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Article

Addressing Equity Asymmetries in General Chemistry Outcomes Through an Asset-Based Supplemental Course

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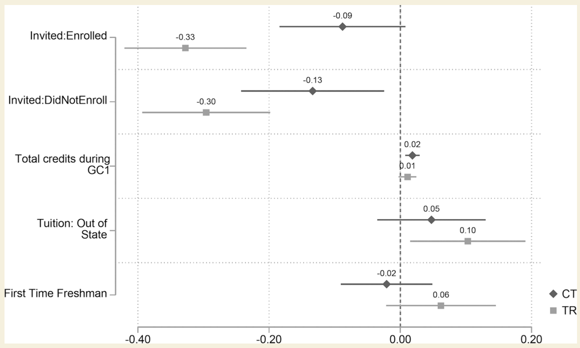
ABSTRACT: Undergraduate first-semester general chemistry (GC1) functions as a gatekeeper to STEM degrees, asymmetrically impacting students who are nonwhite, from lower socioeconomic groups, non-native English speakers, two-year college transfers, and first-generation in college. Nationally, just under 30% of students earn grades of D, F, or withdraw (termed DFW) in GC1; however, DFW rates are much higher for subgroups underrepresented in STEM occupations. Socioeconomic inequalities tend to increase over an individual's lifetime due to the magnification of cumulative disadvantage. Because undergraduate degrees correlate with higher employment and STEM occupations correlate with higher earnings, GC1 represents a critical path point where disparities can be interrupted. The most common strategy employed for GC1 is deficit remediation for students determined to be at risk of DFW. Unfortunately, extensive evidence demonstrates that the use of remediation strategies for GC1 does not sustain benefits for students. In this work, an asset-based approach, less prevalent in higher education than preuniversity, was employed to stress test theories about interrupting disparities in STEM education. This causal-comparative study involving 1,807 observations reports on a 1-credit asset-based supplemental course in which DFW-potential students at a minority-serving institution coenrolled during six semesters. The study outlines this intervention, its impact on GC1 outcomes, and its potential residual impact on progression to the next course in the general chemistry sequence (GC2). Descriptive and hierarchical inferential analysis of the data revealed socially important patterns. The asset-based intervention successfully attracted students with greater cumulative disadvantage. The intervention closed asymmetries between students identified as DFW-potential and ABC-potential in GC1 when a nontraditional curriculum was used but not when a traditional curriculum was used. Mixed results and contingent effects were found for the intervention's impact on subsequent course outcomes. Taking at least 11 credits in the semester of taking GC1 provided an inoculate for participants in the asset-based intervention, increasing the likelihood of passing GC2.



KEYWORDS: *chemistry education research, general chemistry, gatekeeper course, racial equity, gender equity, underrepresentation, asset-based intervention*

INTRODUCTION

Equity Asymmetries and Cumulative Disadvantage

Moral and fiscal imperatives are connected in addressing the function of the first semester of undergraduate general chemistry (GC1) as a "gatekeeper" to STEM degree attainment. An undergraduate education correlates positively with employment prospects and annual earnings.[1] STEM occupations that require bachelor's degrees command the highest salaries and have the lowest unemployment rates.[2] The effects of cumulative disadvantage are evident in STEM professions. Cumulative disadvantage is a theory that provides a widely accepted explanation for the magnification of inequities over a person's lifetime, as well as over generations, by the accumulation of advantages and disadvantages.[3] For example, in 2019, over half of students in public K-12 education in the U.S. were in school systems that were racially concentrated, with 27% of students in predominantly nonwhite school districts (having more than 75% nonwhite students) and 26% in predominantly white school districts (having more than 75% white students).[4] Due to funding structures for public education that have been challenged and upheld by the U.S. Supreme Court, nonwhite U.S. school districts were funded in 2019 on average at \$11,682 per student, while white school districts were funded at \$13,908 per student.[4] Benefits accumulate because those with initial advantages tend to receive access to better education (in the example), leading to higher paying jobs, and subsequently better healthcare; the

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reverse also occurs to confer cumulative disadvantages.[5,6] In such ways, inequities broaden over time and across generations, which leads to disproportionate representations of the overall population in STEM occupations in many dimensions, including race and ethnicity, gender, as well as membership of lesbian, gay, bisexual, transgender, queer, intersex, asexual, and other terms (LGBTQIA+) communities.[1,7]

Students whose STEM degree aspirations are curtailed by being "weeded out" through course outcomes of D or F or withdrawing (termed DFW) in GC1 add this to their accumulated disadvantages. In a study of 32 diverse higher education institutions in the U.S., GC1 was examined as one of three courses with high DFWI[8] rates (the other two were Calculus 1 and Introductory Accounting).[9] According to this study, the DFWI rate nationally for GC1 is 29.4%. Underneath this, however, in examination of overlapping subsets of race and socioeconomic status, white students experience a DFWI rate of 26.3%, female and male students differ with 25.8 and 33.9% DFWI rates. Pell-eligible and non-Pell-eligible students have 32.4 and 28.3% DFWI rates, first-generation college students have a 32.8% DFWI rate, Native Hawaiian or Other Pacific Islander students have a 41.7% DFWI rate, Hispanic and Latino[10] students have a 42.0% a DFWI rate, Black and African American students have a 47.2% DFWI rate, and American Indian and Alaska Natives have a 54.5% a DFWI rate. Consequently, GC1 represents a critical path point where the accumulation of disadvantage and promotion of inequities can be interrupted.

Addressing inequities in GC1 is further important because DFW[11] rates in GC1 have a strong relationship with retention, which impacts not only students' access to future opportunities but also the fiscal health of colleges and universities in the U.S. Higher education institutions in the U.S. are increasingly facing challenges due to demographic changes and declining enrollments, the intensification of revenue losses due to inflation and the COVID-19 emergency, the inability to raise tuition due to competition, and increasing costs from measures taken to control inflation.[12] The national study referenced above found that students who took GC1 and continued at the same institution the following year had a DFW rate of 25.9% in GC1, while GC1-takers who were in good overall academic standing and left the institution within one year of taking GC1 had a DFW rate of 49.2% in GC1.[9] Thus, as there is a relationship between higher DFW rates in GC1 (nearly double) and leaving the institution, actions that higher education institutions can take to improve equity in GC1 are likely to aid in maintaining enrollment, which benefits an institution's fiscal health, as well as benefiting the institution's students and their future careers.

Addressing Equity Asymmetries in General Chemistry

The pernicious nature of cumulative disadvantage results in a large fraction of students belonging to groups that have historically been marginalized in the U.S. beginning GC1 with knowledge and skills that do not match those of their peers from historically privileged backgrounds. Differences in starting points in GC1 are further exacerbated by the COVID-19 pandemic's impacts on primary and secondary education, as lower socioeconomic, less educated, and racial minority populations sustained greater unemployment, reduced access to food and housing, and higher death rates.[13,14] Within higher education institutions, inequities can be addressed through revising gatekeeper courses or making structural changes to academic programs. In course content and its conveyance, changes can be made to curricular materials (e.g., through use of open education resources[15] and emphasis of depth over breadth[16]), to instruction (e.g., through use of less passive learning and more student-centered approaches[17,18]), and to assessment (e.g., through changing how exam questions are evaluated[19]). In addition, inequities can be addressed by course-level efforts that intersect with learning, such as text messages reminding students to study.[20] Course-level interventions, either separate courses substituted for GC1 or as supplemental courses taken alongside GC1, can also address inequities.

Addressing inequities through course-level interventions that directly support students with accumulated disadvantages can be considered to have two main perspectives available: (1) recognizing deficits that students have and educating to provide students with the missing skills and knowledge and/or (2) recognizing the assets that students bring and working with them to identify ways to rely on these for increased success. Deficit examination has been the primary approach to studying the DFW problem in GC1, and remediation to address specific deficits that are demonstrated by selection methods based on this literature has been the primary model for addressing achievement gaps in gatekeeper courses.[21,22] The research literature includes many studies of what students who are "at-risk" of DFW in GC1 lack − they have poor scores on general achievement tests such as SATs[23] and particularly on verbal scores,[24] they have weak logical and scientific reasoning skills,[25] they have done fewer laboratory experiments in high school chemistry,[26] and they lack positive attitudes and self-concept.[27] Researchers have also looked for indicators of success in GC1 which point to further deficits.[27−31] Exam 1 scores have been shown to be a strong predictor of final course grade in GC1,[30] and logical reasoning skills also appear to have strong predictive power.[32] However, many predictors reported in the literature may not be generalizable to all students at all kinds of higher education institutions. There is considerable evidence, for example, that achievement tests (SATs) are weak predictors of college success, especially for students who are first-generation in college, not white, or non-native English speakers.[33,34]

Generally, course-level interventions are often explicitly described as "remedial" by the literature and stakeholders. structured either as separating DFW-potential students into special sections of GC1 in which interventions for these students occur alongside GC1 learning, or employing placement tests or prerequisites to determine whether students should first take an introductory chemistry course that includes addressing missing content and skills prior to enrolling in GC1.[35,36] Setting aside whether existing course-level interventions involve deficit- or asset-based perspectives, or a combination, two broad synthesis studies[35,36] on the impacts of courses for DFW-potential students at multiple types of institutions report that the majority of interventions, while helpful in the semester of the intervention, do not yield positive effects for at-risk students that last beyond GC1. In addition, peer comparison studies have shown that the long-term effects of such interventions in GC1 on students are indistinguishable from no intervention.[37,38] The problem appears immune to a wide variety of strategies that have been attempted in such interventions, including emphasis on problem solving and vocabulary, cooperative and peer-led

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learning, emphasis on study skills and attendance, flipped classrooms and self-study modules, fewer topics and math remediation, and use of pass/fail options. The persistent shortcomings of remediation, compounded by the likelihood of mounting impacts of the COVID-19 pandemic on disparities, signal the importance of testing alternatives to remediation.

Anti-Deficit Perspective and Asset-Based Interventions

Commonalities exist across the literature[39−42] on approaches in postsecondary STEM education to support students who are likely to have accumulated disadvantages. Successful interventions: (1) frame students' diverse experiences as assets rather than something to be rectified, (2) support identity development in STEM, (3) build supportive communities through racial and gender representation, and (4) reframe assessment experiences as opportunities for learning rather than measures for sorting students into educational pathways. The Anti-Deficit Achievement Framework for Students of Color in STEM[43] was developed as a lens for understanding what enables success despite accumulated disadvantages. The framework advocates that, "instead of relying on existing theories and conceptual models to repeatedly examine deficits, researchers using this framework should deliberately attempt to discover how some students of color have managed to succeed in STEM" (ref 43, p. 68). The framing of research from an anti-deficit perspective can be paired with the design of interventions and inquiries from an asset-based perspective.

Asset-based,[44] strengths-based,[45] and funds of knowledge[46] models have overlapping definitions, and substantial literature on both asset-based perspectives[47] and how they differ from deficit-based thinking[48,49] undergirds these models. Interventions based on the models provide alternatives to remediation by supporting "a pedagogical shift from problems to possibilities." (ref 45, p. 228) Akin to the intervention tested in the study reported in this article, Yosso's Community Cultural Wealth model[50] is often followed in asset-based intervention designs as a way of intentionally acknowledging the value brought to learning by students of color. This model describes six types of assets (called "cultural wealth") that students who are typically more excluded from higher education possess and rely upon throughout their education: (1) aspirational wealth is maintaining hopes and dreams for the future in the face of barriers, (2) linguistic wealth is skills attained through communicating in different languages or cultures, (3) familial wealth is community history, memory, and cultural intuition, (4) social wealth is networks that provide institutional and emotional support, (5) navigational wealth is ways of maneuvering through social institutions that are exclusive, and (6) resistant wealth is how to oppose behavior that promotes inequality.

The design and use of asset-based approaches in STEM higher education courses is not (yet) widely adopted. For example, a recent review[51] of studies of asset-based interventions in K-12 and postsecondary STEM education that employed the Community Cultural Wealth model[50] found that most studies of postsecondary-level interventions have so far occurred in undergraduate engineering. In addition, most studies followed qualitative research methodologies: in the 33 studies examined in the review, two used quantitative methods, six used mixed methods, and 25 used qualitative methods of analysis. Nonetheless, there is also a need for more quantitative studies in order to gauge the broader value of asset-based interventions, especially in STEM disciplines in higher education.[51,52] Empirical studies related to the Community Cultural Wealth model often use counternarratives of individuals as a mechanism to amplify the voices of students who do not look like the people who comprise norms that are often taught as the pioneers of STEM and examples to emulate. Counternarratives (noun) are a methodological tool in qualitative research for understanding students' experiences from their perspectives by including contextual aspects from the students' viewpoints on their educational and broader experiences.[53] The conceptualization of learning can then rely on rigorously built resources in order to be counternarrative (adjective) by foregrounding the assets, such as cultural wealth, of students in how their learning is designed to take place, particularly in schools and higher education institutions with nonmajority student populations. Another problem that compounds the existing literature on interventions is the overuse of Western educated industrialized rich and democratic (WEIRD) participants in research studies, particularly undergraduate students.[54] Aligned with the cumulative disadvantage model, a contributing factor in the overrepresentation of WEIRD students in educational studies is the accumulation of facilities at research institutions, which are largely predominantly white institutions, that then yield more research funding being awarded to these institutions.[55] Sampling gatekeeper courses in many research studies may not properly account for inequities in advantage and differences in cultural wealth represented by enrolled students in these courses. Research that is dutiful to the 21st-century student body must design and employ different types of studies − ones that involve and account for both a diverse set of student participants and a greater contextual diversity − in order to produce a more robust extant literature (and, consequently, an extant literature that can yield actionable results for educators).

The quantitative comparison research study reported here overcomes the limitations of previous studies. First, the study is undertaken at a minority-serving institution, an educational context in which nonwhite, immigrant-origin, and first-generation college students from low socioeconomic backgrounds comprise the majority of undergraduates. Second, the study examines the impacts on students of an asset-based supplemental chemistry course taken by students at risk of DFW outcomes in GC1. Third, this study aims to excavate more about what works to support the success of students whose experiences are underrepresented in research. Fourth, by leveraging an asset-based approach to designing an intervention to increase GC1 outcomes for DFW-potential students, this study contributes to the counternarrative[34] thrust of cultural wealth models in education. It does so by privileging and amplifying the experiences of students in a STEM gatekeeper course whose experiences are less well represented in the literature.

This research study addresses two questions: (1) What impact does the asset-based intervention have on students' GC1 outcomes? (2) What impact does the asset-based intervention have on students' persistence to and outcomes in GC2?

■ METHODS

Research Design

The overall objective of this study was to examine the extent to which the asset-based supplemental chemistry course intervention benefited

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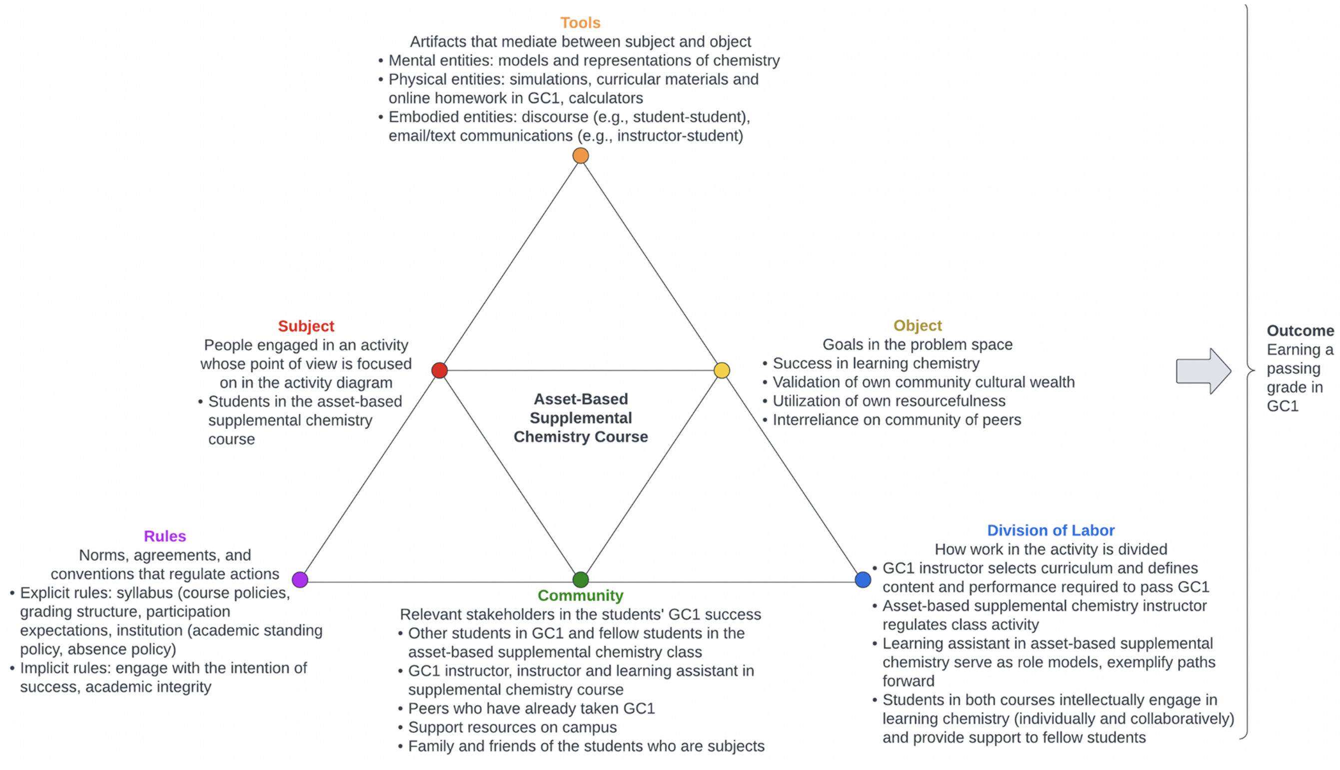

Figure 1. Representation of the Activity Theory design of the asset-based supplemental chemistry course.

the students whom it was theorized and designed to support. The analysis of the intervention's impacts involved descriptive and inferential statistics. The theoretical perspective in making assumptions in the analysis was the cumulative disadvantage theory. The choice of research questions was framed by the Anti-Deficit Achievement Framework. The intervention is replicable and causal claims can be advanced from the analysis, but there are limits to generalizability because this study is not an experiment and is not replicable. Specifically, there was no random assignment, and conditions at other institutions would differ. The implications of this are taken up further in the limitations.

Students were invited to the intervention based on academic preparation factors (e.g., prior GPA; eligibility determination is detailed further below), and invited students were given the choice whether to enroll in the intervention. The observations, therefore, are not independent. Due to the empirical nature of the inquiry related to determining how an intervention impacted outcomes, a causal-comparative research design was adopted, in which the groups to be compared were formed based on pre-existing variables that defined the groups.[56] The design was *ex post facto*, as there was no random assignment to the treatment group.[57] Because some analytical tools used in research studies assume that observations are independent, measures were taken in this study to address the interdependence of observations. One approach that has been taken in studies with such complications is to statistically equalize the group differences by propensity weighting;[58] however, this approach is most appropriate when comparing similar interventions or interventions where the demographics of the groups do not shape group membership; thus, this strategy was not employed here. An approach to studying complex interrelationships and processes is to use structural equation modeling, such as understanding the effects of campus racial climate on students' degree completion through mechanisms of students' involvement in activities and various commitments.[59] However, this study does not test the relative impacts and pathways of different processes. Because the intervention and invitation of students, as well as the research questions, were theory-driven, the approach taken in this study was to identify and exclude the use of confounding variables (i.e., related to the explanatory variable of group membership as well as GC1 and GC2 outcomes). By empirical justification, academic preparation factors used in determining invitations were not included in the analytical models because they are confounding variables. By theoretical justification, variables associated with cumulative disadvantage (race and socioeconomic status) were taken as confounding variables as the intervention was designed to be most beneficial for and desirable to students with a higher likelihood of DFW outcomes in relation to these variables. After excluding these variables, the overall impact of the intervention was assessed by use of a hierarchical linear model with class membership as level 2 and student data as level 1, using regression models with dependent variables associated with two courses: grade outcomes in GC1 (Research Question 1) and persistence to and grade outcomes in GC2 (Research Question 2).

University Context

This study took place at an urban public minority-serving institution that is primarily a commuter campus. The university has a Carnegie classification as a doctoral university with high research activity (R2). The university enrolls between 15,000 and 16,000 students annually. Among undergraduate students, 59% are first-generation college students, many are from immigrant-origin families representing over 130 countries, about one-third of matriculating students each year transfer from another higher education institution, and about 42% of undergraduate students receive Pell grants (a proxy for low socioeconomic status). In fall 2021, 55.2% of the 12,269 undergraduate students identified as U.S. residents of an ethnicity that is federally considered of minority status (Black/African American, Cape Verdean, Hispanic of any race, Asian, American Indian/Alaskan Native, Hawaiian/Pacific Islander, or two or more races), 33.9% identified as white, 6.2% were international (nonresident) students, and 4.7% did not report their ethnicity.[60] Federal minority status, for U.S. residents, is a variable that is highly correlated with cumulative disadvantage.[61]

Asset-Based Supplemental Chemistry Course Intervention

The asset-based supplemental chemistry course was designed based on Activity Theory[62,63] to leverage students' personal resources to further their success in chemistry. The basic tenet of Activity Theory is that human (a subject's) activity toward achieving goals (object) is mediated by tools. For example, the learning (object) by a student (subject) is mediated through many kinds of tools, such as organized work during lessons, use of instruments in the lab and simulations on a computer, models such as the periodic table and kinetic molecular theory, and dialogue with the instructor and other students. A subsequent generation of Activity Theory clarified categories of mediative artifacts into tools, rules, the community, and division of labor. This subsequent generation of the theory was deemed to be of overarching relevance to both the implementation and research design because it considers the student in relation to the larger system, which is consistent with the cumulative disadvantage rationale for the intervention. Specifically, Activity Theory brings attention to the objective of the activity. For example, for the activity of being a student who is taking GC1, this includes the outcome (passing GC1), the objective (learning chemistry), the tools that mediate this success (e.g., online homework, lectures, PhET simulations), the community (other students, GC1 professor, support resources on campus, students' support systems off campus, etc.), rules (explicit and implicit norms for how to succeed in GC1, expectations for success in school), and division of labor (expected roles of students, professor, peers). Figure 1 illustrates the structure of the Activity Theory design of the asset-based supplemental chemistry course that underlies the activity of being a student in this course.

Activity Theory framed the interpretation of "asset-based" that was applied to the intervention and, consequently, to differentiating the asset-based supplemental chemistry course from other approaches to addressing the asymmetries in GC1 performance that tend to occur across socioeconomic variables. The assumptions that instructors make about what students are capable of is embedded in the asset-based approach of the intervention under study here (Figure 1). Specifically, the asset-based assumptions include that students bring valuable resources (Community Cultural Wealth) to the activity of learning chemistry. Thus, class activities (tools in Activity Theory) are designed to incorporate and rely upon these resources. As well, for other vertices of Activity Theory, the roles of the instructor, near-peer undergraduate learning assistant, and students in the course are designed to involve learning from one another (division of labor in Activity Theory), and shape norms that are both explicit (e.g., weekly emails/texts from the instructor or learning assistant to every student to check in on them) and implicit (e.g., scheduling classes to occur in classrooms where students are seated at large round tables and there is no "front" of the classroom) are established (rules in Activity Theory). An expansive connection to other students (community in Activity Theory) is enacted by relying on the expertise of near-peers (e.g., panels of advanced peers are led by learning assistants twice per semester) and engaging in allyship, advocacy, and coconspiracy (e.g., learning assistants attend GC1, share example notes from class with students, and offer to attend office hours of the GC1 instructor with students). In contrast, deficit-based assumptions center on the deficiencies that students bring to learning chemistry. For example, a deficit-based intervention may observe motivation as one exogenous predictor of what happens in school, and thus may assume that students lack motivation, as well as mathematical abilities and study skills. A deficit-based approach may center activity on the object of remedying these deficits by creating merit-based initiatives and methods of cooperative study with peers (rules in Activity Theory), drilling algebraic manipulations during class and bringing professionals who use chemistry in their work to generate motivation and excitement about chemistry (tools in Activity Theory), and facilitating study groups that engage in productive ways of working on homework together (community and division of labor in Activity Theory). The ways in which activity occurs depends to a great extent on the assumptions made by the designers and implementers of an intervention and how activity is structured (e.g., including intentional training for instructors and undergraduate learning assistants on asset-based pedagogy). Of course, aspects of interventions may not be purely deficit-based or asset-based in nature. How motivation is considered in an intervention is a good example of this. Motivation may be seen as an exogenous predictor of what happens in school, thus indicating whether a deficit has been improved (an object in Activity Theory); meanwhile, motivation also can be seen as an indication of the success of efforts by instructors to increase the relevance of chemistry for students by connecting curriculum to students' lives, career aspirations, and real-world issues (tools in Activity Theory).

This study of an intentionally asset-based intervention was primarily theorized with an Anti-Deficit perspective that took into account interlocking student-success centered ideas (e.g., Community Cultural Wealth, cumulative disadvantage, peer-to-peer instruction) with reliance on the four distilled claims from relevant empirical literature, as summarized earlier. The resulting curricular plan includes relation (students relying on each other, learning each other's strengths), usage (e.g., calculator skills as a context for sharing various ways that students and instructors use them), practice (e.g., specialized language of chemistry and how understanding it can be aided by knowing other languages; many students in the course were multilingual), and study (e.g., ways of using practice exams that more advanced peers share) goals. Ref 64 contains a study of the critical course components, and the syllabus, curriculum, instructional materials, an example semester, and other resources are available in the Associated Content.

The asset-based approach is illustrated through an example activity in the asset-based supplemental chemistry intervention that involves selecting and arranging dominoes of conversions to solve dimensional analysis problems. This activates strong strategies that students who are most impacted by cumulative disadvantage are adept at and can channel toward visually rich collaborative problem solving. Many students who live with their families and commute to campus are used to navigating substantial responsibilities. They rely on similar processes in their daily lives, planning forward from the beginning and backward from the end of most days. For example, their schedules may need to fit with when to wake younger siblings or their own children, prepare their breakfasts and lunches, and bring children to daycare or school before going to campus to attend classes. Meanwhile, mid-days are often transformed by managing calls with a child's or sibling's school, translating meetings via phone for their parents, and paying bills, while also doing homework in between classes. Students plan backward based on when to pick up children and grocery shop, and they organize time to do homework after their children's or younger siblings' bedtime. A similar example of backward-and-forward planning using navigational wealth is present when students share with peers their ways to manage utility bills when there are insufficient funds to pay them, by strategically cycling which bills are paid late so as not to have utilities turned off when a bill is twice paid late. In such ways, relevant assets derive from experiencing poverty. When students employ this type of navigational wealth, they plan both forward and backward, simultaneously evaluating the efficacy of different possible pathways to solving problems. These strategies map well to solving many types of problems in chemistry, including dimensional analysis and reaction prediction, which also appear in GC2 and later chemistry courses.

The 1-credit asset-based supplemental chemistry course ran in sections (two to four per semester) with enrollment limits of 25 students. Each section met twice weekly for 50 min, with the course meeting time and day block being determined after an analysis of course enrollment patterns with the goal of serving most students. Eligibility to enroll in the asset-based supplemental chemistry course for all semesters in this study was determined by the probability of DFW outcome in GC1 set at a historically high DFW rate of the GC1 course (50%). The initial design of the intervention took place prior to the COVID-19 pandemic. To explore how to use academic preparation variables to identify DFW-potential students to invite to the intervention, the ACS Toledo exam (an instrument with three components − mathematics, scientific reasoning, and prior chemistry knowledge − that is used by many colleges and universities for similar purposes) was administered with all students in GC1 for two semesters (spring and fall 2019) prior to beginning the asset-based supplemental chemistry course. The binary outcome variable of GC1 grades (ABC or DFW) for students in both 2019 semesters was modeled by binary logistic regression, with results that the

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Table 1. Features of the GC1 Classes

characteristic	manifestation
lecture and enrollment	class sizes ranged from 96 to 241 students. Lectures were taught by chemistry faculty and took place in a 500-seat auditorium with two large screens on which the instructor projected material while lecturing. Time during class included lectures, problem solving by students, and feedback data to check understanding.
exams	three or four midterm exams were administered during lecture at even points during the semester. These included multiple-choice questions and problems. All classes employed multiple-choice final exams that were administered at the end of the semester.
discussion section	students were required to attend a one-hour discussion section, capped at 35 students, once per week in which attendance was taken. During discussion, students worked in groups on solving chemistry problems related to lecture material while the instructor circulated. All discussion were taught by faculty in the chemistry department.
homework	students were assigned weekly homework problems from the online homework system associated with the curriculum used in the course.
grading scheme	the grading scheme was similar in most classes. This included homework (20%), in-class assessments (40−45%), discussion attendance (5−10%), and final exam (20−30%). Two of the four TR classes, however, weighted the final exam higher (at 30%) than all CT and three of the TR classes (at 20%). The lowest midterm grade was not counted in the course grade. Neither overall grades nor exam scores were fit to a curve in any of the classes.

mathematics and scientific reasoning components of the Toledo exam accounted for 17.8% of the outcome's variance.[65] This was deemed a sufficient method for predicting whom to invite, given that a more expansive model with 36 variables accounted for 36.2% of variance for similar predictions.[26] For spring 2020, the Toledo exam was administered to all GC1 students during the first week of the semester and invitations were determined based on cutoff scores on the ACS Toledo placement exam that predicted a 50% or higher likelihood of a DFW outcome in GC1. When the university moved to remote operation, the in-person proctored ACS Toledo exam could not be used, so pre-intervention institutional data were used to build an academic index predictive model based on an inferential binary logistic regression model. Demographic and socioeconomic variables were not included in the inferential model to avoid creating confounding variables for the research. Contender academic preparation variables based on the research literature were tested with historical GC1 outcome data. The most successful model included high school or transfer school GPA, grade in the student's most recent math course, and whether the student was retaking GC1. The academic index model was used for determining invitations for fall 2020 onward. In all semesters of the study, invitations were sent to eligible students by email. Information about the asset-based supplemental chemistry course was communicated via email, announcements in GC1 classes, announcements in the GC1 laboratory (a separate corequisite course), and drop-in information sessions. In semesters that began in-person (spring 2020, fall 2021, spring and fall 2022), an information table was also staffed outside the lecture hall during the first week of classes.

GC1 Course

GC1 is the first course in a two-semester introductory sequence in the ACS-approved chemistry program at the university where the study took place. The GC1 course introduces fundamental principles of chemistry and basic chemical concepts. These include stoichiometry, states of matter, atomic structure, the periodic table, molecular structure and bonding, and states of matter based on kinetic molecular theory. Participants in the study were enrolled in GC1 classes in spring and fall semesters during calendar years 2020, 2021, and 2022. A review of the syllabi for all GC1 classes in the study revealed common characteristics of the GC1 classes (see Table 1). One of the semesters under study (spring 2020) began in-person and switched to remote at midpoint due to the COVID-19 pandemic, two of the semesters (fall 2020, spring 2021) were entirely remote, and one of the classes in spring 2021 was hybrid (about half of students attended remotely). The wide postpandemic literature in educational journals suggests that the greatest impacts of COVID-19 on higher education occurred during spring 2020 and fall 2020 semesters; however, this was not the case at the university where this study occurred (this is explained in further detail in the Limitations). COVID-19 has been demonstrated to have had more adverse outcomes for minorities,[13,66−68] and this very likely will have continuing repercussions for these students as they continue their higher education. Several other differences also existed among the GC1 classes; however, these were too varied to be tested in the comparative analysis. This is discussed in more detail in the Limitations. Nonetheless, as there is an extensive literature in preuniversity educational research that has shown that the teacher is the single most important factor in a K-12 student's education,[69] which class a student was in was expected to have an impact on student outcomes in both GC1 and GC2.

Two different curricula were used. For both curricula, the instructors based their lecture slides on those provided with the curriculum, assigned online homework from the system that accompanies the curriculum, and provided groupwork problems for weekly discussion classes that corresponded to the curriculum. At this university, the laboratory is a separate course and follows a different curriculum than either of the two curricula used in the GC1 lecture course. Two of the instructors, who taught five of the classes (all in fall semesters), used *Chemistry: The Central Science*,[70] which is a traditional curriculum that follows a topical sequence. Four of the instructors, who taught seven of the classes (one in fall and six in spring semesters), used *Chemical Thinking*,[71] which organizes the content of chemistry around central questions of the discipline (e.g., how to identify substances, how structure accounts for physical properties and reactivity). None of the GC1 classes included in this study were taught by any of the authors of this article. The *Chemical Thinking* curriculum has been demonstrated to result in narrower performance gaps between female and male students, and between underrepresented and white students.[72,73] The balance of math-based and conceptual questions on exams varied by the curriculum used. Exams in classes with the traditional curriculum favored math-based questions, while exams in classes with *Chemical Thinking* favored conceptual questions. Prior research has shown that courses that favor math-based questions on exams tend to result in lower performance by Hispanic and Black students.[74]

Participants, Research Ethics, Comparison Groups, and Variables Examined

In total, 1,807 instances of enrollment in 12 classes of GC1 across six semesters of the study were treated as discrete observations. A total of 1,610 unique students are included in the data; because some students took GC1 more than once, there are 1,807 instances of enrollment.[75] The trajectories of the students from GC1 to GC2 in the immediately adjacent term were also studied. Five students were excluded from this analysis because they were erroneously enrolled in GC2 without having passed the GC1 course. The remaining 1,802 instances (1,605 unique students) comprised the population studied in the second research question.[76]

Of 862 eligibility determinations for enrollment in the asset-based supplemental chemistry course among the 12 GC1 classes taken across the six semesters included in the study, 262 (30.4%) enrolled in the intervention. The study included three comparison groups: the treatment group enrolled in the asset-based supplemental chemistry course (Group 1), the group of eligible/invited students who did not enroll in the asset-based course (Group 2), and the group of students who were not eligible/invited (Group 3). The study was approved under exempt status by the university's Institutional Research Board (Protocol #2019157). All students were considered participants and were informed of their participation in the study through announcements made in GC1 classes and emails sent to students. The use of institutional data complied with the Family Educational Rights and Privacy Act (FERPA). Data included GC1 and GC2 course grades for all students. No incomplete (I) grades occurred in the data. Some students elected a pass/fail option;[77] in cases of P grades, the Institutional Research Office provided the letter grades underneath.

The study examined several variables for instance of enrollment from each of the six semesters in the study, including GC1 and GC2 outcomes, socioeconomic proxies, social identity indicators, and academic preparedness proxies. Collectively, these variables proxy for which students were most likely to be impacted by cumulative disadvantage, e.g., self-identified ethnicities defined by the federal government as having minority status, female-identifying students,[78] Pell-eligible students, first-generation college students, and older students. The study included admit type (whether student is a first-year or a transfer student) in the analysis. Doing so accounts for the U.S. Department of Education's Integrated Postsecondary Education Data System (IPEDS) reporting statistics, which only include first-time first-year freshmen.[79] Age and admit type were predicted to coalesce in students who were more likely not to be first-year students, and indeed age and transfer admission were related (with sample correlation coefficient of 0.560, $p < 0.001$). Descriptions of all variables included in the data are provided in the Supporting Information. Since some variables could change over time (e.g., Pell eligibility), variables for students who enrolled multiple times were included for the semester in which they enrolled in GC1.

Hierarchical Linear Modeling

The data are nested in nature, with students in different classes (*GC1 Class*) taught by various instructors. Here, this means that the data are clustered in that observations (in this case the GC1 and GC2 outcomes of interest) from the same cluster (in this case the class) are likely to be more similar than observations from different clusters. This also means that the total variance of any equation modeling the impact of covariates on the outcomes of interest includes between-cluster variance and within-cluster variance. By identifying the level by which observations cluster and by differentiating between the fixed effects and random effects impinging upon the dependent variable, hierarchical linear modeling techniques (as a variance-component modeling technique) decompose the total variance, account for unmeasured heterogeneity among the data, and avoid the problem of underestimating the standard errors of parameters associated with using standard linear modeling techniques.[80]

In recognition of the robust K-12 literature showing the substantial impact of teachers on student outcomes,[69] intraclass correlations were evaluated to determine the extent to which the inferential models would benefit from hierarchical linear modeling (HLM) techniques. When null models (GC1 and GC2 outcomes dependence only on class) were run, intraclass correlations indicated that 5.9% of the overall variance of GC1 grades and 9.6% of GC2 grades depended on class. While there is "no consensus on a cut-off point," (ref 81, p. 62), given the extant literature on teacher impact, hierarchical linear models with class at level 2 were built for all inferential analyses. Given the animating research questions, this study endeavored to unpack the within-cluster and between-cluster covariate effects by leveraging the HLM random-slopes modeling technique, which enables simultaneous estimation of the random intercepts and random slopes. The former estimation approach, HLM random-intercepts modeling, showcases how the overall quantities identifying the outcome of special interest (in this case an ABC outcome in GC1 and GC2) may vary over clusters (in this case the classes) after controlling for covariates, whereas the latter estimation approach, HLM random-slopes modeling, showcases how the effect of a particular covariate (in this case group membership) may also vary over the clusters.[82] All variance-component models were derived using the multilevel melogit/mixed commands in Stata 16.1 with the maximum likelihood estimator option to produce the parameter estimates. For parsimony, the study assumes zero random intercept and slope covariance and thus does not estimate the correlation matrix.[83]

Dependent Variables (Research Question 1)

Investigation of the impact of the asset-based supplemental chemistry course involved examining the dependence of students' GC1 course outcomes on the independent variables. Two measures of GC1 outcomes were studied. First, because a course grade of C− is a prerequisite for enrollment in GC2, qualifying grades were binned as ABC and assigned a binary outcome value of 1, while nonqualifying grades were binned as DFW and assigned a binary outcome value of 0. This enabled a connection to research literature that refers to DFW rates. This binary variable, *GC1 Outcome*, was referenced to the DFW outcome as the excluded baseline. The second measure of GC1 outcomes studied was grade outcomes, *GC1 grade*. GC1 grades included all letter grades (e.g., A, A−, B+, B, B−, etc.) as well as W (13 possible values).

Dependent Variables (Research Question 2)

As with Research Question 1, the investigation of the impact of the asset-based supplemental chemistry course examined the dependence of students' GC2 course outcomes on the independent variables. Only students with ABC outcomes in GC1 could advance to GC2. Corresponding to Research Question 1, two measures of GC2 outcomes were studied. First, binary ABC and DFW outcomes in GC2 were studied for students who were eligible to advance to GC2; this excluded attrition (i.e., students with ABC outcomes in GC1 who did not advance to GC2 in the adjacent term). Second, full GC2 outcomes (*GC2 Outcome for Those Eligible*) were studied, consisting of assigned grades, withdrawal (W), and attrition. As with Research Question 1, the investigation of the impact of the asset-based supplemental chemistry course examined the dependence of students' GC2 course outcomes on the independent variables.

Level 1 Independent Variables (Research Questions 1 and 2)

Investigation of the impacts of the asset-based supplemental chemistry course on students' GC1 outcomes involved analysis by *Comparison Group*, including Group 1 (*Invited:Enrolled*), Group 2 (*Invited:DidNotEnroll*), and Group 3 (*NotInvited*), the latter of which was the baseline referenced. Other variables of interest were associated with student characteristics and the features of the GC1 classes (level 2) that the students were enrolled in. Due to multicollinearity, measures for instructor-specific variables were not used.[84]

Student characteristics included how many total credits a student was taking during the semester while enrolled in GC1 (*Total Credits During GC1*),[85−87] tuition residency status (*Tuition*, as in-state or not in-state) in the semester in which the student was enrolled in GC1 and *Admit Type* (first-time freshman or transfer). Characteristics of the twelve GC1 classes included which *Curriculum* was used in the GC1 class (TR = Traditional, or CT = *Chemical Thinking*).[88] Categorical and binary variables were referenced to excluded baselines, which were assigned to the value that had the larger fractional distribution. *Tuition* (out of state, or in state) was referenced to having in-state tuition, *Admit Type* was referenced to being a first-time freshman, and *Curriculum* was referenced to TR. This modeling strategy enabled the investigation of the impact of a student's conjoined circumstances on the probability of outcomes in GC1 and GC2.

Analytical Approach: Descriptive and Inferential Analyses

The study endeavored to answer the two research questions by examining descriptive statistics of the variables of interest and of the outcome data; by examining inferential statistics, including the employment of hierarchical binary logistic regression and HLM OLS regression models to ascertain the relationships between the variables of interest and the GC1 and GC2 outcomes and by examining the plots of results from the regression models. For ease of interpretation, tables that are presented report odds ratios for the hierarchical binary regression models, and figures depict the average marginal effects (AMEs). Stata 16.1 was used for all equation estimations and plotting.

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Table 2. Race and Socioeconomic Status Variables for Samples in the Comparison Groups and the Overall Study Population

variable	group 1 *invited:enrolled* mean[a]	SD	group 2 *invited:didnotenroll* mean[a]	SD	group 3 *notinvited* mean[a]	SD	overall mean[a]	SD
race variables								
Asian[b,c]	0.11	0.32	0.18	0.39	0.21	0.41	0.19	0.39
Black/African American[c,d]	0.27	0.45	0.22	0.42	0.14	0.34	0.18	0.39
Hispanic[c]	0.31	0.46	0.25	0.43	0.20	0.40	0.23	0.42
two or more races	0.034	0.18	0.040	0.20	0.031	0.17	0.034	0.18
other racial minority	0.0076	0.087	0.0067	0.081	0.011	0.10	0.0089	0.094
White[c,d]	0.18	0.39	0.24	0.43	0.33	0.47	0.28	0.45
non-resident	0.046	0.21	0.042	0.20	0.038	0.19	0.040	0.20
not specified	0.031	0.17	0.020	0.14	0.037	0.19	0.030	0.17
socioeconomic status variables								
female[b]	0.77	0.42	0.65	0.48	0.69	0.46	0.69	0.46
first-generation student[c,d]	0.56	0.50	0.51	0.50	0.39	0.49	0.46	0.50
pell eligible[b,c]	0.63	0.48	0.53	0.50	0.49	0.50	0.52	0.50
age (years)	20.6	2.95	20.2	2.74	20.1	3.42	20.2	3.15
first-time freshman	0.79	0.41	0.80	0.40	0.81	0.39	0.80	0.40

[a]Based on reference of 1.0 for the sample, except for Age which is reported in years. [b]Group 1 and Group 2 are different ($p < 0.05$). [c]Group 1 and Group 3 are different ($p < 0.05$) [d]Group 2 and Group 3 are different ($p < 0.05$)

Descriptive Analysis. The descriptive analysis endeavored to excavate the potential existence of cumulative disadvantage by examining the distribution proportions on key variables per membership in the three comparison groups. As such, three objectives drove the descriptive analysis:

(1) To describe who was invited to participate in the asset-based supplemental chemistry course intervention (Groups 1 and 2), and whether the characteristics of students who were invited or not aligned with findings from the literature about the differential impacts of cumulative disadvantage.

(2) To examine whether the opportunity to enroll in the intervention was taken up differently by students based on characteristics associated with cumulative disadvantage and

(3) To highlight patterns in the distributions of students in comparison groups and among variables in the causal model that related to withdrawing from GC1 and advancing to GC2.

The descriptive analysis informed the inferential analysis; thus, objectives 1 and 2 of the descriptive analysis are presented here in Table 2. Results show that factors typically associated with cumulative disadvantage were associated with grade outcomes: identifying as female, being a first-generation student, identifying as a member of a minority group associated with cumulative disadvantage (Hispanic, Black/African American, and Other Racial Minority), belonging to lower socioeconomic groups (using Pell eligibility as a proxy), and being a nontraditional student (i.e., starting GC1 when older than 18 or 19 years old, using age and whether the student was a first-time freshman as proxies).

Given how the intervention was structured (i.e., how students were identified for group membership), there was not a random assignment of students to groups and thus normal distributions were not expected across comparison groups. Accordingly, the results by group membership in Table 2 are unsurprising and indeed were expected. Tests were run to determine which differences were significant. ANOVA analyses were run using the Tukey method, which adjusts for the number of pairwise comparisons, to examine whether there were significant differences in the group means and between which groups those mean differences appeared. These results are reported in superscripts on variables in Table 2. As a complementary examination of group differences, Kruskal−Wallis tests (a nonparametric rank test for means) were run and verified that the medians indeed differed among groups.

Objective 3 of the descriptive analysis relates to the study of persistence to GC2. For this, a comparison set from the larger Group 2 (*Invited:DidNotEnroll*) was created to match all instances in Group 1 (*Invited:Enrolled*). This was organized by matching on the three factors that were most correlated with enrolling in the intervention: gender, Pell eligibility, and first-generation status. To do this, an equal number of Group 2 instances with the same combination of the three variable values was randomly selected to match instances in Group 1 with that combination.[89,90] To examine patterns in the distributions of students in the comparison groups and among variables in the causal model that related to withdrawing from GC1 and to not advancing to GC2 (i.e., Attrition defined as meeting the prerequisite to enroll in GC2 but not enrolling in it), the matched sets from Group 1 (*Invited:Enrolled*) and Group 2 (*Invited:DidNotEnroll*) were compared via descriptive statistics. Findings from this analysis are reported in the Results.

Inferential Analysis. Given the collinearity between select variables that were theoretically driven predictors (see Table 2) and the probability of group membership, a parsimonious modeling technique was utilized when constructing the hierarchical logistic and linear equations because it accomplished the desired level of explanation with as few predictor variables as possible. This enabled foregrounding the impact of the asset-based supplemental chemistry course on student outcomes, disentangling class-specific and student-specific influences, and differentiating between degrees of academic preparedness and cumulative disadvantage. Taken together, this comparative-causal study, complete with a parsimonious model and plotted average AMEs, highlights how enrollment in the asset-based supplemental chemistry course impacts the odds of GC1 and GC2 success associated with group membership and select variables, as well as the AMEs related to obtaining an ABC or DFW outcome in GC1, and obtaining a specific grade outcome in GC2.

Hierarchical Linear Regression: Binary Logistic and OLS Regression Models (Research Question 1)

Hierarchical binary logistic regression was employed to model the dependence of the GC1 course outcome on class (level 2) and the independent variables (level 1). Binary logistic regression was utilized because the dependent variable was measured as 0 or 1; thus, a nonlinear relationship between the independent variables and the outcome must be accounted for. It was expected that, if the intervention was effective, being in Group 1 (*Invited:Enrolled*) would result in a higher odds ratio than being in Group 2 (*Invited:DidNotEnroll*). It was also expected that being in Group 1 or Group 2 would result in lower odds ratios than being in Group 3 (*NotInvited*), as the accumulation of disadvantage is unlikely to be eliminated in a single semester. The goodness of fit of the hierarchical binary logistic regression models was tested via the Hosmer−Lemeshow method,[91]

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to compare observed and expected proportions of ten equally sized groups (decile default). The goodness of fit of the hierarchical linear regression models was tested via standard Aikake information criterion (AIC), Bayesian information criterion (BIC), and Wald χ^2 tests.

HLM OLS regression was employed to model the dependence of GC1 grade outcomes, with a total of 13 grade outcomes (i.e., A, A−, B+, B, ··· D−, F, and W), with W given the lowest value (1) and A given the highest (13), on class (level 2) and the independent variables (level 1). The study envisions instructors as giving out grades across the range of letter grades, not simply as a sequence of binary outcomes. As Group 3 (*NotInvited*) was the excluded baseline, it was expected that Group 1 (*Invited:Enrolled*) and Group 2 (*Invited:DidNotEnroll*) would both exhibit negative relationships (corresponding to significant negative logit coefficients, as well as significant odds ratios less than 1) for higher GC1 grades (grades of A, A−, B+, B, B−, C+, C, and C−). It was also expected that Group 1 would exhibit less negative relationships for some of these grades than Group 2 would. It was further expected that, given prior research showing that the *Chemical Thinking* curriculum results in performance gap reductions,[47,48] the CT variable (when referenced to the traditional curriculum) would exhibit positive relationships for upper grades relative to W. As students who are taking more credits were anticipated to be more traditionally enrolled in higher education, it was expected that *Total Credits During GC1* would exhibit more positive relationships with higher grades. As out-of-state tuition status and non-Pell eligibility is a conjoined proxy for wealth, opposite cumulative disadvantage, the expectation was a positive correlation when *Tuition* was out-of-state and placement in the higher grades. Lastly, as the composition of the transfer *Admit Type* could include students who transferred from two-year colleges (which has a relationship with socioeconomic status) and students who transferred from four-year colleges (unknown relationships), there was no expectation for this variable related to the theories that framed the study.

A plot of the AMEs of each independent variable set to their observed values (not set to their means) reveals much about influences of each independent variable on the dependent variable. In this study, in line with the social science methods adopted, AMEs were calculated instead of marginal effects at the means (the latter is where the mean value of every variable would be substituted in the model) because the data are about people and there are variables (such as the binary variables for gender or for race) for which a mean value makes little interpretable sense (since no real person could have such values). The resulting AME provides the average effect in the estimation sample of the dependent variable on the probability associated with the binary outcome. Put differently, because the expected change in a probability of achieving a 1 (of a binary dependent variable where 0 is the lowest and 1 is the highest) depends on the values of the independent variables, AMEs represent the differences in probabilities and thus enable a researcher to isolate the effect of one variable given values on the other independent variables. An AME value can be considered as analogous to a partial derivative, in that the AME on an outcome with respect to a specific explanatory variable is calculated by holding the other variables at their observed values while changing that one explanatory variable of interest. Thus, the AME provides information on the magnitude by which an outcome changes when a specific explanatory variable changes. For all variables, the AME is computed as the average of all the marginal effects from each observation. With regard to interpreting the impact of each independent variable, the interpretation is relatively straightforward. When estimating the AME results from a binary logistic regression, the resulting AME number for a continuous independent variable reflects the degree to which an increase (usually a one-unit change) in the independent variable impacts the expected probability of obtaining the highest value (1) on the binary outcome (the dependent variable). For noncontinuous (i.e., categorical) independent variables, the resulting AME number represents the difference in the probability between the lowest value and the target value of the independent variable of obtaining the highest value on the dependent variable.

Hierarchical Linear Regression: Binary Logistic and OLS Regression Models (Research Question 2)

To explore Research Question 2, the study adopted the same hierarchical linear modeling techniques as Research Question 1: hierarchical binary logistic regression to model the dependence of the binary GC2 course outcome (1 = ABC, 0 = DFW) on class (level 2) and the independent variables (level 1); and HLM OLS regression to model GC2 grade outcomes on the same variable and employed the same goodness of fit methods. The study coded the grade outcomes (i.e., A, A−, B+, ··· D−, F, and W), so that Attrition was excluded and W was given the lowest value (1) and A was given the highest value (13). The same expectations related to the independent covariates (or variables) applied as the analysis for Research Question 1, with acknowledgment that because GC2 had a prerequisite of C− in GC1, only students with ABC outcomes in GC1 could advance to GC2.

An examination of the AMEs for each independent variable revealed much about the relationship. Given the study's focus on whether the intervention disrupted the effects of cumulative disadvantage, the study turned to examining the impact of the intervention in conjunction with academic preparedness. The mechanism employed was examining a plot of adjusted predictions for representative (APR) values for the continuous variable of *Total Credits During GC1* and for the categorical variable of *Comparison Group* membership, leaving all other variables at their observed values. This analysis made it possible to isolate the effects of variables of interest under different conditions.

■ RESULTS

Results are showcased for the three groups compared: students who were eligible to enroll in the asset-based supplemental chemistry course intervention and elected to do so (Group 1), students who were eligible and did not enroll in the intervention (Group 2), and students who were not eligible and therefore not invited to enroll (Group 3). Figure 2 provides an overall depiction of the trajectories and outcomes for the aggregated observations in the study.

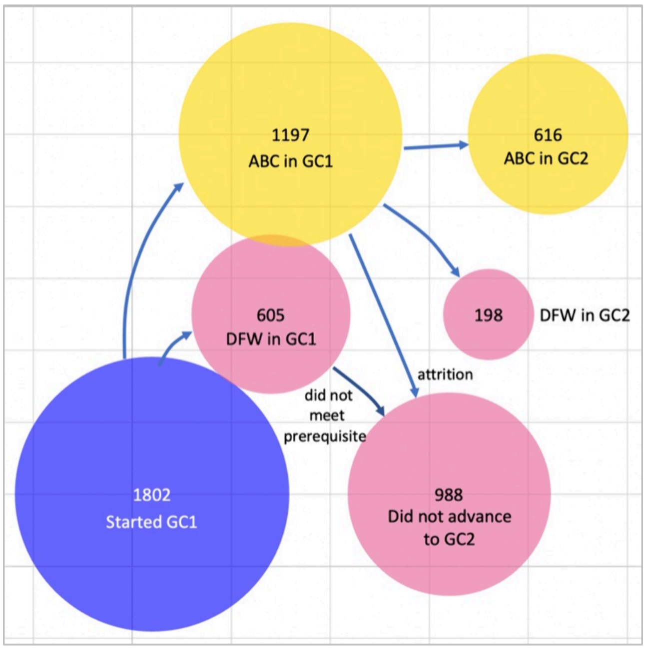

Figure 2. Bubble plot illustrating the 1,802 instances of GC1 course takers in the 12 classes during six semesters trajectories from GC1 to GC2 in the subsequent term.

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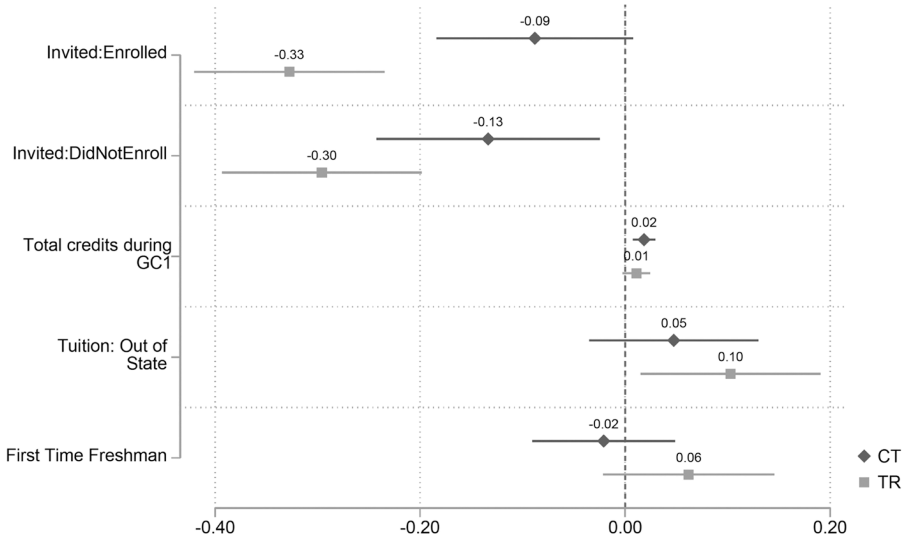

Figure 3. Average marginal effects (AMEs) on GC1 outcomes in the hierarchical binary logistic regression models by different curriculum conditions. AMEs represent the differences in probabilities and thus enable a researcher to isolate the effect of one variable given values on the other independent variables. The result is the average change in the probability. Numbers reflect the degree to which an increase in the variable impacts the expected probability of obtaining the highest value (1) on the binary outcome. Positive values correspond to positive probability relationships. A variable is significant if it does not cross the vertical line at 0.00. 95% confidence intervals are shown, and the value of the AME is shown above each point.

Research Question 1: Impacts of the Asset-Based Intervention on Students' GC1 Outcomes

Table 2 reports findings from the descriptive analysis and indicates that students who were eligible and invited (Groups 1 and 2) differed from students who were not eligible (Group 3) by all expected variables associated with cumulative disadvantage except age. In other words, students who were female, first-generation, and Pell-eligible, as well identifying with an ethnicity considered to be a federal minority status, were all more likely to be eligible. Eligible students who elected to enroll in the asset-based supplemental chemistry course (Group 1) also differed from eligible students who did not enroll (Group 2) by all but one of the variables associated with cumulative disadvantage. Being Asian[92] was more associated with being in Group 3 (not eligible/invited) and least associated with being in Group 1 (eligible and elected to enroll in the intervention). *Admit Type* (first-time freshman or transfer student) was similar across groups.

Regression Analysis

The results of the hierarchical binary logistic regression model revealed noteworthy relationships between independent variables and binary GC1 outcomes (see Table S2 in the Supporting Information). In the Supporting Information, Table S3 presents the odds ratios of the variables, and Figure S1 provides an example of how goodness of fit was assessed.[93] The hierarchical binary logistic regression analysis isolates the direct effects of individual variables in the sample of all observations. Aligned with expectations, being in either Group 1 or Group 2 resulted in greater probability of having lower GC1 outcomes ($p < 0.001$) compared to the reference of being in Group 3. Different from expectations, when isolated as one variable, being in a GC1 class that used the *Chemical Thinking* (CT) curriculum did not have a different probability of overall grade outcomes than being in a class that used the traditional curriculum. Aligned with expectations, having taken more credits while taking GC1 was associated with higher probability of having a GC1 outcome of ABC ($p < 0.001$), and having a tuition residency class other than in-state (i.e., out of state) conferred a higher probability of having a better GC1 grade outcome ($p < 0.05$).

The three semesters whose instructional modalities were most immediately impacted by the COVID-19 pandemic − spring 2020, fall 2020, and spring 2021 − coincided with classes 1−6 (see Table S6 in the Supporting Information) in which the *Chemical Thinking* curriculum was used in 5 of the 6 classes. This correspondence suggested that a comparison of the two curriculum conditions in relationship to the comparison groups (whose composition had a relationship with cumulative disadvantage) could be fruitful, i.e., the interactive effects may reveal useful causal explanation.

Figure 3 shows the AMEs for the hierarchical binary logistic regression model of GC1 outcomes by curriculum used in the classes, and Table S3 in the Supporting Information provides the odds ratios for these data in tabular form. Figure 3 represents two plots overlaid: the AMEs for all observations using the CT curriculum, and the AMEs for all observations using the TR curriculum. When separated by curriculum, being in different comparison groups matters. As shown in Figure 3, the traditional curriculum differentially impacted the students with greater cumulative disadvantage who were targeted by the intervention, as these students exhibited a 30−33% point decrease in the probability of obtaining an ABC outcome in GC1. Meanwhile, when the *Chemical Thinking* curriculum was used, there was no statistically significant difference between students in the intervention and students who were not invited. The AME value of −0.09 being below 0.00 indicates that the mean likelihood of ABC outcomes for Group 1 (*Invited:Enrolled*) students in the CT curriculum condition was lower than the mean likelihood for Group 3 (*NotInvited*) students, but the two distributions are not statistically different at the $p < 0.05$ level. In other words, the asset-based intervention in combination with use of the *Chemical Thinking* curriculum made it possible for DFW-potential students (in Group 1) to

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Table 3. Frequencies of GC1 Course Outcomes in Grades by Comparison Group and Overall[a]

grade	Group 1 (*Invited:Enrolled*)	Group 2 (*Invited:DidNotEnroll*)	Group 3 (*NotInvited*)	total
A	15(5.6%)	34(12.8%)	217(81.6%)	266(100%)
A−	22(12.6%)	35(20.1%)	117(67.2%)	174(100%)
B+	13(14.0%)	22(23.7%)	58(62.4%)	93(100%)
B	19(14.6%)	35(26.9%)	76(58.5%)	130(100%)
B−	23(13.5%)	65(38.0%)	83(48.5%)	171(100%)
C+	9(9.1%)	35(35.4%)	55(55.6%)	99(100%)
C	19(14.4%)	62(47.0%)	51(38.6%)	132(100%)
C−	22(17.7%)	47(37.9%)	55(44.4%)	124(100%)
D+	11(15.9%)	35(50.7%)	23(33.3%)	69(100%)
D	7(13.5%)	26(50.0%)	19(36.5%)	52(100%)
D−	10(20.8%)	22(45.8%)	16(33.3%)	48(100%)
F	33(18.8%)	78(44.3%)	65(36.9%)	176(100%)
W	59(21.6%)	104(38.1%)	110(40.3%)	273(100%)
total	262(14.5%)	600(33.2%)	945(52.3%)	1807(100%)

[a]Percentages in parentheses are relative to the total in each row.

achieve GC1 outcomes that were not statistically different from ABC-potential students (in Group 3).

The odds ratios in Table S3 provide the same information as the AME plot. Odds ratios are proportions of the likelihood of an event occurring to the likelihood that it will not occur. An odds ratio greater than 1.0 indicates greater likelihood of occurrence than the reference (i.e., a positive relationship), while an odds ratio less than 1.0 corresponds to a negative relationship. Odds ratios occurring with significant differences are marked with stars showing degrees of significance (see footnote to Table S3). Because the study assumes an unknown standard deviation of GC1 outcomes in the overall student population, *t*-statistics are reported in parentheses below each odds ratio (reflecting whether the coefficient is equal to zero). Looking at the odds ratio results from the hierarchical binary logistic regression in Table S3, holding all other variables constant at their observed values, within the traditional curriculum (TR condition), there was a significant difference in the odds of students who were invited to the intervention achieving an ABC outcome in GC1 compared to the not invited students (OR = 0.242, 95% CI [0.16, 0.37] as computed by the model), with the odds of achieving an ABC outcome therefore being about 25% as high (or about 75% lower) for Group 1 (*Invited:Enrolled*) compared to Group 3 (*NotInvited*). Conversely, for Group 2 (Invited:NotEnrolled) students in GC1 classes that followed a nontraditional curriculum (CT condition) the odds of achieving an ABC outcome decreased by 49% compared to Group 3 (*NotInvited*) (OR = 0.508, 95% CI [0.29, 0.90]), holding all other variables constant. The AMEs depicted in Figure 3 reiterate these points.

Additionally, the probability of a more positive GC1 outcome resulted from having a tuition classification other than in-state (i.e., out-of-state) when classes used the traditional curriculum, but not when classes used the *Chemical Thinking* curriculum. Another way of reading this (0.10) is that for students in the sample under the traditional curriculum, the expected difference in predicted probability of obtaining an ABC outcome (*GC1 Outcome* = 1) is 0.10 greater for an out-of-state student (probability of 0.67, as calculated by the model) relative to an in-state student (probability of 0.57, as calculated by the model), thus representing an expected difference of a 10-percentage point increase (shown in Figure 3). Given the conjoined nature of in-state tuition status with Pell eligibility, this suggests that use of the traditional curriculum may have differentially favorable benefits for students from higher socioeconomic groups.

An HLM OLS regression model was used to examine the effects of variables on the GC1 letter grades of A through W (13 grade outcomes: A = 13, A− = 12, B+ = 11,··· C− = 6, ··· F = 2, W = 1). Table 3 provides the distributions of students in grade outcomes who were in different comparison groups. Table 4 presents the coefficients of the HLM OLS regression model for the GC1 grade outcomes whose observations are shown in Table 3.

Table 4. Coefficients of Variables in the HLM OLS Regression Model of GC1 Course Outcomes as Grades (W = 1 through A = 13); Excluded Baselines are Group 3 (*NotInvited*), CT (Curriculum in GC1), *Tuition Status* (In State), and *Admit Type* (Transfer)[a]

variable	coeff.
Group 1 (*Invited:Enrolled*)	−2.283***(0.427)
Group 2 (*Invited:DidNotEnroll*)	−2.409***(0.328)
Group 3 (*NotInvited*)	
TR curriculum	−1.040*(0.525)
CT curriculum	
total credits during GC1	0.167***(0.039)
Tuition (out of state)	0.849**(0.279)
Tuition (in state)	
Admit Type (first-time freshman)	−0.102(0.246)
Admit Type (transfer)	
constant	6.410***(0.642)
var.(1.comparison)	1.244(0.908)
var.(2.comparison)	0.748(0.551)
var.(_cons)	0.650(0.349)
var.(residual)	15.15***(0.509)
observations	1807

[a]LR test vs. linear model: χ^2 (3) = 82.72. Prob > χ^2 = 0.0000. Random slope and random intercept model, standard errors in parentheses. log likelihood (model) = −5043.05. d.f. = 11. AIC = 10108.09. BIC = 10168.58. Wald χ^2 (6 d.f.) = 117.31. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

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Table 5. Variables for Group 1 and the Matched Set from Group 2[a]

	Group 1 *Invited:Enrolled*		matched set from Group 2 *Invited:DidNotEnroll*		all students in Group 1 and matched set from Group 2	
variable	mean	SD	mean	SD	mean	SD
GC1 curriculum (CT = 1, TR = 2)	1.49	0.50	1.50	0.50	1.50	0.50
total credits during GC1**	14.52	2.25	14.05	3.08	14.28	2.70
Tuition (in state = 1, out of state = 2)	1.11	0.31	1.10	0.29	1.10	0.30
Admit Type (first-time freshman = 0, transfer = 1)	0.21	0.41	0.23	0.42	0.22	0.42
cumulative GPA in term before GC1*	2.35	1.31	2.14	1.40	2.25	1.36
GC1 outcome (DFW = 0, ABC = 1)	0.54	0.50	0.53	0.50	0.53	0.50
total	262		262		524	

[a]*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

The coefficients in Table 4 resulting from the HLM OLS regression analysis provide more specificity than the hierarchical binary logistic regression about the differences in outcomes. As expected, students who were eligible for the intervention performed less well in GC1 than students who were not eligible. Specifically, the HLM OLS model delineates that students in Group 1 (*Invited:Enrolled*) had GC1 outcomes that were lower than students in Group 3 (*NotInvited*), but not as low as those of students in Group 2 (*Invited:DidNotEnroll*) when compared to Group 3 (*NotInvited*). The curriculum used in GC1 had an impact on grades outcomes. A student's movement toward the highest outcome (13 = A) was decreased by being in a class using the traditional (TR) curriculum ($p = 0.048$) relative to being in a class using the *Chemical Thinking* (CT) curriculum. Two other differences also were significant. Holding covariates at their observed values, taking more credit hours while enrolled in GC1 led to greater likelihood of higher grades ($p < 0.001$). Having tuition residency status that was not in-state (i.e., out-of-state) resulted in a greater likelihood of higher grades ($p = 0.002$) relative to being an in-state student (an average marginal effect of 0.84, or an increase on the W-to-A grade scale of 0.84). The random-effects portion of the table shows that the estimated residual variance (or overall variance of the level 1 error term) was 15.15 and is significant. This residual variance gives further indication that instructors and instruction mattered in shaping GC1 outcomes. The within-class random slopes for the invited/noninvited groups were not significant. The variance for the random effects at the class level is 0.65, representing how the classes vary in their intercepts.

Research Question 2: Impacts of the Asset-Based Intervention on Students' GC2 Persistence and Outcomes

More than half (54.8%) of the 1,802 students in the study population for Research Question 2 did not advance to GC2 in the subsequent term (see Figure 2). Of the 988 students who did not advance, a little over 60% could not advance due to a DFW outcome in GC1. The remainder (labeled "attrition") who did not advance to GC2 (a little under 40%) were students who met the prerequisite for GC2 but did not take the course the following term. As noted in the Introduction, there are many reasons why attrition occurs (e.g., stopping out), and the descriptive and causal analyses can only shed light on reasons related to conditions and variables examined in this study.

Among students who met the GC1 grade prerequisite to advance to GC2, similar fractions of students who used the CT (424 of 917, or 46.2%) vs the TR (390 of 885, or 44.1%) curriculum in GC1 advanced to GC2 in the immediately subsequent term. Part of this may be related to repeating GC1. GC1. Students in the sample who repeated GC1 at least once during the semesters in the study overwhelmingly came from fall semester classes (126 of the 683 students, or 18.4%, from fall 2020 and fall 2021 vs 51 of the 658 students, or 7.8%, from spring 2020, spring 2021, and spring 2022), and these students may have a different likelihood of advancing to GC2 than students who had ABC outcomes upon their first enrollment in GC1. Likely because spring was adjacent for the latter, 69.4% (93 of 134) of the adjacent repeats of GC1 occurred during spring semesters. The CT curriculum was used in all spring classes and in one fall class of GC1. Based on probability, then, there is a higher likelihood that spring cohort students who did not continue to GC2 were students who were retaking GC1. However, there are also two other prerequisites for enrollment in GC2 whose data were not included in the study: a D− or higher in Precalculus, and a D− or higher in the GC1 lab (which is a separate course from GC1). At this university, Precalculus has DFW rates that rival GC1. Thus, it is likely that F or W outcomes in Precalculus also contributed to students not advancing immediately to GC2 even when a student did not have a DFW outcome in GC1 that prevented GC2 enrollment.

Within the bounds of the data included in this study, to excavate information about the impact of the asset-based supplemental chemistry course on not advancing to GC2 in the subsequent semester (termed "attrition" in this study), a matched set of students from Group 2 (*Invited:DidNotEnroll*) was compared to students in Group 1 (*Invited:Enrolled*). Of the 262 students in Group 1, more than half, 142 students (54.2%), met the C− prerequisite in GC1 to advance to GC2. One additional student in Group 1 repeated GC1 in the summer, met the C− prerequisite in GC1, and then enrolled in GC2 in the fall). Of these 143 Group 1 students, 52 (36.4%) obtained ABC outcomes in GC2 in the subsequent term, 39 (27.3%) had DFW outcomes in GC2 (one of these 39 was the student who repeated GC1 in the summer), and 52 (36.4%) did not enroll in GC2 in the subsequent term (attrition outcome). Of the 262 students in the matched set from Group 2, a smaller number, 138 students (52.7%), met the prerequisite for GC2. Of these 138 Group 2 students, 64 (46.4%) had ABC outcomes in GC2, 29 (21.0%) had DFW outcomes, and 45 (32.6%) did not enroll in GC2 in the subsequent term. Table 5 shows comparisons of these two samples by relevant variables examined Research Question 1, as well as one additional variable. The additional variable (cumulative GPA at the university in the semester prior to taking GC1) was not examined in Research Question 1 due to

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Table 6. Frequencies of GC2 Course Outcomes in Grades by Comparison Group and Overall[a]

grade	Group 1 (*Invited:Enrolled*)	Group 2 (*Invited:DidNotEnroll*)	Group 3 (*NotInvited*)	total
A	12(7.5%)	22(13.8%)	126(78.8%)	160(100%)
A−	4(5.1%)	21(26.6%)	54(68.4%)	79(100%)
B+	5(10.0%)	13(26.0%)	32(64.0%)	50(100%)
B	8(10.5%)	22(28.9%)	46(60.5%)	76(100%)
B−	10(14.5%)	17(24.6%)	42(60.9%)	69(100%)
C+	5(9.6%)	13(25.0%)	34(65.4%)	52(100%)
C	4(5.4%)	26(35.1%)	44(59.5%)	74(100%)
C−	4(7.1%)	19(33.9%)	33(58.9%)	56(100%)
D+	8(25.8%)	13(41.9%)	10(32.3%)	31(100%)
D	6(20.0%)	11(36.7%)	13(43.3%)	30(100%)
D−	9(22.5%)	13(32.5%)	18(45.0%)	40(100%)
F	9(20.9%)	15(34.9%)	19(44.2%)	43(100%)
W	7(13.0%)	23(42.6%)	24(44.4%)	54(100%)
total	91(11.2%)	228(28.0%)	495(60.8%)	814(100%)

[a]Percentages in parentheses are relative to the total in each row.

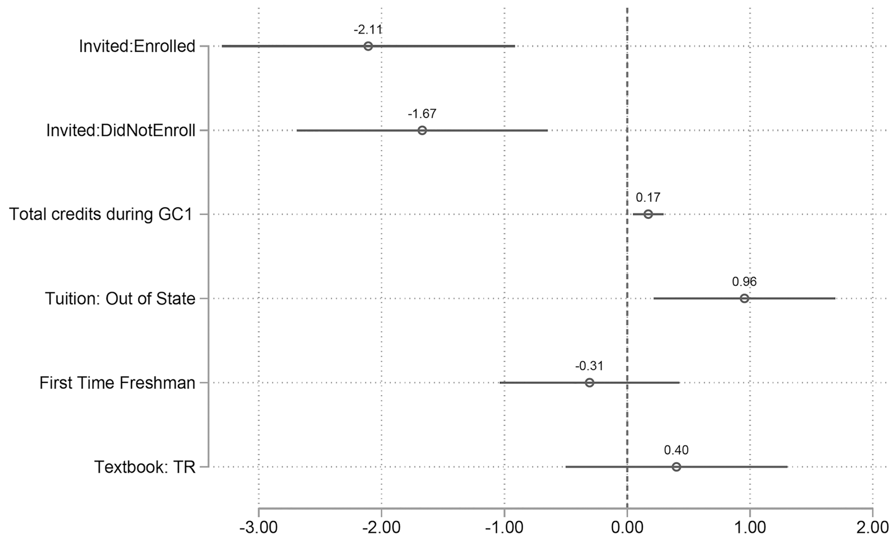

Figure 4. AMEs of variables in the HLM OLS regression model for GC2 outcomes, shown with 95% confidence intervals. The GC2 outcomes modeled were W (1), F (2), D− (3), ··· through A (13). Values with confidence intervals that cross the 0 line indicate no statistically significant effect. Positive values indicate movement toward the A outcome. The excluded baselines are Group 3 (*NotInvited*), CT (curriculum in GC2), *Tuition Status* (in state), and *Admit Type* (transfer).

its collinearity with one of the variables used to determine invitations, GPA at the institution (high school or transfer college) that the student attended prior to enrollment at the university. However, since both Group 1 and Group 2 were invited, and invitations were based on a variable that was collinear with how eligibility was determined, then theoretically there is not a reason to exclude this variable when comparing Groups 1 and 2. The other two variables used in determining eligibility — most recent math course grade and whether the student had previously taken GC1 — were present for too few of the students to be useful in the comparison. Values for cumulative GPA in the term before GC1 were missing for students who enrolled in GC1 during their first semester at the university. In all, this value was missing for 19.8% of Group 1 students and 26.3% of the matched set of Group 2 students. ANOVA tests were run to determine which differences between the matched sets were significant. Cumulative GPA and the number of credits taken during GC1 differentiated the groups, with the former being significant at the $p < 0.10$ level ($p = 0.088$) and the latter being significant at the $p < 0.05$ level ($p = 0.047$). In other words, there are two levels of GPA differences in Table 5 that can explain the difference in attrition between the matched groups, implying that there is an association between having a higher cumulative GPA and not advancing to GC2 in the adjacent semester. However, since the asset-based supplemental course in which students in Group 1 were enrolled was a 1-credit course, being enrolled in this course likely accounts for why the total credits taken during GC1 is higher for students in Group 1, leaving cumulative GPA prior to taking GC1 as a variable that can explain the difference in attrition between the matched groups.

Regression Analysis. As with GC1, the study employed hierarchical binary logistic regression to model the binary GC2 outcomes (ABC vs DFW). Table S5 (see Supporting Information) presents the odds ratios of this model, with excluded baselines shown as dashes. As with GC1 outcomes, this model revealed a negative relationship ($p < 0.001$) between being in Group 1, as well as a negative relationship ($p < 0.05$) between being in Group 2, and the probability of moving toward the ABC outcome in GC2. No other relationships were significant.

Also parallel to the GC1 analysis, an HLM OLS regression model was built for GC2 grade outcomes along a range from W to A grade (values of 1−13), i.e., Attrition was not included. The frequencies of GC2 grades are presented in Table 6. The corresponding AME analysis is provided in Figure 4 and the coefficients of the HLM OLS regression model for GC2 grade outcomes are provided in Table 7. As shown in Figure 4, being in Group 1 (*Invited:Enrolled*) or Group 2 (*Invited:DidNotEnroll*) when students took GC1 corresponded to having lower GC2 grade outcomes than being in Group 3 (*NotInvited*). The coefficients of the model, in Table S5 (see Supporting Information), show the level of significance as $p < 0.001$ (for Group 1 compared to Group 3) and $p < 0.01$ (for Group 2 compared to Group 3). While the mean grades of Group 2 students were slightly higher than Group 1 students, the GC2 grade outcomes of students in Groups 1 and 2 did not differ from each other, as shown by the overlapping 95% confidence intervals for these variables in Figure 4. Having taken more credits while taking GC1 corresponded to a greater likelihood of moving toward an ABC outcome in GC2 ($p < 0.01$, as indicated in Table 7). Within the bounds of the data, it is not possible to determine whether these relationships may have occurred due to the skewed presence of larger numbers of students who took GC1 in fall semesters repeating GC1 in spring semesters. Additionally, and aligned with the finding from the corresponding model for GC1, the AME plot shows that having a tuition status of out-of-state resulted in having higher GC2 grade outcomes ($p < 0.05$, as indicated in Table S4). No differences in GC2 grade outcomes were attributable to *Admit Type* (first-time freshman vs transfer student) or to which curriculum was used in GC2 (TR vs CT).

Table 7. Coefficients of Variables in the HLM OLS Regression Model of GC2 Grade Outcomes (1 = W, 2 = F, 3 = D−, 4 = D, ···, 6 = C−, ···, 12 = A−, 13 = A)[a,b]

variable	coeff. (std. err.)
Group 1 (*Invited:Enrolled*)	−2.108***(0.608)
Group 2 (*Invited:DidNotEnroll*)	−1.668**(0.521)
Group 3 (*NotInvited*)	
TR curriculum	0.401(0.459)
CT curriculum	
total credits during GC1	0.171**(0.0626)
Tuition (out of state)	0.955*(0.376)
Tuition (in state)	
Admit Type (first-time freshman)	−0.307(0.373)
Admit Type (transfer)	
constant	6.305***(0.968)
var.(1.comparison)	2.231(1.616)
var.(2.comparison)	2.058(1.206)
var.(_cons)	0.513(0.323)
var.(residual)	12.54***(0.634)
observations	814

[a]The excluded baselines are Group 3 (*NotInvited*), CT (curriculum in GC2), *Tuition Status* (in state), and *Admit Type* (transfer). [b]LR test vs. linear model: χ^2 (3) = 52.83 Prob > χ^2 = 0.0000. Random slope and random intercept model, standard errors in parentheses. log likelihood (model) = −2203.67. d.f. = 11. AIC = 4429.34. BIC = 4481.06. Wald χ^2 (6 d.f.) = 38.26. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Because there was a strong relationship between credits taken while enrolled in GC1 and students' GC2 outcomes, regardless of the curriculum used in GC1, probabilities derived from adjusted prediction at representative (APR) values were calculated to understand how GC2 outcomes were predicted by credits taken while enrolled in GC1 while holding all other covariates at their observed values. These details add another level of richness to the results shown in Figure 4. Figure 5 shows predicted values for the GC2 grade outcome groups (13 values, W through A). This figure is analogous to a vapor pressure curve, where the boiling point may be read as the number of credits (on the horizontal axis) that inoculate students against deleterious effects of other variables. Observed values in the data set of credits taken while enrolled in GC1

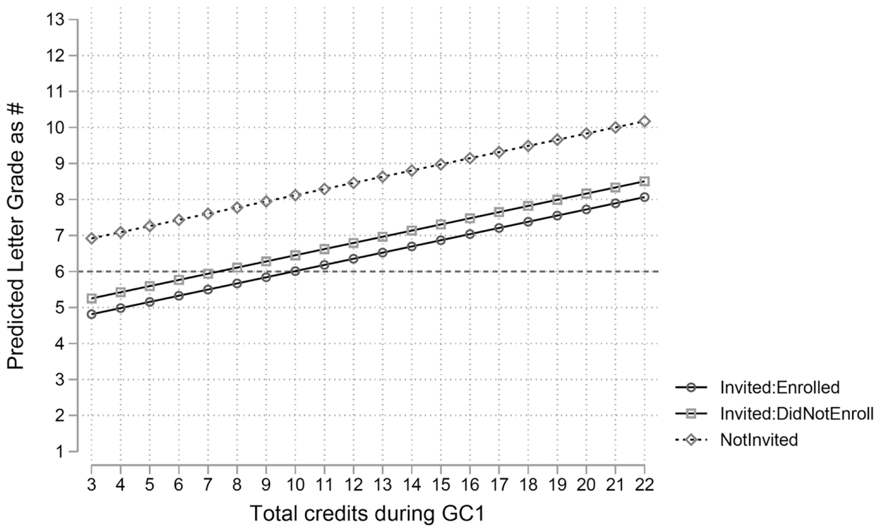

Figure 5. APR values for GC2 outcomes, based on the HLM OLS regression model. GC2 grades are theorized as being on a linear 13-point scale, related to total credits enrolled in during the semester of taking GC1, and separated by comparison group. GC2 outcomes depicted along the vertical axis correspond to W at the lowest end (value of 1), followed upward by F, D−, D, D+, etc., up to A (value of 13). The horizontal dashed line corresponds to the minimum grade of C− that is a prerequisite to enrollment in the next chemistry course, Organic Chemistry 1, which is taken by most students in the population.

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ranged from 3 to 22, based on total enrolled credits immediately after the add-drop deadline, i.e., any courses from which a student elected to withdraw (W outcome) were also included in the number. Since GC1 is a 3-credit course, students who were taking 3 credits were enrolled only in GC1 that semester. Table 7 presents the OLS coefficients for GC2 outcomes of the HLM OLS regression model on which Figure 5 is based.

Figure 5 shows that students in Group 3 (*NotInvited*) had a greater likelihood of GC2 grade outcomes at or above C− than D+ or below no matter how many credits they were taking, but their ABC likelihood increased as they were enrolled in more total credits. For Group 2 (*Invited:DidNotEnroll*), the inoculation point of having a greater likelihood of a grade outcome of C− or higher was 8 credits, and for Group 1 (*Invited:Enrolled*), the inoculation point was 11 credits. This suggests that greater cumulative disadvantage can be inoculated by concurrently enrolling in at least two more courses in addition to GC1 (given that most courses carry 2−4 credits).

■ DISCUSSION AND IMPLICATIONS

The outcomes of three groups were compared for 12 classes of students across six consecutive terms in which an asset-based supplemental chemistry course intervention was offered. Students who were invited to enroll in the intervention corresponded to factors predicting greater cumulative disadvantage (belonging to underrepresented minority groups, female, first-generation college students, and Pell-eligible), and students who elected to enroll concentrated this even further, indicating that the intervention succeeded in recruiting and appealing to the population of students whose success the intervention was designed to enhance.

When a traditional curriculum (TR condition) was followed in GC1 classes, students who were invited to the intervention exhibited a 30−33% point decrease in the probability to have an ABC outcome in GC1 relative to noninvited students. Meanwhile, invited students whose GC1 classes followed a nontraditional curriculum (CT condition) exhibited only a 9−13 percentage point decrease in the probability to have an ABC outcome in GC1 relative to noninvited students. However, for students in the CT curriculum who were enrolled in the intervention, this difference was not significant (Figure 3). The intervention's impacts were also studied for students' advancement to GC2 in the subsequent term. The rate of not advancing to GC2 in the subsequent term ("attrition") of students who attained ABC outcomes in GC1 was highest for students who were in the intervention during GC1 and lowest for noninvited students. A comparison of relevant variables for all students in the intervention with ABC outcomes in GC1 and matched (by gender, first-generation, and Pell eligibility) students who were invited and did not enroll in the intervention produced very weak evidence, within the bounds of the data collected in the study, to illuminate why this might be. The only variable with a potential relationship to the difference in attrition vs ABC outcomes in GC2 was the cumulative GPA of students in the semester prior to taking GC1.

An examination of the graph (Figure 5) depicting adjusted predicted probabilities at representative values (APRs) derived from the equation in Table 7, revealed much: Credit load during the semester of enrollment in GC1 provided differential inoculation against DFW outcomes in GC2 for students who were eligible to enroll in the intervention. Students in Group 2 (*Invited:DidNotEnroll*) had a greater likelihood of an ABC outcome than a DFW outcome if they were taking at least 8 total credits during the semester in which they were enrolled in GC1, and for Group 1 students (*Invited:Enrolled*) this threshold was 10 credits. In other words, taking at least 10 credits (including the 3-credit GC1 course) provided a better inoculation against non-DFW outcomes students who were identified as eligible for the intervention.

The results from this study are most relevant for higher education institutions that have high diversity in their undergraduate student populations along several federally determined and self-identified dimensions: race/ethnicity, gender, Pell eligibility, first-generation college student, and admit type (transfer students and first-time freshman), as well as for tuition residency (in state or out of state). The analysis underscores four takeaways.

First, the intervention successfully targeted students with greater likelihood of cumulative disadvantage (Table 2). In addition, among students who were eligible and invited, students with higher propensity for cumulative disadvantage elected to enroll in the asset-based supplemental chemistry course intervention (Table 2). This suggests that use of an academic index that includes immediate prior school GPA (high school or transfer institution), grade in the most recent math course taken, and whether the student is retaking GC1 is a valuable combination of predictors for identifying students who can benefit from the asset-based supplemental intervention.

Second, the intervention closed equity asymmetries in GC1 in a single semester when the GC1 course used a nontraditional curriculum that has demonstrated benefits for equity improvements. Specifically, this study showed that students who participated in the asset-based supplemental chemistry course and whose GC1 classes used the *Chemical Thinking* curriculum (Group 1, CT condition) had GC1 course outcomes that were not statistically different than their peers with the same curriculum who were not eligible for the intervention (Group 3, CT condition) (Figure 3). Prior research on student performance outcomes when using nontraditional curricula have shown that such curricular choices also can link to more equitable framing of other aspects of GC1. This can include placing lower weight on high-stakes exams in the overall grade,[73] having more student-centered activity and less lecture time during class,[94] and designing a ratio of conceptual-to-mathematical emphasis on assessments that is higher than in courses with traditional curricula.[74] The analysis in the present study is unable to decouple these factors from the curriculum used. For example, while two of the classes with the TR condition had a heavier emphasis on high-stakes exams in the overall grade, three had nearly the same grading scheme as the classes with the CT condition, although as noted earlier, exams in the classes with the TR condition had a higher emphasis on mathematics (vs conceptual) than the classes with the CT curriculum. Use of the CT curriculum, with attendant heavier basis of the overall grade on course components other than high-stakes exams, has been shown to be associated with reduced race and gender gaps for students at a Hispanic-serving R1 university,[74,94] and this study now adds evidence that when using this curriculum, likely with higher conceptual-to-mathematics emphasis on high-stakes exams that accompanies the CT curriculum, an asset-based supplemental intervention closes these gaps at a

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majority minority R2 university. The choice of curriculum is decided at either the department or instructor level at institutions. An implication of this study is that departments or instructors choosing a nontraditional curriculum, such as *Chemical Thinking*, is likely to close gaps in cumulative disadvantage without harming students who have greater cumulative advantage.

Third, students who enrolled in the asset-based intervention when they were in GC1 (Group 1) had lower GC2 outcomes than their peers who were invited and did not enroll (Group 2) as well as their peers who were not invited (Group 3) (Figure 4). Furthermore, students who were invited but did not enroll (Group 2) in the intervention during GC1 did not differ statistically in GC2 outcomes from students who were not invited (Group 3). This may be due to compounded factors. For example, students in the intervention withdrew from GC1 at higher rates than their peers who were invited but did not enroll (Table S4), suggesting a possibility that students in the intervention may have gained a greater awareness of their ability to perform well in GC1 and/or a higher degree of agency in decision making related to GC1 through participation in the asset-based supplemental course. This phenomenon also may be due to a relationship between degree of cumulative disadvantage (Group 1 being highest) and higher likelihood of stopping out. Sense of belonging in a GC1 course can play a role in attrition (i.e., not taking GC2 in the subsequent semester), particularly for women across the range of grade outcomes,[95] however the study reporting GC1 belonging's relevance in attrition was conducted at a highly selective, residential, primarily white private institution, so it is unclear whether the finding is generalizable to a public minority-serving primarily commuter institution. Nevertheless, belonging, which was not measured in the study in this article, may be worth including in future studies.

Fourth, taking closer to full-time credits in the semester of taking GC1 has an inoculative effect for GC1 outcomes for all students, and it appears to scale with likelihood for cumulative disadvantage. At the inoculation point, the likelihood of an ABC outcome in GC2 (when taken in the semester subsequent to an ABC outcome in GC1) varied by the comparison group. It is also notable that first-time freshmen across all comparison groups had significantly higher probability of GC1 outcomes of C and D grades than transfer students (Table 3). Given that there was a moderate correlation between credits taken during GC1 and transfer admit status, this suggests that the challenges that first-time freshmen experience in GC1 could be addressed by taking GC1 alongside at least two other classes and/or by enrolling in the asset-based supplemental chemistry course if they are determined to be eligible. As noted in the Introduction, from an institutional fiscal health perspective, supporting the academic success of GC1 students with greater DFW potential and increasing their persistence to GC2 make good sense. There is also evidence suggesting that this matters more for Latina/o and Black students and may matter most for Black STEM majors. Research in the past 15 years using national data shows that Black and Latina/o students are now as likely to enter STEM majors as their White peers.[96,97] However, more recent research, also based on national data, shows that these peer groups differ by departure pathways, i.e., changing majors vs discontinuing higher education.[98] Whereas Black and Latina/o students have comparable rates as White students in both departure pathways when they discontinue a non-STEM entry major, pathways differ when the entry major is STEM. Black and Latina/o students who depart STEM majors are more likely to discontinue their higher education while their White peers are more likely to change major and persist toward degree completion. Taking into consideration social background (e.g., parental education, family income, gender, working part-time or full-time) and institutional characteristics (e.g., sector, selectivity), the average marginal effects for Latina/o students decreases to having nonsignificant differences from White students, but differences between Black and White students remain substantial.

Five main structural aspects of institutions explain time to degree completion[99] − mission, size, selectivity, diversity, and wealth − and students at less wealthy, less selective, and more highly diverse institutions have longer degree completion times than the perceived norm of four years. This suggests that at higher education institutions that share fit with these aspects, such as the one where this study was conducted, faculty and staff who advise students on course selections may further support students' success by exploring possibilities with students on ways to arrange academic plans with consideration of prior cumulative GPA and how many courses students can concurrently take (with taking at least 5 to 8 other credits concurrently with GC1 to advantage likelihood of a successful outcome in GC1) when making decisions about when to enroll in GC1. However, it is also important to bear in mind that the findings relevant to advising students align with course taking behavior that is aligned with "traditional" norms. Nonetheless, it may be useful to consider that a "full" course load of four or five courses is not necessary, statistically speaking, to gain advantage.

While what is examined in this study is a content-related direct intervention with students with the potential of DFW outcomes in GC1, it is worth noting that multitudes of studies address how other changes make a difference in addressing inequities in GC1, other gatekeeper courses, STEM courses more generally, and in the broader campus culture. While these are beyond the scope of this study, it is important to recognize that a single intervention in higher education has limited impact. To address inequities on a larger scale requires holistic change,[100,101] including multiple interventions at curricular and program levels, as well as structural and cultural changes at program and campus levels, such as mathematics placement policy changes, multiple mathematics pathways, and the development of corequisite courses.[102−105] In addition, students who are experiencing challenges may either stop out (i.e., take time away from college and then return) or drop out (i.e., discontinue higher education). Stopping out of college does not equate to dropping out, although grades in specific courses, chemistry among them, as well as Pell eligibility and being a first-generation student, are among the strongest predictors of stopping out.[106] Researchers have also reported on reasons for stopping out that are beyond the scope of this study, including financial aid issues, class scheduling, students' assessment of whether a degree is needed for their future, and sense of belonging on campus.[107]

LIMITATIONS

GC1 instructor characteristics, days and times that classes met, and instructional modalities were unable to be modeled for research ethics reasons and therefore their impacts cannot be reported, but they likely had an impact.[108] Table S6 in the Supporting Information provides characteristics of the 12 classes with care not to compromise research ethics. To further

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support the point that GC1 class characteristic likely played a role in GC1 impacts, in addition to the information in Table S6, and constrained by the goal of not compromising research ethics, it is noted that all white instructors had < 5 semesters of teaching experience, no male teachers taught in the morning, there were no nonwhite male instructors, and no nonwhite instructors used the CT text. A quasi-experimental study could have illuminated instructor effects, but at most universities, it is not possible to control which faculty are assigned to teach which classes. Put another way, unless a university serves an enormous number of students, a wide range of instructors will not be available for students to choose classes based on instructor characteristics. Thus, variables other than instructor characteristics must be considered for increasing the likelihood of positive outcomes for students who are most impacted by cumulative disadvantage.

Other unaccounted for factors may explain outcomes. For example, some reasons for differences between Groups 1 and 2 have unknown relationships with cumulative disadvantage. Findings from related qualitative data indicate that one reason that invited students reported for not enrolling was that the times the classes were offered were schedule conflicts. A second reason was associated with credit hours. If a student was enrolled in fewer than 12 credits, adding the 1-credit course would result in a tuition increase that was prohibitive for some students. Also, first-year students and students with lower GPAs were unlikely to receive permission for a credit overload to enroll in the 1-credit asset-based supplemental chemistry course if they were already enrolled in 17 credits.

Finally, the entire study occurred under the auspices of the COVID-19 pandemic, and it is not possible to quantify the extent to which various aspects of the pandemic impacted students and instructors in different semesters. Three of the six semesters studied in this intervention occurred during the period when university operations shifted to remote instruction due to the COVID-19 pandemic. In addition, the pandemic disproportionately impacted populations that have high overlap with the enrollment at the university where this study was conducted, and students who have higher propensity for cumulative disadvantage were also more likely to have endured greater negative impacts from the pandemic, which certainly contributed to challenges in the in-person semesters following remote instruction. Partial evidence is seen in comparing grades in different semesters. The syllabi indicate consistent grading schemes, and mean grades from spring 2020 and fall 2020 did not differ by more than one standard deviation from the mean grade of the other four semesters combined.[109] Given that the study occurred at a public university that enrolls mostly in-state students who attended public high schools, the greater the cumulative disadvantage, the more likely first-time freshmen were to have completed high school in a school district where students' educations were more substantially disrupted by the pandemic. Thus, disparities in inputs and outputs to success in high school were present among students in in-person semesters included in the study as well. These influences were not separately accounted for in independent variables in the study, but they likely contributed further impacts in relation to the degree of cumulative disadvantage that occurred in the different comparison groups.

CONCLUSIONS

Overall, when using an eligibility determination that is associated with cumulative disadvantage, the asset-based supplemental chemistry course is beneficial to students in GC1 when combined with use of a nontraditional curriculum (*Chemical Thinking*). Inoculation against negative GC2 outcomes can be achieved by taking at least 8−11 credits total in the semester of GC1, in association with a student's degree of cumulative disadvantage. The combination of all of these − (1) use of a nontraditional curriculum in GC1, (2) taking at least two other courses while taking GC1, and (3) enrolling in the asset-based supplemental chemistry course if eligible based on an academic index model that scales with cumulative disadvantage − is likely to result in the greatest benefits toward closing equity asymmetries in GC1. Because GC1 is a critical path point in STEM pathways, this would lead to increased retention of students and increased graduation rates among students with greater cumulative disadvantage, which is likely to have an impact on increasing diversity in the STEM workforce so that it better reflects the population of the United States while also improving the fiscal health of higher education institutions.

ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/jacsau.3c00192.

List of variables, descriptions, and values or ranges, and additional tables and figures from the quantitative analyses (PDF)

Asset-based supplemental chemistry course syllabus, curriculum, instructional materials, guidance for instructors and learning assistants, and related materials (ZIP)

Example semester of instructional materials, including PPTs, lesson plans, handouts for students, annotated answers for instructors, and associated materials (ZIP)

Reproducible Stata code and, to protect confidentiality of the students (to comply with IRB), the data set without race/ethnicity and some of the socioeconomic status variables, for analysis of the data using the statistical analyses conducted in this study (ZIP)

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Author Contributions

The manuscript was written through contributions of all authors. All authors have given approval to the final version of the manuscript. CRediT: **Hannah Sevian** conceptualization, data curation, formal analysis, funding acquisition, investigation, methodology, project administration, resources, supervision, validation, writing-original draft, writing-review & editing; **Tyson D. King-Meadows** data curation, formal analysis, investigation, methodology, software, visualization, writing-review & editing; **Klaudja Caushi** conceptualization, investigation, resources, writing-review & editing; **Tamari Kakhoidze** investigation, resources, writing-review & editing; **Jessica M. Karch** conceptualization, investigation, writing-review & editing.

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Notes

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ABBREVIATIONS

AME, Average marginal effect
APR, Adjusted prediction of representative (value)
DFW, Grades of D or F, or withdrawal from a course
GC1, First course in a two-semester sequence of general chemistry
GC2, Second course in a two-semester sequence of general chemistry
GPA, Grade point average (scale from 0 to 4)
HLM, Hierarchical linear model
IPEDS, Integrated Postsecondary Education Data System
OLS, Ordinary least-squares
WEIRD, Western educated industrialized rich and democratic

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(10) Throughout the article, this and other words that have multiple spellings in the literature are used in the way that they appear in the work that is cited or otherwise referenced. For reporting of federal race/ethnicity data by the university, the spelling convention follows federal reporting usage, e.g., in the Common Data Sets that the university posts.

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(75) Of the 1,630 unique students, 177 enrolled in the course more than once. At the university, students are permitted to retake a limited number of courses a second time. Withdrawing (W) from a course does not count as having taken the course in this policy, but W outcomes are included in the data in this study.
(76) Because GC2 taken only in the adjacent semester after GC1 was included, and an ABC outcome in GC1 was a prerequisite to GC2 enrollment, all students in the study who took GC2 were unique instances of GC2 taking. Only students who enrolled in the six fall and spring semesters when the asset-based supplemental chemistry course was offered are included in the study. GC1 is offered in the summer with no corresponding supplemental chemistry course in the summer. Students who repeated GC1 during the summer after a DFW outcome in GC1 in a spring semester, and who earned a grade in GC1 in summer that met the prerequisite and then took GC2 in the fall, were included as students taking GC2 in the adjacent semester after GC1.
(77) As a response to the COVID-19 pandemic, for spring 2020, fall 2020, and spring 2021, the university permitted students to opt for pass/fail in multiple courses, temporarily suspending the university policy permitting the pass/fail option in one course per semester and a maximum of 8 pass/fail options in total. During the policy suspension, the pre-requisite minimum grade in GC1 was pass (P) instead of C−. The research obtained grades underneath P grades and some students in fall 2020 and spring 2021 advanced to GC2 in the subsequent term with grades of D−, D, or D+ because they met the pre-requisite under the policy suspension.
(78) Gender was self-reported on applications to the university. During the period in which this study was conducted, the application only included two selection options for gender, female and male. Biological sex and gender identity differ. There is no way to know which of these was the interpretation of students when self-reporting in response to this question on their application to the university.
(79) Admit type was included for two reasons. First, it is an academic variable that is not associated with cumulative disadvantage or with the academic index that was used to determine eligibility for the intervention, so it presented a possibility to learn whether this variable influenced GC1 outcomes. Second, most higher education institutions are required to publicly report Common Data Sets that report on first-time first-year freshmen, so if admit type turned out to influence GC1 outcomes, this could be a useful variable for similar institutions to consider when designing supports and advising students who take GC1.
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(84) Variables related to instructor characteristics were unable to be used as independent variables due to skewed data where there was not enough differential distribution across the options of the variables. To check for possible collinearity, the authors conducted and examined the coefficients from a correlation matrix of the variables in the study. Nothing was found that warranted any of the variables unassociated with the theoretical framing of the intervention (cumulative disadvantage) to be excluded from the regression analyses. That is, the absolute values of no coefficients were equal to or above 0.7.
(85) Advanced placement credits were not included in this variable. Furthermore, compared to other states, students in this state have extremely limited opportunities for either dual enrollment or early college. Thus, nearly all credits taken prior to GC1 were from transfer institutions. See refs 86 and 87.
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(88) The Semester (of six possible) in which the class took place was collinear with class, as two GC1 classes took place each semester, therefore Semester could not be included as an independent variable.
(89) In two instances, there was one less instance in Group 2 than Group 1 of a particular combination; in these cases, a previously

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unselected instance was randomly selected from among the nearest combination (different by value of one factor) of Group 2 instances that had the largest number of instances.
(90) Due to randomization, the matching of all Group 1 students to a subset of students in Group 2 is not reproducible.
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(92) Asian means Asian American and includes many ethnicities.
(93) Figure S1 shows the calibration plot using the Hosmer-Lemeshow goodness of fit test for the hierarchical binary logistic regression full model for GC1 outcomes. The means of ten equally sized groups of observations are plotted and compared to the predicted outcome probabilities of obtaining an ABC in GC1. The model shows that for low values of the probability of an ABC outcome, the model slightly overpredicts the probability, the model underpredicts between a probability of about 0.65 to 0.7, slightly overpredicts around a probability of about 0.75, and predicts well at a probability of 0.8 and higher.
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(108) The 12 GC1 sections in which students were enrolled during the six semesters of the study were taught by six different instructors. Two of the instructors were non-white and four were white. All but one instructor was female. Three of the sections, all in fall semesters, occurred as 50-minute lectures three days per week on weekday mornings; the other nine sections (three in fall, six in spring semesters) occurred as 75-minute lectures two days per week on weekday afternoons. Four sections (two in fall, two in spring) were taught remotely (synchronously in Zoom) due to COVID-19. Three sections were taught in a mixed modality. Five sections (four in fall, one in spring) were taught in-person.
(109) Considering grade equivalents on a 4-point scale (e.g., A = 4, A− = 3.7, B+ = 3.3, etc.), the mean GC1 grades and standard deviations in spring 2020 and fall 2020, respectively, were 2.742 (SD 1.108) and 2.061 (SD 1.266). The mean GC1 grade and standard deviation for all other semesters combined were 1.930 (SD 1.200). While the range of grades was broader and the means higher in spring 2020 and fall 2020, neither of these differ by more than one standard deviation from the mean of the other four semesters.

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