## Counting on Math Faculty

Examining the Role of<br>Faculty and Instructional Practices in Students' Gateway Math Success

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Education Equity Solutions (EES)
conducts research and facilitates learning to drive equity-centered policy change in higher education. We work to ensure education policy is informed by a deep understanding of research evidence and grounded in the experiences of students and practitioners, especially those from systematically excluded communities.

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## Introduction

Over the past decade, community colleges have made widespread changes to mathematics placement policies, course structures, and curriculum. This has resulted in increases in the numbers of students who successfully complete college mathematics, yet college mathematics continues to be a barrier to degree completion, particularly for Black and Latine ${ }^{1}$ students (Braithwaite et al., 2020; Dadgar et al., 2021; Hodara, 2013).

Persistently low success rates in introductory college-level math courses (gateway math courses hereon) negatively impact degree completion, as well as STEM participation among aspiring STEM students, particularly women, American Indian, Black, and Latine students (Bickerstaff et al., 2022; Brathwaite et al., 2020; Park, Ngo, \& Melguizo, 2021; Park \& Ngo, 2021). Community college students who successfully complete gateway math are more likely to earn an associate's degree (Belfield et al., 2019) and are 50 percent more likely than their peers to transfer to a four-year institution (Johnson \& Meija, 2020).

To support community colleges to continue to improve success in gateway mathematics, more information is needed on the factors that lead to course success. Empirical research has largely focused on the

[^0]role of student attributes and academic preparation (Andrews \& Tolman, 2021; Quarles et al., 2020). This research has found that students' demographic background, socio-economic status, and prior academic preparation are associated with a students' success in college courses, with high school GPA being the most important predictor of student success (Andrews \& Tolman, 2021). For colleges seeking strategies to improve student success, these findings may help identify which students need additional support, but they do not provide direction on how to intervene. In this paper we examine a broader array of factors affecting student success including the influence of faculty and instructional practices.

To provide actionable insights on how to continue to increase the numbers of students who complete gateway math, we examine how important students' individual faculty, student demographics, prior academic experiences, and gateway math course attributes are in explaining students' success in passing a gateway math course. We then use survey and syllabi data to examine how specific instructional practices are associated with student success, and the promise they show in helping to close equity gaps by race. Specifically, we examine the following two research questions:

1. What role do individual faculty play in promoting students' success in passing a gateway math course with a grade of C or higher?
2. How do specific instructional practices promote gateway math success for students overall, and those who are Black or Latine?

## Prior Literature:

Most of the literature on college student success focuses on student characteristics including demographics, prior preparation and, more recently, students' "cultural capital" but ignores the role of institutions and faculty (Andrews \& Tolman, 2021; Quarles et al., 2020). This literature has generally revealed that student demographic characteristics and measures of student preparation both predict student success including in math courses, with high school GPA being the best predictor of student success compared with student background or other measures of prior preparation (Belfield \& Crosta, 2012; Andrews \& Tolman, 2021; Scott-Clayton, 2014).
Conversely, in K-12 research, there has been an abundance of studies on the effect of individual faculty on student outcomes, which have generally found large effects for all students, but especially for BIPOC students (Rockoff, 2004; Gordon et al., 2006; Mujis and Reynolds, 2017). For example, one study found that the cumulative effects of four highly qualified teachers assigned to Black students would essentially close the Black-White achievement gap (Gordon et al., 2006). Two single college and single subject studies conducted in higher education reached a similar conclusion. A 1991 study at one university found that among students taking a Review of Economics course, faculty were the most important source of variation in student success (Watts \& Bosshardt, 1991). Similarly, a recent study that focused on introductory statistics courses at one college found individual faculty played a bigger role in students' success than student background or course characteristics (Newell \& Sabawi, 2022).

Empirical evidence on which instructional practices promote success for students overall or help close racial gaps in success rates is limited. Most studies on instructional practices in higher education have been qualitative with a few exceptions. These studies have found transparency in course assignments, measured by faculty sharing a grading rubric with students, and provision of examples of successful past assignments, resulted in a host of positive student outcomes including reduced course attrition (Ferrari et al., 2015). A large study on faculty growth mindset that included 15,000 students across 13 STEM departments found faculty attitudes towards intelligence (being malleable versus fixed) were highly predictive of students' success, with racial achievement gaps in courses taught by faculty with a 'fixed mindset' being twice as large as those in courses taught by faculty with a 'growth mindset' (Canning et al., 2019).

Qualitative studies based on student interviews and focus groups have highlighted the importance of proactively providing support to students. These studies have found that the students most needing academic supports, such as tutoring or other supports, are the least likely to access them unless they are proactively offered or help-seeking is encouraged (Cox, 2009; Dadgar, Venezia \& Nodine, 2013). Research also suggests that when students can help and learn from each other, it creates a safe and nurturing space for learning (Bonham \& Boylan, 2011).

There is also some evidence for practices that reduce racial equity gaps in successful course completion with several studies finding Black students especially benefit from practices that affirm their identities and sense of belonging (for a review see Bickerstaff et al., 2022). For example, a study conducted at a private university found that when Black students' doubts about their sense of belonging were mitigated, their grades and other long-term academic outcomes improved. Notably, this intervention had no discernible impact on White students (Brady et al., 2020; Walton \& Cohen, 2007). Another study found students of color randomly assigned to review syllabi and listen to an audio welcome message that included language reflecting philosophy on multicultural diversity performed better on a comprehension quiz compared with colorblind or control conditions (Good et al., 2020). Research focusing on Black students have found that HBCU graduates overwhelmingly cited supportive faculty and mentors as the reason for their academic success. Compared to non-HBCU graduates, HBCU graduates were 33 percentage points more likely to strongly agree their professors cared about them, 23 percentage points more likely to feel supported, and 6 percentage points more likely to have an "encouraging mentor" (Brathwaite et al., 2021).

## Data

## Study Colleges

We partnered with four community colleges in California for our study. The colleges were selected for their variation in geography, total student enrollment, and the racial diversity of the student body. The community colleges are located in urban, rural, and suburban areas in different regions of the state. Their total student enrollments range from small ( $\sim 4,000$ students) to large ( $\sim 36,000$ students).

Evidence of innovation, as well as progress toward supporting students of color in gateway math courses, was also used as a criterion for selection because it enabled us to glean, learn from and share innovative and equity-focused instructional practices as reflected in faculty syllabi and surveys.

## Data Sources

We used student, course, and faculty-level administrative data, provided by the four study colleges, from the Winter 2020 through Spring 2022 academic terms to examine the role of student demographics, prior academic preparation, gateway math course attributes, individual, and faculty characteristics on students' success in passing a gateway math course (Research Question 1).

Next, we matched student, course, and faculty administrative data from the Spring 2022 term with a survey of faculty who taught gateway math courses during that semester, and conducted an analysis of their gateway math course syllabi to examine how specific instructional practices are associated with student success overall and by students' race (Research Question 2).

## Sample

The sample we used to examine the role of individual faculty in promoting student success in gateway math courses includes 22,827 students who were enrolled in 704 gateway math courses taught by 159 faculty at one of the four study colleges between winter 2020 and spring 2022. This includes all student enrollments in gateway math with non-missing values for the study's primary variables (described in the Estimation Approach). ${ }^{2}$ Our analytic sample includes a total of 29,815 observations that are unique by student, course, and term.

To examine how specific instructional practices are associated with student success, both overall and by student race, we matched responses from faculty survey and syllabi to the student administrative data for spring 2022. Our full sample for spring 2022 includes 3,695 students enrolled in 185 gateway math courses taught by 104 faculty. For survey analysis, we were able to match 2,884 students enrolled in 137 gateway math courses and taught by 78 faculty who responded to the survey (the survey response rate was $75 \%$ ). The survey analytic sample includes a total of 2,907 observations, unique by student and course. For syllabi analysis, we were able to match course syllabi to 150 gateway math courses enrolling 3,029 students and taught by 91 faculty. The syllabi analytic sample includes a total of 3,046 observations unique by student and course.

[^1]

## Student and Faculty Characteristics

Students enrolled in gateway math identify as Latine (51\%), Asian (19\%), White (19\%), and Black $(5 \%)$. Fewer than 6 percent identify as two or more races, Native Hawaiian/Pacific Islander, or did not report race/ethnicity. While the majority of students identify as Latine, just over half of faculty identify as White, and only 15 percent identify as Latine (see Appendix A, Table 1 for complete student characteristics and Appendix A, Table 2 for complete faculty characteristics).

Most students enrolled in gateway math identify as Latine, whereas most faculty teaching gateway math identify as White.

Figure 1. Proportions of Students and Faculty by Race/Ethnicity


Note: Figure depicts the racial/ethnic identities among students enrolled in gateway math and faculty teaching gateway math between winter 2020 and spring 2022. If racial/ethnic groups were evenly represented between students and faculty, the lines in the figure would be straight.

Source: Authors' analysis of colleges' data.

## Course Enrollment

The majority of course enrollments are in Statistics (58.1\%), followed by College Algebra (17.3\%), and Pre-Calculus ( $13.4 \%$ ). The remaining enrollments are in Quantitative Reasoning ( $6.3 \%$ ), and Gateway Math for Business ( $5.0 \%$; see Appendix A, Table 3 for complete course characteristics).

## Student Pass Rates by Race

Students who identify as Latine or Black pass gateway math at much lower rates than students who identify as Asian or White, and this pattern persists across all types of gateway math courses.

Students who identify as Latine or Black pass gateway math at much lower rates than students who identify as Asian or White.

Figure 2. Course Pass Rates by Race and Course Type


Source: Authors' analysis of colleges' data.

## Estimation Approach

To examine the role of faculty on student outcomes in gateway math courses, we estimate a series of multi-level OLS regression models. Our primary outcome of interest is whether a student passes their gateway math course with a grade of C or higher. Our analyses typically include the following student, course, and faculty-level determinants of student success in gateway math:

- Student demographics: Age, disability status, eligibility for California College Promise Grant, gender, race/ethnicity, and veteran status.
- Student's prior academic preparation: High school GPA, and whether the student enrolled in a gateway math course in a previous term.
- Which high school students attended: An indicator for the high school students attended. This variable potentially captures both the impact of high school quality, high school peer effects, and a student's socio-economic status.
- Course attributes: Course length in weeks, class size, course type (Statistics, College Algebra, Pre-Calculus, Quantitative Reasoning, and Gateway Math for Business).
- Student's instructor: An indicator for the instructor a student has for gateway math OR Faculty characteristics and prior grading: Faculty race/ethnicity, gender, age, and the average pass rate in all gateway math courses they taught in the previous term.

We also include college and term indicators to account for variation across study schools and terms (in the pooled sample). All models include robust standard errors, clustered at the faculty level, to account for the non-independent nature of students taking gateway math with the same faculty.

For research question 1, we estimate a series of regression models using different combinations of the predictors described above. Our primary interest in these models is in the adjusted R-squared (adj. R2) value as a measure of the variation in our outcome that can be explained by the model's predictors. ${ }^{3}$

For research question 2, our predictor of interest is the individual survey or syllabi subdomain. We regress our outcome on this individual subdomain in addition to a set of the predictors named above. Our preferred model specification includes controls for student demographics, student's prior academic preparation, course length in weeks, course type, and college. This model excludes all covariates we believe to be endogenous to the faculty member (class size, faculty race/ethnicity, gender, age, and prior grading) in order to allow these characteristics to covary with the individual survey and syllabi items. In addition to our preferred specification, we estimate a series of additional models that add controls for these endogenous characteristics.

## Findings

## What role do individual faculty play in promoting students' success in passing a gateway math course with a grade of C or higher?

We begin by estimating a series of regression models to examine the importance of individual faculty, relative to other student and course determinants of student success, in determining whether a student passes their gateway math course with a grade of C or higher. Using the full sample, we regress our outcome (whether a student passes their gateway math course with a grade of C or higher) on student demographics, prior academic preparation, the high school the student attended, course attributes,

[^2]and the student's instructor. The adjusted R-squared for the full model is 0.205 , meaning this set of covariates explains 20.5 percent of the variation in our outcome.

To identify the approximate contribution of individual faculty to the adjusted R-squared, after accounting for all other student and course predictors, we estimate a restricted model that excludes faculty indicators and compare this model's adjusted R-squared to the full model's adjusted R-squared. This analysis shows that individual faculty account for 34 percent of the total variation explained by the model, after accounting for other student and course predictors. We continue this approach to identify the relative contribution of each set of predictors to the overall model after all other characteristics have been accounted for.

## Faculty are the most important predictors of student success in gateway math.

Our analysis shows that the relative contribution of faculty to students passing gateway math with a C or higher is far greater than any other set of student, high school, or course characteristics. Whereas individual faculty accounts for 34 percent of the explained variation, students' prior academic preparation accounts for 14 percent, high school indicators 11 percent, student demographics 7 percent, and course attributes 1 percent (for details see Appendix B, Table 1).

Individual Faculty explain more variation in passing gateway math with a C or higher, after controlling for all other student and course characteristics, than any other set of student or course characteristics.

Figure 3. Contribution of Each Factor to Students' Likelihood of Passing Gateway Math $34 \%$


[^3]Across nearly all student racial/ethnic groups, faculty are the most important predictor of student success (for students identifying as Black, the student's high school explains 30 percent of the variation in the outcome compared to 29 percent explained by the student's instructor).

Individual Faculty matter across student racial/ethnic groups, after controlling for all other student and course characteristics.

Figure 4. Contribution of Each Factor to Student's Likelihood of Passing Gateway Math by Student Race


Note: Percentages indicate the approximate contribution of the named set of covariates (e.g., student's instructor) to the total variation in a student passing gateway math with a grade of C or higher that can be explained by the full model, after controlling for all other covariates (e.g., student demographics, prior academic preparation, high school student attended, course attributes, college, and term). Percentages are calculated by dividing the difference in adjusted R-squared between the full and restricted models (the full model includes all covariates, and the restricted model omits the named set of covariates) by the full model's adjusted R-squared.

Source: Authors' analysis of colleges' data.
Findings are consistent across different time periods, student samples, and outcomes.

As noted above, we find that individual faculty explain more of the variation in our outcome than any set of student or course characteristics, after accounting for other determinants of student success. We also find this result holds across nearly all student racial/ethnic groups. To test the robustness of our analysis, we estimate a series of regression models to examine the role each set of predictors plays independently in determining whether a student passes their gateway math course with a grade of C or higher. Using the full sample, our model that includes only faculty indicators continues to explain more variation in our outcome (adj. $\mathrm{R}^{2}=0.113$ ), than models that included only measures of student
demographics (adj. $\mathrm{R}^{2}=0.055$ ), student academic achievement (adj. $\mathrm{R}^{2}=0.061$ ), high school indicators (adj. $\mathrm{R}^{2}=0.071$ ), or course attributes (adj. $\mathrm{R}^{2}=0.085$ ). These findings are consistent by student race/ethnicity, as well: For all student racial/ethnic groups in our data, faculty indicators explain the most variation in passing gateway math with a C or higher (see Appendix C, Table 1).

Our primary analytic sample pools all gateway math course enrollments between winter 2020 and spring 2022, while imputing high school GPA for 24 percent of cases with missing data. Our findings continue to hold in a complete case analysis, which only includes students with non-missing values for high school GPA, as well analyses restricted to the spring 2022 term. Additionally, we find that our results are robust across our study outcomes. Faculty explain more variation in passing gateway math with a C or higher, passing gateway math with a B or higher, student grade in gateway math, and whether a student withdraws from gateway math, than student demographics, prior academic preparation, the high school the student attended, and gateway math course attributes (see Appendix C, Tables 2 and 3 ).

## Faculty gender and age are NOT highly predictive of student success; we cannot draw conclusions about the consequences of faculty race because we have too few Black and Latine faculty in our sample.

So far, our analyses have shown that individual faculty play a significant role in determining student outcomes in gateway math courses. The importance of faculty holds across student racial/ethnic groups and analytic samples both before and after accounting for other student and course characteristics.

Our method for analyzing the role of faculty uses an indicator for each faculty that encompasses everything about that individual faculty including faculty experience, training, background, practices, preferences, mindsets, and other characteristics. In our data, the only faculty characteristics we had access to were age, gender, and race/ethnicity. We can use these data to start to explore what it is about faculty that is important to student outcomes by examining how these characteristics predict student success in gateway math.

We begin by regressing our outcome (students passing gateway math with a C or higher) on student demographics, student academics, high school attended, and course characteristics. This model explains 13.6 percent of the variation in the outcome and does not include any information specific to the faculty (i.e., age, gender, or race/ethnicity). As noted previously, when we add faculty indicators to this model, which account for everything about each individual faculty, we are able to explain 20.5 percent of the variation. This increase in explained variation is due to both observable and unobservable faculty characteristics.

When faculty age, gender, and race/ethnicity are added to the model (in lieu of faculty indicators), the model's explanatory power increases slightly from 13.6 percent to 14.2 percent. This means that, in our sample, faculty age, gender, and race/ethnicity are not very predictive of students' likelihood of passing gateway math with a C or higher. Prior research has shown that having community college
faculty who are BIPOC is beneficial for students who are also BIPOC (Fairlie et al., 2014). Unfortunately, our sample includes very few Black or Latine faculty, so we are unable to examine the role of faculty race on student success.

## How do specific instructional practices promote gateway math success for students overall, and those who are Black or Latine?

A central question in our paper is understanding the "Black Box" of instruction and, in particular, how specific instructional strategies can support student success, especially for Black and Latine students who have lower pass rates compared with Asian and White students. As discussed earlier, previous research, which has been mainly qualitative, has identified practices that may benefit one or more student groups. Our goal is to empirically assess the value of practices identified in prior literature that have been highlighted as promising by the researchers and faculty that comprise our advisory group.

We use a faculty survey and a syllabi rubric as two ways to glean information about the use of evidencebased classroom practices, including assessment and grading, classroom culture, pedagogy, and the faculty member's commitment to equity, in gateway math courses.

To understand the relationship between specific instructional practices and student success, we linked the results from the survey of faculty who taught gateway math courses during the spring 2022 semester and a review of the syllabi with student, course, and faculty-level data from spring 2022. Our faculty survey response rate was 75 percent and we matched syllabi to 81 percent of courses taught in spring 2022.

In the absence of direct classroom observations, which are costly, faculty surveys and syllabi allow us to glean instructional practices and give us a window into a faculty member's belief about instruction, their students and themselves. The literature on the importance of syllabi suggests they can help support student success in a course, especially when they describe the faculty member's expectations for the student, such as learning objectives, purpose and plan for the course, information about assignments and grading, and other course requirements (Parkes \& Harris, 2002; Thompson, 2007). Empirical studies have found that syllabi are important tools that predict students' perceptions about an instructor and the course. One study found that when syllabi were randomly manipulated to have a friendly tone, students perceived the faculty teaching the courses with the manipulated syllabi as more approachable (Harnish \& Bridges, 2011). In a similar study, students who were randomly assigned to review "learner centered" syllabi rated the faculty as more caring and receptive (Richmond, Slattery, Mitchell, Morgan, \& Becknell, 2016).

To create the survey and syllabi instruments, we reviewed the literature and, working with a group of experts and faculty, identified four domains of evidence-based instructional practices deemed relevant to student success. The domains were identified because they were supported by multiple empirical or qualitative research studies or were highlighted by our advisory group as promising. All domains and subdomains were used for the development of the faculty survey and syllabi instruments except
for domain 2 . We only used the syllabi to examine pedagogical practices because it was impossible to glean classroom pedagogy from the syllabi. For a full list of subdomains see Appendix D, Table 1.

We start by estimating a series of regression models to examine the relationship between instructional practices (gleaned from the survey and syllabi) and whether students pass gateway math with a grade of C or higher. Each model regresses the outcome on an individual subdomain from the survey or syllabi (our predictor of interest) while controlling for student demographics, prior academic preparation, the high school a student attended, course length in weeks and course type, and the college the student attends (see Appendix D, Tables $1 \& 2$ for full results).

Our preferred model controls for all student background characteristics (student demographics, prior academic preparation, high school attended), and all course related characteristics, with the exception of class size, which is potentially endogenous to the faculty teaching the course (faculty who are particularly effective with students may have higher course enrollments). For Black students, we find that the coefficients (and statistical significance) are consistent across models with different specifications. For example, when we add controls for the faculty member's pass rates in the previous semester, faculty member's age, race and gender, the coefficients remain similar and statistically significant regarding the practices that benefit Black students (see Appendix D, Table 3).

## Specific Instructional Practices are Linked with Success for Black and Latine Students

Across the survey and syllabi, we find several practices that predict the success of Black and Latine students. By contrast, none of the practices are statistically significant for White students, and the only practice that is significant for Asian students is Transparent Expectations and Grading practices. Because they mostly benefit Black and Latine students, these instructional practices have the potential to narrow or close the current racial equity gaps in gateway math success. Below are the practices that are linked with the success of one or more groups of students.

Implementing growth-oriented and transparent assessment and grading practices: These practices include providing feedback to students on how to improve class performance or offering opportunities to practice before exams and projects. Another aspect is being clear and transparent in the course syllabi about course expectations and grading criteria or showing solutions with examples. Our research found these practices were positively associated with passing gateway math for Black, Latine, and Asian students.

Offering accommodations equitably: This practice involves recognizing that students face life challenges and may need accommodations. For example, the syllabus may offer accommodations for missed work due to unforeseen circumstances and makes it clear when these accommodations will be granted. Equitable enforcement is an essential element of this practice. For example, faculty may take steps to inform all students when an exception to a stated class policy applies. Such communication ensures all students, not just those who know how to advocate for themselves, can benefit from extended deadlines and other exceptions. Our research showed these practices were positively associated with passing gateway math for Black and Latine students.

Encouraging students to seek help and communicating support: Encouraging help-seeking and front-loading supportive messaging includes destigmatizing the need for assistance. For example, syllabi may include information outlining when a student should ask for help or clarify that coming to see the instructor is not a burden. Our research showed these practices were positively associated with passing gateway math for Black students.

Fostering belonging: Fostering belonging includes creating intentional opportunities for students to connect with each other and work together. This may include faculty assuring students that concerns about belonging are normal and do not reflect inadequate academic potential. Finally, faculty may help students navigate college by sharing how to address faculty, location of office hours and lab, or what to include in an email to the instructor. Our research showed these practices were positively associated with passing gateway math for Black students.

Taking responsibility for addressing racial equity: For example, a syllabus may include norms on how students should respect individual differences or provide guidelines for engaging in group work in ways that show diverse backgrounds are valued. Our research showed these practices were positively associated with passing gateway math for Black students.

Given that the groups with the lowest pass rates in gateway math benefitted the most from these practices, these approaches have the potential to reduce racial disparities. These practices consistently advanced the success of Black students, followed by Latine students. None of the practices discernibly helped White students, and only one appeared to significantly strengthen the success of Asian students. Our findings align with previous studies that have found interventions aimed at improving students' sense of belonging and mitigating self-doubt about mathematics improved grades and longterm academic outcomes for Black students while having no discernible impact on White students (Brady et al 2020; Walton \& Cohen, 2007).

Surprisingly, the pedagogical practices domain was the only area where we did not have any subdomains that were statistically significant for any student groups. One caveat is that our instruments may not be accurately measuring pedagogical practices. In other words, rather than the conclusion that pedagogy does not matter, we observe that future research should use other methods for assessing pedagogy. For example, direct classroom observation may be necessary for accurately measuring their occurrence.

A second caveat related to our analysis is that instructional practices may be correlated with other instructional practices and mindsets that may also be supporting student success. In other words, faculty who employ specific instructional practices are likely to be interacting with students in other ways that support their success.

## Discussion

Years of structural reform in community college math, such as replacing long sequences of remedial courses with corequisite support and offering math that is relevant to students' majors, have increased and diversified students enrolling in and completing gateway math (Brathwaite et al., 2020; Mejia et al., 2021; Bickerstaff et al., 2022). Despite these important gains, gateway math courses continue to see overall low success rates and disparities in completion by race. This study's key findings about the significant impact of faculty and their instructional practices have important implications for how community colleges can improve equitable outcomes in gateway math in order to put more students on the path to college success and increase STEM participation and college completion.

This research indicates that shifting away from assessing, sorting, and tracking students and moving toward resourcing and supporting faculty development may be a more powerful strategy for accelerating gateway math success and increasing equity in college outcomes. Possibilities include making disaggregated data on student success readily available to faculty, and providing them with high-quality professional development on how to implement evidence-based practices in the classroom. Other opportunities involve compensating all faculty, including part-time faculty, for the time they spend in meetings, trainings, and other spaces where they receive or offer mentorship to peers. Faculty should also be front and center in research, policy, and practices that examine and scale effective and equity-focused instruction.

More research is needed to dig deeper into the impact of faculty and their instructional practices on students' gateway math success. Specific areas for additional inquiry include the role of faculty race or prior faculty training on student success. In addition, more research is needed to understand the effect of instructional practices on students' college persistence and success. Importantly, research must also investigate the types of supports needed to help faculty adopt evidence-based instructional practices. Finally, future research should study and systematically document the institutional and state policies that create barriers to institutionalizing equitable math instruction and recommend approaches that facilitate faculty development and the adoption of practices that lead to equitable outcomes.

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## Appendix A

Table 1: Characteristics of students enrolled in gateway math courses

|  | $\begin{gathered} \text { Winter } 2020 \\ \text { Spring } 2022 \\ (\mathrm{n}=22,827) \\ \hline \end{gathered}$ | $\begin{aligned} & \text { Spring } 2022 \\ & (\mathrm{n}=3,695) \end{aligned}$ |
| :---: | :---: | :---: |
| Student race/ethnicity |  |  |
| American Indian/Alaska Native | 0.2\% | $<1 \%$ |
| Asian | 19.3\% | 19.2\% |
| Black | 4.9\% | 5.5\% |
| Latine | 51.4\% | 50.9\% |
| Native Hawaiian/Pacific Islander | 0.2\% | <1\% |
| Two or More Races | 4.0\% | 3.7\% |
| Unknown | 1.2\% | 1.2\% |
| White | 18.8\% | 19.1\% |
| Student gender |  |  |
| Female | 56.7\% | 55.2\% |
| Male | 43.1\% | 44.8\% |
| Non-binary | 0.1\% | * |
| California College Promise Grant eligible |  |  |
| No | 40.0\% | 36.4\% |
| Yes | 60.0\% | 63.6\% |
| Student has a disability |  |  |
| No | 95.4\% | 95.3\% |
| Yes | 4.6\% | 4.7\% |
| Student is a veteran |  |  |
| No | 98.0\% | 97.9\% |
| Yes | 2.0\% | 2.1\% |
| Student enrolled in gateway math in previous term |  |  |
| No | 69.0\% | 57.6\% |
| Yes | 31.0\% | 42.4\% |
| Student age | 23.4 | 23.4 |
| Student high school GPA | 3.0 | 3.0 |

Note: Table displays characteristics of students enrolled in a gateway math course anytime between Winter 2020 and Spring 2022 and characteristics of students enrolled in a gateway math course in Spring 2022.
Source: Authors' analysis of colleges' data.

Table 2: Characteristics of gateway math faculty

|  | Winter 2020 - <br> Spring 2022 <br> $(\mathrm{n}=159)$ | Spring 2022 <br> $(\mathrm{n}=104)$ |
| :--- | :---: | :---: |
| Faculty race/ethnicity | $0.6 \%$ | $0.0 \%$ |
| American Indian/Alaska Native | $22.0 \%$ | $24.0 \%$ |
| Asian | $1.9 \%$ | $1.9 \%$ |
| Black | $14.5 \%$ | $14.4 \%$ |
| Latine | $2.5 \%$ | $3.8 \%$ |
| Native Hawaiian/Pacific Islander | $3.8 \%$ | $2.9 \%$ |
| Two or More Races | $3.8 \%$ | $4.8 \%$ |
| Unknown | $50.9 \%$ | $48.1 \%$ |
| White |  |  |
| Faculty gender | $48.4 \%$ | $51.0 \%$ |
| Female | $51.6 \%$ | $49.0 \%$ |
| Male | 50.5 | 49.5 |
| Faculty age | $52.5 \%$ | $50.2 \%$ |
| Average pass rate (C or higher) for faculty in prior term/sections |  |  |

Note: Table displays characteristics of faculty who taught a gateway math course anytime between Winter 2020 and Spring 2022 and characteristics of faculty who taught a gateway math course in Spring 2022.

Source: Authors' analysis of colleges' data.
Table 3: Characteristics of gateway math sections

|  | Winter 2020 - <br> Spring 2022 <br> $(\mathrm{n}=704)$ | Spring 2022 <br> $(\mathrm{n}=185)$ |
| :--- | :---: | :---: |
| Course type indicator | $17.3 \%$ | $18.9 \%$ |
| College Algebra | $5.0 \%$ | $5.4 \%$ |
| Gateway Math for Business | $13.4 \%$ | $12.4 \%$ |
| Pre-Calculus | $6.3 \%$ | $7.0 \%$ |
| Quantitative Reasoning | $58.1 \%$ | $56.2 \%$ |
| Statistics | 14.1 | 15.9 |
| Course length (in weeks) | 27.3 | 23.1 |
| Total course enrollment |  |  |

Note: Table displays characteristics of gateway math courses taught anytime between Winter 2020 and Spring 2022 and characteristics of gateway math courses taught in Spring 2022.
Source: Authors' analysis of colleges' data.

## Appendix B

Table 1: Approximate contribution of each factor to the full model

|  | (A) | (B) | (C) |
| :--- | :---: | :---: | :---: |
|  | Adjusted <br> R-squared <br> (AR2) | Change in AR2 <br> from restricted to <br> full model <br> ( Restricted <br> AR2 - Full AR2) | Approximate <br> contribution to full <br> model <br> (= Change in AR2 <br> / Full AR2) |
| Full Model (predictors include student <br> demographics, student prior academic <br> preparation, high school student attended, <br> course attributes, student's, college, and term) | 0.20 | $\mathrm{~N} / \mathrm{A}$ |  |
| Restricted models (include all full model predictors, excluding covariates named below): | N/A |  |  |
| Student demographics | 0.19 | 0.01 | $7 \%$ |
| Prior academic preparation | 0.18 | 0.03 | $14 \%$ |
| High school student attended | 0.18 | 0.02 | $11 \%$ |
| Course attributes | 0.20 | 0.00 | $1 \%$ |
| Student's instructor | 0.14 | 0.07 | $34 \%$ |

Note: Table displays adjusted R-squared statistics and the process by which the approximate contribution of each set of variables to the full model is determined. The "Full Model" value displayed in Column A is the adjusted R-squared statistic from an OLS regression model estimated with cluster-robust standard errors (clustered at the instructor) that regresses whether the student earned a C grade or higher in gateway math on student demographics, student prior academic preparation, high school student attended, course attributes, student's instructor, college, and term. The "Restricted Models" in Column A display the adjusted R-squared statistics from similar models to those described above that omit the named set of covariates. For example, the adjusted R -squared value for the student demographics restricted model is obtained by regressing whether the student earned a C grade or higher in gateway math on student prior academic preparation, high school student attended, course attributes, student's instructor, college, and term. The values displayed in Column B represent the change in adjusted R-squared values between restricted and full models. Column C displays the approximate contribution of each set of variables to the full model, which is calculated by dividing the change in adjusted R-squared (between the restricted and full models) by the full model's adjusted R -squared.
"Student demographics" covariates include age, disability status, eligibility for California College Promise Grant, gender, race/ethnicity, and veteran status. "High school student attended" includes an indicator the high schools students attended. "Course attributes" includes course length in weeks, class size, and course type (Statistics, College Algebra, Pre-Calculus, Quantitative Reasoning, and Gateway Math for Business). "Student's instructor" includes an indicator for the faculty a student has for gateway math.
Source: Authors' analysis of colleges' data.

## Appendix C

Table 1: Contribution of factor in explaining whether students pass gateway math with a grade C or higher, overall and by student race and ethnicity.

|  | Full Sample <br> $(\mathrm{n}=29,815)$ | Asian <br> $(\mathrm{n}=6,055)$ | Black <br> $(\mathrm{n}=1,401)$ | Latine <br> $(\mathrm{n}=15,534)$ | Two or More <br> Races <br> $(\mathrm{n}=1,166)$ | White <br> $(\mathrm{n}=5,200)$ |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: |
| Student <br> demographics | 0.055 | 0.009 | 0.015 | 0.013 | 0.010 | 0.026 |
| Student prior <br> academic <br> preparation | 0.061 | 0.063 | 0.051 | 0.059 | 0.035 | 0.060 |
| High school <br> student <br> attended | 0.071 | 0.050 | 0.087 | 0.042 | 0.065 | 0.081 |
| Course <br> attributes | 0.085 | 0.069 | 0.096 | 0.057 | 0.078 | 0.090 |
| Student's <br> instructor | 0.113 | 0.120 | 0.111 | 0.118 | 0.120 | 0.118 |

Note: Table displays adjusted R-squared statistics from OLS regression models estimated with cluster-robust standard errors (clustered at the instructor) that regress whether the student earned a C grade or higher in gateway math on the named set of covariates (e.g., "Student Demographics") in addition to college and term indicators for the full sample and by student race/ethnicity. "Student demographics" covariates include age, disability status, eligibility for California College Promise Grant, gender, race/ethnicity, and veteran status. "High school student attended" includes an indicator the high schools students attended. "Course attributes" includes course length in weeks, class size, and course type (Statistics, College Algebra, Pre-Calculus, Quantitative Reasoning, and Gateway Math for Business). "Student's instructor" includes an indicator for the faculty a student has for gateway math.
Source: Authors' analysis of colleges' data.
Table 2: Contribution of each set of variables to explain whether students pass gateway math with a grade C or higher, overall and by and by analytic samples.

|  | MVN Imputation <br> Primary analytic <br> sample; $\mathrm{n}=$ <br> $29,815)$ | Complete Case <br> $(\mathrm{n}=22,826)$ | MVN Imputation <br> - Spring 2022 <br> $(\mathrm{n}=3,744)$ | Complete Case - <br> Spring 2022 <br> $(\mathrm{n}=3,014)$ |
| :--- | :---: | :---: | :---: | :---: |
| Student demographics | 0.055 | 0.066 | 0.044 | 0.038 |
| Student prior academic <br> preparation | 0.061 | 0.060 | 0.036 | 0.035 |
| High school student attended | 0.071 | 0.065 | 0.038 | 0.025 |
| Course attributes | 0.085 | 0.033 | 0.068 | 0.035 |
| Student's instructor | 0.113 | 0.114 | 0.098 | 0.095 |

Note: Table displays adjusted R-squared statistics from OLS regression models estimated with cluster-robust standard errors (clustered at the instructor) that regress whether the student earned a C grade or higher in gateway math on the named set of covariates (e.g., "Student Demographics") in addition to college and term indicators across different analytic samples. "Student demographics" covariates include age, disability status, eligibility for California College Promise Grant, gender, race/ethnicity, and veteran status. "High school student attended" includes an indicator the high schools students attended. "Course attributes" includes course length in weeks, class size, and course type (Statistics, College Algebra, Pre-Calculus, Quantitative Reasoning, and Gateway Math for Business). "Student's instructor" includes an indicator for the faculty a student has for gateway math. MVN = multivariate normal distribution
Source: Authors' analysis of colleges' data.

Table 3: Contribution of each set of variables to explain whether students' success in gateway math

|  | Passing gateway <br> math with a C or <br> higher <br> Primary analytic <br> sample; $\mathrm{n}=$ <br> 29,815 ) | Passing gateway <br> math with a B or <br> higher <br> Primary analytic <br> sample; $\mathrm{n}=$ <br> $29,815)$ | Student grade in <br> gateway math <br> Primary analytic <br> sample; $\mathrm{n}=$ <br> $29,815)$ | Student <br> withdrawal from <br> gateway math <br> Primary analytic <br> sample; $\mathrm{n}=$ <br> $29,815)$ |
| :--- | :---: | :---: | :---: | :---: |
| Student demographics | 0.055 | 0.071 | 0.083 | 0.023 |
| Student prior academic <br> preparation | 0.061 | 0.065 | 0.089 | 0.058 |
| High school student attended | 0.071 | 0.084 | 0.108 | 0.073 |
| Course attributes | 0.085 | 0.098 | 0.126 | 0.078 |
| Student's instructor | 0.113 | 0.121 | 0.151 | 0.094 |

Note: Table displays adjusted R-squared statistics from OLS regression models estimated with cluster-robust standard errors (clustered at the instructor) that regress the outcome variable on the named set of covariates (e.g., "Student Demographics") in addition to college and term indicators. "Student demographics" covariates include age, disability status, eligibility for California College Promise Grant, gender, race/ethnicity, and veteran status. "High school student attended" includes an indicator the high schools students attended. "Course attributes" includes course length in weeks, class size, and course type (Statistics, College Algebra, Pre-Calculus, Quantitative Reasoning, and Gateway Math for Business). "Student's instructor" includes an indicator for the faculty a student has for gateway math.

Source: Authors' analysis of colleges' data.

## Appendix D

Table 1: The relationships between instructional practices gleaned from faculty surveys and whether students pass gateway math with a C grade or higher

| Survey subdomain | Full Sample $(\mathrm{n}=2,907)$ | $\begin{gathered} \text { Asian } \\ (\mathrm{n}=544) \end{gathered}$ | $\begin{gathered} \text { Black } \\ (\mathrm{n}=151) \end{gathered}$ | Latine $(\mathrm{n}=1,462)$ | Two or More Races ( $\mathrm{n}=106$ ) | $\begin{aligned} & \text { White } \\ & (\mathrm{n}=602) \end{aligned}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Growth-oriented grading | $\begin{aligned} & \hline 0.048+ \\ & (0.026) \\ & \hline \end{aligned}$ | $\begin{gathered} \hline 0.027 \\ (0.035) \end{gathered}$ | $\begin{gathered} \hline 0.023 \\ (0.165) \end{gathered}$ | $\begin{aligned} & \hline 0.073^{*} \\ & (0.031) \\ & \hline \end{aligned}$ | $\begin{array}{r} \hline-0.142 \\ (0.380) \\ \hline \end{array}$ | $\begin{gathered} \hline 0.005 \\ (0.062) \\ \hline \end{gathered}$ |
| Practice prior to assessment | $\begin{aligned} & 0.054^{*} \\ & (0.022) \\ & \hline \end{aligned}$ | $\begin{gathered} 0.012 \\ (0.052) \\ \hline \end{gathered}$ | $\begin{gathered} \hline 0.061 \\ (0.105) \\ \hline \end{gathered}$ | $\begin{aligned} & \hline 0.061^{*} \\ & (0.028) \\ & \hline \end{aligned}$ | $\begin{aligned} & \hline-0.013 \\ & (0.156) \\ & \hline \end{aligned}$ | $\begin{gathered} 0.036 \\ (0.037) \\ \hline \end{gathered}$ |
| Immediate feedback from faculty \& peers | $\begin{gathered} 0.021 \\ (0.026) \\ \hline \end{gathered}$ | $\begin{gathered} 0.008 \\ (0.037) \\ \hline \end{gathered}$ | $\begin{gathered} \hline 0.107 \\ (0.105) \\ \hline \end{gathered}$ | $\begin{aligned} & 0.052^{*} \\ & (0.025) \\ & \hline \end{aligned}$ | $\begin{gathered} 0.066 \\ (0.174) \\ \hline \end{gathered}$ | $\begin{array}{r} \hline-0.060 \\ (0.038) \\ \hline \end{array}$ |
| Transparent expectations and grading | $\begin{array}{r} \hline-0.029 \\ (0.025) \\ \hline \end{array}$ | $\begin{aligned} & \hline-0.047 \\ & (0.042) \\ & \hline \end{aligned}$ | $\begin{gathered} \hline 0.087 \\ (0.125) \\ \hline \end{gathered}$ | $\begin{gathered} \hline 0.002 \\ (0.030) \\ \hline \end{gathered}$ | $\begin{array}{r} \hline-0.022 \\ (0.208) \\ \hline \end{array}$ | $\begin{gathered} \hline-0.093+ \\ (0.050) \\ \hline \end{gathered}$ |
| Offering accommodations equitably | $\begin{aligned} & \hline 0.054^{*} \\ & (0.021) \\ & \hline \end{aligned}$ | $\begin{aligned} & \hline 0.062+ \\ & (0.034) \\ & \hline \end{aligned}$ | $\begin{gathered} \hline 0.015 \\ (0.153) \\ \hline \end{gathered}$ | $\begin{aligned} & \hline 0.057^{*} \\ & (0.025) \\ & \hline \end{aligned}$ | $\begin{aligned} & \hline-0.178 \\ & (0.323) \\ & \hline \end{aligned}$ | $\begin{gathered} \hline 0.025 \\ (0.058) \\ \hline \end{gathered}$ |
| Emphasizing reasoning over memorization | $\begin{gathered} \hline 0.001 \\ (0.008) \\ \hline \end{gathered}$ | $\begin{aligned} & \hline-0.003 \\ & (0.013) \\ & \hline \end{aligned}$ | $\begin{gathered} \hline 0.030 \\ (0.052) \\ \hline \end{gathered}$ | $\begin{gathered} \hline 0.003 \\ (0.011) \\ \hline \end{gathered}$ | $\begin{aligned} & \hline-0.018 \\ & (0.066) \\ & \hline \end{aligned}$ | $\begin{aligned} & \hline-0.007 \\ & (0.017) \\ & \hline \end{aligned}$ |
| Fostering conceptual understanding | $\begin{gathered} \hline 0.006 \\ (0.031) \\ \hline \end{gathered}$ | $\begin{array}{r} \hline-0.034 \\ (0.054) \\ \hline \end{array}$ | $\begin{gathered} \hline 0.068 \\ (0.149) \\ \hline \end{gathered}$ | $\begin{gathered} \hline 0.038 \\ (0.034) \\ \hline \end{gathered}$ | $\begin{array}{r} \hline-0.165 \\ (0.292) \\ \hline \end{array}$ | $\begin{gathered} \hline-0.124 \\ (0.078) \\ \hline \end{gathered}$ |
| Integrating knowledge of students in course design | $\begin{gathered} \hline 0.017 \\ (0.023) \\ \hline \end{gathered}$ | $\begin{aligned} & \hline-0.010 \\ & (0.048) \\ & \hline \end{aligned}$ | $\begin{gathered} \hline 0.124 \\ (0.154) \\ \hline \end{gathered}$ | $\begin{gathered} \hline 0.044 \\ (0.034) \\ \hline \end{gathered}$ | $\begin{aligned} & \hline-0.074 \\ & (0.203) \\ & \hline \end{aligned}$ | $\begin{aligned} & \hline-0.001 \\ & (0.042) \\ & \hline \end{aligned}$ |
| Interactive learning experience | $\begin{gathered} \hline 0.020 \\ (0.027) \\ \hline \end{gathered}$ | $\begin{gathered} \hline 0.004 \\ (0.046) \\ \hline \end{gathered}$ | $\begin{gathered} \hline 0.015 \\ (0.192) \\ \hline \end{gathered}$ | $\begin{gathered} \hline 0.022 \\ (0.035) \\ \hline \end{gathered}$ | $\begin{aligned} & \hline-0.235 \\ & (0.258) \\ & \hline \end{aligned}$ | $\begin{gathered} \hline 0.007 \\ (0.063) \\ \hline \end{gathered}$ |
| Growth mindset | $\begin{aligned} & \hline 0.122^{*} \\ & (0.053) \\ & \hline \end{aligned}$ | $\begin{gathered} \hline 0.085 \\ (0.075) \\ \hline \end{gathered}$ | $\begin{aligned} & 0.452+ \\ & (0.262) \\ & \hline \end{aligned}$ | $\begin{gathered} \hline 0.085 \\ (0.068) \\ \hline \end{gathered}$ | $\begin{gathered} \hline 0.354 \\ (0.399) \\ \hline \end{gathered}$ | $\begin{gathered} \hline 0.141 \\ (0.106) \\ \hline \end{gathered}$ |
| Inclusivity | $\begin{array}{r} \hline-0.017 \\ (0.030) \\ \hline \end{array}$ | $\begin{gathered} \hline 0.017 \\ (0.059) \\ \hline \end{gathered}$ | $\begin{array}{r} \hline-0.180 \\ (0.176) \\ \hline \end{array}$ | $\begin{gathered} \hline 0.003 \\ (0.037) \\ \hline \end{gathered}$ | $\begin{aligned} & \hline-0.045 \\ & (0.223) \\ & \hline \end{aligned}$ | $\begin{gathered} \hline-0.079 \\ (0.057) \\ \hline \end{gathered}$ |
| Fostering belonging | $\begin{gathered} \hline 0.009 \\ (0.019) \\ \hline \end{gathered}$ | $\begin{aligned} & \hline 0.042+ \\ & (0.023) \\ & \hline \end{aligned}$ | $\begin{aligned} & \hline-0.027 \\ & (0.119) \\ & \hline \end{aligned}$ | $\begin{gathered} \hline 0.016 \\ (0.021) \\ \hline \end{gathered}$ | $\begin{gathered} \hline 0.047 \\ (0.104) \\ \hline \end{gathered}$ | $\begin{aligned} & \hline-0.022 \\ & (0.028) \\ & \hline \end{aligned}$ |
| Acknowledgement of equity gaps | $\begin{gathered} \hline 0.008 \\ (0.030) \\ \hline \end{gathered}$ | $\begin{aligned} & \hline 0.056+ \\ & (0.033) \\ & \hline \end{aligned}$ | $\begin{gathered} \hline-0.113 \\ (0.200) \\ \hline \end{gathered}$ | $\begin{gathered} \hline-0.009 \\ (0.047) \\ \hline \end{gathered}$ | $\begin{array}{r} \hline-0.070 \\ (0.277) \\ \hline \end{array}$ | $\begin{array}{r} \hline-0.013 \\ (0.092) \\ \hline \end{array}$ |
| Taking responsibility for equity gaps | $\begin{gathered} \hline 0.043 \\ (0.040) \\ \hline \end{gathered}$ | $\begin{array}{r} \hline-0.018 \\ (0.053) \\ \hline \end{array}$ | $\begin{aligned} & \hline 0.466^{*} \\ & (0.193) \\ & \hline \end{aligned}$ | $\begin{gathered} \hline 0.044 \\ (0.053) \\ \hline \end{gathered}$ | $\begin{gathered} \hline 0.238 \\ (0.302) \\ \hline \end{gathered}$ | $\begin{gathered} \hline 0.046 \\ (0.071) \\ \hline \end{gathered}$ |

Note: Table displays OLS regression coefficients and cluster-robust standard errors (clustered at the instructor). $+\mathrm{p}<0.10 ; * \mathrm{p}<0.05$ communicate the results of $t$-tests that examine whether the coefficient is different than zero. The dependent variable is whether the student earned a C grade or higher in gateway math and the survey item (shown) is the independent variable of interest. All models include controls for student demographics, academics, high school attended, course length and type, and college. Each cell represents a separate model (i.e., survey items were estimated individually).

Source: Authors' analysis of colleges' data.

Table 2: The relationships between instructional practices gleaned from faculty syllabi and whether students pass gateway math with a C grade or higher

| Syllabi subdomain | Full Sample $(\mathrm{n}=3,046)$ | $\begin{gathered} \text { Asian } \\ (\mathrm{n}=568) \end{gathered}$ | $\begin{aligned} & \text { Black } \\ & (\mathrm{n}=170) \end{aligned}$ | Latine ( $\mathrm{n}=1,551$ ) | Two or More Races $(\mathrm{n}=114)$ | $\begin{aligned} & \text { White } \\ & (\mathrm{n}=599) \end{aligned}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Growth-oriented grading | $\begin{gathered} -0.027+ \\ (0.016) \end{gathered}$ | $\begin{gathered} 0.007 \\ (0.024) \end{gathered}$ | $\begin{aligned} & 0.151^{*} \\ & (0.074) \end{aligned}$ | $\begin{gathered} -0.033+ \\ (0.019) \end{gathered}$ | $\begin{aligned} & -0.149 \\ & (0.105) \end{aligned}$ | $\begin{aligned} & -0.060 \\ & (0.036) \end{aligned}$ |
| Transparent expectations/grading | $\begin{aligned} & 0.060+ \\ & (0.030) \end{aligned}$ | $\begin{gathered} 0.102 * * \\ (0.037) \end{gathered}$ | $\begin{aligned} & 0.316+ \\ & (0.172) \end{aligned}$ | $\begin{gathered} 0.044 \\ (0.043) \end{gathered}$ | $\begin{gathered} 0.138 \\ (0.401) \end{gathered}$ | $\begin{gathered} 0.010 \\ (0.056) \end{gathered}$ |
| Offering accommodations equitably | $\begin{gathered} 0.030 \\ (0.020) \end{gathered}$ | $\begin{gathered} 0.019 \\ (0.024) \end{gathered}$ | $\begin{aligned} & 0.127 * \\ & (0.055) \end{aligned}$ | $\begin{gathered} 0.031 \\ (0.022) \end{gathered}$ | $\begin{gathered} 0.133 \\ (0.139) \end{gathered}$ | $\begin{gathered} 0.035 \\ (0.034) \end{gathered}$ |
| Supportive Messaging | $\begin{gathered} 0.011 \\ (0.017) \end{gathered}$ | $\begin{gathered} 0.031 \\ (0.031) \end{gathered}$ | $\begin{aligned} & 0.104 * \\ & (0.052) \end{aligned}$ | $\begin{aligned} & -0.006 \\ & (0.020) \end{aligned}$ | $\begin{aligned} & -0.064 \\ & (0.116) \end{aligned}$ | $\begin{gathered} 0.033 \\ (0.035) \end{gathered}$ |
| Inclusivity | $\begin{gathered} 0.007 \\ (0.018) \end{gathered}$ | $\begin{aligned} & -0.004 \\ & (0.027) \end{aligned}$ | $\begin{gathered} 0.060 \\ (0.067) \end{gathered}$ | $\begin{gathered} 0.016 \\ (0.022) \end{gathered}$ | $\begin{gathered} 0.143 \\ (0.253) \end{gathered}$ | $\begin{gathered} 0.009 \\ (0.035) \end{gathered}$ |
| Fostering belonging | $\begin{gathered} 0.048 \\ (0.041) \end{gathered}$ | $\begin{gathered} 0.046 \\ (0.054) \end{gathered}$ | $\begin{aligned} & 0.187 * \\ & (0.080) \end{aligned}$ | $\begin{gathered} 0.044 \\ (0.039) \end{gathered}$ | $\begin{aligned} & -0.001 \\ & (0.336) \end{aligned}$ | $\begin{gathered} 0.046 \\ (0.066) \end{gathered}$ |
| Encouraging help-seeking | $\begin{gathered} 0.032 \\ (0.023) \end{gathered}$ | $\begin{gathered} 0.041 \\ (0.034) \end{gathered}$ | $\begin{aligned} & 0.144^{*} \\ & (0.061) \end{aligned}$ | $\begin{gathered} 0.024 \\ (0.026) \end{gathered}$ | $\begin{aligned} & -0.051 \\ & (0.162) \end{aligned}$ | $\begin{gathered} 0.041 \\ (0.039) \end{gathered}$ |
| Acknowledgement of equity gaps | $\begin{gathered} 0.018 \\ (0.015) \end{gathered}$ | $\begin{gathered} 0.029 \\ (0.023) \end{gathered}$ | $\begin{gathered} 0.009 \\ (0.069) \end{gathered}$ | $\begin{gathered} 0.026 \\ (0.018) \end{gathered}$ | $\begin{aligned} & -0.044 \\ & (0.200) \end{aligned}$ | $\begin{gathered} 0.002 \\ (0.026) \end{gathered}$ |
| Taking responsibility for equity gaps | $\begin{gathered} 0.027 \\ (0.024) \end{gathered}$ | $\begin{gathered} 0.032 \\ (0.037) \end{gathered}$ | $\begin{aligned} & 0.125+ \\ & (0.063) \end{aligned}$ | $\begin{gathered} 0.025 \\ (0.028) \end{gathered}$ | $\begin{aligned} & -0.081 \\ & (0.216) \end{aligned}$ | $\begin{gathered} 0.011 \\ (0.034) \end{gathered}$ |

Note: Table displays OLS regression coefficients and cluster-robust standard errors (clustered at the instructor). $+\mathrm{p}<0.10 ; * \mathrm{p}<0.05$ communicate the results of $t$-tests that examine whether the coefficient is different than zero. The dependent variable is whether the student earned a C grade or higher in gateway math and the syllabi item (shown) is the independent variable of interest. All models include controls for student demographics, academics, high school attended, course length and type, and college. Each cell represents a separate model (i.e., syllabi items were estimated individually).
Source: Authors' analysis of colleges' data.

Table 3: The relationships between instructional practices gleaned from faculty syllabi and whether Black students pass gateway math with a C grade or higher, by model specification

| Syllabi subdomain | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Growth-oriented grading | $\begin{gathered} \hline 0.036 \\ (0.031) \end{gathered}$ | $\begin{gathered} \hline 0.032 \\ (0.033) \\ \hline \end{gathered}$ | $\begin{gathered} \hline 0.028 \\ (0.034) \end{gathered}$ | $\begin{gathered} \hline 0.106 \\ (0.075) \\ \hline \end{gathered}$ | $\begin{aligned} & \hline 0.151^{*} \\ & (0.074) \\ & \hline \end{aligned}$ | $\begin{aligned} & \hline 0.150^{*} \\ & (0.072) \\ & \hline \end{aligned}$ | $\begin{aligned} & \hline 0.153^{*} \\ & (0.073) \\ & \hline \end{aligned}$ | $\begin{gathered} \hline 0.201 * * \\ (0.073) \\ \hline \end{gathered}$ | $\begin{aligned} & \hline 0.219^{*} \\ & (0.084) \\ & \hline \end{aligned}$ |
| Transparent expectations/grading | $\begin{gathered} 0.189 * * * \\ (0.046) \\ \hline \end{gathered}$ | $\begin{gathered} 0.160^{* *} \\ (0.051) \\ \hline \end{gathered}$ | $\begin{gathered} 0.172^{* *} \\ (0.051) \\ \hline \end{gathered}$ | $\begin{aligned} & 0.308+ \\ & (0.156) \\ & \hline \end{aligned}$ | $\begin{aligned} & 0.316+ \\ & (0.172) \end{aligned}$ | $\begin{aligned} & 0.298+ \\ & (0.167) \\ & \hline \end{aligned}$ | $\begin{aligned} & 0.314+ \\ & (0.171) \end{aligned}$ | $\begin{gathered} \hline 0.361 \\ (0.251) \\ \hline \end{gathered}$ | $\begin{gathered} \hline 0.350 \\ (0.242) \\ \hline \end{gathered}$ |
| Offering accommodations equitably | $\begin{gathered} 0.071 * * \\ (0.023) \end{gathered}$ | $\begin{gathered} 0.071^{* *} \\ (0.023) \end{gathered}$ | $\begin{gathered} 0.073 * * \\ (0.023) \end{gathered}$ | $\begin{aligned} & 0.118^{*} \\ & (0.054) \end{aligned}$ | $\begin{aligned} & 0.127 * \\ & (0.055) \end{aligned}$ | $\begin{aligned} & 0.128^{*} \\ & (0.057) \end{aligned}$ | $\begin{aligned} & 0.131 * \\ & (0.059) \end{aligned}$ | $\begin{aligned} & 0.160 * \\ & (0.076) \end{aligned}$ | $\begin{aligned} & 0.168^{*} \\ & (0.082) \end{aligned}$ |
| Supportive Messaging | $\begin{aligned} & \hline 0.049^{*} \\ & (0.024) \\ & \hline \end{aligned}$ | $\begin{aligned} & 0.052^{*} \\ & (0.023) \\ & \hline \end{aligned}$ | $\begin{aligned} & \hline 0.049^{*} \\ & (0.023) \\ & \hline \end{aligned}$ | $\begin{aligned} & \hline 0.130^{*} \\ & (0.050) \\ & \hline \end{aligned}$ | $\begin{aligned} & \hline 0.104^{*} \\ & (0.052) \\ & \hline \end{aligned}$ | $\begin{aligned} & \hline 0.105^{*} \\ & (0.052) \\ & \hline \end{aligned}$ | $\begin{aligned} & \hline 0.111^{*} \\ & (0.052) \\ & \hline \end{aligned}$ | $\begin{gathered} 0.104 \\ (0.064) \\ \hline \end{gathered}$ | $\begin{aligned} & \hline 0.136^{*} \\ & (0.060) \\ & \hline \end{aligned}$ |
| Inclusivity | $\begin{gathered} \hline 0.017 \\ (0.026) \\ \hline \end{gathered}$ | $\begin{gathered} \hline 0.012 \\ (0.028) \\ \hline \end{gathered}$ | $\begin{gathered} \hline 0.005 \\ (0.029) \\ \hline \end{gathered}$ | $\begin{gathered} \hline 0.010 \\ (0.073) \\ \hline \end{gathered}$ | $\begin{gathered} \hline 0.060 \\ (0.067) \\ \hline \end{gathered}$ | $\begin{gathered} \hline 0.053 \\ (0.071) \\ \hline \end{gathered}$ | $\begin{gathered} \hline 0.058 \\ (0.071) \\ \hline \end{gathered}$ | $\begin{gathered} \hline 0.047 \\ (0.097) \\ \hline \end{gathered}$ | $\begin{gathered} \hline 0.068 \\ (0.126) \\ \hline \end{gathered}$ |
| Fostering belonging | $\begin{gathered} \hline 0.153 * * * \\ (0.035) \\ \hline \end{gathered}$ | $\begin{gathered} \hline 0.151^{* * *} \\ (0.036) \\ \hline \end{gathered}$ | $\begin{gathered} \hline 0.145 * * * \\ (0.036) \\ \hline \end{gathered}$ | $\begin{gathered} \hline 0.210^{* *} \\ (0.072) \\ \hline \end{gathered}$ | $\begin{aligned} & \hline 0.187^{*} \\ & (0.080) \\ & \hline \end{aligned}$ | $\begin{aligned} & \hline 0.175^{*} \\ & (0.084) \\ & \hline \end{aligned}$ | $\begin{aligned} & \hline 0.186^{*} \\ & (0.081) \\ & \hline \end{aligned}$ | $\begin{aligned} & \hline 0.192+ \\ & (0.100) \\ & \hline \end{aligned}$ | $\begin{aligned} & \hline 0.181+ \\ & (0.105) \\ & \hline \end{aligned}$ |
| Encouraging helpseeking | $\begin{gathered} \hline 0.101^{* *} \\ (0.031) \\ \hline \end{gathered}$ | $\begin{gathered} \hline 0.102^{* *} \\ (0.030) \\ \hline \end{gathered}$ | $\begin{aligned} & \hline 0.097 * * \\ & (0.031) \\ & \hline \end{aligned}$ | $\begin{aligned} & \hline 0.150^{*} \\ & (0.069) \\ & \hline \end{aligned}$ | $\begin{aligned} & \hline 0.144^{*} \\ & (0.061) \\ & \hline \end{aligned}$ | $\begin{aligned} & \hline 0.136^{*} \\ & (0.065) \\ & \hline \end{aligned}$ | $\begin{aligned} & \hline 0.153^{*} \\ & (0.063) \\ & \hline \end{aligned}$ | $\begin{aligned} & \hline 0.159^{*} \\ & (0.067) \\ & \hline \end{aligned}$ | $\begin{aligned} & \hline 0.188^{*} \\ & (0.072) \\ & \hline \end{aligned}$ |
| Acknowledgement of equity gaps | $\begin{gathered} \hline 0.039 \\ (0.041) \\ \hline \end{gathered}$ | $\begin{gathered} \hline 0.037 \\ (0.042) \\ \hline \end{gathered}$ | $\begin{gathered} \hline 0.035 \\ (0.040) \\ \hline \end{gathered}$ | $\begin{gathered} \hline-0.034 \\ (0.082) \\ \hline \end{gathered}$ | $\begin{gathered} \hline 0.009 \\ (0.069) \\ \hline \end{gathered}$ | $\begin{gathered} \hline-0.007 \\ (0.071) \\ \hline \end{gathered}$ | $\begin{gathered} \hline 0.006 \\ (0.067) \\ \hline \end{gathered}$ | $\begin{gathered} \hline-0.033 \\ (0.117) \\ \hline \end{gathered}$ | $\begin{aligned} & \hline-0.042 \\ & (0.118) \\ & \hline \end{aligned}$ |
| Taking responsibility for equity gaps | $\begin{gathered} \hline 0.106^{* *} \\ (0.039) \\ \hline \end{gathered}$ | $\begin{gathered} \hline 0.107^{* *} \\ (0.039) \\ \hline \end{gathered}$ | $\begin{gathered} \hline 0.103 * * \\ (0.038) \\ \hline \end{gathered}$ | $\begin{gathered} \hline 0.106 \\ (0.079) \\ \hline \end{gathered}$ | $\begin{aligned} & \hline 0.125+ \\ & (0.063) \\ & \hline \end{aligned}$ | $\begin{gathered} \hline 0.114 \\ (0.070) \\ \hline \end{gathered}$ | $\begin{aligned} & \hline 0.125^{*} \\ & (0.060) \\ & \hline \end{aligned}$ | $\begin{aligned} & \hline 0.150+ \\ & (0.080) \\ & \hline \end{aligned}$ | $\begin{aligned} & \hline 0.161^{*} \\ & (0.077) \\ & \hline \end{aligned}$ |
| Models include: |  |  |  |  |  |  |  |  |  |
| College and term indicators | X | X | X | X | X | X | X | X | X |
| Student demographic variables |  | X | X | X | X | X | X | X | X |
| Student prior academic preparation variables |  |  | X | X | X | X | X | X | X |
| High school student attended |  |  |  | X | X | X | X | X | X |
| Course length in weeks and course type |  |  |  |  | X | X | X | X | X |
| Faculty prior grading |  |  |  |  |  | X |  |  | X |
| Course enrollment |  |  |  |  |  |  | X |  | X |
| Faculty demographics |  |  |  |  |  |  |  | X | X |

Note: Table displays OLS regression coefficients and cluster-robust standard errors (clustered at the instructor). $+\mathrm{p}<0.10 ; * \mathrm{p}<0.05$; ${ }^{* *} \mathrm{p}<0.01 ;{ }^{* * *} \mathrm{p}<0.001$ communicate the results of t -tests that examine whether the coefficient is different than zero. All models include all Black students enrolled in a gateway math course in spring 2022 that could be matched to a syllabus in our data ( $\mathrm{n}=170$ ). The dependent variable is whether the student earned a C grade or higher in gateway math and the syllabi subdomain (shown) is the independent variable of interest. Additional independent variables are specified for each set of models. Model 5 is our preferred specification, also shown in Table 2. Models 6 through 9 add additional variables believed to be endogenous to the faculty member, while models 1 through 4 are more parsimonious and less prone to overfitting. Our findings are consistent across model specifications.

Source: Authors' analysis of colleges' data.


[^0]:    ${ }^{1}$ In this paper, we use the terms Latine to describe people who come from, or have family roots coming from, countries in Latin America and the Caribbean. Other terms used in the research literature and public surveys include Hispanic, Latino, or Latinx.

[^1]:    ${ }^{2}$ We use multiple imputation to impute missing values of high school GPA for 24 percent of our sample.

[^2]:    ${ }^{3}$ Because we are interested in making comparisons across models with varying numbers of predictor variables, our statistic of interest is the adjusted R-squared (as opposed to the traditional R-squared). Adjusted R-squared is penalized when nonsignificant predictors are included in a model, whereas R-squared values will always increase with the total number of model predictors. By using adjusted R -squared we are better able to determine which model has greater explanatory power regardless of the number of predictors included in that model.

[^3]:    Note: Percentages indicate the approximate contribution of the named set of covariates (e.g., student's instructor) to the total variation in a student passing gateway math with a grade of C or higher that can be explained by the full model, after controlling for all other covariates (e.g., student demographics, prior academic preparation, high school student attended, course attributes, college, and term). Percentages are calculated by dividing the difference in adjusted R-squared between the full and restricted models (the full model includes all covariates, and the restricted model omits the named set of covariates) by the full model's adjusted R-squared. Percentages do not sum to 100 as the contributions of college and term are not conveyed in the figure.
    Source: Authors' analysis of colleges' data.

