



# **The Labor Market Returns to Math Courses in Community College**

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## **Abstract**

This paper examines the returns to math courses relative to courses in other subjects for students in community college. Using matched college transcript and earnings data on over 80,000 students entering community college during the 2000s, we find that college-level math coursework has an indirect positive effect on award completion that is stronger than that of coursework in other subjects. In terms of direct effects, we find mixed evidence on the direct effect of enhanced math skills on earnings over other college-level skills. Overall, the combined direct and indirect effect appears to be adverse: compared with other courses or college pathways, more math coursework in community college is modestly associated with relatively lower earnings in later adulthood. However, this association is sensitive to modeling, and we do find heterogeneous results by gender, race/ethnicity, and initial college ability, as well as by math field and level.

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# 1. Introduction

A significant body of evidence has found that math skills have especially high and durable economic value both at the individual and aggregate levels. The academic value of math skills is evident from early childhood and persists through the high school and college years; these gains then transfer into the labor market such that earnings are higher for persons with more math preparation (Duncan et al., 2007; Jamison, Jamison, & Hanushek, 2007; Rose & Betts, 2004). Directly, these math skills may influence earnings insofar as they are relatively more valuable than other forms of human capital in the labor market. For example, the National Academy of Sciences, the National Academy of Engineering, and Institute of Medicine (2007) catalogued an inventory of technological innovations (in, e.g., transport, communications, energy power, and information processing) that relied on advanced math. Indirectly, math skills may raise earnings through their effects on credential attainment, such as completion of high school or college (Aughinbaugh, 2012). Given these benefits, there is continued policy pressure on practitioners to improve the math skills of students.

However, almost all the research to date has looked at high school math. The evidence on college math is very sparse. Yet, in concert with policies to improve high school math, there is now an intensive policy movement toward improving college-level math skills. Several strategies are being developed, although so far they have not been very successful (Hodara, 2013). One strategy is early assessment—helping high school students avoid math remediation in college by providing information on their math readiness prior to enrollment. In itself this information seems to be an insufficient incentive for students to enhance their math skills in high school; furthermore, collaboration between schools and colleges is often not very deep. A related strategy is to provide pre-enrollment supports for students, such as summer bridge programs or boot camps. Thus far, the limited available evidence shows these supports have only weak effects. A third strategy is the reform of developmental (remedial) math, including the shortening of the remedial sequence or better aligning remedial courses with college-level requirements. These reform strategies vary substantially but overall the evidence shows “trivial to small” effects. A final strategy is to improve college math instruction, often through the use of innovative technology. Although promising, the increased use of computer-mediated math instruction has had mixed results so far.<sup>1</sup>

For college-level math, these reform strategies have two presumptions. One is that the way to enhance math skills is to improve the quality of existing math instruction. This is problematic because most students take hardly any college-level math. Looking at community college students across the United States, only 40 percent complete an introductory math course,

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<sup>1</sup> On summer bridge programs, a recent randomized controlled trial found no difference in college-level math pass rates after two years between those who participated in the program and those who did not (Barnett, Bork, Mayer, Pretlow, Wathington, & Weiss, 2012). On compressing courses, modularization, and learning communities, Hodara (2013, Appendix B) reported weak effects. On improving math instruction, student collaboration and pedagogic use of multiple representations have been shown to have some positive effects on math achievement (Chappell, 2006).

and more than half of all students leave college without any college-level math (US DOE, 2012). Thus, many students would be unaffected by these reforms. But the more fundamental presumption is that enhancing college-level math is economically valuable. For a broad swath of students, however, there is very little evidence as to whether this presumption is valid and thus whether it is worth redesigning the math coursework students take in college.

In this paper, we estimate the labor market returns to college math for community college students. We begin by reviewing evidence on the importance of math skills: we juxtapose the substantial evidence on high school math skills with the dearth of evidence on college math skills. We then specify our model for estimating the labor market effects of college math skills. Our estimation sample is two full cohorts of community college students in North Carolina for whom we have full transcript data and labor market data up to nine years after first enrollment. Few community college students intensively study math subjects, so our analysis pertains to general math skills (not skills associated with math majors). We estimate earnings gains for incremental math skills for the full cohort and for subgroups of students. Finally, we conclude with a discussion of the implications of policies that seek to improve math skills in community college students.

## **2. The Economic Value of Math Skills**

### **Math Skills in High School**

For high school students, a substantial body of research highlights the importance of math course-taking on educational attainment. There is a clear association with high school graduation. Using data from the Educational Longitudinal Study of 2002 (ELS:2002), Bozick and Lauff (2007) reported that 52 percent (61 percent) of students who take no (basic) math graduate, whereas almost every student who takes calculus graduates. Using hierarchical linear modeling with data from the National Education Longitudinal Study of 1988 (NELS:88), Lee and Burkam (2003) estimated that a one-standard-deviation increase in 10th-grade math GPA reduces the odds of dropping out of high school by one-third (see also Zvoch, 2006). These gains in high school affect college attendance: using a fixed effects specification, Aughinbaugh (2012) estimated that students who take advanced math in high school are 17 percentage points more likely to enroll in college; and, using a regression discontinuity design, Cortes, Goodman, and Nomi (2013) found sizeable increases in college enrollment for students assigned to “double-dose” algebra. Also, more high school math is associated with lower math remediation in college (Long, Iatarola, & Conger, 2009). Finally, advanced math in high school is strongly associated with completion of college, with an impact even greater than that of high school GPA and socioeconomic status (Adelman, 1999). Although consistently large, these attainment effects do vary by gender and race.

Even as this evidence is not causal, it consistently emphasizes the benefits of more advanced math skills. Thus, these skills are likely to improve labor market outcomes, either directly through increased productivity and or indirectly through their association with further human capital attainment.

Indeed, most evidence thus far has found that math skills—measured during high school—have a powerful effect on earnings (see Altonji, Blom, & Meghir, 2012, Table 2). Again this evidence is based on correlational studies, which typically estimate the overall—direct and indirect—effects of math. In reviewing four studies, Hanushek (2006) estimated an earnings premium from a one-standard-deviation increase in math test scores of 12 percent. Goodman (2012), exploiting the differential timing of state-level increases in high school graduation requirements in the 1980s, found that post-reform students took more math courses and earned significantly more than those who had faced weaker pre-reform math requirements. Using the National Longitudinal Survey of Youth of 1979 (NLSY79), Blackburn (2004) found the math subtests of the Armed Forces Qualification Test (AFQT) administered to teenagers to have the strongest correlation with later earnings: a one-standard-deviation increase in the numerical operations score increased wages by 2.8 percent. In contrast, using NELS:88, Rose (2006) found weak effects, in part because of the heterogeneity of test scores on graduation probabilities. Also, using instrumental variables specifications on NELS:88 and ELS:2002 data, Gaertner, DesJardins, and McClarty (2014) found no clear effect of high school Algebra II on earnings a few years after high school.

However, using High School and Beyond data with a 10-year follow-up, Rose and Betts (2004) estimated the effects of each math course on earnings separately: progressively stronger impacts were evident for more advanced math, with calculus credits having a very strong influence on earnings. Staying in school for an extra year, but with a course load with no math, added only 2 percent to earnings; if the extra year included calculus in the course load, earnings were 9 percent higher (Rose & Betts, 2004, Table 4).<sup>2</sup> Finally, Koedel and Tyhurst (2012) used a resume-based experiment to identify significant hiring advantages for applicants with greater math skills.

The evidence from high school also shows that enhancing math skills may be differentially effective on earnings. For racial/ethnic minorities, Goodman (2012) showed that higher math requirements for Black males can explain almost the entire wage premium from a year of additional schooling. For gender, Rose (2006) found the overall null effect did not hold for female students, who obtained a 9 percent advantage when their math test scores were one standard deviation higher (and reported higher labor market participation rates). Finally, looking across the ability distribution, Rose (2006, Table 5) reported significantly higher earnings as math scores of those in the bottom quartile of ability improved, with weaker gains for those with

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<sup>2</sup> Similar results are found internationally (on evidence from a pilot program in Denmark, see Joensen & Nielsen, 2009; for England, see Dolton & Vignoles, 2002).

greater math skills. Hence, improving math skills in school may help close earnings gaps across subgroups.

## **Math Skills in College**

By contrast, there has been very little research on the value of college math in terms of either its direct skills effect or its indirect attainment effect. Studies have looked at remedial math and college success, typically concluding that it does not help students succeed in college (Bailey, Jeong, & Cho, 2010). Also, using a regression discontinuity design for remedial math course-taking, Martorell and McFarlin (2011) found no effect on earnings. Hodara and Xu (2014) also found a null effect of remedial math on earnings. But this failure may be because of either adverse selection into remediation, or incorrect assignment to remediation, or the delay to enrollment in college-level courses (Scott-Clayton, Crosta, & Belfield, 2014). Using NELS:88, Adelman (2006) did find some—but not consistent—evidence that college-level math courses are important for college completion; however, this descriptive study looked only at bachelor’s degree receipt.

At the four-year college level, there is evidence that majoring in math yields high labor market returns. Several studies have focused on the returns to STEM majors. Olitsky (2012) found high returns (of 5–28 percent) for students who majored in STEM compared with other subjects using propensity score matching (see also Melguizo & Wolniak, 2012). Thomas and Zhang (2005) found college math credits—bundled with engineering credits—to have a significant impact on earnings relative to other subjects taken by college graduates. Across postsecondary education including two-year colleges, most evidence on the association between college math and earnings comes from studies examining the returns to broadly defined disciplines such as social sciences or business (Hamermesh & Donald, 2008). Generally, these studies find higher returns for more quantitative disciplines (for a review of community college benefits, see Belfield & Bailey, 2011). From community college transcripts of displaced workers, Jacobson, LaLonde, and Sullivan (2005) calculated that a year of “more technically oriented vocational and academic math and science courses” raised earnings by 14 percent (29 percent) for male students (female students). In contrast, less technically oriented courses yielded no payoff. However, these studies identified the returns to a math major or to subjects with substantial math content.

Our focus is on the returns to general math skills across the population of community college students. Few of these students are math majors, and many who begin as math majors either transfer to a four-year institution, do not complete, or switch majors. (For math majors, particularly those who obtain bachelor’s degrees, the returns are likely to be strongly associated with occupational choices.) Rather, most math courses are for non-math majors who typically struggle to complete college-level math requirements even as these are either required or at least strongly recommended. At issue is whether these courses are more valuable than other courses.



Evidence on general math has implications for the trend of reform strategies noted above. These strategies are directed toward improving the math skills of the general population (see Gaertner et al., 2014). They might give students the option to major in math. But they are mostly broad-based strategies or, insofar as they are targeted at specific groups, these groups are typically those who are struggling with math and not those who would be prospective math majors. Yet, if only math majors benefit from college math, these reforms may be misdirected.

As well, our analysis has implications for the large evidence base on high school math. That evidence shows that at least some components of the returns to math are returns to additional attainment (insofar as the direct and indirect effects are distinguished; Heckman, Stixrud, & Urzua, 2006). But it does not provide detail on that attainment. Possibly, students who do well in math in high school take more (advanced) math in college, so the high school math effect might partially be attributable to enhanced college math skills. High school math might prepare students for their college math requirements: these students might more easily pass their college math requirements or avoid developmental math and so advance more quickly toward completion.<sup>3</sup> If college math affects earnings, then the role of high school math—insofar as it is correlated with college math—needs to be reinterpreted.<sup>4</sup>

Given the above evidence, our hypotheses are as follows. First, community college students who take more college-level math credits are more likely to complete an award. Second, students who take more college-level math credits have higher post-college earnings. Critically, these tests of the benefits of college-level math must be relative to other courses students take in college. The preponderance of evidence shows that any college coursework will yield earnings benefits—and *ipso facto* such coursework is necessary in order to complete a college award. At issue is whether coursework in math is more beneficial than coursework in other subjects (i.e., whether the returns to math credits exceed the returns to non-math credits). Given the heterogeneity identified in other studies, we expect these benefits to be differentially effective by gender, race/ethnicity, and ability, as well as to have greater effects for advanced math (over remedial and introductory math).

However, it is possible that the associations may be in the opposite direction—there may be an adverse effect of math—or the direct and indirect effects may offset each other (e.g., there may be a positive indirect effect but a negative direct effect). If more students are required to take math, then the pool of math students will include those with little aptitude for or interest in math; these students may accumulate less human capital from a math course than from a course for which they were prepared or which they had chosen voluntarily. If the quality of math instruction is inferior, students may gain more from other courses. Also, if these college math courses are the terminal levels of math students take or are unrelated to subsequent coursework, they will not serve as useful preparation for future courses. Finally, if the job tasks performed by

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<sup>3</sup> In a subgroup analysis, Rose and Betts (2004, p. 503) found their results to be sensitive to mediating effects of postsecondary education.

<sup>4</sup> It may be that math skills are picking up other attributes, such as motivation, or that they align with the enrollment preferences of colleges and that prior studies have failed to adequately adjust for these factors.

community college students do not require math skills (e.g., if computerization has reduced the need for general numeracy skills), these courses are unlikely to increase productivity. Possibly, math may have a negative direct effect on earnings, and this negative effect may partially offset or even dominate the positive attainment effect.

### 3. Model for Estimating Returns to Math Courses

Our modeling approach looks at both the direct and indirect effects of college-level math courses and compares these with the direct and indirect effects of coursework in all other subjects.

The first estimation is of the indirect effect (i.e., the association between math and completion of any award in college). We estimate a logistic regression of the following form:

$$\text{Prob}(AWARD) = \alpha + \beta_A MATH + \theta_A NONMATH + \gamma X \quad (1)$$

The *AWARD* measure includes any credential earned either at the community college (diploma, certificate, or associate degree) or at a subsequent transfer college (bachelor's degree) within nine years of first enrollment. The *MATH* variable is measured in several ways.<sup>5</sup> The first is the number of college-level credits in math courses, which may be compared with the number of college-level credits in other courses. The second measure is a set of binary indicators of college pathways: students are grouped into those with and without college-level math and then into those with and without remedial math; the default pathway is a student without any college-level math credits and without any remedial math credits. As well, more detailed analysis is performed with math fields (e.g., algebra) and with a distinction between 100-level and 200-level math courses. Throughout, the residual category of *NONMATH* captures all college-level coursework other than math (with the exception of the field-specific estimates). Finally, equation (1) includes a detailed set of personal characteristics and individual college performance measures (e.g., first semester GPA and college fixed effects [given as the vector *X*]).

Straightforwardly, the  $\beta_A$  coefficient on *MATH* should be positive—more coursework must almost automatically increase the probability of award receipt. Of interest here is the relative effect of *MATH* compared with other coursework, that is, whether the  $\beta_A$  coefficient on *MATH* is positive and greater than the  $\theta_A$  coefficient for *NONMATH*. Given the evidence cited above, the expectation is for  $\beta_A > \theta_A > 0$ . In addition, differential effectiveness—heterogeneity in earnings gaps across gender, race/ethnicity, and initial college performance—is expected.

To estimate the effect of math on earnings, we apply a conventional (Mincerian) earnings equation:

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<sup>5</sup> Community college students may accumulate math skills in non-math courses. Given the many course offerings and lack of information, it is not feasible to code each non-math course to account for its math content. Moreover, it seems unlikely that such courses devote substantial instruction time to math but rather rely on students' general math knowledge. We therefore assume that whatever math is acquired in these courses is common across all students.

$$Y = \alpha + \beta_{Y1}MATH + \theta_{Y1}NONMATH + \psi AWARD + \gamma X + \phi EXP + \sigma EXP^2 \quad (2)$$

$$Y = \alpha + \beta_{Y2}MATH + \theta_{Y2}NONMATH + \gamma X + \phi EXP + \sigma EXP^2 \quad (3)$$

Earnings  $Y$  are measured in dollars at 7–9 years after first enrollment and are the average of any non-zero reported earnings per quarter. Given the potential for both direct and indirect effects, we anticipate the coefficient on  $MATH$  to be positive and exceed that for  $NONMATH$  ( $\beta_Y > \theta_Y > 0$ ). In addition, we expect math to be differentially effective across subgroups and to have stronger impacts for advanced math. Equation (2) includes the award earned by the student. Conditional on their award, differences in the returns to math credits therefore reflect course mix rather than attainment (see Flores-Lagunes & Light, 2010). So the coursework coefficients represent only the indirect effect: controlling for award, math credits are expected to have the stronger effect ( $\beta_{Y1} > \theta_{Y1} > 0$ ). Equation (3) excludes award and therefore identifies the direct and indirect effects combined. The expectation is that the overall effect will be greater for math coursework ( $\beta_{Y2} > \theta_{Y2} > 0$ ). In addition, we estimate equation (3) with the sample divided according to final award status (including no award). These estimations show the overall effect of math credits.

There are two significant and related challenges in using the coefficients from equations (1) to (3) to identify the effect of math on awards and earnings. One challenge is specific to our analysis and relates to remediation—many students who enter community college do not have college-ready skills, and this is particularly the case with math. Thus, many students are assigned to remedial math, and even those taking college-level math may be doing so to refresh (rather than augment) their math skills. This remedial confounding also applies to non-math coursework, but the distinction is the greater extent of math remediation in college. As noted above, remedial coursework is not positively associated with earnings, and the effect may be stronger for math remediation. Therefore, we adjust for remedial credits throughout, and our estimation using pathway indicators separates out remedial from non-remedial students. As well, we exclude remedial students in subsample analyses.

The second challenge is the common one of selection effects—only students who expect math to be beneficial will take math coursework, which leads to positive selection. (An adverse selection effect may exist if college-level math is required for completing an award.) Controlling for a detailed array of observable characteristics prior to taking math will partly mitigate this bias. In equation (2) we are also controlling for award, which should absorb some ability bias up to and including performance in college.

As a further investigation of endogeneity, we estimate instrumental variables specifications of equations (2) and (3). Based on patterns of enrollment reported above, it appears not to be necessary to fulfill a math requirement (even for award completion). Students can therefore select math courses, which is likely to be affected by the availability of math courses at the college. Therefore, our instrument for college math enrollment is the college-wide average number of math credits per student and the proportion of students who take no math

(controlling for college-wide demographic characteristics). The college-level math-taking rate is likely to be high when math courses are easily available to students and where the college norm emphasizes math. Neither of these factors is likely to be endogenous to the student's choice of college. (These instruments have been used in the high school context by Altonji [1995] and Malamud [2012].) In addition, we apply two other instruments. One is the college-wide rate of math-taking of award recipients. Colleges with higher rates are those where math more closely serves as a requirement and so where students will have fewer chances to opt out. Lastly, we instrument for the proportion of online courses at the college. Xu and Jaggars (2013) found that student course choices are sensitive to the mode (online or other) in which courses are offered and that math courses are much less likely to be taught online. A college with a high online presence is therefore making it easier for students to take non-math courses.

## 4. Dataset

We use data for all community college students in the North Carolina Community College System (NCCCS). The data are merged from three sources of information.

First, we have transcript data for all first-time-in-college, credit-seeking students across all 58 North Carolina community colleges for the academic years 2002–03 through 2004–05. The transcript data contain information on courses taken, grades earned, and awards received, as well as basic personal information (e.g., age, gender, race/ethnicity) and financial aid received (loans and grants per semester). Next, these transcript data were merged with student-level data from the National Student Clearinghouse (NSC). The NSC tracks students as they transfer to other Title-IV eligible colleges, as more than one third of all community college students do (Hossler et al., 2012). The NSC dataset includes information on institutions attended, enrollment durations at other institutions, and awards obtained. The third dataset is from the North Carolina Department of Commerce Unemployment Insurance (UI) records. The UI earnings data are collected on a quarterly basis from UI-covered employers and include total earnings from all jobs, as well as industrial classifications. Data are available up to the first quarter of 2012. All earnings are adjusted for inflation to be expressed in 2010 dollars using the quarterly Consumer Price Index for Urban Wage Earners and Clerical Workers (CPI-W).

The merged dataset has detailed information for over 80,000 students on college performance and labor market outcomes 7–9 years after initial enrollment. These data allow us to link college performance to earnings for a large sample of students who undertake heterogeneous pathways through college. Also, because they are taken from administrative records, our earnings data are not biased due to imputation, self-reporting, or non-response. However, the dataset does have some deficiencies. The transcript data do not include information on schooling in high school, so we do not know the amount of math skills students already possess. Within the NSC data, field of study is not reliably recorded so these data are only used to identify transfer

students and awards from other colleges. Finally, the UI earnings dataset excludes independent contractors, military personnel, some federal personnel, and those working in the informal sector (e.g., casual laborers), which compose approximately 10 percent of all civilian workers. Persons who move out of state are also not included. Nevertheless, we have an earnings match for over 90 percent of all students. (Individuals with no wage record are excluded from our analysis.)

## 5. Results

### Math in Community College

Table 1 shows descriptive frequencies for our sample and the credit accumulation patterns of all community college students statewide.

Emphatically, students take very little formal math: the students in our dataset accumulated only 1.3–1.6 credits in math courses compared with 25–30 non-math credits. Further, these students enrolled in even fewer advanced math courses: they had only 0.1–0.2 credits in 200-level math compared with the 5.5–7.2 credits accumulated in other 200-level subjects. The math course credits are divided approximately evenly across statistics, calculus, and algebra, although most of the credits are in “other math.” This last category encompasses math courses that span a range of college-level math topics. Notably, many community college students take remedial math: the math accumulated at community college is split approximately equally between remedial and college-level math. On average, students earn just over one remedial math credit each, which is the same amount as their college-level math credits. The bottom left panel of Table 1 shows the patterns of course-taking across all students. Only 27 percent (31 percent) of all female (male) students took some college math. Even accounting for the proportion of students with only remedial math (14 percent of women and 10 percent of men), significantly more than half of all students did not take any math courses at community college.

Table 1 also shows these frequencies for students who did not complete an award. Compared with completers these students had even fewer math credits (0.6 among women, 1.0 among men), very few 200-level math credits, and only a small proportion of their math credits were in algebra or calculus. (Non-completers had approximately the same number of remedial credits as completers.) Looking across all their credits, non-completers had course patterns that had even less math than completers: only 15 percent of women and 20 percent of men took any college-level math.

**Table 1: Course Patterns: Math and All Other Subjects**

|                                   | All Students  |               | Students With No Award |               |
|-----------------------------------|---------------|---------------|------------------------|---------------|
|                                   | Female        | Male          | Female                 | Male          |
| Math credits (college-level)      | 1.25 [2.45]   | 1.64 [3.22]   | 0.64 [1.79]            | 0.96 [2.46]   |
| 100-level                         | 1.19 [2.26]   | 1.41 [2.60]   | 0.61 [1.69]            | 0.85 [2.08]   |
| 200-level                         | 0.07 [0.64]   | 0.23 [1.37]   | 0.03 [0.42]            | 0.11 [0.93]   |
| Statistics                        | 0.16 [0.76]   | 0.14 [0.74]   | 0.06 [0.50]            | 0.07 [0.53]   |
| Pre-calculus                      | 0.17 [0.95]   | 0.34 [1.44]   | 0.09 [0.69]            | 0.22 [1.16]   |
| Calculus                          | 0.06 [0.62]   | 0.22 [1.26]   | 0.03 [0.39]            | 0.11 [0.88]   |
| Algebra                           | 0.29 [1.03]   | 0.44 [1.32]   | 0.16 [0.79]            | 0.27 [1.05]   |
| Other math                        | 0.58 [1.35]   | 0.50 [1.26]   | 0.30 [1.01]            | 0.30 [1.00]   |
| Non-math credits (college-level)  | 30.15 [30.46] | 25.09 [27.23] | 17.59 [19.93]          | 16.47 [19.81] |
| 100-level                         | 23.14 [22.77] | 20.26 [20.72] | 14.20 [15.71]          | 13.67 [15.75] |
| 200-level                         | 7.23 [9.83]   | 5.51 [8.50]   | 3.49 [5.94]            | 3.07 [5.75]   |
| Math credits (remedial level)     | 1.49 [3.07]   | 1.05 [2.57]   | 1.36 [2.95]            | 1.00 [2.50]   |
| Non-math credits (remedial level) | 1.51 [3.89]   | 1.01 [3.16]   | 1.61 [4.05]            | 1.07 [3.24]   |
| <i>Course patterns (%):</i>       |               |               |                        |               |
| With CL math / No rem math        | 18%           | 23%           | 10%                    | 15%           |
| With CL math / With rem math      | 9%            | 8%            | 5%                     | 5%            |
| No CL math / With rem math        | 14%           | 10%           | 17%                    | 12%           |
| No CL math / With rem nonmath     | 33%           | 28%           | 31%                    | 27%           |
| No CL math / No rem any           | 26%           | 31%           | 37%                    | 41%           |
| Observations                      | 49,187        | 31,083        | 31,083                 | 21,112        |

*Note.* Sample is all first-time-in-college students who enrolled in an NCCCS college in 2002–04. Standard deviations in brackets.

This low level of coursework in math has implications for the selectivity of students into math. For our sample of community college students, math was not compulsory: indeed, many of the completers did not have any math credits. It appears that students can select into (or out of) math courses. Thus, the pool of math-taking students is unlikely to be dominated by students with low aptitude in, or weak preference for, math.

### **College Math and Award Receipt**

Based on equation (1), Table 2 shows the association between award receipt and course-taking (see table notes for covariates). The first columns of Panel A show straightforwardly that students are more likely to receive an award if they have more college-level credits. Notably, the effect on completion is greater if these credits are in math ( $\beta_A > \theta_A$ ), although the difference between the coefficients is only statistically significant for male students (F-test).<sup>6</sup>

Overall, students with more math relative to other courses have a higher probability of completion. As shown in the right-hand columns of Table 2, math credits are differentially effective in boosting attainment. On average, the effects are greater for male students than female students ( $\beta_{Am} > \beta_{Af}$ ) and greater for high-GPA than low-GPA students; however, math effects are greater for racial/ethnic minority students (and the strongest for female racial/ethnic minority students).<sup>7</sup>

As an alternative, Panel B of Table 2 shows the effects of taking any math on the probability of award completion. These effects (odds ratios) are relative to a student who did not take any college-level math and was not in remediation (math or non-math). The results are consistent with Panel A. Students who took college-level math were much more likely to graduate even if they also took remedial math. As with Panel A, the math effects are heterogeneous: they are greater for female and racial/ethnic minority students (but do not vary across student first-semester GPA).

Overall, there is evidence for the indirect effect of math on earnings: taking more math courses relative to other courses is associated with a higher probability of award completion.

### **College Math and Earnings**

Table 3 shows the associations between course credits and enrollment patterns with earnings measured up to nine years after first enrollment. The results are from estimation of equations (2) and (3), where the former includes all controls as well as the credential earned by the student and the latter excludes the credential earned and is estimated across the entire sample and for subgroups with different credentials.

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<sup>6</sup> Students with more remedial credits are less likely to complete an award (coefficients not reported). Yet, this adverse effect is less for students with math remedial credits than for students with non-math remedial credits.

<sup>7</sup> These patterns do not always correspond to those found in analyses of high school math.

**Table 2: Determinants of Award Receipt: Math and Other Subjects**

| Effect on Award Receipt  | Female             |                        |                    | Male               |                        |                    |
|--|--------------------|------------------------|--------------------|--------------------|------------------------|--------------------|
|  | All                | Racial/Ethnic Minority | GPA < 2.7          | All                | Racial/Ethnic Minority | GPA < 2.7          |
| <i>Panel A: Credits:</i>   |                    |                        |                    |                    |                        |                    |
| CL credits math ( $\beta_A$ )  | 0.07***<br>[0.01]  | 0.11***<br>[0.01]      | 0.04***<br>[0.01]  | 0.08***<br>[0.01]  | 0.09***<br>[0.02]      | 0.06***<br>[0.01]  |
| CL credits non-math ( $\theta_A$ )                                       | 0.06***<br>[0.00]  | 0.06***<br>[0.00]      | 0.05***<br>[0.00]  | 0.04***<br>[0.00]  | 0.05***<br>[0.00]      | 0.04***<br>[0.00]  |
| <i>Panel B: Relative to students who took no math and no remediation</i> |                    |                        |                    |                    |                        |                    |
| With CL math / No rem math   | 1.54***<br>[0.03]  | 1.89***<br>[0.06]      | 1.40***<br>[0.06]  | 1.43***<br>[0.04]  | 1.47***<br>[0.09]      | 1.26***<br>[0.06]  |
| With CL math / With rem math   | 2.13***<br>[0.05]  | 2.42***<br>[0.08]      | 1.90***<br>[0.08]  | 2.00***<br>[0.06]  | 2.20***<br>[0.13]      | 1.87***<br>[0.10]  |
| No CL math / With rem math   | -0.16***<br>[0.04] | -0.21***<br>[0.07]     | -0.21***<br>[0.07] | -0.32***<br>[0.06] | -0.56***<br>[0.12]     | -0.21**<br>[0.09]  |
| No CL math / With rem nonmath  | -0.52***<br>[0.03] | -0.57***<br>[0.06]     | -0.65***<br>[0.06] | -0.44***<br>[0.04] | -0.66***<br>[0.09]     | -0.51***<br>[0.07] |
| N (equal for both panels)  | 49,187             | 15,312                 | 18,451             | 31,384             | 7,537                  | 14,833             |

*Note.* Logistic regression of award receipt of first-time-in-college 2002–2004 cohorts. Panel A presents coefficients; panel B contains odds ratios. Panel A includes remedial credits in math and non-math. Award receipt includes any certificate, diploma, associate degree, or bache'or's degree or above. Model includes: individual characteristics (race/ethnicity [3 groups], single parent, high school graduate, disability, enrollment age [2 groups], financial aid amounts, and expected financial contribution), first-semester college GPA, college fixed effects, and intent in first semester (6 groups). College fixed-effects included. GPA < 2.7 based on first-semester college GPA. Robust standard errors in brackets.

\*\*\*  $p < .01$ . \*\*  $p < 0.05$ . \*  $p < 0.1$ .



**Table 3: Quarterly Earnings Gains: Math and Other Subjects**

| Effect on Quarterly Earnings (\$):                                       | Female          |                 |                 |                    |                  | Male             |                  |                 |                        |                   |
|--|-----------------|-----------------|-----------------|--------------------|------------------|------------------|------------------|-----------------|------------------------|-------------------|
|  | (1)             | (2)             |                 |                    |                  | (1)              | (2)              |                 |                        |                   |
|  | Net of Award    | By Award Status |                 |                    |                  | Net of Award     | By Award Status  |                 |                        |                   |
|  | All             | All             | No Award        | Assoc. Degree      | Bachel. Degree+  | All              | All              | No Award        | Assoc. Degree          | Bachel. Degree+   |
| <i>Panel A. Credits:</i>   |                 |                 |                 |                    |                  |                  |                  |                 |                        |                   |
| Math CL credits ( $\beta_Y$ )  | -61***<br>[10]  | -18*<br>[10]    | 85***<br>[14]   | -187***<br>[19]    | 2<br>[23]        | 3<br>[11]        | 33***<br>[11]    | 43***<br>[16]   | -36*<br>[22]           | 57**<br>[27]      |
| Non-math CL credits ( $\theta_Y$ )                                       | 14***<br>[1]    | 29***<br>[1]    | 6***<br>[1]     | 25***<br>[3]       | 0<br>[4]         | 1<br>[2]         | 8***<br>[1]      | 1<br>[2]        | -2<br>[5]              | -15***<br>[5]     |
| <i>Panel B: Relative to students who took no math and no remediation</i> |                 |                 |                 |                    |                  |                  |                  |                 |                        |                   |
| With CL math / No Rem math   | 12<br>[60]      | 838***<br>[56]  | 776***<br>[77]  | -1,311***<br>[140] | -65<br>[163]     | -35<br>[85]      | 356***<br>[79]   | 180*<br>[105]   | -814***<br>[267]       | -423*<br>[247]    |
| With CL math / With Rem math   | -126<br>[81]    | 909***<br>[77]  | 579***<br>[103] | -1,324***<br>[204] | 397<br>[304]     | -43<br>[131]     | 451***<br>[125]  | 661***<br>[176] | -<br>1,088***<br>[368] | -1,017**<br>[485] |
| No CL math / With Rem math   | -214***<br>[60] | -257***<br>[62] | -11<br>[67]     | -832***<br>[222]   | -441<br>[294]    | -373***<br>[107] | -374***<br>[107] | -304**<br>[121] | -1,094**<br>[520]      | -918**<br>[430]   |
| No CL math / With Rem nonmath  | -598***<br>[49] | -764***<br>[50] | -309***<br>[55] | -1,020***<br>[146] | -983***<br>[220] | -402***<br>[74]  | -439***<br>[74]  | -322***<br>[87] | -580**<br>[241]        | -344<br>[371]     |
| R-squared  | 0.174           | 0.148           | 0.159           | 0.170              | 0.145            | 0.198            | 0.189            | 0.207           | 0.209                  | 0.172             |
| Observations   | 49,187          | 49,187          | 31,083          | 8,170              | 6,549            | 31,384           | 31,384           | 21,112          | 3,610                  | 3,934             |

*Note.* Average quarterly earnings in 2011 (expressed in 2010 dollars). First-time-in-college cohorts 2002–04. Panel A includes remedial credits in math and non-math. All models include: individual characteristics (race/ethnicity [3 groups], single parent, high school graduate, disability, enrollment age [2 groups], financial aid amounts, and expected financial contribution), first-semester college GPA, college fixed-effects, and intent in first semester (6 groups). Model (1) includes highest credential earned (certificate, diploma, associate degree, or bachelor’s degree or above). College fixed-effects included. Robust standard errors in brackets.

\*\*\*  $p < .01$ . \*\*  $p < .05$ . \*  $p < .1$ .

Results for equation (2) therefore identify the effect of incremental math coursework beyond that necessary to complete an award—the direct effect of math skills on earnings. Results for equation (3) identify the combined direct and indirect effect of math skills.

Results in Panel A show that for female students college-level credits in math are *negatively* associated with earnings net of the credential earned (with no effect for male students). By contrast, non-math college-level credits are *positively* associated with earnings for female students (again with no effect for male students).<sup>8</sup> Looking at college pathways in Panel B, we find no statistically significant difference between non-remedial students who took college-level math and those who did not. Overall, there is no evidence for a direct effect of more intensive coursework in math leading to higher earnings, controlling for award completion. Instead, there is some evidence that more coursework in other fields is more valuable. For male students, there is no statistically significant evidence on the returns to math or other courses.

The results for equation (3) in Table 3 also show the combined direct and indirect effect (i.e., award status is not controlled for). Looking at all female students, here too the effect of math credits is negative and the effect for non-math credits is positive. These results indicate that the negative direct effect is more than offsetting the positive indirect effect. However, results in Panel B show that students whose college work included college-level math (regardless of remediation) had much higher earnings than students whose college work did not. For these pathways, the positive indirect effect is being combined with a null direct effect to yield an overall positive effect of math. For all male students, the math effect is stronger: results in panels A and B show male students have higher earnings when they have more math (whether they have an award or not). This result is consistent with a null direct effect (equation [2]) and a positive indirect effect.

When the sample is split across student groups the results are mixed. For both female and male students the effects of math depend on whether or not the student completes an award. For female students who complete either an associate degree or transfer on and complete a bachelor's degree, the effects of math credits and coursework are negative and are more adverse than for non-math.<sup>9</sup> Again, there is no clear evidence of a positive direct effect of math skills on earnings for either female or male students and for either Panel A or Panel B. However, results for students who did not complete an award were consistently positive: more college-level math is associated with higher earnings, and this effect is greater than for college-level non-math. For those without an award, math credits (or a math pathway) are more valuable than other credits (or non-math pathways).<sup>10</sup>

To test for differential effectiveness of math coursework, Table 4 shows the results for subgroups (for specification [3] excluding credentials).

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<sup>8</sup> Also, math remedial credits are negatively associated with earnings and, although this is unsurprising, there is no negative association for non-math remedial credits (coefficients not reported).

<sup>9</sup> For these students, we do not have information on the math courses taken at the transfer colleges.

<sup>10</sup> Sensitivity testing for the non-completers also shows that the higher the proportion of courses taken in math, the higher are earnings even after controlling for the total number of credits earned. Details available from the authors.

**Table 4: Quarterly Earnings Gains: Math and Other Subjects by Subgroup**

| Effect on Earnings (\$):   | Female                        |                 |                 |                 | Male                          |                  |                |                  |
|--|-------------------------------|-----------------|-----------------|-----------------|-------------------------------|------------------|----------------|------------------|
|  | Racial/<br>Ethnic<br>Minority | White           | GPA<br>< 2.7    | GPA<br>> 2.7    | Racial/<br>Ethnic<br>Minority | White            | GPA<br>< 2.7   | GPA<br>> 2.7     |
| <i>Panel A: Credits</i>  |                               |                 |                 |                 |                               |                  |                |                  |
| Math CL credits ( $\beta_Y$ )  | 17<br>[20]                    | -80***<br>[11]  | -37**<br>[15]   | -74***<br>[13]  | 55**<br>[26]                  | -3<br>[12]       | 21<br>[15]     | 0<br>[16]        |
| Non-math CL credits ( $\theta_Y$ )                                       | 6***<br>[2]                   | 18***<br>[1]    | 13***<br>[2]    | 14***<br>[1]    | 0<br>[3]                      | 1<br>[2]         | 0<br>[2]       | 3<br>[2]         |
| <i>Panel B: Relative to students who took no math and no remediation</i> |                               |                 |                 |                 |                               |                  |                |                  |
| With CL math / No rem math   | 362***<br>[112]               | -74<br>[70]     | 262***<br>[96]  | -108<br>[76]    | 102<br>[168]                  | -48<br>[97]      | 293**<br>[117] | -180<br>[119]    |
| With CL math / With rem math   | 251*<br>[134]                 | -184*<br>[101]  | -16<br>[121]    | -159<br>[108]   | 769***<br>[253]               | -231<br>[153]    | 249<br>[173]   | -84<br>[197]     |
| No CL math / With rem math   | -64<br>[96]                   | -261***<br>[77] | -225**<br>[87]  | -180**<br>[83]  | -101<br>[170]                 | -459***<br>[134] | -47<br>[132]   | -602***<br>[178] |
| No CL math / With rem nonmath  | -406***<br>[81]               | -686***<br>[61] | -485***<br>[69] | -678***<br>[68] | -287**<br>[130]               | -436***<br>[90]  | -178*<br>[92]  | -618***<br>[122] |
| R-squared  | 0.168                         | 0.177           | 0.193           | 0.149           | 0.208                         | 0.186            | 0.179          | 0.181            |
| Observations   | 15,313                        | 33,874          | 18,451          | 30,736          | 7,537                         | 23,847           | 14,833         | 16,551           |

*Note.* Average quarterly earnings in 2011. First-time-in-college cohorts 2002–04. All models as per Table 3 Model 2. Panel A includes remedial credits in math and non-math. Robust standard errors in brackets.

\*\*\*  $p < .01$ . \*\*  $p < .05$ . \*  $p < .1$ .

**Table 5: Quarterly Earnings Gains: Math Fields and Levels**

|                                    | Female          |                 |                |                 |                 | Male            |               |              |                 |                 |
|------------------------------------|-----------------|-----------------|----------------|-----------------|-----------------|-----------------|---------------|--------------|-----------------|-----------------|
|                                    | Net of Award    | By Award Status |                |                 | Net of Award    | By Award Status |               |              |                 |                 |
|                                    | All             | All             | No Award       | Assoc. Degree   | Bachel. Degree+ | All             | All           | No Award     | Assoc. Degree   | Bachel. Degree+ |
| <i>A. Credits by field:</i>        |                 |                 |                |                 |                 |                 |               |              |                 |                 |
| Statistics credits                 | 157***<br>[31]  | 230***<br>[32]  | 238***<br>[51] | 134***<br>[50]  | 204***<br>[59]  | -7<br>[42]      | 46<br>[43]    | 15<br>[63]   | -43<br>[80]     | 87<br>[83]      |
| Precalculus credits                | -103***<br>[21] | -79***<br>[21]  | 17<br>[34]     | -183***<br>[41] | -91**<br>[39]   | -19<br>[21]     | -2<br>[21]    | 30<br>[30]   | -87**<br>[44]   | 2<br>[48]       |
| Calculus credits                   | 46<br>[40]      | 85**<br>[40]    | 227***<br>[76] | -17<br>[56]     | 67<br>[65]      | 53*<br>[28]     | 83***<br>[29] | 57<br>[46]   | 53<br>[51]      | 125**<br>[51]   |
| Algebra credits                    | -89***<br>[20]  | -55***<br>[20]  | 60**<br>[28]   | -208***<br>[41] | -81*<br>[45]    | 14<br>[23]      | 54**<br>[23]  | 54*<br>[33]  | -3<br>[43]      | -31<br>[61]     |
| Other CL math credits              | -192***<br>[15] | -142***<br>[15] | 44**<br>[20]   | -444***<br>[28] | -107**<br>[44]  | -74***<br>[25]  | -52**<br>[25] | 46<br>[34]   | -267***<br>[50] | -52<br>[78]     |
| Non-math CL credits ( $\theta_y$ ) | 15***<br>[1]    | 31***<br>[1]    | 6***<br>[1]    | 26***<br>[3]    | 2<br>[4]        | 2<br>[2]        | 10***<br>[1]  | 1<br>[2]     | 0<br>[5]        | -12**<br>[6]    |
| <i>B. Credits by level:</i>        |                 |                 |                |                 |                 |                 |               |              |                 |                 |
| Math 100-level credits             | -82***<br>[11]  | -38***<br>[11]  | 67***<br>[15]  | -218***<br>[21] | -11<br>[26]     | -19<br>[14]     | 12<br>[13]    | 38**<br>[18] | -67**<br>[30]   | 5<br>[35]       |
| Non-math 100-level credits         | 10***<br>[2]    | 22***<br>[1]    | 8***<br>[2]    | 13***<br>[3]    | -5<br>[6]       | -3<br>[2]       | -2<br>[2]     | -2<br>[3]    | -5<br>[6]       | -19**<br>[8]    |
| Math 200-level credits             | 77**<br>[38]    | 111***<br>[38]  | 244***<br>[72] | 64<br>[56]      | 60<br>[60]      | 48*<br>[26]     | 71***<br>[26] | 56<br>[44]   | 28<br>[44]      | 117**<br>[47]   |
| Non-math 200-level credits         | 24***<br>[3]    | 49***<br>[3]    | 2<br>[4]       | 52***<br>[5]    | 13<br>[10]      | 17***<br>[6]    | 40***<br>[5]  | 13<br>[10]   | 7<br>[10]       | 5<br>[15]       |
| <i>Observations</i>                | 49,187          | 49,187          | 31,083         | 8,170           | 6,549           | 31,384          | 31,384        | 21,112       | 3,610           | 3,934           |

*Note.* Average quarterly earnings in 2011. First-time-in-college cohorts 2002–04. All models as per Table 3 Model 2 and include math and non-math remedial credits. Robust standard errors in brackets.

\*\*\*  $p < .01$ . \*\*  $p < .05$ . \*  $p < .1$ .

Consistent with prior literature on high school math, college-level math is differentially effective by race/ethnicity and initial performance. For female students, math credits are not disadvantageous for racial/ethnic minority (Black and Hispanic) students compared with the statistically significant and large disadvantage for White students. Also, the disadvantage is not as large for students with lower GPAs ( $< 2.7$ ). By contrast, credits in other disciplines are consistently positively associated with earnings. For male students, the pattern is the same but few coefficients are statistically significant.

Table 5 replicates the earnings estimations for Table 3 with specific math courses and levels identified. Although the overall effect of math credits on earnings is negative, there are clear differences across math fields (Panel A). Credits in calculus and (for female students) in statistics convey significant and positive gains in earnings. In contrast, credits in other college-level math courses are associated with significantly lower earnings. Results are also different across levels of coursework (Panel B). Generally, 100-level math courses convey lower (and typically negative) returns compared with 100-level non-math courses. However, 200-level math courses convey higher (and positive) returns compared with 200-level non-math courses. Hence, more advanced math courses (in field or level) are associated with higher earnings.

Finally, to isolate the effects of remedial math we re-estimate Table 2 and the top panel of Table 3 excluding students in remediation. The results without remedial students are highly consistent with those in Tables 2 and 3: the indirect effect is positive (math raises completion probabilities); controlling for award, the direct effect is negative; but for those without an award, the direct effect is positive (results not reported here). Math credits are relatively valuable for students who do not complete.

### **College Math and Earnings: Instrumental Variables Estimates**

To account for possible selection effects in course-taking, we estimate a series of instrumental variables (IV) specifications of equations (2) and (3). Overall, these IV results are consistent with the main findings from Table 3.

Table 6 replicates the analysis in Table 3, using mean college-level math credits as an instrument for student-level math credits. The results are very similar although the coefficients and standard errors are substantially inflated in the IV specifications. (Appendix Table A.1 reports the first stage equation, which indicates the college-level average math credits IV is strongly predictive of student-level math enrollment, and specification tests.) Across the full sample of students, non-math credits have a positive impact on earnings, but math credits do not. The adverse effect of math was primarily found for students who completed associate degrees. Those who did not complete an award were better off if they have taken math courses.

**Table 6: Quarterly Earnings Gains: Math and Other Subjects—Instrumental Variables Estimation**

|  | Female        |                 |                   |                      |                    | Male             |                   |                   |                   |                   |
|--|---------------|-----------------|-------------------|----------------------|--------------------|------------------|-------------------|-------------------|-------------------|-------------------|
|  | (1)           | (2)             |                   |                      |                    | (1)              | (2)               |                   |                   |                   |
|  | Net of Award  | By Award Status |                   |                      |                    | Net of Award     | By Award Status   |                   |                   |                   |
|  | All           | All             | No Award          | Assoc. Degree        | Bachel. Degree+    | All              | All               | No Award          | Assoc. Degree     | Bachel. Degree+   |
| <i>Panel A: Credits</i>  |               |                 |                   |                      |                    |                  |                   |                   |                   |                   |
| Math CL credits ( $\beta_Y$ )  | -55<br>[117]  | 212*<br>[120]   | 1,003***<br>[209] | -706***<br>[163]     | -181<br>[238]      | -399***<br>[149] | -59<br>[144]      | 276<br>[214]      | -533***<br>[206]  | -188<br>[260]     |
| Non-math CL credits ( $\theta_Y$ )                                       | 14***<br>[4]  | 20***<br>[5]    | -28***<br>[8]     | 37***<br>[5]         | 11<br>[15]         | 22***<br>[8]     | 14*<br>[8]        | -10<br>[12]       | 19**<br>[9]       | 4<br>[21]         |
| <i>Panel B: Relative to students who took no math and no remediation</i> |               |                 |                   |                      |                    |                  |                   |                   |                   |                   |
| With CL math / No rem math   | -534<br>[688] | 530<br>[702]    | 1,877*<br>[1,009] | -3,995***<br>[1,308] | 3,340**<br>[1,615] | -211<br>[857]    | 1,991***<br>[761] | 1,655<br>[1,019]  | -3,217<br>[2,589] | -1,203<br>[2,089] |
| With CL math / With rem math   | -232<br>[316] | 877***<br>[262] | 965***<br>[227]   | -3,043***<br>[997]   | 2,986**<br>[1,261] | -16<br>[429]     | 1,197***<br>[319] | 1,133***<br>[304] | -2,585<br>[2,192] | -1,592<br>[1,700] |
| Observations   | 49,187        | 49,187          | 31,083            | 8,170                | 6,549              | 31,384           | 31,384            | 21,112            | 3,610             | 3,934             |

*Note.* Average quarterly earnings in 2011. First-time-in-college cohorts 2002–04. Robust 2SLS estimation. Instrumental variable: mean college-level math credits per college and college-wide proportions by gender/race/ethnicity, enrollment age, financial aid, single parent. All models as per Table 3 (except college fixed-effects are not included). Panel B coefficients for no college-level math not reported. Robust standard errors in brackets.

\*\*\*  $p < .01$ . \*\*  $p < .05$ . \*  $p < .1$ .

Analysis using the three alternative instruments yields consistent results. Controlling for student awards, the number of math credits is negatively associated with earnings and the number of non-math credits is positively associated with earnings. This penalty is also clear for students with associate degrees. Again, the opposite relationship holds when we look just at those who did not complete an award. For non-completers, the more math credits they had, the higher their earnings. Using college-wide instruments, these conclusions appear robust to selectivity into math courses.

## 6. Conclusion

Based on the evidence from studies of high school, there is a compelling case for encouraging high school students to study math more intensively. But this conclusion has been extrapolated to infer that the same is true for students in college, and a series of reform strategies have been developed to improve the quality of existing math provision. However, there is almost no evidence that college-level math coursework (outside of majoring in math) is academically and economically valuable. Moreover, to properly interpret this evidence it is necessary to examine both the direct effect on labor market outcomes and the indirect effect on attainment by comparison of college math coursework with coursework in other fields.

Overall, our analysis of community college students yields mixed evidence. First, we note the paucity of math taken by community college students—only one or two math credits on average per student and with the modal pathway through college involving no college-level math. *Prima facie*, it seems unlikely that students are over-investing in math courses. Also, it seems unlikely that for these students college-level math is a confounder on the effect of high school math on earnings. Indeed, relative to other coursework, credits in math are associated with higher probabilities of award receipt. This attainment effect should therefore lead to higher earnings indirectly.

However, our results for the association between math coursework and earnings lead to a more cautionary conclusion. Relative to other credits or pathways, there is sparse evidence that math has a strong impact on earnings and some evidence that it has a weak one. This conclusion is consistent with a positive attainment effect but a negative direct effect: math helps students graduate but the specific math skills acquired in community college are not especially valuable in the labor market. In correspondence with the evidence for high school, however, we do find differential effects by gender, race/ethnicity, and ability, and that the benefits of advanced math are relatively strong. Additional math coursework may therefore help close earnings gaps across student groups.

Our analysis has focused on community college students and on the returns to math course-taking for students who are not math majors and who indeed take few math courses. These are the majority of sub-baccalaureate students and—given math’s differential effects on

high school students' earnings—these might be the group for whom more math is presumed to be most beneficial. Yet, at least from our evidence, encouraging these students to take more math courses may not be helpful, especially if these courses replace other courses. We can only speculate on the reasons for this ineffectiveness. It may be that math courses convey fewer skills than other courses, in which case reform strategies to boost the quality of math instruction and curriculum standards may be appropriate. It may be that, with very high non-completion rates, the signal of an award outweighs the value of any specific courses taken in community college. Alternatively, students who take math courses (even college-level math) may be rectifying their weaker math skills from high school, and our covariate controls are unable to pick up this adverse selection. Finally, if math courses are poorly integrated into students' programs of study, they will fail to complement the skills learned in other courses and instead serve as just a hurdle to overcome. Overall, this evidence suggests that—before promoting further math in community college—more attention needs to be paid to how math coursework can be made more valuable in boosting labor market productivity.



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## Appendix

**Appendix Table A.1: Quarterly Earnings Gains: Instrumental Variables Specification Tests**

|   | Female              |                     |                     |                     |                     | Male                |                     |                     |                     |                     |
|---|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|
|   | (1)                 | (2)                 |                     |                     |                     | (1)                 | (2)                 |                     |                     |                     |
|   | Net of Award        | By Award Status     |                     |                     |                     | Net of Award        | By Award Status     |                     |                     |                     |
|   | All                 | All                 | No Award            | Assoc. Degree       | Bachel. Degree+     | All                 | All                 | No Award            | Assoc. Degree       | Bachel. Degree+     |
| <i>First stage equation:</i>                            |                     |                     |                     |                     |                     |                     |                     |                     |                     |                     |
| College-wide average math credits<br>(coefficient [se]) | 0.529***<br>[0.035] | 0.512***<br>[0.036] | 0.352***<br>[0.034] | 0.953***<br>[0.106] | 1.020***<br>[0.151] | 0.631***<br>[0.058] | 0.582***<br>[0.059] | 0.526***<br>[0.056] | 0.987***<br>[0.248] | 1.271***<br>[0.271] |
| Adjusted R-squared                                      | 0.34                | 0.32                | 0.23                | 0.21                | 0.39                | 0.35                | 0.34                | 0.26                | 0.20                | 0.38                |
| Robust F(8, n-k)  | 39.7                | 39.3                | 19.6                | 16.1                | 7.7                 | 24.2                | 24.6                | 17.5                | 5.9                 | 4.9                 |
| <i>IV specification tests:</i>                          |                     |                     |                     |                     |                     |                     |                     |                     |                     |                     |
| Robust Chi <sup>2</sup> (1)                             | 0.00<br>(1.00)      | 3.51<br>(0.06)      | 21.4<br>(0.00)      | 11.1<br>(0.00)      | 0.63<br>(0.43)      | 7.65<br>(0.00)      | 0.42<br>(0.52)      | 1.16<br>(0.28)      | 6.96<br>(0.01)      | 0.91<br>(0.34)      |
| Overidentification Score Chi <sup>2</sup> (7)           | 187.6<br>(0.00)     | 249.0<br>(0.00)     | 99.1<br>(0.00)      | 35.2<br>(0.00)      | 36.9<br>(0.00)      | 193.2<br>(0.00)     | 241.8<br>(0.00)     | 137.1<br>(0.00)     | 22.3<br>(0.01)      | 14.7<br>(0.04)      |
| Observations  | 49,187              | 49,187              | 31,083              | 8,170               | 6,549               | 31,384              | 31,384              | 21,112              | 3,610               | 3,934               |

*Note.* First stage equation for individual-level college math credits accumulation. Instrumental variable: mean college-level math credits per college and college-wide proportions by gender/race/ethnicity, enrollment age, financial aid, single parent. Second stage equation in Table 6. Robust standard errors in brackets.

\*\*\*  $p < .01$ . \*\*  $p < .05$ , \*  $p < 0.1$ .

**Appendix Table A.2: Quarterly Earnings Gains: Math and Other Subjects—Alternative Instrumental Variables Estimations**

|  | Female       |                 |                   |                  |               | Male             |                 |                |                 |               |
|--|--------------|-----------------|-------------------|------------------|---------------|------------------|-----------------|----------------|-----------------|---------------|
|  | (1)          | (2)             |                   |                  |               | (1)              | (2)             |                |                 |               |
|  | Net of Award | By Award Status |                   |                  |               | Net of Award     | By Award Status |                |                 |               |
| All                                      | All          | No Award        | Assoc. Degree     | Bachel. Degree+  | All           | All              | No Award        | Assoc. Degree  | Bachel. Degree+ |               |
| <i>A. Incl. distance learning as IV:</i> |              |                 |                   |                  |               |                  |                 |                |                 |               |
| Math CL credits ( $\beta_Y$ )            | -57<br>[117] | 208*<br>[120]   | 976***<br>[207]   | -652***<br>[157] | -176<br>[238] | -464***<br>[144] | -141<br>[138]   | 209<br>[206]   | -521**<br>[204] | -224<br>[260] |
| Non-math CL credits ( $\theta_Y$ )       | 14***<br>[4] | 20***<br>[5]    | -27***<br>[8]     | 36***<br>[5]     | 11<br>[15]    | 26***<br>[8]     | 19**<br>[8]     | -7<br>[11]     | 18*<br>[9]      | 7<br>[21]     |
| <i>B. IV % take any math:</i>            |              |                 |                   |                  |               |                  |                 |                |                 |               |
| Math CL credits ( $\beta_Y$ )            | -66<br>[117] | 193<br>[119]    | 985***<br>[205]   | -784***<br>[165] | -131<br>[232] | -246*<br>[135]   | 15<br>[134]     | 302<br>[201]   | -178<br>[173]   | -147<br>[237] |
| Non-math CL credits ( $\theta_Y$ )       | 14***<br>[4] | 21***<br>[5]    | -28***<br>[8]     | 39***<br>[5]     | 8<br>[15]     | 14**<br>[7]      | 10<br>[8]       | -12<br>[11]    | 4<br>[8]        | 1<br>[19]     |
| <i>C. IV % need math to complete:</i>    |              |                 |                   |                  |               |                  |                 |                |                 |               |
| Math CL credits ( $\beta_Y$ )            | -16<br>[117] | 203*<br>[120]   | 1,031***<br>[210] | -732***<br>[164] | -153<br>[234] | -185<br>[132]    | 16<br>[135]     | 385**<br>[194] | -256<br>[180]   | -173<br>[235] |
| Non-math CL credits ( $\theta_Y$ )       | 12***<br>[4] | 21***<br>[5]    | -29***<br>[8]     | 38***<br>[5]     | 10<br>[15]    | 11<br>[7]        | 10<br>[8]       | -16<br>[11]    | 7<br>[8]        | 3<br>[19]     |
| R-squared                                | 0.165        | 0.129           | 0.035             | 0.086            | 0.119         | 0.142            | 0.172           | 0.193          | 0.075           | 0.136         |
| Observations                             | 49,187       | 49,187          | 31,083            | 8,170            | 6,549         | 31,384           | 31,384          | 21,112         | 3,610           | 3,934         |

*Notes:* Average quarterly earnings in 2011. First-time-in-college cohorts 2002–04. Instrumental variables (IV): Panel A, percent courses online; Panel B, percent students take any math; Panel C, percent completers who took math. IVs in all specifications: college-wide proportions by gender/race/ethnicity, enrollment age, financial aid, single parent. All models as per Table 3 (except college fixed-effects are not included). Robust standard errors in brackets.

\*\*\*  $p < .01$ . \*\*  $p < .05$ . \*  $p < .1$ .