPA scale. Columns (2) and (3) are linear probability models of binary outcomes. Standard errors for all models are clustered at the instructor level, shown in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 10. Non-Humanized courses

	(1) Course grade	(2) Course persist	(3) Course pass
Academy	-0.169 (0.110)	-0.021 (0.035)	-0.044 (0.043)
URM	-0.358*** (0.028)	-0.026*** (0.005)	-0.064*** (0.006)
Academy*URM	0.174 (0.125)	0.007 (0.028)	0.052 (0.044)
Course FE	X	X	X
Term FE	X	X	X
Instructor FE	X	X	X
Student controls	X	X	X
Constant	7.626 (4.029)	-1.930* (0.829)	-2.000 (1.037)
Observations	31592	35403	35403

Note: URM students include American Indian/Alaska Native, Black, Latinx, Native Hawaiian/Pacific Islander, and multiracial students. White and Asian students are the omitted category. Student controls include gender, major, age, cohort, enrollment status (full-time/part-time), and first-time student status. Column (1) is a continuous outcome on a 0-4 GPA scale. Columns (2) and (3) are linear probability models of binary outcomes. Standard errors for all models are clustered at the instructor level, shown in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 11. Course-level: Class enrollment

	(1)	(2)	(3)	(4)
Post	3.497 (2.623)	2.266 (3.130)	-0.756 (2.589)	-0.391 (2.550)
Course FE				X
Term FE		X	X	X
Instructor FE			X	X
Constant	32.888*** (0.995)	36.541*** (2.553)	32.697*** (1.718)	27.561*** (1.857)
Observations	820	820	820	820

Note: Unit is at instructor-course level. Outcome is course enrollment in counts. Variation comes from 19 unique instructor-course combinations that have pre- and post- observations. Standard errors for all models are clustered at the instructor level, shown in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 12. Course-level: Share URM

	(1)	(2)	(3)	(4)
Post	-0.006 (0.054)	-0.018 (0.067)	-0.048 (0.032)	-0.049 (0.032)
Course FE				X
Term FE		X	X	X
Instructor FE			X	X
Constant	0.640*** (0.024)	0.396*** (0.054)	0.698*** (0.023)	0.775*** (0.023)
Observations	838	838	838	838

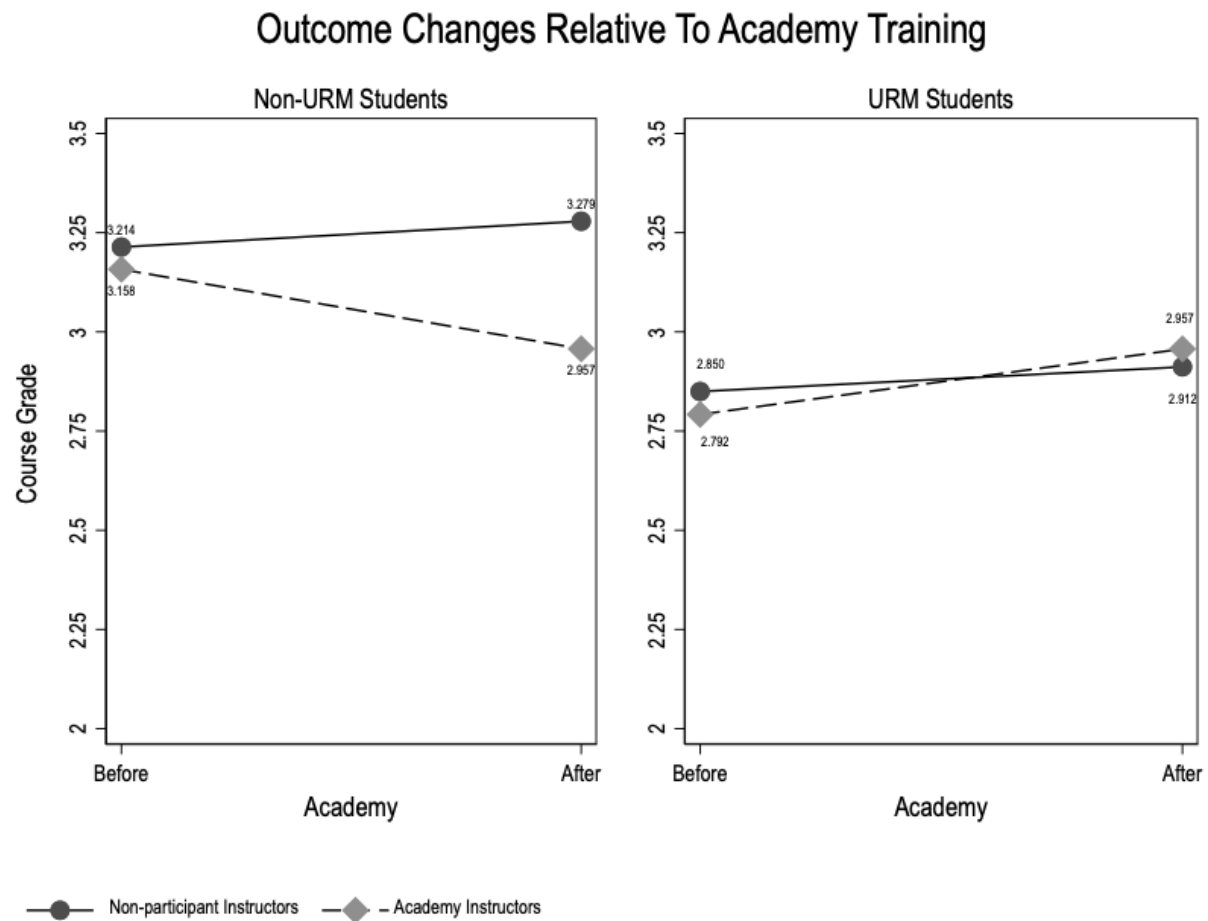
Note: Unit is at instructor-course level. URM students include American Indian/Alaska Native, Black, Latinx, Native Hawaiian/Pacific Islander, and multiracial students. Variation comes from 19 unique instructor-course combinations that have pre- and post- observations. Standard errors for all models are clustered at the instructor level, shown in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 13. Course-level: average Cumulative GPA of incoming students

	(1)	(2)	(3)	(4)
Post	-0.201* (0.101)	-0.287* (0.111)	-0.204 (0.140)	-0.223 (0.141)
Course FE				X
Term FE		X	X	X
Instructor FE			X	X
Constant	2.677*** (0.041)	2.809*** (0.112)	2.677*** (0.076)	2.261*** (0.081)
Observations	843	843	843	843

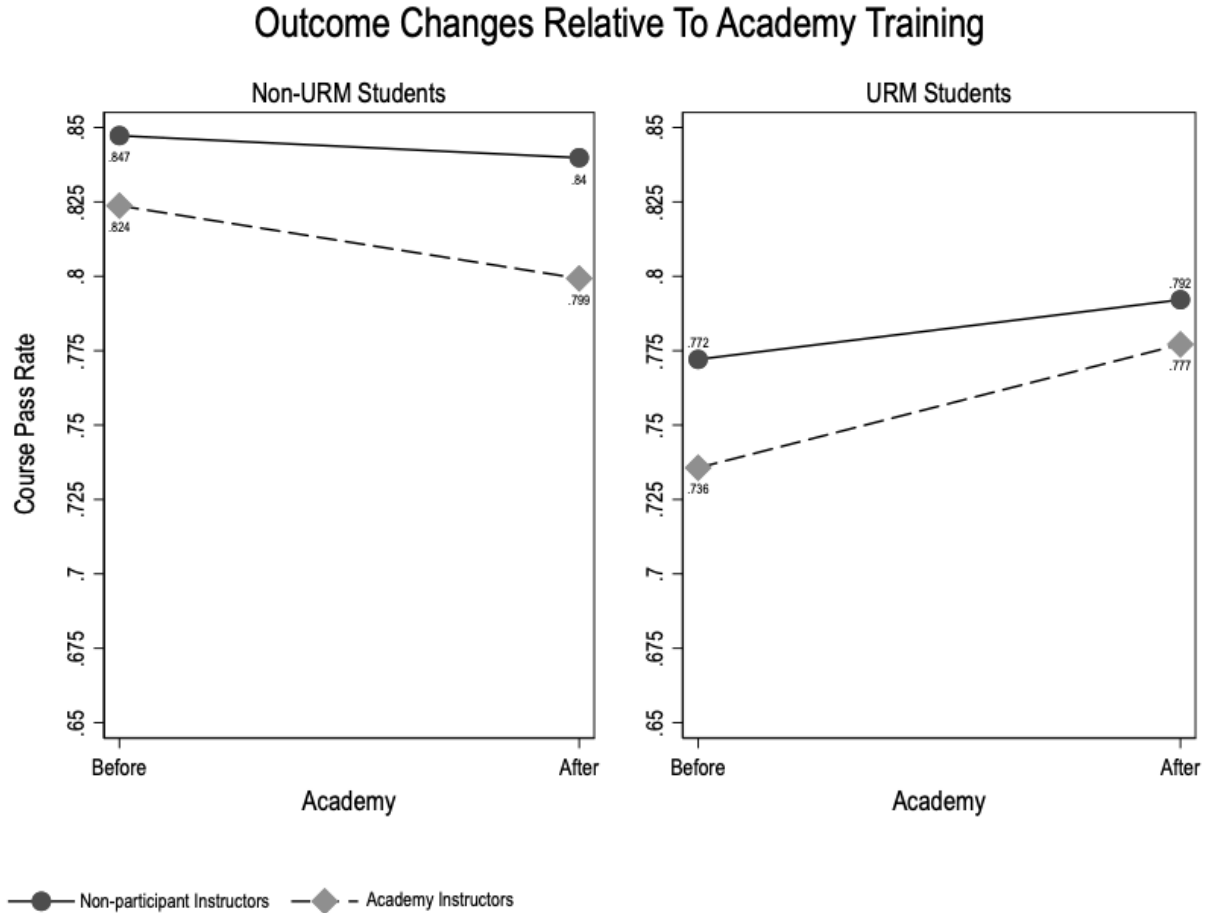
Note: Unit is at instructor-course level. Outcome is GPA on a 4-point scale. Variation comes from 19 unique instructor-course combinations that have pre- and post- observations. Standard errors for all models are clustered at the instructor level, shown in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Figure 1. Changes in course grades for URM versus non-URM students



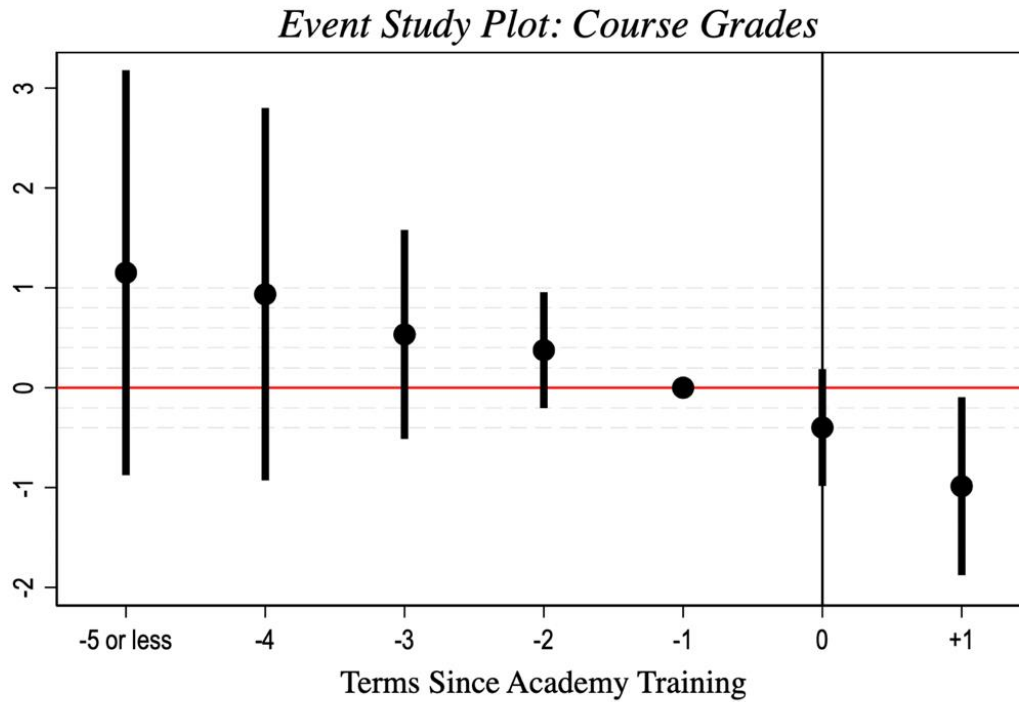
Notes: Full sample has 11,239 observations from non-participating instructors in the before period; 989 in the after period. Full sample has 2,219 observations from the Academy instructors in the before period; 377 in the after period. URM students include American Indian/Alaska Native, Black, Latinx, Native Hawaiian/Pacific Islander, and multiracial students. URM only sample has 3,782 observations from non-participating instructors in the before period; 397 in the after period. URM only sample has 764 observations from Academy instructors in the before period; 140 in the after period. Non-URM students include Asian and White students. Non-URM only sample has 7,215 observations from non-participating instructors in the before period; 581 in the after period. Non-URM only sample has 1,408 observations from Academy instructors in the before period; 234 in the after period.

Figure 2. Changes in course pass rates for URM versus non-URM students



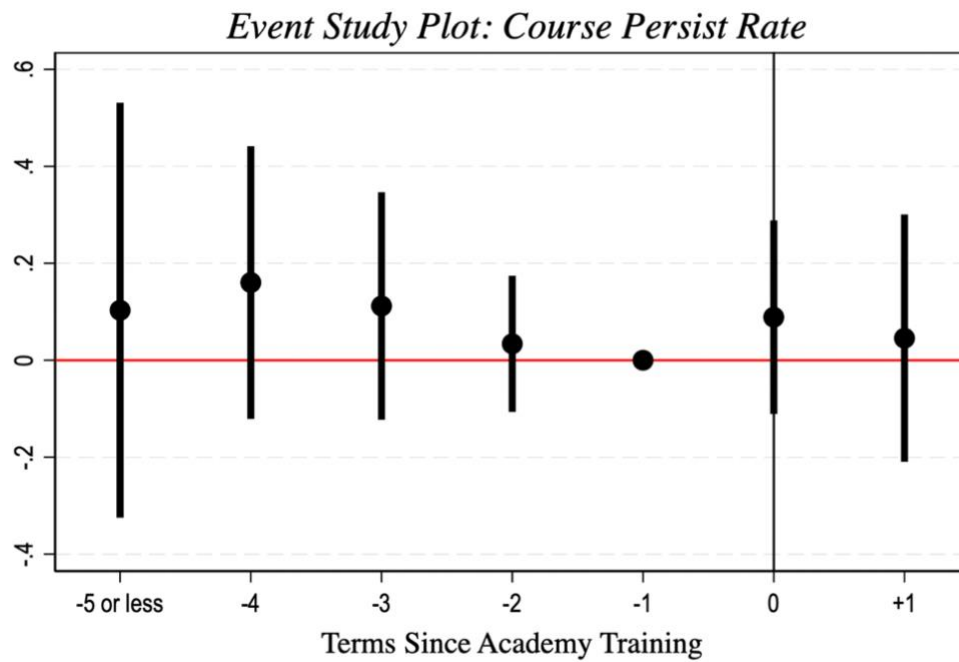
Notes: Course pass is equal to one if course grade is A, B, C, D, or P; and zero if course grade is F or W. Full sample has 12,668 observations from non-participating instructors in the before period; 1,138 in the after period. Full sample has 2,569 observations from the Academy instructors in the before period; 444 in the after period. URM students include American Indian/Alaska Native, Black, Latinx, Native Hawaiian/Pacific Islander, and multiracial students. URM only sample has 4,383 observations from non-participating instructors in the before period; 457 in the after period. URM only sample has 923 observations from Academy instructors in the before period; 166 in the after period. Non-URM students include Asian and White students. Non-URM only sample has 8,014 observations from non-participating instructors in the before period; 668 in the after period. Non-URM only sample has 1,594 observations from Academy instructors in the before period; 274 in the after period.

Figure 3. Event study for course grades



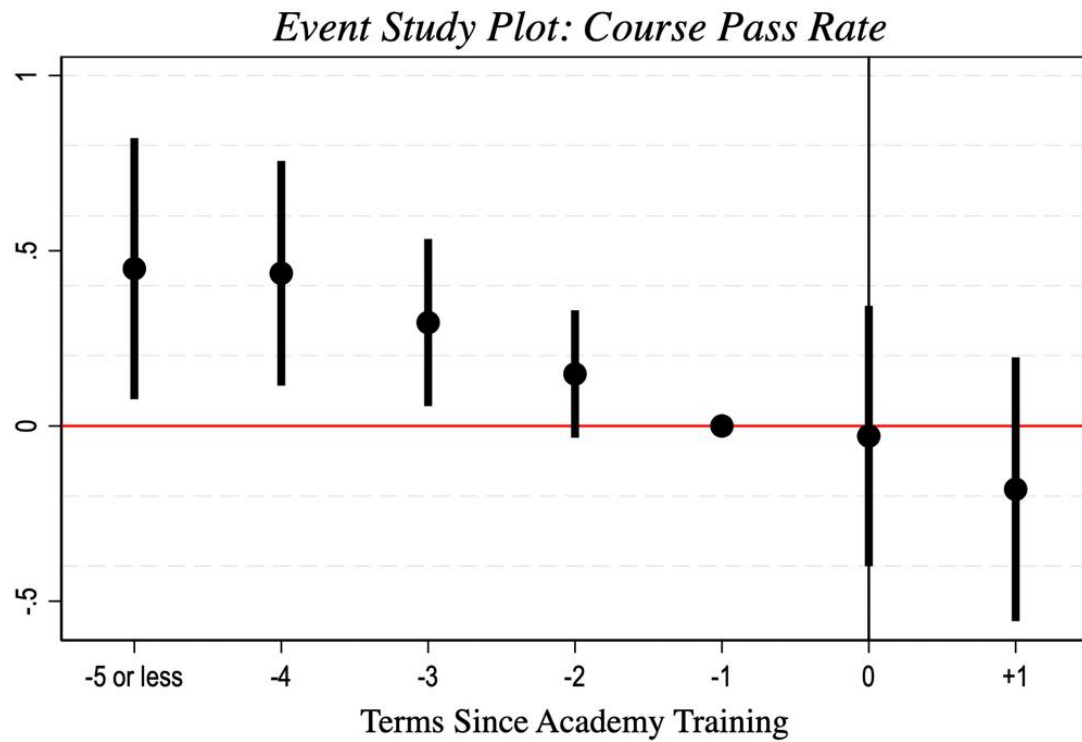
Notes. OLS coefficient estimates (and their 95% confidence intervals) are reported. The reference term is set to be one term prior to the academy.

Figure 4. Event study for course persistence



Notes. OLS coefficient estimates (and their 95% confidence intervals) are reported.
The reference term is set to be one term prior to the academy.

Figure 5. Event study for course pass rate



Notes. OLS coefficient estimates (and their 95% confidence intervals) are reported.
The reference term is set to be one term prior to the academy.

Appendix

Table A1 – Table A5. Institutional demographics by campus

A1. CCC 1 (2022-23 Enrollment)	Count	Percent
American Indian/Alaska Native	107	0.37
Asian	651	2.27
Black	1,779	6.21
Filipino	519	1.81
Latinx	19,345	67.57
Pacific Islander	38	0.13
Multiracial	988	3.45
White	4,970	17.36
Unknown	231	0.81
	28628	100.00

A2. CCC 2 (2022-23 Enrollment)	Count	Percent
American Indian/Alaska Native	126	1.93
Asian	160	2.46
Black	577	8.86
Filipino	85	1.30
Latinx	3,057	46.93
Pacific Islander	29	0.45
Multiracial	295	4.53
White	2,120	32.55
Unknown	65	1.00
	6514	100.00

A3. CCC 3 (2022-23 Enrollment)	Count	Percent
American Indian/Alaska Native	39	0.89
Asian	60	1.37
Black	79	1.80
Filipino	58	1.32
Latinx	3,515	79.98
Pacific Islander	0	0.00
Multiracial	96	2.18
White	548	12.47
Unknown	0	0.00
	4395	100.00

A4. CCC 4 (2022-23 Enrollment)	Count	Percent
American Indian/Alaska Native	82	0.3
Asian	4061	12.6
Black	646	2.0
Filipino	726	2.2
Latinx	8550	26.5
Pacific Islander	60	0.2
Multiracial	1511	4.7
White	15102	46.8
Unknown	1532	4.7
	32270	100

A5. CSU (Fall 2023 Enrollment)	Count	Percent
American Indian/Alaska Native	108	2.01
Asian	163	3.04
Black	163	3.04
Latinx	1627	30.30
Multiracial	380	7.08
White	2712	50.50
Other/Unknown	217	4.04

Note: Table A1 through Table A5 shows enrollment by ethnicity for 2022-23 academic year; sourced from California Community Colleges Chancellor's Office. Table A5 shows enrollment by ethnicity for Fall 2023; sourced from CSU campus website.

CONCLUSION

This dissertation began with a central question: do community colleges deliver on the promise of access? More specifically, under what conditions does expanded access translate into meaningful opportunity for students? While community colleges and online learning have significantly broadened participation in higher education, the findings of this dissertation suggest that access alone is not sufficient. Instead, opportunity depends on how access is structured, navigated, and experienced.

Students face significant uncertainty when navigating transfer pathways. As shown in Chapter 1, disparities in transfer outcomes are preceded by disparities in access to information, communication networks, and institutional knowledge. Although students report high aspirations and confidence, they vary systematically in how they understand transfer requirements and evaluate their likelihood of success. These findings demonstrate that inequality emerges not only in whether students transfer, but earlier in the sensemaking processes that shape how they interpret and pursue transfer opportunities. Transfer, as the primary pathway to a bachelor's degree for community college students, is therefore a critical space where inequality is produced and reinforced.

Students also make strategic decisions under constraint, particularly in the context of online learning. Chapter 2 shows that enrollment in asynchronous courses is not random, but reflects students' efforts to balance education with work and other responsibilities.

Asynchronous learning functions as a form of flexibility that enables participation, especially for time-constrained students. However, this flexibility comes at a cost: asynchronous courses are associated with lower academic performance, and these penalties are broadly shared rather than

concentrated among specific groups. Importantly, flexibility does not eliminate inequality-- it reshapes how inequality is experienced.

Instructional environments are also important for shaping student outcomes. Chapter 3 demonstrates that pedagogical practices, particularly those that emphasize connection, flexibility, and student-centered design, can improve engagement and narrow equity gaps in online STEM courses. By linking changes in instructor beliefs and practices to student outcomes, this study shows that pedagogy can serve as a meaningful lever for equity. At the same time, the findings highlight the limits of instructional interventions. While humanizing practices improve outcomes for historically underserved students, they do not fully eliminate disparities and may produce complex distributional effects within classrooms.

Together, these findings yield important implications for policy and practice. First, improving equity in transfer requires addressing the structural complexity of transfer systems themselves, rather than relying on one-time, localized interventions. Chapter 1 shows that students differ not in their aspirations, but in their access to institutional knowledge and their ability to navigate opaque processes. While one approach could be to provide students information, the more transformative solution would be to simplify the processes. This would move the burden from students to institutions. Simplifying articulation agreements, improving alignment across institutions, and providing clearer, more standardized pathways to transfer can reduce the burden placed on students to interpret and navigate fragmented systems. In this way, equity in transfer depends not only on what students know, but on how accessible and navigable the system is in the first place.

The findings from Chapter 2 suggest the need to reframe asynchronous learning as a necessary component of access rather than a secondary or lower-quality option. Students enroll in asynchronous courses to manage competing demands, particularly work and financial responsibilities. This indicates that flexibility is essential for participation. Expanding asynchronous and online course offerings can therefore support access for time-constrained students. However, because this flexibility is associated with academic costs, expansion must be paired with careful attention to course design and support structures.

Chapter 3 highlights the role of pedagogy as a key lever for improving equity in online learning environments. As online instruction shifts greater responsibility onto students, institutions must take a more active role in supporting learning through intentional course design and instructional practices. One of the ways institutions can do this is by investing in the capacity of their instructors. Expanding professional development opportunities, particularly for online STEM instructors, and investing in training that emphasizes humanizing, student-centered approaches can help mitigate some of the academic challenges associated with less structured environments. In this sense, pedagogy represents a way for institutions to take back some of the responsibility that has shifted onto students, ensuring that flexibility does not come at the expense of support.

This dissertation contributes to a growing body of research that shifts attention from access as an outcome to access as an experience. By examining how students make sense of transfer, how they navigate flexible learning environments, and how instructional practices shape engagement, the findings highlight the multiple points at which inequality can emerge, even within systems designed to expand opportunity. Ultimately, the promise of access will remain

incomplete unless institutions move beyond expansion alone and toward the intentional design of pathways that enable all students to translate opportunity into success.