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Developmental Education in North Carolina Community Colleges

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Abstract

This paper contributes to the empirical literature on remediation in community colleges by using policy variation across North Carolina's community colleges to examine how remediation affects various outcomes for traditional-age college students. We find that being required to take a remedial course (as we define it in this paper) either in math or in English significantly reduces a student's probability of success in college and also the probability that a student ever passes a college-level math or English course. Among students who are required to take a remedial course in their first semester, however, we find no adverse effects on the probability of returning for another semester. We also find differential effects by a student's prior achievement level, family income and gender. Despite the difference in the methodologies, our main findings are generally consistent with, albeit somewhat more negative, than those from prior studies based on regression discontinuity designs.

Introduction

The nation's community colleges have an increasingly important role to play in educating recent high school graduates. This role reflects the growing importance for individuals of obtaining some form of post-secondary education, the non-selectivity of community college admissions policies, and the lower annual tuition costs to students of community college compared to a four-year college. Students enroll in the curriculum programs of community colleges with a variety of goals. Some aspire to obtain diplomas in a specific applied field, such as hospitality management, while others aspire to associates degrees either in an applied area, such as criminal justice technology, or in one of a number of general education fields. Still others hope to earn sufficient college-level credits to transfer to a four-year institution. Most, however, fail to attain any of those goals.

Given the open admissions policies of community colleges, it is not surprising that many students arrive unprepared for college-level work and are referred to one or more remedial, or developmental, courses for which they receive no college credit.[1] Nationally, 42 percent of first-year undergraduates at 2-year public institutions in 2007/08 reported taking at least one remedial course after high school graduation and 23.9 percent were enrolled in a remedial course in that year (Aud et al, 2011, Table A-22-1.)   By giving students an opportunity to address their academic deficiencies, such remedial courses could potentially promote greater success in college than if such courses were not available. Alternatively, remedial courses might reduce the probability of success by discouraging or stigmatizing students or by lengthening the college experience, which would make it more expensive given the limits on eligibility for federal Pell Grants. High dropout rates at community colleges make attention to remedial education a pressing policy concern.

[1] The terms remedial and developmental are used interchangeably in this paper. The North Carolina Community College System on which this paper is based typically uses the term developmental.

National data show that students who ever enroll in remedial courses are far less likely to complete a degree than those not in remedial courses.[2] This observation provides no information, however, on the effectiveness of remedial courses because the students who enroll in remedial courses have weaker academic skills than those who do not enroll in such courses. A number of recent studies have used rigorous empirical methods, with specific attention to the nonrandom selection of students into remedial courses, to examine the effects of remedial courses on college persistence or success. As we discuss below, one well-known study identifies the effects of remediation by using policy variation across colleges, several studies use regression discontinuity designs that focus on the students just below and above the cut point for mandatory enrollment, and a few use random assignment designs to examine specific programs intended to substitute for or to supplement standard remedial courses. The results have been mixed, with only one study (Bettinger and Long, 2009) finding consistently positive effects of remediation on subsequent student outcomes.[3]

Our paper contributes to this empirical literature by using policy variation across colleges to examine how enrollment in remedial courses in North Carolina's community colleges affects various outcomes, including whether the student is successful in community college, whether the student subsequently passes a college level math or English course, and whether the student returns the following semester. North Carolina serves as an appropriate state for this study because of its large public community college system with 58 public colleges that cover the whole state. Only two states have more community colleges – California with 111 and Texas with 64 (Povasnik & Planty, 2008) NCES, Supplement, 2008).[4] In addition, the analysis is timely, given the state's strong commitment to its

[2] Based on 12th graders in 1992 who enrolled in postsecondary education, students in remedial reading courses had a college success rate (defined as completing a degree or certificate by 2000) of 30 percent compared to 69 percent for those not in remedial courses. The comparable percentages for math are 42 percent and 69 percent. (U.S. Department of Education, 2004)

[3] In addition, an unpublished study (Jepsen, 2006) on remediation in California also finds positive effects.

[4] Different sources report slightly different numbers. Note that this report lists 59 community colleges in North Carolina, with the 59th most likely being a private college. According to IPEDS data, there are 60 public community colleges in North Carolina (which includes 2 schools of nursing), 63 in Texas, and 118 in California.

community college system and its ongoing efforts to improve it.

Because the state's individual community colleges used demonstrably different criteria one from another for placing students in remedial courses during the period of our study, we are able to follow the example of Bettinger and Long (2009) in their study of public institutions of higher education in Ohio. Specifically, we use policy variation across community colleges, combined with distance to the nearest college, to identify the effects of the remedial courses on student outcomes. In contrast to those authors, however, we are able to link community college students to their middle and high school records in North Carolina public schools. Access to these administrative records provides us with background information on all community college students, not just those who took a college entrance test such as the ACT. Hence we need not restrict our analysis, as did Bettinger and Long, to students aspiring to a four-year degree. Because of that restriction, the Bettinger and Long paper is far more applicable to remediation in four-year colleges than to community colleges, both of which were included in their analysis.

In contrast to their positive findings, we find that being assigned to take remedial courses (as we define it in this paper) either in math or in English significantly reduces a student's probability of success in college, where success includes a variety of outcomes consistent with the different reasons students attend community college. We also find that being assigned to take a remedial course reduces the probability that a student ever passes a college-level math or English course. Among students who are assigned to take a remedial course in their first semester, however, we find no adverse effects on the probability of returning for another semester. Although the findings related to college outcomes are even more negative than much of the current wisdom about remedial education (see, for example, Bailey, 2009), they are fully consistent with the recent findings of Clayton-Scott and Rodriguez (2012) who study remediation in six community colleges in a single large urban area. The findings are clearly sobering and raise difficult policy issues about how to address the deficiencies that many students bring to community college.

In the following sections, we place our study in the current policy context and summarize previous research. We then describe our data and methods, present our results, and discuss the policy implications.

Policy context and conceptual foundation

The mission of the country's community colleges is broad. It justifies short-term training programs designed to serve the interests of local business, courses to enhance the skills of adults, programs to allow high school dropouts to obtain a high school equivalency degree (a GED), and programs intended for recent high school graduates interested in gaining skills for a job or preparing for further education. We focus in this paper on this latter set of programs, which are typically referred to as curriculum programs. Students in such programs seek to obtain diplomas, associates degrees, or course credits that permit them to transfer to a four-year institution.

North Carolina has two separate systems of postsecondary education – the University of North Carolina (UNC) system with 16 four-year institutions, and the North Carolina Community College System with 58 two-year colleges. "Articulation agreements" between the two systems specify the requirements for students to transfer from community colleges to four-year institutions. North Carolina has long been a leader among the states in the development and use of community colleges and, as of 2008, about 40 percent of the postsecondary enrollments in the state were in community colleges, in contrast to 35 percent in the country as a whole (Snyder & Dillow, 2010).[5] The state's community

[5] *Digest of Education Statistics 2009*, Table 214. In full-time-equivalent units, the public two-year share of all postsecondary enrollments in the U.S. was 27%, compared to 31% in North Carolina (Table 219).

colleges use an open admissions policy for all US citizens who are 18-years or older and who are high school graduates.[6]

In the U.S, remedial education courses have historically been available at both two- and four-year colleges. During the past several years, however, more than a dozen states have moved to stop funding remedial classes at four-year institutions and to require students who need remedial courses to take them at a community college. Presumably, the main goal is to keep costs down, given that faculty salaries and other costs are typically far lower at community colleges than at four-year institutions. Moreover, community colleges are, arguably, in a better position to meet the needs of struggling students than are the four-year colleges that are more oriented toward academically successful students.

Within North Carolina, four-year institutions still provide remedial courses, but the remediation rate in those institutions for first time freshman who graduated from high school the previous year declined from 14.6 percent in 1993/94 to 8.4 percent in 2010/11 (UNC General Administration, 2012). In contrast, as of 2009, 61 percent of first time credential-seeking students in the state's community colleges were enrolled in at least one developmental reading course in English, reading or math, and 33 percent were enrolled in two or more (Loney, 2011). Thus, the state's community colleges play a significant role in providing remedial courses, which are typically called developmental courses in North Carolina. Such courses have uniform course numbers (all below 100) across the colleges. In math, the course numbers start at 50 and rise to 95 while in English they start at 60 and rise to 95.

The community colleges in North Carolina use a variety of methods for determining college readiness. Unless students have met established scores on the SAT or ACT, the colleges require newly

[6] Undocumented immigrant students are admitted if they graduated from a US high school but they are not considered NC residents, and legal residents have priority for admission to programs with limited capacity https://www.nccommunitycolleges.edu/state_board/SBCC%20Agendas%20&%20Attachments/2012/MAY%202012/POL%206.pdf

enrolled students to take placement tests in reading, writing, and mathematics using assessments that include the ASSET, COMPASS, or ACCUPLACER, but during the period of our study there was considerable variation in assessment and placement policies across the NCCCS institutions (Loney, 2011).[7]

As spelled out by Scott-Clayton and Rodriguez (2012), remedial education serves three potential functions, not all of which are intended or desired. The first and most positive function is the developmental function. From this perspective, remedial courses are intended to develop the skills that students need to succeed in college level courses for which they may be initially unprepared. To highlight that function, many community college systems, including the North Carolina system, use the term “developmental” rather than “remedial” to describe such courses. The measure of success with respect to this function would be subsequent enrollment and success in college level courses, and, ideally, an increased probability of earning a degree or enough credits to transfer to a four-year institution.

A second, less positive function of remedial courses is to discourage students from continuing in college and from taking the more challenging courses they need to graduate. By sending a signal to students that they are not ready for college level work, referral to remedial courses may lower a student’s self-esteem, may be stigmatizing, or simply may represent an additional barrier to college success in that remedial courses cost money and take time but do not provide college credit. To make matters worse, some people believe remedial course work in math is not necessary and simply serves as an unnecessary barrier to the accumulation of potentially value human capital in subject areas that do

[7] In 2007, the NCCCS started to implement a uniform placement policy across the system’s 58 colleges and all now use some combination of SAT/ACT scores or COMPASS> ASSET and ACCUPLACER tests to determine placement into developmental courses but with differing thresholds. Not until the fall of 2013, will the procedures be similar across the colleges. At that time, all North Carolina community colleges will implement a customized ACCUPLACER assessment, which will include online interventional and preparation tools for students. http://press.collegeboard.org/releases/2012/north-carolina-community-colleges-use-accuplacer-statewide-diagnostic-and-placement-test

not require math (Hacker, 2012). Importantly, this discouragement mechanism may well affect students who never enroll in a developmental course. Concern about the requirement that they will need one or more remedial courses, for example, may induce some students not to enroll in a college with a stringent remediation policy, either by not enrolling in any college or, if they have the option, of enrolling in a community college with less stringent requirements. In addition, enrolled students may simply choose not to comply with a referral to a remedial course and, as a result, may be restricted from taking college level courses in that field. Among the outcome measures that would shed light on the discouragement mechanism is the rate at which students persist in college.

The third function identified by Scott-Clayton and Rodriguez (2012) is the diversion function. This function refers to the possibility that remedial courses are used to divert struggling students away from college level courses largely to assure that the level of those courses will not be diminished by the presence of students who cannot do the work. In this sense, remedial courses serve a tracking function which could, in theory, serve the best interests of both groups of students – high achieving students benefit by being in classes with other high achieving students and low achieving students get the attention they need to overcome their initial academic deficiencies. At the same time, if the remedial courses do not serve the development function discussed above, it is hard to make the case that they are beneficial to the low achieving students except to the extent that students gain skills that are useful to them in the absence of additional college-level work.

Prior research

As we have already noted, our analysis is in the spirit of the Bettinger and Long (2009) study of college remediation in Ohio. Both papers use administrative data and identify the causal effects of remediation by exploiting the facts that remediation policies differ across colleges and that students live closer to some colleges than to others. One significant difference between the two papers is that

Bettinger and Long examine remediation in all public institutions of higher education (other than technical two-year colleges) in Ohio, including both four-year colleges and community colleges, while we focus exclusively on North Carolina's community colleges. Bettinger and Long (2009) report a number of positive effects of remediation on outcomes in Ohio, including a 12 percentage point reduction in the probability of dropping out of college and an 11 percentage point increase in the likelihood of graduating within six years. Such findings would be consistent with the developmental function of remedial education.

Like us, Bettinger and Long study outcomes for students who enter college either right after or shortly after graduating from high school, but, unlike us, they were forced to limit their sample to students who took the ACT, the standard test used for college entry in Ohio. That was the case because they relied on information from the ACT reports and questionnaires for many of their individual-level explanatory variables, including math and English ACT scores. The use of ACT data means that the students in the community college portion of their sample included only those who signified their intent to complete a four-year degree on their community college application, which, in their sample, accounted for about only about half of the traditional age students who attend community colleges (Bettinger and Long, 2009, p. 740, footnote 8). [8] For that reason, we believe that the Ohio study provides limited insight into the effects of remedial programs on typical community college students.

An alternative approach is to use a regression discontinuity strategy to estimate the effects of remediation, which is feasible only in states, cities, or institutions that have uniform cutoff scores for participation. The findings based on this approach, which focuses on students with test scores just

[8] In a separate chapter for a special issue of a journal (published before the 2009 paper but based on an earlier version of that paper) the authors report some positive effects for remediation in community colleges. Those results, however, are neither fully documented nor explained in the published chapter, and, in any case, are not transferable to the far larger group of community college students in Ohio who do not aspire to a four-year degree. In their 2005 chapter on remediation in community colleges, Bettinger and Long report that community college students who were placed in math remediation were about 15 percent more likely than comparable students not placed in remedial math to transfer to a four year college and refer the reader to an earlier version of the 2009 paper for the details of the model. They present no community-college specific tables of results, however, either in the more complete 2009 paper or in the shorter chapter.

below and above the cut point, have been negligible or mixed. Martorell and McFarlin (2011) found that remediation in Texas had no effect on the probability of passing a college-level math course, transferring to a four-year college or completing a degree. Calcagno and Long (2008) found somewhat more mixed results in Florida. Although students scoring just below the cut off (and hence required to enroll in remedial courses) were slightly more likely to persist into the second year than those scoring just above the cutoff, the authors found no effect of remediation on college-level (non-remedial) math courses or completing a certificate or associates degree or on transferring to a four-year college, and negative effects for reading across a number of outcomes. Similarly, Scott-Clayton and Rodriguez (2012), who examine outcomes in six community colleges in an unidentified large urban district, find no evidence that remedial courses successfully prepare students for success in college level courses, with some of the effects being negative. For example they find that students assigned to math remediation were 5 percentage points less likely to pass college-level math than were students not assigned to remediation. Overall, none of these studies provides support for the developmental function of remedial education within community colleges. At the same time, they find little or no discouragement effect, as measured by a reduced probability of returning the following term or year. Scott-Clayton and Rodriguez (2012) conclude that the main function of remedial education courses in practice is to divert less well-prepared students from college level courses.

A major limitation of the regression discontinuity strategy for identifying causal impacts is that, strictly speaking, it applies only to students whose test scores are close to the threshold, and therefore sheds little light on how remediation might affect weaker students who might potentially derive either more or less positive benefits from remediation than those at the margin. Indeed, if the cut point were sufficiently well chosen and remediation were costless, one might expect those who were just below the cut point, and hence required to take remedial education, to receive little or no benefit from taking the course.[9] In contrast, the policy variation strategy used both by Bettinger and Long (2009) and in the present study can shed light on the average impacts of remediation on a broader set of students. Moreover, provided the apparent variation across colleges in the criteria for placing students in remedial courses is sufficiently wide, it also permits one to estimate effects for students with different characteristics. As discussed further below, our use of policy variation across community colleges in North Carolina allows us to examine heterogeneous effects by 8th grade test scores, gender and eligibility (during their school years) for free or reduced price lunch.

Finally, some researchers have used experimental designs to look at specific programs designed to substitute for or to supplement regular remedial courses. Barnett et al, 2012, for example, used a random assignment strategy to evaluate the outcomes of eight development summer bridge courses in Texas in 2009 and Visher et al. (2012) report findings from random assignment studies at six community colleges of a developmental "learning community" model intended to enhance the experience of students as they participate in remedial courses. At best, the findings that emerge from studies of this type are mixed. The Texas study found that the summer bridge program generated small positive effects on completion of college level courses in math but none in reading, and no effects on college persistence. The studies of learning communities found some very small positive effects on course credits in subjects other than math, but like the Texas study, found no effects on college persistence (Visher et al, 2012). Studies based on random assignment are appealing because that approach minimizes selection biases. At the same time, experimental research of this type works best for the evaluation of specific policy interventions, and is far less suitable for evaluating the broader issues associated with current remediation policies across community colleges that affect close to half of

[9] Clayton-Scott and Rodriguez 92012) are able to investigate this issue in a limited way by separating their sample into low, medium, and high school achievers to determine different responses to being assigned to remediation, albeit all of which are based on the same cut point in test scores. Interestingly, they find that at the given test score cut point, the higher ability students (as measured by their high school performance) were less likely to succeed than the lower ability students.

all students.

Data and Model

We use rich administrative data on North Carolina students from two main sources: the North Carolina Community College System with its 58 colleges and the state's K-12 system. The data were made available to us through the North Carolina Education Research Data Center (NCERDC) in a form that both preserved confidentiality and permitted us to match student records from the two data sets. The combined data set allows us to use information from a student's earlier schooling career to predict subsequent success in a community college. In particular we use information on students' 8th grade test scores in math and reading, information on their free lunch status, parents' education level as reported on the 8th grade test, and whether they were identified as disabled or gifted.

Our analytic sample starts with all students who were in 8th grade in a North Carolina public school in 1999, who took the eighth grade math or reading required state tests in that year, and who subsequently first enrolled in a curriculum program in a North Carolina community college any time between 2001 and the spring of 2009. The samples differ slightly for math and English because a few of students have a test score for one of the 8th grade tests but not the other. If a student were to progress from 8th grade through 12th grade at a normal rate, the student would graduate in 2003 and would be ready for college in the fall of that year. Some students progress somewhat faster and many do not proceed directly to college. In all models we control for year of first community college course. Unfortunately, we had to exclude all students who attended 8th grade in Wake or Mecklenburg counties because we were not able to match a sufficient number of records for students in those counties to the community college records.[10] As we note below, we further restricted the sample in various ways for different parts of the analysis depending on the outcome variable of interest.

We start with a straightforward model of the following form:

$$\text{Outcome}_{ij} = \alpha + \beta\, C_{ij} + \gamma \mathbf{X}_{ij} + \varepsilon_{ij} \qquad (1)$$

where Outcome_{ij} refers to an outcome for the i^{th} student attending college j, C_{ij} refers to enrollment by the ith student in a development course (of a particular type) in the jth college, $\mathbf{X}_{ij}$ is a vector of measurable student characteristics and ε_{ij} is a random error term. The main outcome variable is the probability of success at a community college, where, consistent with the range of aspirations of community college students, success is broadly defined: It includes earning an associate's degree, earning a diploma in an applied field, or passing at least 10 transferable courses within 4 years of the first term. The transferable course requirement is on the low end of what is required for transfer to a UNC campus.[11] Other outcomes include: ever passing a college level math (or English) course, returning to college after taking any math (or English) course, and returning to college after taking a developmental math (or English) course.

Developmental courses are differentiated by subject and by level, but we include only one type of development course in the model at a time. For math, the three variables are: any developmental math course, and developmental math courses with numbers less than or equal to 70 and those with numbers less than or equal to 60. For English, the two variables are any developmental English and developmental English courses with numbers less than or equal to 85.

[10] As a result, we were not able to construct instrumental variables for the two community colleges serving those areas: Wake Technical Community College and Central Piedmont Community College and consequently also had to eliminate from the sample students in other countries for whom one of those two colleges was the closest to their high school.

[11] Transfer is guaranteed for a community college student to some UNC campus if a) the student has AA or AS, b) has 44 general education core credits, or c) has 30 hours, 6 each from English, math, natural science, social science, foreign language — Comprehensive Articulation Agreement.

Summary information on sample sizes, outcomes, and enrollment in developmental courses is reported in Table 1.[12] The top panel shows that about 48 percent of the more than 17,000 students in the basic sample enrolled in at least one developmental math course and about 37 percent in at least one developmental English course. Among the math students enrolling in any developmental math, two out of five never took a college math course. Among the students enrolling in developmental English, more than three of five never took a college English course. The bottom panel shows the sample sizes and proportions of students who met the criterion for each of the four outcome measures, which are defined in the notes to the table. The sample sizes differ depending in part on how many years are needed for each outcome measures and in part on the criteria. Despite our relatively broad definition of college success, only 28 percent (in both the math and English samples, which are almost identical) of the students met at least one of the criteria for success. The rate of ever passing a college level course after taking a developmental course in the specified field is only 32% for math, but about 55% for English. College persistence rates, defined as returning for a second semester, are relatively high – about 75 for those who took any math or English course in the first semester and about 85 percent for those who took a developmental course in the first semester.

For a number of reasons, the simple model portrayed in equation 1 is likely to generate biased estimates of the parameter β, the effect of enrolling in a developmental course. One concern arises because of left-out variables. Although the model controls for measurable student characteristics, including the student's performance in 8th grade, it does not account for knowledge at the time of college entry or for other hard-to-measure characteristics such as weak motivation or an erratic high school record. Because students who are weaker along such dimensions are more likely to be referred

[12] The specific math courses that constitute the aggregates (with percent of developmental course takers in parentheses) are MAT 050 (6.3); MAT 060(50.3), MAT 070 (29.4); MAT 080 (13.7); MAT 090 (0.20), MAT 095 (0.1). The specific English courses (with percent of developmental course takers in parentheses) are ENG 060 (1.2), ENG 070 or RED 070 (4.9), ENG 075 (2.5); ENG 080 or RED 080 (28.7), ENG 085 (8.4); ENG090 or RED090 (45.0); ENG 095 (9.1).

to developmental courses and also to have lower success rates in college than students with comparable measured characteristics, failure to control for those dimensions would lead to downward biased estimates of effects, that is, estimates that are too negative.

Differential rates of compliance with college referral policies, however, could push the bias in the other direction. That would be the case, for example, if, among the students who are referred to remedial courses, those who are most likely or most motivated to succeed – perhaps because they aspire to transfer to a four year institution -- are the most likely to comply by taking the mandated course or courses. Stated the other way around, students who are less likely to succeed in developmental and subsequent college-level courses may be more likely than other students to delay taking the mandated developmental course and may drop out of college before they do so. In addition, in making their decisions about which college to attend, such students may avoid the colleges that have strict remediation standards. These compliance patterns would imply that the simple model would generate coefficients that would be biased upward, that is, that are more positive than the true effect of compliance in the form of taking a developmental courses.

To avoid these biases we use an instrument for enrollment in a developmental course that is independent of the decisions of any individual student. To that end, we make use of variation across the state's community colleges in the probability that a student with a particular 8^{th} grade achievement level will enroll in a developmental course. Thus, we replace a student's actual enrollment in a developmental course with a college-specific variable that reflects the behavior of students like the student in question. The shift from a student-specific variable to a college-specific variable defined for the college that the student actually attends, however, would not suffice because some students may take the strictness of a community college's remediation policy into account in deciding in which college to enroll. To avoid having to enroll in a developmental math course, for example, a student with a mediocre aptitude for math might select a community college with a more lenient math remediation policy rather than one with a more stringent policy. We address this compliance issue by assigning each student to the remediation policy in the community college or satellite campus of a multi-campus college that is the shortest distance from the high school attended by the student rather than the college the student actually attends. Finally, we add college-specific indicator variables to the model to account for all the average observed and unobserved factors that are associated with the probability of student success across colleges. Such factors might include, for example, the mix of students the college serves and the support it provides to them. The following discussion explains the instrumental variable approach in more detail.

We construct a separate instrument for each level of developmental math or English listed in Table 1 above. We illustrate the approach for "any developmental math "course, but the procedure is the same for each of the other course groupings. We have no information on the formal rule or policy that each college uses for referring students to take developmental education courses. Nor is there information on the scores on any of the assessments that colleges use to make those decisions. As a substitute, we infer the actual practice of each college from the enrollment patterns that we observe in the data. This strategy means that implicitly we are incorporating both the formal policies that the colleges have adopted to make referrals and the informal policies that may permit students to find ways to get around the requirement embodied in the formal policy, a practice that Bailey (2009) reports is quite common in community colleges. For simplicity, we refer to the resulting instrument as the de facto, or effective, assignment variable.

To construct the instrument for "any developmental math" course, we first divide the students into quartiles defined by their 8^{th} grade math scores, with Q1 being the lowest and Q4 the highest quartile. As would be expected, the average proportion of students across all 56 colleges (the full set of 58 minus those serving Wake and Mecklenburg counties) in any developmental math course is inversely related to the 8th grade achievement quartile. The averages range from 89 percent in Q1, to 80 percent for Q2, to 61 percent for Q3, and to a low of 29 percent for Q4.

If colleges pursued similar policies with respect to math remediation—either formal or informal -- relatively similar proportions of students in any given quartile across colleges would enroll in at least one developmental math course. To the extent that the colleges pursue different strategies, we would expect the proportions to differ. Figure 1 shows that the proportions differ substantially across colleges, especially among students with 8th grade test scores in quartiles 2 and 3. The probability that students in quartile 2 of the 8th grade math test-score distribution will end up in a developmental math course ranges from 26 percent in Gilford Technical College to 100 percent in Pamlico Community College. For students in quartile 3, the probability ranges from 11 percent in Mayland Community College again to 100 percent in Pamlico. As we explain below the inclusion of college fixed effects in our models means that we identify effects of remediation by the variation across quartiles within colleges. Fortunately, there is sufficient within-college variation to implement this strategy. The ratio of the percentages for quartile 2 relative to quartile 3, for example, varies from 1.00 (in Pamlico – 100 percent in Q2 vs. 100 percent in Q3) to 4.50 in Mayland – 50 percent in Q2 vs. 11 percent in Q3 – with a mean of 1.39 and a standard deviation of 0.47. In other words, the proportion of quartile 2 students who take a remedial math course exceeds the proportion of their higher achieving quartile 3 counterparts who take such a course by 39 percent across colleges, with a lot of variation around the mean.

These proportions, calculated separately by quartile and community college for "any developmental math course" represent the basic building blocks for our instrumental strategy. The next step is to assign the college-specific proportions to individual students. Because students may decide which college to attend in part based on the college's remediation policy, a possibility we alluded to above, we do not simply assign students to the policies in the colleges they attend. Instead, following the example of other researchers (e.g. Bettinger and Long, 2009), we assign students to colleges based on distance because studies have shown it to be a reliable exogenous determinant of where students choose to go to college. Specifically, in the absence of information on where the student lives, we attribute to the student the relevant remediation proportion at the community college (or campus of a multi-campus community college) that is closest to the student's high school.[13] Thus, the instrument can be interpreted as the probability that a student from a given high school and with an 8th grade math test score in the particular quartile would be required to take a developmental course in math.

We construct separate instruments of this form for each category of developmental course for both math and English. Their usefulness as instruments, however, depends crucially on their predictive power in a first-stage regression of the following form in which the subscript k refers to the college that is closest to the student's high school:

$$\mathrm{C}_{ijk} = \mathrm{a}_k + \mathrm{b}\,\mathrm{Z}_k + \mathrm{c}\mathbf{X}_{ijk} + \mathrm{e}_{ijk} \qquad (2)$$

The variable Z denotes the relevant instrument (associated with the particular developmental course) for the student, and the student characteristics included in the **X** vector are identical to those in equation 1. The model includes fixed effects for each community college which are depicted by the a_k intercept terms that differ across colleges. We also estimated the first stage equations without community college fixed effects but prefer the equations with them. The fixed effects control for both measurable and unmeasurable differences across the community colleges that could be confounded with the instrument.

Table 2 reports first stage equations for the math and English instruments, with the dependent variable taking on the value 1 if the student enrolled in any developmental course in the relevant subject, and 0 otherwise. For simplicity of interpretation, all the models are estimated using ordinary

[13] Community colleges are spread throughout the state and have defined service areas that cover the entire state. We initially assigned students to the community college that serves the high school they attended. Upon examination of the data, however, we realized that many students do not attend that college but instead attend the college closest to their high school. Based on the criterion for a strong instrument discussed later in the text, the closest college generates a far stronger instrument than the college that serves a particular high school.

least squares. The samples for these regressions are those that are relevant for the analysis of the broadest outcome measure, the probability of success in community college, and differ slightly between the two subjects based on the availability of 8th grade test scores. The table includes two equations for each subject, one without community college fixed effects and one with them.

The key coefficients of the instruments appear in the first row. The patterns indicate that the instrument is highly predictive of the dependent variable in both versions of the model and in both subjects, with the expected positive signs. Moreover, the associated F statistics are well over 10 and hence are large enough for the instruments to be deemed strong predictors of the corresponding endogenous variables. Despite the slightly larger coefficients of over 0.8 on the instrument in columns 1 and 3 and the higher F statistics, we prefer the equations with the community college fixed effects and include them in all our subsequent analysis. In the absence of college fixed effects, the instruments could well be correlated with characteristics of specific community colleges that affect the outcomes of interest. The finding that the inclusion of the college fixed effects (see columns 2 and 4) slightly reduces the magnitude across the two subjects is consistent with this concern. These coefficients imply that more than three quarters of the students in community colleges comply with the inferred remediation policy for students like themselves at the community college nearest to their high school.

Although the coefficients on the control variables are of less direct interest, we report them in part to show the set of student level control variables included in all parts of our modeling effort, to further justify our inclusion of college-specific fixed effects, and to provide some information on who enrolls in remedial math and English. Without the fixed effects the pattern of coefficients across student quartiles (8th grade math for the math equations and 8th grade English for the English equations) as shown in columns 1 and 3 is hard to justify; with the fixed effects the coefficients are no longer statistically significant. Most of the other coefficients do not differ much between the two specifications, with the probability of enrolling in a developmental course being greater for females, black students, and students who were ever on free and reduced price lunch during their school years. Not surprisingly, students who are identified in high school as gifted are far less likely than their counterparts to enroll in a developmental course in college. A few differences emerge across the two subjects. Asian students, for example, are more likely than white students to be in a developmental course in English but not in math, while students identified as having an exceptionality (i.e. a disability) are more likely than other students to enroll in a developmental course in English but not in math.

Comparable instruments are needed for each category of developmental course (e.g. math courses numbered less than or equal to 70 or English courses numbered less than or equal to 85), and for each subject (math and English). Moreover, because the samples differ across the four outcome variables, the instruments must be constructed and tested separately for each outcome variable. The full set of coefficients on the instruments from 18 separate first-stage regressions are reported in Appendix Table A2. Each estimate is the coefficient of the relevant instrument in a first-stage regression for which the dependent variable is the probability of enrolling in a course of the specified type. The full set of control variables, including the college fixed effects, are included in each regression. The entries in the first row of Appendix Table A2 simply repeat the relevant coefficients in columns 2 and 4 in the previous table. As indicated by the large F statistics in square brackets under each coefficient, every one of the 18 instruments meets the criterion for a strong instrument.

Basic results

We estimate and report key results for three versions of equation 1, augmented with college-specific fixed effects: an ordinary least squares (OLS) version, a reduced form (RF) version, and a two-stage-least squares (2SLS) version. In all three versions, the estimated coefficients on the C variable, or an instrument for that variable, are of primary interest. In the OLS version, the relevant variable is an indicator that takes on the value 1 if the student was in the specified type of developmental course and

0 otherwise. As we highlighted earlier, the OLS models are likely to generate biased estimates of how enrollment in developmental courses affect student outcomes, but the direction of bias is not clear.

In the reduced form version of the model, the student-specific information on whether a student enrolled in the remedial class is replaced with the college-specific instrument denoting the probability that students like him/her take the course. The reduced form estimate provides an answer to the question: What is the average effect across the state's community colleges of college-specific assignment to a developmental course? We remind the reader that the term "assignment" in this context reflects both the formal and informal policies of each college. This reduced form estimate is analogous to what is called an intent-to-treat (ITT) effect in the experimental research literature in that it represents the effects averaged over students who comply with the relevant college assignment policy and those who do not. The major difference from the standard ITT model is that instead of having a 0-1 treatment variable, our treatment variable is the probability-of-being-assigned to the treatment. The reduced form estimates are our preferred results.

For completeness, we also present results from the two-stage least squares model. In this version, the endogenous developmental course enrollment variable in equation 1 is replaced with the student-specific enrollment rate that emerges as the predicted value from the relevant first-stage regression (equation 2). Under certain assumptions, the resulting 2SLS estimate can be interpreted as the average effect of remediation on the students who actually enroll in remedial courses, which, in the experimental literature would be referred to as the "treatment on the treated" effect. Given that only about three quarters of the students comply with the assignment policy in their closest community college (as documented by the coefficients of the instrument in the first stage regression), these estimates will be larger than the reduced form estimates.

For this treatment-on-the-treated interpretation to be valid, however, we must assume that the assignment variable affects college persistence or outcomes exclusively through its effect on enrollment in a remedial course. In fact, however, one can imagine a number of ways that being assigned to a remedial course could change the outcomes of interest even if the student were never to enroll in the intended remedial course. Because some students, especially those right out of high school, for example, may have inflated views of their readiness for college, learning that most students like themselves end up in developmental courses could serve as an unwelcome reality check that reduces their confidence in their likelihood of success, and, thereby lowers their college performance. In addition, the enrolled student who delays complying with the assignment recommendation may not have access to the college level courses she needs to succeed in college. Finally, the knowledge that a college has a stringent remediation policy may reduce the probability that the student enrolls in college at all, or may induce her to choose a different college, which may affect her probability of college success. We find these potential violations of the required assumptions to be sufficiently compelling for us to play down the 2SLS results and for us to emphasize, instead, the reduced form results.

We present the results into two groups: those that refer to college success and passing a college level course (Table 3) and those that refer to short run college persistence (Table 4) The first group sheds light on the effectiveness of the developmental function of remedial courses and the second on the discouragement function. In each table the three key estimates are reported separately by subject, with math results in the top panel and English results in the bottom panel. All the models include the full set of control variables reported above for the first stage regressions, including college fixed effects. The full reduced form regressions for any developmental math or English are reported in tables A.3 and A.4.

We begin with the math results in Table 3, starting with the OLS estimates in column 1. The -0.022, -0.057, and -0.063 estimates for the success outcome indicate that even after controlling for a large set of student characteristics and community college fixed effects, enrollment in developmental math courses is associated with lower rates of college success, with the coefficients becoming more negative the lower is the level of the developmental course. For example, initial enrollment in very low-level developmental math courses (those with numbers less than or equal to 60) is associated with a 6.3 percentage point reduction in college success, where success is defined as attaining a diploma, an associate degree or completing 10 transferable courses within four years of starting in a community college. The pattern of OLS results is similar for "passing a college math course" within four years of starting in the community college, with the coefficients being even more negative. All else held constant, a student who enrolled in a low level developmental math course is 10.8 percentage points less likely on average to pass a college level math course within four years than a comparable student who did not enroll in any developmental math course.

The OLS patterns for enrollment in English developmental courses, shown in the first panel of column B reveal a similar pattern as for math, but with somewhat larger negative effects in each category. The estimates imply that a student who enrolled in a low level English course (numbered <=85) was 9.2 percentage points less likely on average to achieve college success and 15.8 percentage points less likely to pass a college level English course within four years than a comparable student who did not enroll in a developmental English course.

We remind the reader, however, that the OLS results could well be biased estimates of the causal effect of remediation on the two outcomes. Hence we turn now to our preferred reduced form estimates in column 2. The reader should bear in mind that these estimates refer not to actual enrollment in a developmental course, but rather to de facto, or effective, assignment to such a course, where we have inferred effective assignment from the college-level data on actual enrollment patterns. Moreover, a one-unit change in the assignment variable now corresponds to a change of 100 percentage points in the chance of assignment, all else constant.

With respect to both outcome variables and for both subjects, all the signs in column 2 are negative and statistically different from zero. We interpret the results as follows: Effective assignment to a developmental math course with a number equal to or below 60 reduces college success by 17.9 percentage points and the probability of passing a college math course by 22.2 percentage points. The negative effects of assignment to remedial English in panel B are comparable. Assignment to an English course with a number less than or equal to 85, for example, reduces college success by 17.4 percentage points and the probability of passing a college level English class by 23.9 percentage points. The fact that these RF estimates are more negative than the OLS estimated effects even though they represent an average across both compliers and noncompliers suggests that the hypothesized downward bias of the OLS estimates associated with left- out variable is overwhelmed by the hypothesized upward bias associated with differential compliance behavior.[14]

Moreover, these effects are sizable given that the average college success rates in our sample is only 28 percent, and the pass rates for college courses in math is 32 percent and in English 55 percent. From a policy perspective, however, it might make more sense to consider the effects not of a 100 percentage point difference in assignment (which corresponds to a change of one unit as the probability goes from 0 to 1) but rather a one standard deviation change, and also to translate the effects into percentages. The standard deviation implicit in figure 1 for and eighth grade test score quartiles Q2 and Q3 is about 0.15. Hence a 1 standard deviation difference in assignment to math remediation (for a course <= 60) would reduce the probability of college success rate by about 10.0 percent (i.e. 0.179*0.15/0.28) and the passing rate on a college math course also by about 10.0 percent (i.e. 0.222*0.15/0.32). Similarly, a 1 standard difference in assignment to English remediation (for a course <=85) would reduce the probability of success in college by 9.0 percent (i.e. 0.174*0.15/0.28) and the probability of passing a college level English course by 7.0 percent (i.e. 0.239*0.15)/0.55).

[14] Of interest is that in Bettinger and Long's (2009) negative OLS coefficients in their analysis of remediation become positive in the reduced form model that they report, which implies that that the 2SLS results would also be positive. We attribute the difference in findings between our study and the Bettinger and Long study to the fact that they restricted their sample to students planning to attend a four-year college.

For reasons we have already explained we are reluctant to interpret the 2SLS estimates in the third column as the effects of remediation on those who were remediated. Nonetheless, we include them for the sake of completeness, and because some readers may be more comfortable with that interpretation than we are. Not surprisingly, in absolute value terms the estimates exceed the reduced form estimates by about 30 percent, which simply reflects the fact that they apply only to those who were remediated.

Results for the persistence measures are reported in Table 4, which follows the same structure at Table 3, with math results in panel A and English in panel B. The first persistence variable takes on the value 1 if the student returned to college after taking any math (English) in the first term regardless of whether the course was a remedial course, and 0 otherwise. The sample in this case is all students who took math (English) in the first term. The second persistence variable takes on the value 1 if the student returns to college after taking any developmental math (English) course. For this second set of regressions, the sample is restricted to students who took a developmental math (English) course at any point within the first four years of enrollment. For this second outcome measure, we are comparing persistence of students who took a low-level developmental math (English) course to those who took a higher level developmental math (English) course.

Emerging from the table is the observation that, with one exception, remediation appears to have had little or no effect on persistence, at least as have measured it. This conclusion is based on our preferred reduced form estimates in column 2, where most of the coefficients are small and statistically insignificant. The one exception is that, among the students who ever take a remedial English course, assignment to a very low level developmental English course reduces the probability that a student will return for another term compared to students assigned to a more advanced developmental course.

The bottom line is not very encouraging. The negative effects of remediation reported in Table 3 provide no support for the conclusion that remediation serves the development function of remediation. Contrary to the intended goal of providing students with the skills they need to succeed in college, assignment to math or English remediation reduces the probability not only of overall college success but also the probability of simply passing a college level course in the remediated field. On a somewhat more positive note, we find at most limited evidence that remediation adversely affects college persistence in the short run.

Effects by subgroup

The results reported thus far should be interpreted as the effects of remediation averaged across all students. Implicit in the basic specifications is the constraint that remediation has the same average effect on different types of students. In fact, though, one might expect the effects to differ depending on the student's math or reading ability, as measured by 8th grade test scores, and possibly by the student's gender or family income level. In this section we look at the extent to which the effects differ by such subgroups. To simplify the analysis, we use just one category of developmental math (courses <=to 70) and one category of developmental English (courses <= 85). In addition, we restrict the analysis to two outcome variables, college success and passing a college-level English or math class.[15] Finally, we present results only for the preferred reduced-form specifications.

Although we do not present the first stage equations, which provide information on the strength of the instruments, we note that they take the same form as in equation 2 but require more equations. For the model with interactions by achievement quartile for math, for example, four first-stage regressions are needed that predict the probability that a student in each quartile takes a developmental math course <= 70, Moreover, each of the four first- stage regressions includes four quartile-specific instruments. Although not every instrument is statistically significant in every equation,

[15] We have estimated similar interaction models for the persistence measures but no differential patterns emerged.

most are, and in all cases the F statistics for the instruments in each first stage equation are well over 10.

The estimated effects of assignment to remediation by subgroup are reported in Table 5. Although each regression includes the full set of control variables listed in table 1, we report coefficients only for the interaction terms for each subgroup category, and, for comparison, the main effects for each category, where the main effects now refer to students not assigned to remediation. The patterns indicate that the magnitudes of the negative effects of remediation on the two outcome variables differ across subgroup categories.

Consider, first, students who are in the lowest quartile of 8th grade math or English scores and who were assigned to remediation (by our criteria) in math or English (see first row of the table). The effects of remediation for these low achieving students – relative to comparable students not assigned to remediation-- are all negative and statistically significant. The estimates imply that remediation for this group, whether in math or English, reduces both their probability of college success and their probability of passing a college course in the specified subject by about 16 to 30 percentage points. For students in second quartile of 8th grade achievement, we find negative and statistically significant coefficients for math remediation with respect to both outcome variables but insignificant (although also negative) estimates for English remediation. For students with achievement in quartiles 3 or 4, remediation in math appears to reduce the probability of ever passing a college math course, but no other effects can be statistically distinguished for either math or English remediation. Thus, the two clearest patterns are 1) that students in the bottom of the 8th grade achievement distribution are the most adversely affected by remediation in math and English and 2) that remediation in math reduces the probability that a student at any 8th grade achievement level will ever take a college level math course.

Reported in the rows below the interaction terms are the main effects for the achievement variables, in this case expressed relative to quartile 1 students. Thus the entries are estimates of the effects for those having a high 8th grade test score in the specified quartile relative to those having quartile 1 test scores, but only for students not subject to remediation. Consistent with our expectations, Quartile 4 students have higher probabilities of passing college courses than do lower quartile students. Moreover, quartile 4 students have a higher probability of college success than quartile 1 students, but, somewhat surprisingly, no differences emerge across achievement quartiles with respect to college success for students not subject to math remediation.

Panel B refers to interactions between gender and remediation. In light of prior research showing that labor market returns to community college degrees are typically higher for women than for men (Belfield and Bailey, 2011; Marotte et al, 2005)**,** women should have stronger incentives to succeed than do men. The statistically significant positive coefficients of 0.137 and 0.102 for female students not subject to remediation in the college success models are consistent with this expectation. Among students who are subject to remediation, however, we find that remediation reduces college success more for women than for men. Although we do not have a good explanation for this gender difference, we can rule out one possible mechanism. As shown in the columns for passing college level courses, remediation does not appear to have larger adverse effect on the probability of subsequently passing a college level course in the remediated field for women than for men. Indeed the adverse in math appears to be larger for males than for females.

Finally we turn to the bottom panel in which students are divided by income, as measured by whether they were eligible for free or reduced price lunch while they were in school. Given the financial pressures associated with attending college, we predict that students from low-income families (that is those ever eligible for free or reduced price lunch) are less likely to succeed in college than those from higher income families. And indeed, for those not subject to either math or English remediation we find the expected negative coefficient on the relevant indicator variable in the college success models. Among students subject to remediation, however, we find that remediation reduced the college success of those from higher income families more than those from lower income families. As with the gender differences, we do not have a good explanation for the differential effect. The math results, however, cannot be attributed to differentially adverse effects of remediation in math on passing a college-level math course since the patterns for the two income groups are the same. In contrast, the differentially more adverse effect for the higher income students in passing a college English course could contribute to the explanation for their differentially lower probability of college success.

Thus, all else held constant, we find that remediation has heterogeneous effects across subgroups. With respect to the probability of college success, assignment to remediation appears to have larger adverse effects on students with low 8th grade test scores than those with higher test scores, on female students than on male students, and on students from higher income families than from lower income families. With respect to the probability of ever passing a college level course in the remediated subject, assignment to remediation most adversely affects the students with the lowest 8th grade test scores.

Discussion and conclusion

This study builds on a growing literature on the effectiveness of remediation in community colleges. Using rich administrative data from North Carolina that permit us to link students' school records, including 8th grade test scores, to their subsequent performance in the state's large community college system, we focus on one cohort of traditional-age college students, exploit variations across community colleges in their policies for assigning students to remedial courses, examine multiple outcomes, and examine effects on subgroups defined by their achievement, gender and income levels.

Consistent with several previous studies of remediation in community colleges, we find no support for the developmental function of remedial education for traditional age students. Indeed, we find that de facto assignment to remediation (as we have defined it in this paper) not only is not beneficial but it actually reduces the probability that students will succeed in college or that they will ever pass a college level course in the remediated field. Our use of policy variation across community colleges means that our estimates represent averages based on a far broader range of students subject to remediation than is true for the more common regression discontinuity design used in most other studies. While the regression discontinuity design generates average effects that apply to students with test scores close to the cut point for remediation, ours apply to the full range of students subject to different policies across colleges. Our subgroup finding that students with the lowest achievement levels are more adversely affected by remediation than those with somewhat higher achievement levels, reinforces our conclusion that the true average effect is even more negative than that e indicated by other studies based on regression discontinuity designs.

At the same time, our results differ strikingly from the far more positive results in the one published study based on a similar methodology, the Bettinger and Long (2009) study of remediation in Ohio. As we emphasized earlier, however, that study is not directly applicable to the many students in community colleges who do not aspire to a four-year college degree and who were admitted through open admissions policies.

On a more positive note, we find no evidence that assignment to remediation in North Carolina serves to discourage students from continuing their college career in the short term. Although many students do not persist in college for very long, among those who enrolled in any math or English course in their first term, the probability of returning for another term is no lower for those assigned to a remedial course.

Like Clayton-Scott and Rodriguez (2012), we conclude that the main effect of remedial education courses for traditional age students in community colleges is to divert them away from regular college-level courses. Whether that is desirable or undesirable raises issues beyond the scope of this paper. On the one hand, as long as the students who attend community college get some additional education beyond high school or increase their skills in some way, even if only from 8th to tenth grade math, they are likely to be more successful in the labor market than those who do not. Studies show, for example, that community college education has positive effects on earnings among young workers even for those who do not earn a degree (Marcotte et al, 2005; Kane and Rouse, 1995; Grubb, 2002). Moreover, the diversion of less well prepared students to developmental courses may increase the learning of the better prepared students, either by raising the quality of peers in college-level courses or or by keeping those courses from being watered down to meet the needs of the less prepared students. On the other hand, remediation represents a waste of both college resources and the students' own time and financial resources to the extent that the remedial courses do not further either the students' own goals or societal goals.

Finally, we turn briefly to what these findings might mean for policy makers. We start with the caveat that this study, along with several of the earlier studies, refers only to traditional age students who make up only a portion of all students at community colleges. Other evidence suggests that remediation may have less negative effects for older students (e.g. Calcagno et al, 2006) and an unpublished study (Jepsen, 2006) finds that remedial classes raised the probability that older students in community colleges would transfer to a four-year college or receive a diploma. Such differences are highly plausible given that the nature of the academic deficiencies of older students may differ from those of younger students. The older students might have done fine in high school, for example, but by the time they actually enroll in college they may have forgotten some of what they knew earlier and may simply need to have that material refreshed. In addition, having been working for a few years, they may have a more realistic understanding of their own abilities and what they need to do to earn a degree than do the younger students. Thus, one should not conclude from the present study that remediation is ineffective for all types of community college students.

In addition, we cannot rule out the possibility that the benefits of remedial education would be greater if the methods of delivering the courses were improved. Currently many states, including North Carolina, are investing in various forms of improving such courses or are developing supplemental services or alternative approaches for such students. Unfortunately, some of the most conceptually compelling strategies such as the developmental "learning community" model or summer bridge programs, to which we alluded earlier in this paper, (Barnet et al, 2012; Visher et al, 2012) to date have not generated the desired large positive effects on college persistence and success.

Hence, the most obvious strategy for traditional age community college students is to increase efforts to assure that they gain the skills they need to succeed in college while they are still in high school. That is, indeed a central component of the approach that North Carolina, and other states are now pursuing with the goal being to align high school coursework with college requirements. The present study reinforces the need for that approach.

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Tables and Figures

Table 1. Summary data

Panel A. Enrollments

	Number of students	Percent of students	Number of students	Percent of developmental
Math enrollments	17,167	100%		
No math	4,740	28%		
College math only	4,244	25%		
Any developmental math	8,183	48%		
Developmental math only			5,011	61%
Developmental and college math			3,172	39%
Math <=70			7,078	86%
Math <=60			4,626	57%
English enrollments	17,167	100%		
No English	3,096	18%		
College English only	7,651	45%		
Any developmental English	6,420	37%		
Developmental English only			2,528	39%
Developmental and college English			3,892	61%
English <=85			2,947	46%

Panel B. Outcomes

	Number who meet criteria	Percent of students	Total number in sample
Math			
Success	3,983	28%	14,296
Pass college math	4,644	32%	14,296
Return after math	5,836	76%	7,651
Return after developmental math	5,791	75%	7,772
English			
Success	3,973	28%	14,259
Pass college English	7,800	55%	14,259
Return after English	7,601	77%	9,903
Return after developmental English	4,545	75%	6,061

Note: See Appendix Table 1 for definitions of outcome and independent variables.

Table 2. First stage equations for any developmental math or English

	Math		English	
	(1) Without CC fixed effects	(2) With CC fixed effects	(3) Without CC fixed effects	(4) With CC fixed effects
Instrument	0.841 ***	0.781 ***	0.833 ***	0.781 ***
	(0.026)	(0.060)	(0.025)	(0.045)
EOG Q2	0.031 *	0.020	0.019	0.005
	(0.013)	(0.015)	(0.014)	(0.016)
EOG Q3	0.035 *	0.012	0.036 *	0.008
	(0.016)	(0.022)	(0.018)	(0.024)
EOG Q4	0.071 ***	0.031	0.070 ***	0.035
	(0.021)	(0.038)	(0.021)	(0.030)
Female	0.064 ***	0.064 ***	0.047 ***	0.046 ***
	(0.009)	(0.009)	(0.009)	(0.009)
American Indian	0.061	0.043	0.072 *	0.066
	(0.032)	(0.038)	(0.031)	(0.038)
Asian	0.018	0.026	0.084 *	0.083 *
	(0.045)	(0.046)	(0.041)	(0.041)
Hispanic	-0.077	-0.077	-0.019	-0.012
	(0.042)	(0.042)	(0.037)	(0.037)
Black	0.041 **	0.039 **	0.086 ***	0.090 ***
	(0.013)	(0.013)	(0.013)	(0.013)
Multiracial	0.092	0.091	0.010	0.017
	(0.059)	(0.059)	(0.052)	(0.052)
Parent ed: no HS	-0.050	-0.052	-0.009	-0.010
	(0.053)	(0.053)	(0.054)	(0.054)
Parent ed: some college	-0.025	-0.027	-0.019	-0.017
	(0.014)	(0.015)	(0.014)	(0.014)
Parent ed: college	-0.025	-0.026	-0.030 *	-0.027 *
	(0.014)	(0.014)	(0.013)	(0.014)
Any FRL	0.032 **	0.027 *	0.041 ***	0.039 ***
	(0.012)	(0.012)	(0.012)	(0.012)
Any exceptionality	0.000	0.001	0.043 ***	0.043 ***
	(0.014)	(0.014)	(0.013)	(0.014)
Any AIG	-0.078 ***	-0.077 ***	-0.121 ***	-0.123 ***
	(0.013)	(0.013)	(0.010)	(0.010)
Entry	-0.052 ***	-0.052 ***	-0.042 ***	-0.042 ***
	(0.006)	(0.006)	(0.005)	(0.005)
N	14296	14296	14259	14259
R2	0.226	0.231	0.273	0.277
F-statistic for instrument	571.77	71.20	1370.49	162.76

Notes: Dependent variable takes on the value 1 if the student enrolled in any developmental math or developmental English course and 0 otherwise. See Appendix Table 1 for definitions of outcome and independent variables.

Table 3. Effects of remediation on two college outcome measures

	OLS	Reduced form	2SLS
Panel A. Math			
Success			
Any dev math	-0.022*	-0.198**	-0.254***
	(0.010)	(0.064)	(0.069)
Dev math <=70	-0.057***	-0.227***	-0.308***
	(0.013)	(0.052)	(0.058)
Dev math <=60	-0.063***	-0.179***	-0.236***
	(0.013)	(0.050)	(0.064)
Observations	14,296	14,296	14,296
Pass college math			
Any dev math	-0.069***	-0.211**	-0.270**
	(0.013)	(0.073)	(0.085)
Dev math <=70	-0.109***	-0.266***	-0.361***
	(0.014)	(0.060)	(0.077)
Dev math <=60	-0.108***	-0.222***	-0.293***
	(0.012)	(0.045)	(0.055)
Observations	14,296	14,296	14,296
Panel B. English			
Success			
Any dev English	-0.077***	-0.155**	-0.199**
	(0.011)	(0.054)	(0.072)
Dev English <=85	-0.092***	-0.174**	-0.228**
	(0.009)	(0.057)	(0.076)
Observations	14,259	14,259	14,259
Pass college English			
Any dev English	-0.089***	-0.225***	-0.288***
	(0.013)	(0.063)	(0.084)
Dev English <=85	-0.158***	-0.239***	-0.312***
	(0.016)	(0.068)	(0.087)
Observations	14,259	14,259	14,259

Notes: Each entry comes from a separate regression in which the dependent variable takes on the value of 1 for the specified outcome and 0 otherwise. The full models include all the control variables listed in Table 2, including community college fixed effects. See Appendix Table 1 for definitions of outcome and dependent variables.

Table 4. Effects of remediation on short run college persistence

	OLS	Reduced form	2SLS
Panel A. Math			
Return after math			
Any dev math	0.000	0.049	0.072
	(0.015)	(0.070)	(0.100)
Dev math <=70	0.002	0.028	0.049
	(0.016)	(0.070)	(0.117)
Dev math <=60	-0.027	0.010	0.017
	(0.017)	(0.055)	(0.088)
Observations	7,651	7,651	7,651
Return after developmental math			
Dev math >70	Base	Base	Base
Dev math <=70	-0.004	0.023	0.054
	(0.019)	(0.095)	(0.224)
Dev math <=60	-0.011	-0.006	-0.010
	(0.014)	(0.079)	(0.133)
Observations	7,772	7,772	7,772
Panel B. English			
Return after English			
Any dev English	-0.024*	-0.019	-0.028
	(0.011)	(0.046)	(0.070)
Dev English <=85	-0.036**	-0.122**	-0.159*
	(0.012)	(0.047)	(0.064)
Observations	9,903	9,903	9,903
Return after developmental English			
Dev English >85	Base	Base	Base
Dev English <=85	-0.012	-0.057	-0.110
	(0.015)	(0.087)	(0.168)
Observations	6,061	6,061	6,061

Notes: Each entry comes from a separate regression in which the dependent variable takes on the value of 1 for the specified outcome and 0 otherwise. The full models include all the control variables listed in Table 2, including community college fixed effects. See Appendix Table 1 for definitions of outcome and dependent variables.

Table 5. Effects by subgroup

	College success		Pass college math	
	Math	English	Math	English
Panel A. 8th grade achievement				
I*EOGQ1	-0.247***	-0.181**	-0.313***	-0.161**
	(0.044)	(0.057)	(0.048)	(0.061)
I*EOGQ2	-0.202***	-0.134	-0.206***	-0.102
	(0.048)	(0.081)	(0.059)	(0.080)
I*EOGQ3	-0.102	-0.132	-0.187**	-0.245
	(0.063)	(0.155)	(0.070)	(0.175)
I*EOGQ4	-0.058	-0.339	-0.233*	-0.474
	(0.102)	(0.344)	(0.114)	(0.333)
EOGQ1	Base	Base	Base	Base
EOGQ2	0.008	0.004	-0.023	-0.008
	(0.017)	(0.022)	(0.025)	(0.022)
EOGQ3	-0.028	0.038	0.022	0.055
	(0.021)	(0.031)	(0.025)	(0.032)
EOGQ4	-0.025	0.061*	0.068*	0.099***
	(0.027)	(0.028)	(0.027)	(0.028)
Panel B. Gender				
I*Male	-0.167***	-0.118*	-0.288***	-0.137*
	(0.049)	(0.058)	(0.058)	(0.063)
I*Female	-0.262***	-0.215***	-0.253***	-0.147*
	(0.055)	(0.063)	(0.064)	(0.065)
Male	Base	Base	Base	Base
Female	0.137***	0.102***	-0.013	-0.005
	(0.017)	(0.013)	(0.022)	(0.011)
Panel C. Income				
I*Any FRPL	-0.202**	-0.142*	-0.266***	-0.119
	(0.062)	(0.063)	(0.066)	(0.076)
I*No FRPL	-0.237***	-0.204***	-0.266***	-0.163**
	(0.053)	(0.060)	(0.062)	(0.057)
Any FRPL	-0.065**	-0.058***	-0.010	-0.026
	(0.022)	(0.016)	(0.027)	(0.019)
No FRPL	Base	Base	Base	Base

Notes: All entries are reduced form coefficients. All entries based on full models as in Table 2. "I" refers to the instrument and hence to the fact that the student was assigned to remediation. The entries with no "I" refer to students not assigned to remediation. See Appendix Table 1 for definitions of outcome and dependent variables.

Figure 1. Graphs of instruments for "any developmental math" by community college and quartile

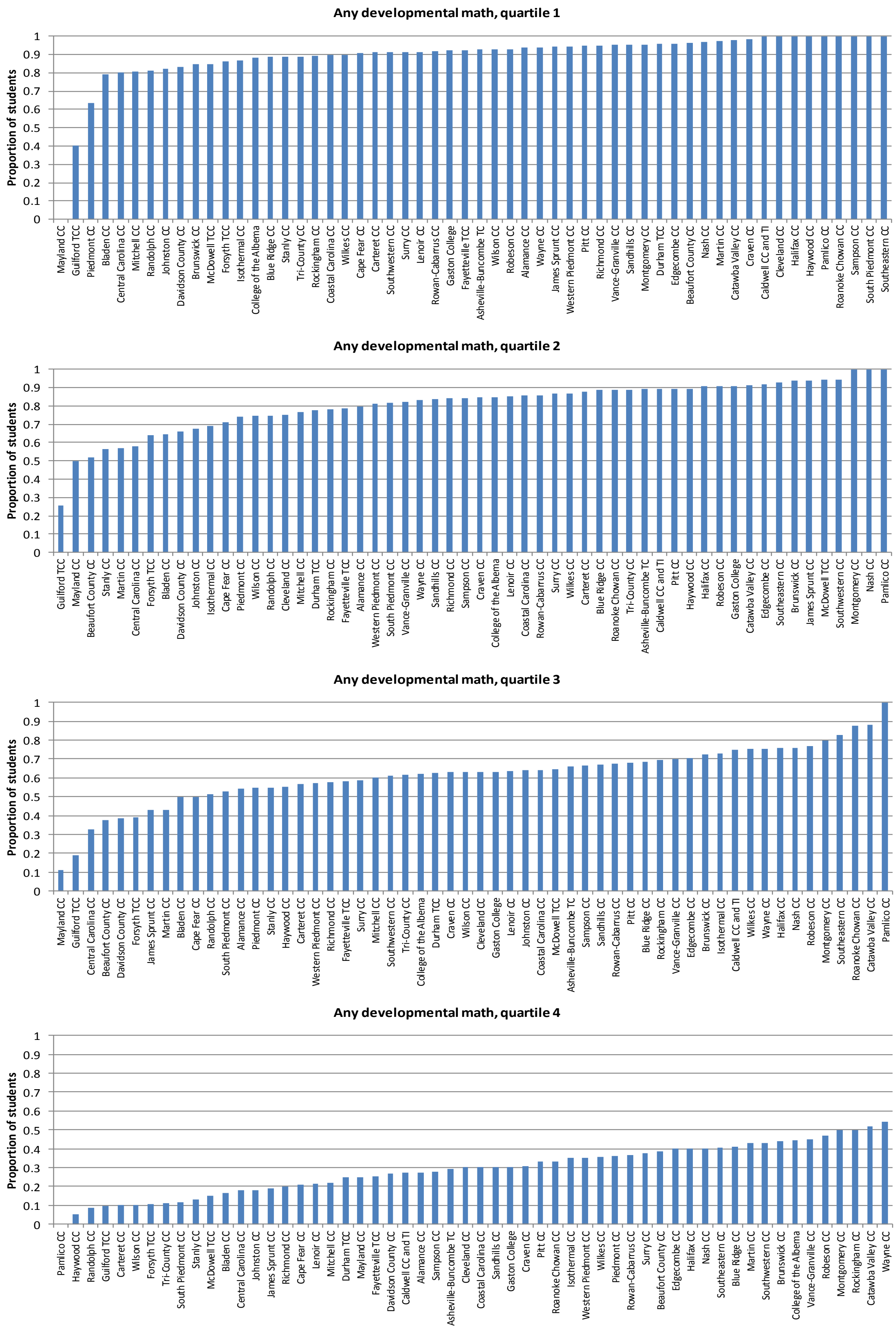

Table A1. Variable definitions

Panel A. Outcome variables

Outcome variable	Definition
Success	Students who earn an Associates degree, earn a Diploma, or passs at least 10 transferable courses within 4 years of first term. It excludes students who are not in the dataset for at least four years.
Pass college math	Students who earn an A, B, or C grade in a college-level math course within 4 years of first term. It excludes students who are not in the dataset for at least four years.
Return after math	Students who return for a second semester after taking developmental or college math in the first semester. It excludes students who did not take a math course in their first semester.
Return after developmental math	Students who return the semester after they take their first developmental math course. It excludes students who never take developmental math.
Pass college English	Students who earn an A, B, or C grade in a college-level English course within 4 years of first term. It excludes students who are not in the dataset for at least four years.
Return after English	Students who return for a second semester after taking developmental or college English in the first semester. It excludes students who did not take an English course in their first semester.
Return after developmental English	Students who return the semester after they take their first developmental English course. It excludes students who never take developmental English.

Panel B. Independent variables

Independent variables	Definition
EOG Q2	An indicator variable equal to 1 when a student scored in the second quartile on the End of Grade test in 8th grade and 0 otherwise
EOG Q3	An indicator variable equal to 1 when a student scored in the third quartile on the End of Grade test in 8th grade and 0 otherwise
EOG Q4	An indicator variable equal to 1 when a student scored in the fourth quartile on the End of Grade test in 8th grade and 0 otherwise
Female	An indicator variable equal to 1 when a student is female and 0 otherwise
American Indian	An indicator variable equal to 1 when a student is American Indian and 0 otherwise
Asian	An indicator variable equal to 1 when a student is Asian and 0 otherwise
Hispanic	An indicator variable equal to 1 when a student is Hispanic and 0 otherwise
Black	An indicator variable equal to 1 when a student is Black and 0 otherwise
Multiracial	An indicator variable equal to 1 when a student is multiracial and 0 otherwise
Parent ed: no HS	An indicator variable equal to 1 when a student's parent did not complete high school and 0 otherwise
Parent ed: some college	An indicator variable equal to 1 when a student's parent completed some college and 0 otherwise
Parent ed: college	An indicator variable equal to 1 when a student's parent completed college and 0 otherwise
Any FRPL	An indicator variable equal to 1 when a student was ever eligible to receive free or reduced price lunch and 0 otherwise
Any exceptionality	An indicator variable equal to 1 when a student was ever classified as having an exceptionality (i.e. learning disabled) and 0 otherwise
Any AIG	An indicator variable equal to 1 when a student was ever classified as being Academically/Intellectually Gifted and 0 otherwise
Entry	Year of first community college course

Table A2. Coefficients on instruments in first stage regressions

	Success	Pass college course in subject	Return after course in subject	Return after developmental course in subject
Panel A. Math				
Any dev math	0.781 ***	0.781 ***	0.686 ***	Base
	(0.060)	(0.060)	(0.082)	
	[71.20]	[71.20]	[29.93]	
Dev math <=70	0.737 ***	0.737 ***	0.576 ***	0.419 ***
	(0.055)	(0.055)	(0.084)	(0.087)
	[75.64]	[75.64]	[35.39]	[31.20]
Dev math <=60	0.758 ***	0.758 ***	0.615 ***	0.583 ***
	(0.043)	(0.043)	(0.079)	(0.100)
	[532.88]	[532.88]	[43.02]	[22.07]
Observations	14,296	14,296	14,296	14,296
Panel B. English				
Any dev English	0.781 ***	0.781 ***	0.678 ***	Base
	(0.045)	(0.045)	(0.067)	
	[162.76]	[162.76]	[88.48]	
Dev English <=85	0.765 ***	0.765 ***	0.772 ***	0.519 ***
	(0.041)	(0.041)	(0.056)	(0.089)
	[199.19]	[199.19]	[508.36]	[45.81]
Observations	14,259	14,259	9,903	6,061

Notes: Dependent variable takes on the value 1 if the student enrolled in the specified developmental course and 0 otherwise. See Appendix Table 1 for definitions of outcome and independent variables. Standard errors indicated by parentheses, and F-statistics indicated by brackets.

Table A3. Reduced form results for Math

Dependent variable:	Success	Pass college math	Return after math
	(1)	**(2)**	**(3)**
Any dev math instrument	-0.198**	-0.211**	0.049
	(0.064)	(0.073)	(0.070)
EOG Q2	0.052**	0.069***	0.042*
	(0.017)	(0.015)	(0.016)
EOG Q3	0.065*	0.127***	0.048
	(0.025)	(0.025)	(0.026)
EOG Q4	0.046	0.156***	0.073
	(0.043)	(0.045)	(0.048)
Female	0.086***	0.006	0.076***
	(0.010)	(0.009)	(0.011)
American Indian	-0.034	-0.064	-0.035
	(0.032)	(0.034)	(0.093)
Asian	0.076	0.236***	0.072
	(0.052)	(0.053)	(0.037)
Hispanic	-0.020	0.026	-0.104*
	(0.031)	(0.033)	(0.050)
Black	-0.096***	-0.056***	-0.035
	(0.016)	(0.014)	(0.018)
Multiracial	-0.020	-0.059	-0.069
	(0.044)	(0.039)	(0.067)
Parent ed: no HS	-0.003	-0.009	0.034
	(0.055)	(0.058)	(0.061)
Parent ed: some college	0.007	0.000	0.021
	(0.013)	(0.016)	(0.015)
Parent ed: college	0.048***	0.050***	0.016
	(0.012)	(0.015)	(0.015)
Any FRPL	-0.044***	-0.010	-0.016
	(0.007)	(0.009)	(0.015)
Any exceptionality	-0.005	-0.012	0.039*
	(0.015)	(0.014)	(0.016)
Any AIG	0.035*	0.013	-0.054*
	(0.015)	(0.018)	(0.026)
Entry	-0.029***	-0.040***	-0.041***
	(0.006)	(0.006)	(0.006)
R2	0.081	0.091	0.040
N	14296	14296	7651
Institution indicator	Yes	Yes	Yes

Note: See Appendix Table 1 for definitions of outcome and dependent variables.

Table A4. Reduced form results for English

Dependent variable:	Success	Pass college English	Return after English
	(1)	**(2)**	**(3)**
Any dev English instrument	-0.155**	-0.225***	-0.019
	(0.054)	(0.063)	(0.046)
EOG Q2	0.023	0.061***	-0.008
	(0.016)	(0.018)	(0.014)
EOG Q3	0.036	0.045	-0.020
	(0.031)	(0.037)	(0.025)
EOG Q4	0.039	0.059	-0.004
	(0.038)	(0.040)	(0.036)
Female	0.081***	0.151***	0.071***
	(0.009)	(0.010)	(0.011)
American Indian	-0.033	-0.051	-0.045
	(0.031)	(0.049)	(0.067)
Asian	0.086	0.057	0.061
	(0.044)	(0.038)	(0.042)
Hispanic	-0.008	-0.007	-0.166***
	(0.027)	(0.035)	(0.048)
Black	-0.104***	-0.115***	-0.067***
	(0.017)	(0.018)	(0.013)
Multiracial	-0.032	-0.012	0.008
	(0.058)	(0.061)	(0.048)
Parent ed: no HS	0.003	0.059	0.010
	(0.048)	(0.062)	(0.052)
Parent ed: some college	0.008	0.036*	0.010
	(0.012)	(0.014)	(0.014)
Parent ed: college	0.051***	0.076***	0.017
	(0.013)	(0.016)	(0.012)
Any FRPL	-0.043***	-0.051***	-0.003
	(0.010)	(0.013)	(0.012)
Any exceptionality	-0.008	-0.050**	0.044**
	(0.013)	(0.015)	(0.014)
Any AIG	0.046**	0.015	-0.025
	(0.016)	(0.013)	(0.019)
Entry	-0.031***	-0.060***	-0.045***
	(0.005)	(0.007)	(0.005)
R2	0.076	0.108	0.042
N	14259	14259	9903
Institution indicator	Yes	Yes	Yes

Note: See Appendix Table 1 for definitions of outcome and dependent variables.