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Exploring the Relationship Between Community College Students' Exposure to Math Contextualization and Educational Outcomes

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Abstract

Low completion rates of math courses pose a major challenge for community college students' educational progress and outcomes. Contextualized instruction has been identified as a promising approach to removing some of the longstanding barriers within math teaching and learning. Still, the empirical base on this topic remains small, with particularly little evidence on how exposure to math contextualization relates to students' longer-term educational outcomes, which bear important implications for institutions' performance metrics and policymaking. We contribute new research on this front by examining how exposure to math contextualization relates to a range of interim and longer-term educational outcomes at a large community college in a Midwestern state. We applied the genetic matching approach to construct a study sample that was balanced in background characteristics between the student group receiving contextualized math instruction and their counterparts enrolled in traditional math courses. We adopted a set of regression analyses based on the matched sample, and found a significant positive relationship between exposure to math contextualization and students' outcome measures, including course performance, term GPA, continuous postsecondary enrollment, credential completion, and upward transfer.

Keywords Active learning · Community colleges · Contextualized instruction · Math contextualization · Technical education · Student outcomes

Students beginning at public 2-year institutions represent a vital population of college attendees who have been historically underserved in postsecondary education. Hailing from more diverse backgrounds relative to students beginning at baccalaureate institutions (Cohen et al., 2014), community college students represent a unique talent pool that propels institutions to invest in efforts toward not only diversification of the student body, but also full participation and equitable outcomes. However, nationally, community college

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students' persistence, completion, and transfer rates remain low (Martin et al., 2014; President's Council of Advisors on Science & Technology, 2012; Snyder et al., 2016), calling for stronger institutional efforts to better serve these students and enhance their educational success in the short and long run.

One particular area of struggle that has been identified as impeding student success is in mathematics (hereafter shortened to math). Indeed, research has shown that math courses at both developmental and college levels act as a gatekeeper that often derails community colleges students' pathways to success (Hagedorn & Kuznetsova, 2016; Perin, 2011; Wang, 2017). Math course completion rates have been low, hovering around 50% for developmental math courses (Chen, 2016; Rutschow, 2019) and 48% for college-level math courses (Chen, 2016). Further exacerbating the issue is the deeply concerning fact that non-completion of math courses often marks the end of a student's college career (Adelman, 2006; Lundy-Wagner, 2014; Wang, 2020).

Clearly, math offerings at community colleges need to be reimagined, improved upon, and potentially reformed to flip the narrative so that they can act as a gateway to student success. Toward this end, a number of innovative approaches to redesigning developmental and college-level math have gained national traction. Notable examples include shortening or accelerating math sequences through compression (Ariovich & Walker, 2014; Kosiewicz et al., 2016; Schudde & Keisler, 2019), co-requisite models (Adams et al., 2009; Jaggars et al., 2015; Ran & Lin, 2019), and revamping early assessment and placement processes through multiple measures (Burdman, 2012; Melguizo et al., 2014; Ngo & Kwon, 2015). While these structural reforms hold promise, instructional changes are as, if not more, critical. One particular area of interest and importance is contextualized instruction as a means to improve teaching and learning experiences within the community college math classroom.

We focus on contextualization not only because of its potential to resolve the math struggle, but also because it rests with what happens within the classroom, an arguably key and primary venue through which the vast majority of community college students experience college. Research has shown that what happens or does not happen within the classroom profoundly affects a community college student's prospects of college progress and completion (e.g., Deil-Amen, 2006; Deil-Amen & Rosenbaum, 2002), especially within math courses (e.g., Wang et al., 2017). Accordingly, when contending with multiple ways to address the larger math reform, it is pivotal to develop teaching approaches that effectively facilitate and enhance students' learning. By situating more abstract subject matter within real-life settings, contextualized instruction has shown promise to enhance student learning, as suggested by evidence on language and literacy instruction (e.g., Gillam et al., 2012; Perin, 2013; Shrum, 2015).

To date, only a handful of empirical studies explicitly examined contextualization in math courses in community college settings (e.g., Parker et al., 2018; Wang et al., 2017), all pointing to contextualization's potential to cultivate positive learning experiences and motivational beliefs among math learners. At the same time, little extant evidence touches upon the connection between math contextualization and students' educational outcomes, such as transfer and completion, which bear important implications for institutions' performance metrics and policymaking across institutional, state, and national levels. Thus, our study is aimed at contributing new research on this front by addressing the following overarching research question: How does exposure to math contextualization relate to community college students' interim and longer-term educational outcomes? The following set of specific questions guide our inquiry:

First, what is the relationship between exposure to math contextualization and students' math course performance, measured by course grade?
Second, what is the relationship between exposure to math contextualization and students' academic performance in the same term, measured by term GPA?
Third, what is the relationship between exposure to math contextualization and students' educational progress and attainment, measured by continuous postsecondary enrollment, credential completion, or upward transfer?

We address our research questions through a set of regression analyses of a matched sample consisting of both students receiving contextualized math instruction and their counterparts enrolled in traditional math courses. Our findings suggest that exposure to contextualization has a significantly positive relationship with these set of outcomes.

Literature Review

In this section, we situate our study by first examining the literature on how contextualization has been shown to be a promising teaching approach across various subjects. Next, we review the literature that specifically touches upon existing evidence speaking to math contextualization's potential impact on community college students.

Contextualization as an Instructional Approach

Contextualization is broadly conceived as an umbrella term that encompasses a wide range of teaching strategies with the goal of purposefully integrating foundational skills—through concrete applications—within contexts aligned with students' academic and career interests (Mazzeo, 2008). By nature, contextualization fosters active learning (Faust & Paulson, 1998; Prince, 2004) by helping students see how to utilize concepts within realistic settings in their future studies as well as work (Rivet & Krajcik, 2008), and by guiding students to investigate real-world problems (Bouillion & Gomez, 2001; Rivet & Krajcik, 2008). Through a contextualized approach, faculty intentionally use problems or examples that are meaningful to students to guide them toward mastery of the content (Edelson et al., 1999; Rivet & Krajcik, 2008).

Although the literature lacks a clearly defined distinction between contextualization and its "opposite"—decontextualization, likely because instructional approaches are more fluid than dichotomously categorized, a common feature of a "decontextualized"[1] approach is heavy reliance on one or more of the following approaches: lecture-based teaching (Levin & Calcagno, 2008), drill and practice (Cox, 2015; Grubb, 2013), and routine questions absent from real-world contexts (Mesa et al., 2011). Overall, "decontextualized" instructional approaches are not conducive to creating opportunities for students to actively engage in authentic applications based on their learning (Levin & Calcagno, 2008) and

[1] We acknowledge that, in reality, very few social activities such as teaching and learning in the classroom can be described as fully decontextualized. Thus, we adopt the term from the literature but put it in quotation marks. In these "decontextualized" classes, examples from real life may well have occurred, but contextualization goes far beyond incidental utilization of real-life examples and is rather an intentional approach guiding curricular design (Valenzuela, 2018).

develop crucial conceptual knowledge and mastery toward deeper math learning (Cox, 2015; Quarles & Davis, 2017).

As an active learning approach, contextualization connects academic content (e.g., reading, writing, and/or math) with meaningful contexts that appeal to students' interests and backgrounds, which has been shown to lead to learning gains (e.g., Perin, 2013; Shrum, 2015). The National Council for Workforce Education (2010) also advocated for the adoption of contextualization given the documented evidence on its efficacy on student learning.

Math Contextualization as a Potential Gateway to Community College Student Success

Despite the importance of math preparation, success rates in both developmental and college-level math courses have been low (Chen, 2016; Rutschow, 2019). Math courses have acted more as a gatekeeper than a gateway to success, especially for underrepresented students (e.g., Bryk & Treisman, 2010). Traditionally, the aforementioned decontextualized approach characterized by an environment with little interaction among students has dominated the community college classroom (Grubb, 2001, 2010), creating a strong disconnect between the learning materials presented in class and real-life contexts (Grubb et al., 1999; Wang et al., 2017).

The extant empirical base on math contextualization at community colleges is small but growing. This literature has demonstrated the potential of contextualization to nurture more active math learning among community college students by allowing students to cultivate the connection between abstract math content with real-life experiences, where they can utilize what they learn in the moment toward true mastery (Baker et al., 2009). In addition, a qualitative study by Wang et al. (2017) revealed that math contextualization helped boost community college students' math self-efficacy beliefs by alleviating their fear of learning math.

Further, math contextualization has been shown to contribute to increased course passing rates (Wiseley, 2009) and math scores (Perin, 2011). In particular, a set of quantitative analyses by Jenkins et al. (2009) and Zeidenberg et al. (2010) compared students enrolled in the Integrated Basic Education and Skills Training (I-BEST) courses—a contextualization model that integrates basic skills education, such as math, with job-training—with similar students enrolled in non-I-BEST options, and found that I-BEST students were more likely to achieve higher scores on basic skills exams, earn college credits, or complete an occupational certificate.

Despite the initial evidence pointing to math contextualization's potential in cultivating positive learning experiences, motivational beliefs, and course performance, research is still scant on math contextualization's impact on longer-term educational outcomes of community college students above and beyond short-term progress.

Conceptual Framework

Our conceptual framework is grounded within Wang's (2017) theoretical model of momentum for community college student success while also integrating relevant higher education literature on students' educational progress in college. The momentum model offers a holistic approach to understanding community college student success. Dynamic in nature and with an intentional focus on the classroom as community college students' primary venue of engagement, the model presents important areas for community colleges to build and support positive momentum toward meaningful and successful educational experiences and outcomes for students. In terms of key domains that build momentum, the model includes three areas: a) the curricular domain that underscores continued educational progress through well-sequenced and scaffolded courses across the curricula, b) the teaching and learning domain that calls for instructional practices that foster active learning and skills to master the subject matter, and c) the motivational domain that is concerned with the development of aspirations, mindsets, perseverance and agency that support students in advancing through college.

The momentum model emphasizes the classroom as a key space of community college students' engagement with their education, thus front centering the teaching and learning domain as a vital venue through which students build momentum toward achieving their educational success (Wang, 2017). The teaching and learning domain particularly situates our study. This domain consists of two subareas: a) cognitive momentum, defined as students' "cumulative progress toward the learning and mastery of the subject matter at hand" (Wang, 2017, p. 284), which is primarily realized by classroom and other educational activities that facilitate students' thinking, understanding, and learning of the content; b) metacognitive momentum, distinct from yet complementary with cognitive momentum, refers to students' capacity to "apply strategies to regulate, adjust, adapt, and assess one's own learning" (Wang, 2017, p. 284), which is cultivated through the processes of planning, problem-solving, and self-regulation that are fundamental for establishing and maintaining academic progress. The momentum model further elucidates that active learning experiences (e.g., through a contextualized approach) are well positioned to cultivate students' cognitive and metacognitive momentum by increasing students' meaningful engagement with the subject matter and providing opportunities to apply their learning to real-world problems. Because contextualized math instruction entails approaches and strategies to support students in becoming active learners, it is a highly plausible mechanism for developing student momentum in the teaching and learning domain, which is linked to students' educational progress and success.

Also integral to conceptualizing this study is a set of individual and contextual factors that have been shown to shape community college student progress and outcomes based on prior literature. These include student background characteristics, such as gender (Ngo & Melguizo, 2020; Wang & Wickersham, 2018), race/ethnicity (Cuellar & Gándara, 2020; Y. L. Zhang et al., 2019), age (Chaves, 2006), first-generation status (Crisp & Delgado, 2014), enrollment intensity (Adelman, 2006; Leinbach & Jenkins, 2008; Wang, 2017), and prior experience with postsecondary education (Laanan & Jain, 2017; Wang, 2020). In addition, financing postsecondary education poses a major concern for community college students (Collier & Parnther, 2021; Hallett & Freas, 2018; Wang, 2020), as many students hail from a low-income background, as often indicated by their Pell eligibility (Park & Scott-Clayton, 2018; Yang, & Venezia, 2020). Also of great relevance is students' initial level of placement into a math sequence, including placement into developmental courses (Bahr et al., 2019; Kosiewicz & Ngo, 2020; Park et al., 2020; Xu & Dadgar, 2018). Community college students' progress and outcomes can be further intricately linked to their educational pathways or programs (Baber, 2018; Bailey, 2015), as well as various instructor attributes, including gender (Bettinger & Long, 2005; Stout et al., 2018), race (Fairlie et al., 2014), age (van derKaay & Young, 2012), years of teaching (Lancaster & Lundberg, 2019), along with part-time employment status (Eagan & Jaeger, 2009; Jaeger, 2008; Jaeger & Eagan, 2009).

Taken together, for community college students, a contextualized math classroom and learning environment would serve as a viable space where they could gain momentum toward achieving their educational goals. Taking into consideration other relevant factors noted above, momentum accumulated via math contextualization would not only translate into students' interim learning outcomes, such as passing the course and earning a good grade, but also would lead to improved long-term educational outcomes, including continuous enrollment, transfer, and completion of credentials.

Method

Research Site and Intervention

Research Site

This study took place at a large public community college in a Midwestern state. The college serves nearly 40,000 students, with 25% being students from underrepresented racial/ethnic backgrounds, over 50% first-generation college students, and about 50% older than the age of 24. This distribution of student demographics largely aligns with the community college student population nationally (American Association of Community Colleges, 2018a). In terms of faculty composition, similar to national trends (American Association of Community Colleges, 2018b), around 80% of the faculty at the research site are white (75% nationally). While we do not assume that this study's results will be fully generalizable to other community colleges or other states, our findings will offer relevant insights and implications for similar institutions, leaders, and faculty grappling with math instruction and contextualization as a promising solution.

Intervention

In Fall 2018, as part of the college's math professional development initiative, five math instructors adopted contextualized instruction for the first time in nine math courses they were teaching during the semester, with three of the five instructors teaching multiple math courses (two teaching two courses, one teaching three courses). In total, these nine courses enrolled 170 students. The instructors teaching these courses received prior professional training on math contextualization that places an intentional and explicit focus on connecting math instruction to real-world applications and engaging students to problem solve in contexts meaningful to them. Both the training and application of contextualization were guided by the working definition: "Contextualization is the design of curriculum AND the way the curriculum is delivered that provides students with the opportunity to engage in 'real work.'" This meant that both the design of the curriculum and the delivery of it through instruction intentionally prioritize activities and content that require students to work on realistic, relevant concepts they would encounter in authentic career and life contexts.

Treatment and Control Conditions

Enrollment in the nine contextualized math courses in Fall 2018 constituted the treatment condition, whereas the "counterfactual" condition involved enrollment in traditional math courses that were taught *without* an intentional goal to contextualize. More specifically, contextualized math courses were characterized by the following two key features that distinguished them from other math courses offered at the college during the same time: First, the contextualized courses followed a curriculum that centered on several common learning outcomes: understanding and applying math concepts, learning about the context, learning/practicing skills critical for real work, questioning, estimating, engaging in discussion, and challenging students themselves to *figure it out*. Second, aligned with these key learning outcomes, the contextualized math courses explicitly integrated in the curriculum predetermined structures, opportunities, and activities to engage students in authentic applications of math content within real-life contexts on a regular and systematic basis. The math courses constituting the control condition were the ones that were taught "business as usual" without these intentional features indicated above.

Study Sample and Data

Data Structure and Sample

Our dataset featured a four-level structure, namely course record, student, course, and instructor levels, each nested within the next level. For the treatment condition, 170 students enrolled in nine contextualized courses taught by five instructors, for a total of 170 course records. No students were enrolled in multiple contextualized courses. For the control condition, 4383 students enrolled in 271 traditional courses taught by 111 instructors, for a total of 4878 course records due to multiple enrollments in traditional courses. Given the fairly small number of contextualized courses and instructors who taught contextualized courses, analysis at the instructor or course level would suffer severely from loss of statistical power. Thus, we decided to focus our analysis at the course record and student levels to ensure adequate statistical power while truthfully answering our research questions, with course performance analyzed at the course record level and other outcome measures analyzed at the student level.

For the course record level analysis, an important issue to address is concurrent enrollment in multiple courses by the same student. In our data, 290 students enrolled in multiple courses during the same term, with 41 enrolled in both contextualized and non-contextualized courses and 249 enrolled in multiple non-contextualized courses. We detail our procedures for handling this issue later under the data analysis section. The course record-level and student-level information is provided in Table 1, where we also describe the study's variables in detail.

The college's institutional research office provided available administrative data that included students' background data and transcript records, instructors' characteristics, as well as course attributes. Data from the National Student Clearinghouse (NSC) were also included to measure student attainment of postsecondary credentials and transfer. A detailed description of the study measures follows.

Outcome Measures

Based on our research questions, we examined the following interim and longer-term outcomes. Interim outcome measures included course grade and Fall 2018 term GPA, and longer-term outcomes were represented by students' cumulative GPA, continuous enrollment, credential completion, and/or upward transfer as of Fall 2019.

Table 1 Descriptive data of full course records and student sample

	Students/records (Treatment group)		Students (Control group)		Course records (Control group)	
Students	170	(3.80%)	4300	(96.20%)		
Course records	170	(3.49%)			4878	(96.63%)
Student attributes						
Race/ethnicity						
White	107	(62.94%)	2533	(58.91%)	2586	(59.00%)
Students of Color	63	(37.06%)	1767	(41.09%)	1797	(41.00%)
Native American	1	(0.59%)	24	(0.56%)	25	(0.57%)
Asian	8	(4.71%)	265	(6.16%)	269	(6.14%)
African American	10	(5.88%)	451	(10.49%)	455	(10.38%)
Hawaiian/Pacific Islander	0	(0.00%)	2	(0.05%)	2	(0.05%)
Hispanic	25	(14.71%)	678	(15.77%)	694	(15.83%)
Multi-Racial	14	(8.24%)	259	(6.02%)	262	(5.98%)
Unknown	5	(2.94%)	88	(2.05%)	90	(2.05%)
Sex						
Male	113	(66.47%)	2038	(47.40%)	2103	(47.98%)
Female	57	(33.53%)	2262	(52.60%)	2280	(52.02%)
Age						
Under 24	135	(79.41%)	2943	(68.46%)	3003	(68.53%)
24 and older	35	(20.59%)	1356	(31.54%)	1379	(31.47%)
First-generation student						
Yes	88	(51.76%)	2632	(61.21%)	2681	(61.17%)
No	82	(48.24%)	1668	(38.79%)	1702	(38.83%)
FAFSA filing status						
No	76	(44.71%)	1820	(42.33%)	1855	(42.32%)
Yes	94	(55.29%)	2480	(57.67%)	2528	(57.68%)
Pell eligibility						
Not eligible	38	(22.35%)	846	(19.67%)	867	(19.22%)
Eligible	56	(32.94%)	1634	(38.00%)	1661	(37.90%)
Unknown	76	(44.71%)	1820	(42.33%)	1855	(42.32%)
Enrollment intensity						
Full-time	124	(72.94%)	2324	(54.05%)	2386	(54.44%)
Less than full-time	46	(27.06%)	1976	(45.95%)	1997	(45.56%)
Academic plan track						
Liberal arts transfer	44	(25.88%)	2231	(51.88%)	2240	(51.11%)
Technical education	74	(43.53%)	340	(7.91%)	398	(9.08%)
Undeclared	52	(30.59%)	1729	(40.21%)	1745	(39.81%)
Math preparation						
Developmental	56	(32.94%)	1490	(34.65%)	1531	(34.93%)
College ready	70	(41.18%)	1524	(35.44%)	1555	(35.48%)
No placement	44	(25.88%)	1286	(29.91%)	1297	(29.59%)
Returning student						
No	85	(50.00%)	1694	(39.40%)	1734	(39.56%)

Table 1 (continued)

	Students/records (Treatment group)		Students (Control group)		Course records (Control group)	
Yes	85	(50.00%)	2606	(60.60%)	2649	(60.44%)
Prior postsecondary credential						
No	166	(97.65%)	4128	(96.00%)	4211	(96.08%)
Yes	4	(2.35%)	172	(4.00%)	172	(3.92%)

	Treatment group		Control group	
Course attributes	9	(3.21%)	271	(96.79%)
Course offering unit				
Offered by math department	6	(66.67%)	146	(53.87%)
Offered by technical programs	3	(33.33%)	28	(10.33%)
Required technical ed course				
Yes	5	(55.56%)	48	(17.71%)
No	4	(44.44%)	223	(82.29%)
Instructor characteristics	5		111	
Race/ethnicity				
White	4	(80.00%)	91	(81.98%)
Faculty of Color	1	(20.00%)	20	(18.02%)
Asian	1	(20.00%)	5	(4.50%)
African American	0	0	1	(0.90%)
Hispanic	0	0	6	(5.41%)
Did not identify	0	0	8	(7.21%)
Sex				
Male	4	(80.00%)	64	(57.66%)
Female	1	(20.00%)	47	(42.34%)
Employment status				
Full-time	2	(40.00%)	26	(23.42%)
Part-time	3	(60.00%)	85	(76.58%)
Age	53.40	(5.59)	54.31	(11.03)
Years teaching at the college	11.20	(4.18)	12.75	(8.24)

Covariates

Based on the conceptual framework and prior literature we delineated earlier, we included a set of covariates that reflect students' background characteristics as well as instructor and course attributes. Students' background consisted of demographic information (i.e., sex, race/ethnicity, age, first-generation status), financial need, enrollment intensity, academic plan track, math preparation, and previous postsecondary enrollment and credentials. Course-level covariates included whether the course was offered in the math department or a technical education program and whether the course counted toward a technical education degree. At the instructor-level, race/ethnicity, sex, employment status, age, and years of teaching at the college were included. See Table 1 for a full list and description of the variables.

Data Analysis

We adopted a matching approach to construct comparable treatment and control groups to reduce the bias of the treatment effect estimation since randomization was not feasible (Holmes, 2013). Although the "gold" standard to evaluate the treatment effect is randomization, in which students would be randomly assigned to the contextualized courses and traditional courses, it was not a realistic approach at the research site, as is the case in many education settings. Student self-selection into the treatment and control conditions may reflect their preexisting differences, introducing bias into the estimation of the treatment effect. To mitigate this concern, we first identified the treatment and control groups based on all available background covariates, followed by an outcome analysis using the matched groups (Stuart, 2010).

Genetic Matching

For both course record-level and student-level analyses, we adopted the genetic matching algorithm to identify a control group, a subset of units in the control condition that was most comparable with their counterparts in the contextualized courses, to estimate the average treatment effect of the treated. Developed by Diamond and Sekhon (2013), the genetic matching algorithm is a multivariate matching method that adopts non-parametric generalization of Mahalanobis distance matching (MDM) to achieve the balance of observed covariates between treatment and control groups. This matching approach directly takes into account all covariates *as well as* their interactions by computing the Mahalanobis distance, thus accounting for the covariance of included covariates. Therefore, it tends to produce exact or close to exact pairs, which is an ideal scenario of estimating causal inference since these pairs form the treated and control groups with a more balanced multivariate distribution of the covariates (Stuart, 2010). Recent research has shown that multivariate matching performs at least similarly or better than univariate matching that is typically used in propensity score matching (PSM) approaches (e.g., nearest neighbor matching, radius matching, and kernel matching) in reducing imbalance (Baser, 2006; King & Nielsen, 2019), but requires a large number of units under the control condition, which is the case for our study. The high control to treatment sample size ratio (over 25) of our study provided an excellent condition for the adoption of genetic matching to produce a sufficient number of matched pairs with the closest possible similarity to each other.

In genetic matching, the generalized Mahalanobis distance between course record/student i and j was defined as follows:

$$\left(X_i, X_j\right) = \left\{ \left(X_i - X_j\right)^T S^{-\frac{1}{2}} W S^{-\frac{1}{2}} \left(X_i - X_j\right) \right\}^{\frac{1}{2}}$$

where X_i and X_j were the covariate values of course record/student i and j, respectively, W was a positive definite weight diagonal matrix, and $S^{\frac{1}{2}}$ was the Cholesky decomposition of the sample variance–covariance matrix of the full control group. By choosing the elements of W, the genetic matching approach weighted each variable according to its relative importance for achieving the best overall balance, which was measured by paired t-tests and non-parametric Kolmogorov–Smirnov (KS) tests between the matched groups, thus optimizing the overall covariate balance (Stuart, 2010). The *W* included the inverse of the variances of covariates.

We employed the genetic matching algorithm to construct analytical samples specific to the level of outcomes and performed 1 to 1 matching with replacement. We adopted 1 to 1 matching since increasing the number of control group units may only lead to limited increment of power that is largely driven by the smaller group size, which is often the treatment group (Cohen, 1988; Stuart, 2010, 2020), as was the case in our study. Further, the genetic matching approach we used facilitates exact or close to exact matching in producing the treatment and control groups. Thus, adopting a high control to treatment sample size ratio in matching may include poor matches that may increase bias (Rubin & Thomas, 2000). To further ensure that our results were robust to different matching scenarios, we also examined 2 to 1 and 5 to 1 matching. For both student- and course record-level matching, the 5 to 1 matching approach did not achieve balance on covariates, with at least one covariate having a standardized mean difference (SMD) value greater than 0.1. For the 2 to 1 matching approach, we were able to achieve balance. Across both scenarios, the relationship between exposure to math contextualization and outcomes that we uncovered based on the 1 to 1 matched sample generally held. Essentially, our course record-level and student-level analyses were based on 170 matched pairs of course records and 170 matched pairs of students, respectively. Due to the complexity of the data structure described earlier, we implemented matching through different procedures that were appropriate for the level of data. For course records, we first identified the 41 students enrolled in both contextualized and traditional courses whose course records from traditional classes served as optimal matches for their course records in contextualized courses. For the remaining 129 students without overlapping enrollment, we then adopted genetic matching by identifying matches in the control group. Matching at the student level was more straightforward, as each student was a unique unit of analysis. We conducted all matching procedures using the R package, Matching (Sekhon, 2011).

We examined the SMD to identify the covariate balance between the groups after matching (Austin, 2009; Harder et al., 2010). More specifically:

$$\mathrm{SMD} = \frac{\hat{p}_{treatment} - \hat{p}_{control}}{\sqrt{\frac{\hat{p}_{treatment}\left(1-\hat{p}_{treatment}\right)+\hat{p}_{control}\left(1-\hat{p}_{control}\right)}{2}}}$$

where $\hat{p}_{treatment}$ and $\hat{p}_{control}$ refer to the probability of being in a specific category (e.g., White) in treatment and control groups. A covariate was considered balanced if the SMD value was smaller than 0.1 (Z. Zhang et al., 2019).

Note that the common support of propensity scores, a prevalent approach to evaluating the quality of propensity score matching (PSM), was not appropriate for our study that used genetic matching. In PSM, each course record's/student's probability of being in the treatment group would be derived by summarizing all covariates into one scalar (Rosenbaum & Rubin, 1983), followed by matching the treatment and control cases according to their distance of propensity scores. However, we conducted genetic matching with the generalized Mahalanobis distance, which was computed using all covariates directly without summarizing the covariates into a single measure. Thus, drawing a single dimension plot to show common support was not appropriate in our study.

Outcomes Analysis

Following genetic matching, we applied a set of ordinal, linear, and multinomial logistic regression analyses on the matched sample to investigate the relationship between exposure to math contextualization and a range of interim and longer-term outcomes with covariates to further reduce bias and standard error (Rubin, 1979). For course record-level analysis, we further adjusted for instructor-level covariates. Course grade was analyzed using ordinal regression given the ordinal nature of the outcome. Term GPA and cumulative GPA were analyzed using linear regression since the measures had more than 10 values. One-year educational progress and attainment were analyzed using multinomial regression given the categorical nature of the outcome variable.

Because our matched data were not independent given the data structure, we estimated sampling errors through bootstrapping with 1,000 replications to obtain reliable results. Within each replication, each pair of treatment and control course records/students was bootstrapped to maintain the balance of covariates. Three commonly used significance levels, 0.05, 0.01, and 0.001, were used to detect the level of statistical significance of the coefficients.

We implemented the set of regression analyses using the R software (R Core Team, 2019). We conducted linear regression and logistic regression analysis using the base R program, and ordinal and multinomial regression analysis using the MASS and nnet package, respectively (Venables & Ripley, 2002).

Sensitivity Analysis

One of the most important assumptions of matching is the ignorability of treatment assignment (Rosenbaum & Rubin, 1983), which indicates that there is not an unobserved confounder that relates to: a) the probability of being in the treatment group while accounting for all observables, and b) the outcome of interest when controlling for the probability of being in the treatment as well as the observed covariates. The ignorability assumption cannot be fully verified given the unobserved nature of such a confounder (Pearl, 2009). Thus, we followed Cinelli and Hazlett (2020) to evaluate the sensitivity of our findings to the existence of an unobserved confounder. Specifically, the two crucial correlations mentioned above were transformed into two partial R-squared values, which introduced the robustness value (RV)—the amount of the residual variance of both selection into treatment and the outcomes to be explained by the unobserved confounder. The RV ranges from 0 to 1. An RV close to 1 indicates that the treatment effect is strong to the extent that even the existence of a confounder that explains close to 100% of the residuals would not change the conclusion. In contrast, an RV close to 0 indicates that a weak confounder may change the conclusion.

Results

Results From Matching

The 170 course records and 170 students in the treatment condition were successfully matched. Table 2 details the results from the balancing test by providing the marginal distributions of the covariates and the SMD values pre- and post-matching. Overall, the balance of marginal distributions of all covariates was improved after matching. For instance, for matching at the level of course records, the largest absolute SMD value decreased from 0.75 (pre-matching) to 0.08 (post-matching). For matching at the student level, the largest absolute SMD value decreased from 0.89 (pre-matching) to 0.05 (post-matching).

Results From Regression Analyses

Table 3 details results from our regression analyses based on the matched sample (derived from genetic matching using the covariates described in Table 2). To account for additional imbalance between the treatment and control groups after matching, we included in the regression models a set of student-, course-, and instructor-level covariates. Regression adjustment using covariates can further reduce bias due to remaining imbalance between the treatment and control groups after matching (Rubin, 1979; Rubin & Thomas, 2000). Covariates that are statistically significant further help explain the outcome variables included in regression adjustment based on a matched sample. Overall, we identified a statistically significant positive relationship between enrollment in contextualized math courses and all outcome measures except a null effect on transfer, holding constant the set of covariates included in the models.

From the ordinal regression, exposure to math contextualization was associated with greater math course performance. The odds of passing (relative to failing) the class and earning higher grades for the contextualized courses is estimated to be 2.55 times the odds for traditional courses when holding other covariates constant. Exposure to math contextualization was also associated with higher term GPA, holding all covariates constant. When looking at longer-term outcomes, enrollment in a contextualized course was related to a higher latest cumulative GPA, as well as greater odds of continuous enrollment (odds ratio value of 1.70) and credential completion (odds ratio value of 3.16), relative to enrollment in a traditional course.

Here we offer some additional details regarding the regression results pertaining to the covariates included in our models. Except part-time enrollment, which had a persistent negative association with all outcome measures, other covariates demonstrated potentially nuanced roles depending on the specific outcome under consideration. For instance, holding other variables constant, race/ethnicity and gender did not turn out to be significant predictors for the outcome measures, except that Students of Color had lower course performance compared with their White counterparts. In addition, older students performed better than their younger counterparts in terms of course grade, term GPA, and cumulative GPA. Compared with those without a declared academic plan track, students on the technical education track had higher term GPA, cumulative GPA, and a higher likelihood to complete a credential; whereas students on the transfer track were more likely to transfer. In addition, returning students were more likely to have a higher cumulative GPA and to transfer, compared with students who started as new freshmen. Also interesting to note, students enrolled in courses taught by younger faculty or part-time instructors tended to receive a higher course grade. For the full set of detailed results from the regression analyses, see Table 3.

Results From Sensitivity Analysis

Results from our sensitivity analysis showed that the estimated contextualization effects would reduce to 0 when the unobserved confounder explained 10% to 17% of the residual variance of both treatment assignment and outcomes; our conclusion would change if the unobserved confounder explained less than 0.01% to 7% of both the residual variances of the treatment assignment and outcomes under the specific sample size. While there are no established, steadfast criteria to evaluate robustness, these residual variance values appear to fall below a reasonably small maximum value. The effect of contextualization on continuous enrollment was the most vulnerable one to an unobserved confounder. In contrast, the contextualization effect on the course grade was the most robust one.

The two RVs of each outcome are listed in Table 4. The contour plots of the RVs are shown in Figs. 1, 2.

Discussion

In this study, we examined the link between exposure to math contextualization and community college students' interim and longer-term educational outcomes. Using genetic matching, we constructed a balanced sample consisting of students enrolled in contextualized courses and their similar counterparts in traditional math courses. We further compared the educational outcomes of this matched sample using a set of regression analyses. Our findings revealed that the students enrolled in contextualized math courses had significantly improved course performance and educational progress and attainment.

The largely positive associations between enrollment in contextualized math courses and student outcomes suggest that, when delivered through a contextualized approach, math is less likely to be a barrier to student success. Contextualization may serve as a powerful tool in improving math success and furthering community college student progress. In light of our conceptual framework, our findings as a whole suggest that contextualized math may indeed act as a generative mechanism for students to accrue momentum toward greater math performance and achieving longer-term college success. For example, our study demonstrates the potential of contextualization to boost curricular momentum in terms of enrollment continuity (Wang, 2017), which supports progression toward credential completion.

Math Contextualization's Immediate and Enduring Role

The positive link between exposure to math contextualization and course performance as indicated in students' course grades and passing rates lends additional support to the small research base (e.g., Wiseley, 2009) and further establishes math contextualization as a significant predictor of immediate academic gains in math. This immediate boost in students' course performance suggests that contextualized math instruction may rapidly and effectively translate into learning conditions conducive to positive math attitudes and learning experiences. As one of the proximal indicators of, and building blocks toward, longer-term academic success, a student's course performance signals, albeit imperfectly, how much they have learned and where they are with regard to attaining their educational goals. Consequently, stronger course performance uncovered in our study not only signals an important short-term benefit of contextualized math instruction, but it also serves as a significant marker of long-term college success. This is especially tenable given the close relationship between passing college-level math courses and college outcomes (e.g., Belfield et al., 2019; Calcagno et al., 2007; Cohen & Kelly, 2019), further reinforced by the

Table 2 Results from balancing tests

	Marginal distributions based on course record data					
	Pre-matching			Post-matching		
	Control group	Treatment group	SMD	Control group	Treatment group	SMD
Student-level covariates						
Student of Color	41.42%	37.06%	– 0.09	35.29%	37.06%	0.04
Female	50.00%	33.53%	– 0.34	30.00%	33.53%	0.08
24 and older	32.39%	20.59%	– 0.27	20.59%	20.59%	0.00
First-generation	61.38%	51.76%	– 0.20	54.12%	51.76%	-0.05
FAFSA filed	57.84%	55.29%	– 0.05	52.94%	55.29%	0.05
Pell eligible	38.02%	32.94%	– 0.11	32.35%	32.94%	0.01
Developmental level	35.03%	32.94%	– 0.04	31.76%	32.94%	0.03
No math placement	29.59%	25.88%	– 0.08	24.71%	25.88%	0.03
Less than full-time	44.35%	27.06%	– 0.37	24.71%	27.06%	0.05
Technical education	12.04%	43.53%	0.75	43.53%	43.53%	0.00
Liberal arts transfer	49.15%	25.88%	– 0.50	26.47%	25.88%	-0.01
Returning student	59.98%	50.00%	– 0.20	51.76%	50.00%	-0.04
Prior postsecondary credential	3.89%	2.35%	– 0.09	2.35%	2.35%	0.00
Course-record-level covariates						
Offered by technical programs	6.97%	25.29%	0.51	25.29%	25.29%	0.00
Required technical ed course	10.45%	37.06%	0.66	37.06%	37.06%	0.00
	Marginal distributions based on student data					
	Pre-matching			Post-matching		
	Control group	Treatment group	SMD	Control group	Treatment group	SMD
Student-level covariates						
Student of Color	41.09%	37.06%	– 0.08	34.71%	37.06%	0.05
Female	52.60%	33.53%	– 0.39	31.18%	33.53%	0.05

Table 2 (continued)

	Marginal distributions based on student data					
	Pre-matching			Post-matching		
	Control group	Treatment group	SMD	Control group	Treatment group	SMD
24 and older	31.53%	20.59%	− 0.25	20.59%	20.59%	0.00
First-generation	61.21%	51.76%	− 0.19	51.76%	51.76%	0.00
FAFSA filed	57.67%	55.29%	− 0.05	54.71%	55.29%	0.01
Pell eligible	38.00%	32.94%	− 0.11	32.94%	32.94%	0.00
Developmental level	34.65%	32.94%	− 0.04	32.94%	32.94%	0.00
No math placement	29.91%	25.88%	− 0.04	24.71%	25.88%	0.03
Less than full-time	45.95%	27.06%	− 0.40	25.88%	27.06%	0.03
Technical education	7.91%	43.53%	0.89	43.53%	43.53%	0.00
Liberal arts transfer	51.88%	25.88%	− 0.55	28.24%	25.88%	− 0.05
Returning student	60.60%	50.00%	− 0.21	51.18%	50.00%	− 0.02
Prior postsecondary credential	4.00%	2.35%	− 0.09	2.35%	2.35%	0.00

SMD (standardized mean difference) value refers to the mean difference of the marginal distributions between the treatment and control group after being standardized by the joint standard deviation. Marginal distributions refer to the probability of being in the treatment or control group after matching. Reference category of each covariate is omitted from the table. The pre-matching and post-matching sample size of the control group is 4,878 and 170 respectively, and the sample size of the treatment group is 170 both pre- and post-matching

Table 3 Results from regression analysis

Dependent variable (n = 340/ 170 pairs)	Interim outcomes					Longer-term outcomes	
	Course performance			Term GPA		Latest cum GPA	
	B	(SE)	Odds Ratio	*B*	(SE)	*B*	(SE)
Intercept				2.26	(0.19)***	2.21	(0.17)***
$\geq C$	2.94	(0.77)***	18.95				
$\geq B$	1.86	(0.76)**	6.42				
$\geq A$	0.31	(0.74)	1.36				
Treatment							
Overall effect Contextualization	0.94	(0.28)***	2.55	0.39	(0.12)**	0.27	(0.10)**
Student-level covariates							
Student of Color	– 0.61	(0.27)*	0.54	– 0.06	(0.14)	– 0.12	(0.11)
Female	0.27	(0.30)	1.32	0.32	(0.16)	0.24	(0.13)
24 and older	1.19	(0.37)***	3.29	0.71	(0.15)***	0.65	(0.13)***
First-generation student	– 0.38	(0.26)	0.68	– 0.16	(0.13)	– 0.10	(0.11)
FAFSA filed	– 0.42	(0.37)	0.65	– 0.02	(0.18)	0.12	(0.12)
Pell eligible	– 0.30	(0.38)	0.74	– 0.11	(0.18)	– 0.16	(0.14)
Developmental	– 0.72	(0.32)*	0.49	– 0.11	(0.15)	– 0.11	(0.11)
No placement	0.03	(0.34)	1.03	– 0.13	(0.17)	– 0.18	(0.15)
Less than full-time	– 1.40	(0.32)***	0.25	– 0.91	(0.18)***	– 0.56	(0.13)***
Technical education	– 0.04	(0.39)	0.96	0.51	(0.16)**	0.42	(0.13)**
Liberal arts transfer	0.04	(0.33)	1.04	0.24	(0.18)	0.28	(0.15)
Returning student	– 0.04	(0.25)	0.96	0.06	(0.13)	0.22	(0.11)*
Prior postsecondary credential	– 0.46	(2.24)	0.63	0.26	(0.35)	0.39	(0.32)
Course-level covariates							
Offered by technical programs	– 0.91	(0.59)	0.40				
Required technical ed course	0.34	(0.61)	1.40				

Table 3 (continued)

Dependent variable (n = 340/ 170 pairs)	Interim outcomes					Longer-term outcomes	
	Course performance			Term GPA		Latest cum GPA	
	B	(SE)	Odds Ratio	*B*	(SE)	*B*	(SE)
Instructor-level covariates							
Faculty of Color	– 0.37	(0.45)	0.69				
Female	0.22	(0.38)	1.24				
Age (by year)	– 0.07	(0.25)*	0.93				
Part-time	1.93	(0.87)*	6.89				
Years teaching at the college	0.01	(0.03)	1.01				

Dependent variable (n = 340 / 170 pairs)	Longer-term outcomes								
	Continuous enrollment (n = 127)			Credential completion (n = 48)			Upward transfer (n = 13)		
	B	(SE)	Odds Ratio	*B*	(SE)	Odds Ratio	*B*	(SE)	Odds Ratio
Intercept	– 0.57	(0.38)	0.57	– 3.56	(0.71)***	0.03	– 4.23	(92.58)**	0.01
Treatment									
Overall effect									
Contextualization	0.53	(0.29)*	1.70	1.15	(0.44)**	3.16	– 0.51	(13.20)	0.60
Student-level covariates									
Student of Color	– 0.18	(0.33)	0.84	0.10	(0.48)	1.11	– 0.65	(32.90)	0.52
Female	0.30	(0.34)	1.35	0.55	(0.54)	1.73	– 0.86	(23.90)	0.42
24 and older	0.40	(0.44)	1.49	0.58	(0.65)	1.79	1.51	(29.36)	4.53
First-generation students	– 0.20	(0.27)	0.82	0.30	(0.43)	1.35	– 0.42	(43.88)	0.66
FAFSA filed	0.08	(0.33)	1.08	0.37	(0.55)	1.45	– 0.23	(21.84)	0.79

Table 3 (continued)

Dependent variable (n = 340 / 170 pairs)	Longer-term outcomes								
	Continuous enrollment (n = 127)			Credential completion (n = 48)			Upward transfer (n = 13)		
	B	(SE)	Odds Ratio	*B*	(SE)	Odds Ratio	*B*	(SE)	Odds Ratio
Pell eligible	− 0.14	(0.38)	0.87	0.31	(0.55)	1.36	1.03	(32.19)	2.80
Developmental	0.00	(0.33)	1.00	0.33	(0.46)	1.39	− 0.76	(35.63)	0.47
No placement	− 0.54	(0.38)	0.58	0.73	(0.57)	2.08	0.01	(27.37)	1.01
Less than full-time	− 0.97	(0.35)**	0.38	− 1.49	(0.81)***	0.23	− 2.93	(37.01)*	0.05
Technical education	0.43	(0.34)	1.54	1.55	(0.53)***	4.71	− 0.10	(29.62)	0.90
Liberal arts transfer	0.57	(0.37)	1.77	− 0.14	(2.37)	0.87	2.62	(55.56)*	13.74
Returning student	0.40	(0.28)	1.49	0.36	(0.43)	1.43	2.18	(49.48)*	8.85
Prior postsecondary credential	− 0.69	(8.17)	0.50	− 14.98	(92.85)*	0.00	− 15.63	(107.79)	0.00

B stands for the regression coefficient of the original data. SE stands for the empirical standard error from 1000 bootstrapping replications. ***, **, * stand for the significance levels 95%, 99%, and 99.9% respectively

Table 4 Results from robustness check

Analysis	Outcome	Robustness value (% of residual variance explained)	
		Bring point estimate to 0	Bring corresponding $p-$ value > .05
One	Course performance	17.00%	7.31%
Two	Term GPA	16.09%	6.42%
Three	Latest cumulative GPA	13.55%	3.58%
Four	Continuous enrollment	9.85%	< 0.01%
	Credential completion	13.45%	3.46%

Robustness checks were conducted for significant *B*s only

larger literature pointing to students' academic performance as one of the most consistent predictors of college persistence and completion (e.g., Sass et al., 2018; Y. L. Zhang et al., 2019).

Our results further resonate with and extend prior research on broader math reforms or curricular models aimed at improving community college student outcomes. Often encompassing contextualized math instruction as one of the components, these initiatives have been empirically shown to be positively linked to community college students' completion of developmental math coursework and academic milestones such as advancing to the next math level, enrolling in and completing college-level math, declaring a major, and accumulating college credit (Cox, 2015; Ngo, 2019; Quarles & Davis, 2017; Schudde & Keisler, 2019; Yamada et al., 2018). Our finding not only lends further credibility to the utility of math contextualization in the reforms, but also highlights it as a potential key ingredient for these reforms' success. In this sense, our study offers deepened and nuanced insights into the generalizability of these positive findings regarding broad-scale reforms by isolating the refined connection between math contextualization and community college student outcomes. That is, while large-scale, evidence-based reforms may be ideal, highly promising instructional strategies such as contextualization can lead the way and serve as a jumping-off point toward larger initiatives or reforms in community colleges. Indeed, our study's finding shows that it is highly plausible that the various types of momentum—cognitive, metacognitive, and motivational (Wang, 2017)—as a result of exposure to math contextualization transmit beyond a single course and extend into ongoing, broader ways in which students navigate postsecondary education and stay more motivated to persist.

Implications for Policy and Practice

Several implications emerged from our study. First, in light of its largely positive relationship with students' outcomes that we uncovered in our study, the adoption of math contextualization appears to be a viable and logical step toward fostering fruitful math learning experiences and educational success among community college students. This recommendation is further backed by promising empirical evidence from recent larger-scale math reforms that integrate math contextualization as one of the components. However, in practice, a contextualized approach is concerningly underutilized (Jenkins et al., 2018; Wang et al., 2017; Wiseley, 2009). Further complicating this problem is that, even when

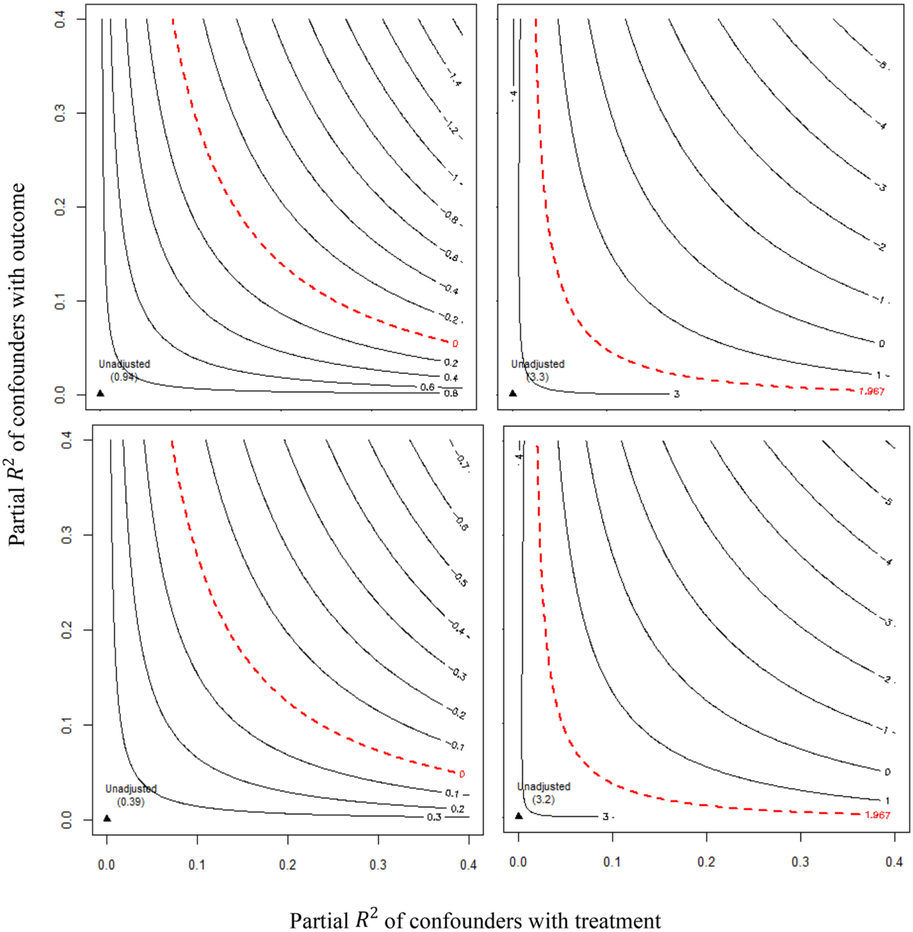

Fig. 1 Sensitivity contour plots for treatment effect on course performance and term GPA. Upper panels: course performance; lower panels: term GPA; left panel: point estimate; right panel: t− value. The red lines show the partial R^2 of the unobserved confounder with treatment and outcome when the point estimate decreases to 0 or the − value > 0.05. Thus, the red line close to the bottom left indicates that the treatment effect was vulnerable; the red line close to the top right indicates that the treatment effect was robust (Color figure online)

contextualization is adopted, the involved courses and programs often concentrate within career and technical education, which does not align with the broad range of educational pathways that mirror an inclusive set of community college students' educational goals, notably transfer (Wang, 2020). In future endeavors, community colleges should not only promote the adoption of math contextualization, but also be particularly intentional about broadening program, instructor, and student access to impactful evidence-based instructional practices such as math contextualization.

Second and related, we are calling for inclusive and motivating institutional policies that encourage practicing contextualization and active learning more broadly. One common challenge in instructional change, in this case encouraging faculty to potentially reform their instruction by moving away from a "decontextualized" tradition, requires significant

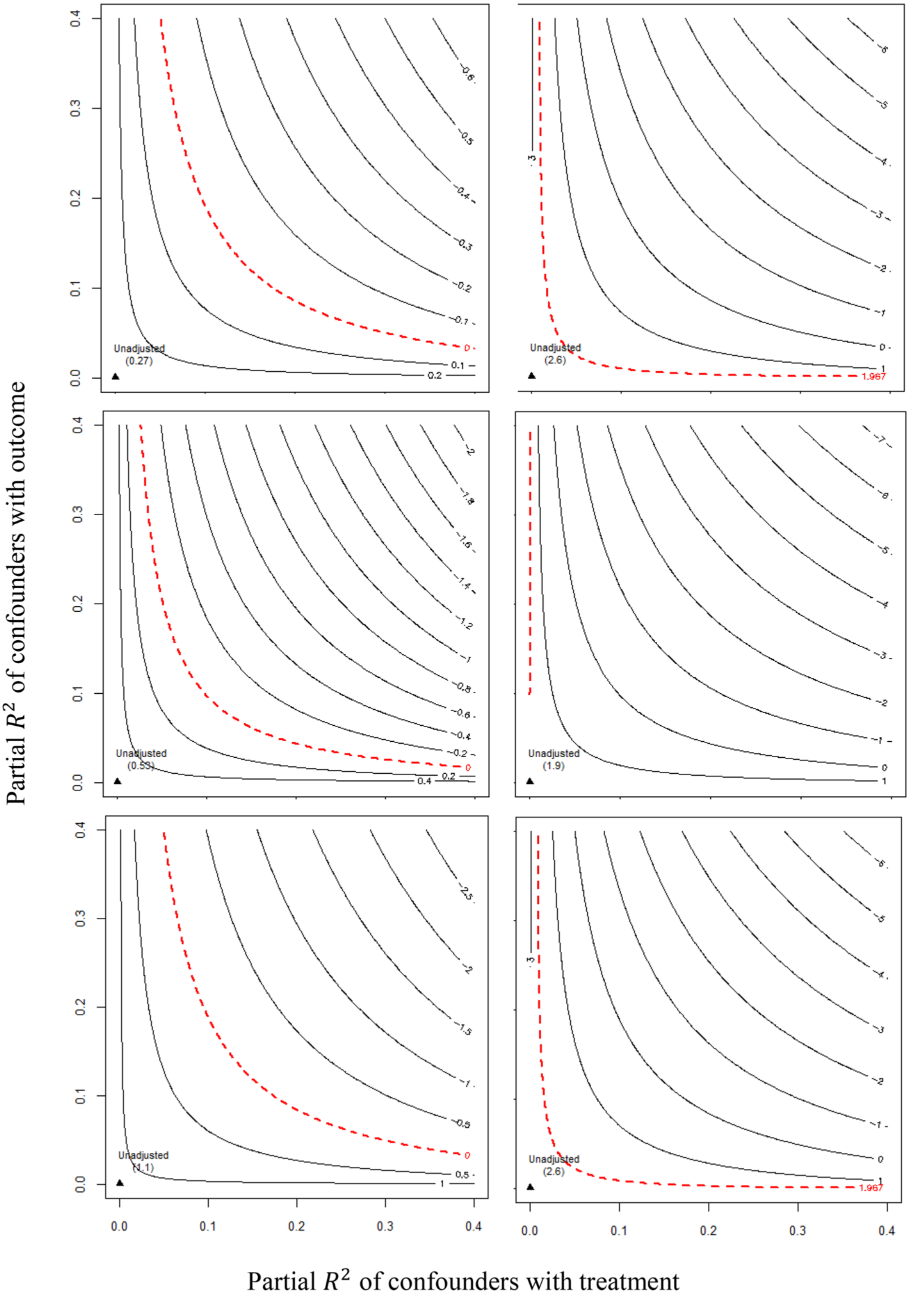

Fig. 2 Sensitivity contour plots for latest cumulative GPA and one− year educational attainment (Continuous Enrollment and Credential Completion). Upper panels: cumulative GPA; middle panels: continuous enrollment; lower panels: credential completion; left panel: point estimate; right panel: t− value. The red lines show the partial R^2 of the unobserved confounder with treatment and outcome when the point estimate decreases to 0 or the − value > 0.05. Thus, the red line close to the bottom left indicates that the treatment effect was vulnerable; the red line close to the top right indicates that the treatment effect was robust (Color figure online)

amounts of time, patience, and professional development. The effort involved may look intimidating in early phases; thus, effective and equitable use of resources becomes critical. This also means that instructional change should not fall solely on faculty. Instead, it should be a collective institutional endeavor. An open collaboration among faculty, administrators, and institutional researchers is pivotal for facilitating relationships, data, tools, support, and development opportunities toward effective change.

Third, it bears great potential to think beyond a singular "high-impact" contextualized math course and move toward cultivating a larger institutional environment that sustains and amplifies the positive effect of contextualization. For instance, since dynamic, meaningful interactions between faculty and students are critical in contextualization practices (Baker et al., 2009; Perin, 2011), institutions should identify and cultivate additional venues beyond the classroom through which faculty and students can interact and communicate. For instance, similar to many other community colleges, the faculty at our research institution have close ties to industry, which represents a viable opportunity to facilitate contextualized learning by drawing upon industry perspectives, contexts, and examples. These extended opportunities could further solidify contextualization's positive effect through strengthened engagement with faculty, a highly predictive factor contributing to community college students' improved short- and long-term outcomes (Schudde, 2019).

Study Limitations and Areas for Future Research

Our study also contains a number of limitations and highlights areas for future research on this topic. To begin, given sample size constraints, we were unable to test the potentially heterogenous effects of different contextualization strategies. This represents a significant direction for future research, as instructional strategies and approaches are profoundly nuanced and diverse, even within the same larger umbrella term of contextualization. Future inquiries that tease out different contextualization strategies in relation to students' learning and outcomes will provide concrete evidence that allows practitioners, researchers, and policymakers to compare particular strategies and make well-informed decisions.

Similarly, given the small subsample sizes in terms of students' race/ethnicity, our quantitative analysis was not able to disaggregate Students of Color into their distinct racial/ethnic backgrounds. Especially given the glaring racial disparities and inequities in community college students' educational outcomes (Crisp & Nuñez, 2014; Jenkins et al., 2018; Moore & Shulock, 2010; Wang, 2020), it is critically important to examine how students from underrepresented groups are affected by interventions and practices designed to benefit all students to ensure that they do not merely serve to advantage those already advantaged (Wang, 2020). Future research on math contextualization should continue to adopt a more disaggregated approach to unpacking racial nuances and differences to fully understand the impact of educational practices on the outcomes of all students, but particularly those historically underserved.

Conclusion

Our study uncovered a positive association between exposure to contextualized math and student outcomes, which illuminates contextualization's potential in empowering students to gain momentum through classroom teaching and learning. This promising relationship may extend into other domains of students' education where they can gain momentum in support of their longer-term success. Future research will benefit from a deeper understanding of math contextualization's impact on the holistic range of spaces where students can gain momentum for improved math performance and college success, as well as adopting a more nuanced approach to unraveling potential (in)equities in the implementation of contextualization and its impact across student subpopulations, especially racially minoritized students.

Overall, our study offers quantitative evidence in support of contextualization as a viable instructional approach to addressing the academic barriers that community college students experience in math, as well as broader adoption of contextualization approaches within larger-scale math reforms at community colleges. Contextualization holds potential value as an integral part of the academic support system that can turn math courses into a gateway, instead of a gatekeeper, for the many historically underserved students concentrated at community colleges.

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