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The Role and Effect of Remedial Education in Two-Year Colleges[*]

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September 2003

ABSTRACT

Remediation has become an important part of American higher education with over one-third of students requiring remedial or developmental courses. At community colleges in particular, over half of entering students are placed into the courses, and in many states, two-year colleges serve as the primary providers of remediation. With the costs of remedial education amounting to over $1 billion each year, many policymakers have become critical of the practice. In contrast, others argue that these courses provide important opportunities for underprepared students. Despite the growing debate and the thousands of underprepared students who enter the community college system each year, little research exists on the role or effects of remediation on student outcomes. This paper addresses these critical issues by examining how community colleges attempt to assimilate students in need of remediation and to prepare them for future college-level work and labor market success. Using a unique dataset of students in Ohio's public higher education system, the papers explores the characteristics and features of remedial education at community colleges, examines participation within the programs, and analyzes the effects of remedial education on collegiate outcomes.

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[*] Please send comments to epb4@weatherhead.cwru.edu and longbr@gse.harvard.edu. The authors thank the Ohio Board of Regents for their support during this research project. Dr. Robert Sheehan, former Associate Vice Chancellor for Performance Reporting and Analysis, and Andy Lechler, HEI Senior Analyst, provided invaluable help with the data. In addition, Cathy Wegmann and Karen Singer Smith provided excellent research assistance. All opinions and mistakes are our own.

I. Introduction

Remediation has become an important part of American higher education. According to a 1996 study by the National Center for Education Statistics (NCES), nearly 30 percent of all incoming first-year students require remedial (or developmental) education in reading, writing, or mathematics, and there is some evidence that remedial enrollments are increasing.[1] Community colleges play a special role in remediation as they provide services to over 60 percent of their first-year students. Many remedial students are underprepared recent high school graduates who leave secondary school without grade-level competency or the proper preparation for college-level material. In addition, large numbers of non-traditional students require remediation and enter higher education to improve their basic skills after being displaced in the labor market. While proponents argue that remediation provides opportunities for underprepared students to gain the competencies necessary for college-level work and skilled employment, critics suggest that it provides disincentives for high school students to adequately prepare for college and that remedial courses may unnecessarily impede individual progress. Others argue that higher education is fundamentally not an appropriate place for precollege-level courses. With an estimated annual cost over $1 billion annually (Breneman and Haarlow 1997), the debate about the merits of investing in remediation has intensified.

In recent years, several major states have argued that community colleges should be the principal provider of remedial courses. However, this is a controversial stance as illustrated by the experience of the CUNY system when it tried to restructure its remedial programs in 1998. With 70 percent of entering freshman failing at least one of the three placement tests and nearly 20 percent of all CUNY students taking remedial basic-skills courses, then-Mayor Rudolph Giuliani argued that the "CUNY university system currently devotes far too much money and effort to teaching skills that students should have learned in high school" (Schmidt, 1998). After much debate and revision to the original proposal, the final decision was made in November 1999 to phase out most remedial education at the system's four-year colleges and focus the courses at community colleges (Hebel, 1999a).

Recent developments suggest more systems are moving more towards this model of concentrating remediation in the community college system. Several other states (Arizona, Florida, Montana, South Carolina, and Virginia) prohibit public universities from offering remediation education (Shedd, Redmond, and Lucy-Allen, 2002). Likewise, during the fall of 2001, the four-year California State University system "kicked out more than 2,200 students – nearly 7 percent of the freshman class – for failing to master basic English and math skills" (Trounson, 2002). This is part of a larger effort in California to encourage students to complete their remediation in the two-year colleges before entering the four-year system.

Within the debate on the provision of remediation, states and higher education institutions even question whether colleges or governments should cover any of the costs of remedial education. For example, in Florida, the legislature elected to require college students to pay the full cost of their remedial course work, an expense estimated to be four times greater than the regular tuition rate (Ignash, 1997). There is also growing support for efforts focused on high schools. Some school districts in Virginia, for example, have taken this so far as to "guarantee" their diplomas. Hanover County pays the remedial expenses of its former students, and the Virginia legislature is trying to get other districts to adopt similar programs (Wheat, 1998). However, even with reform, secondary schools would be unable to prepare all students for postsecondary education. Only 64 percent of students earn a standard high school diploma and many argue that graduation standards do not coincide with the competencies needed in college (McCabe, 2001).

Despite the growing debate on remediation and the thousands of underprepared students who enter the nation's higher education institutions each year, little is known about the effects of remediation on student outcomes. NCES (1996) suggests that freshmen enrolled in remedial classes are less likely to persist into their second year, but this evidence is based on institutional surveys and likely overstates the true effects of remediation by not controlling for student ability and student mobility. The researchers compare students with different backgrounds and fail to track students who stay in academia but transfer to another school. In another study the Ohio Board of Regents

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[1] Most scholars define "remediation" as courses students need to re-take while defining courses that are new

(2001) finds that almost 40 percent of remedial math students never take an additional math course and are less likely to succeed in subsequent math courses. However, this work does not attempt to explain how and why these outcomes differ across students. After assessing the literature on remediation, the Ohio Board of Regents concluded, "there are no known benchmark indicators addressing the success rates of higher education's remediation efforts."

The lack of analysis on the effects of remediation is likely due to the fact that few student-level datasets exist which might shed light on this issue. The ideal dataset should contain extensive information on a student's background, including high school preparation and performance, as well as information about students' progress through college including their experiences with remediation and transfer behavior between schools. Furthermore, detailed knowledge about institutional remediation policies is necessary to understand how individuals are placed into the courses. Using a unique, longitudinal dataset that meets these requirements, this paper explores the characteristics and features of remedial education at community colleges, examines participation in the courses, and analyzes the effects of remediation on student decisions and outcomes. In this way, this paper addresses a hole in the literature and reflects on how higher education attempts to assimilate underprepared students and prepare them for future college-level work and labor market success.

Focusing on math remediation, the paper examines three sets of questions. First, what are the characteristics of remedial education in community colleges and how do community colleges determine who needs to be remediated? Second, who participates in remedial education? How does participation vary by race, gender, income, and high school, and are there any factors that seem to predict the need for remediation? Finally, how does remediation affect student outcomes? How does the college performance, persistence, and transfer behavior of those in remediation compare to other students? Because our analysis is based on placement into a remedial course but not necessarily completion of that course, these results should be interpreted as the effect of the "intention to treat," the primary focus of policymakers.

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material as "developmental." In this paper, we will refer to both types of courses as being remedial.

The data for this analysis are from the Ohio Board of Regents (OBR). Since 1998, the OBR has collected comprehensive information on college enrollment at Ohio's public colleges and universities and linked it with standardized test scores and student questionnaires. For first-time freshmen of 1998-99, the focus of this paper, the data provide extensive information on each student's family background, high school preparation, postsecondary intentions, and progress through college. In addition to the wealth of information available, the data allow one to distinguish between students who withdraw from school altogether and those who transfer to other Ohio public colleges. Therefore, we are better able to measure dropout and transfer rates more effectively than other datasets where such level of detail is not available.

Measuring the effects of remediation on student outcomes can be difficult since students placed into remediation may not be comparable to other students. To avoid such selection bias, we exploit both exogenous variation in college choice and institutional remediation policies. After controlling for selection bias, the results suggest that remedial students have lower GPA's and are less likely to attain a two-year degree within three years of their initial enrollment.

The paper is organized in the following manner. Section 2 describes the data and provides background on the supply and demand for remediation. We discuss the organization, delivery, and placement process into remediation along with the characteristics of students who take remedial courses. Section 3 describes the empirical framework, which is designed to exploit variation in remediation across colleges, and presents evidence about the validity of this strategy. Section 4 presents empirical findings, and Section 5 concludes.

II. The Community College System in Ohio

The Data

The analysis is based on administrative and transcript data available through a collaborative agreement with the Ohio Board of Regents (OBR). We track the over 14,000 first-time, degree-seeking students at 19 state and local public, two-year colleges in Ohio.[2] The paper focuses on the cohort that began in Fall 1998 due to the availability of information on remedial course-taking from the OBR. The students are followed throughout the Ohio public higher education system until Winter 2002. The data include information on students' academic intent, course-taking behavior, and performance. Moreover, if a student took a college entrance exam, which is most likely to be the ACT, then there is self-reported information on high school preparation and performance from the accompanying student survey.

Summary statistics of the student sample can be found in Table 1a. Community college students are on average older, more likely to be minority students, and are less likely to intend on completing a college degree than students enrolling in other campuses. In the Ohio public higher education system, nearly two-thirds of community college students intend to get a two-year or four-year degree, and this group is the focus of this paper. Unfortunately, after three and a half years (Fall 1998 to Winter 2002), many degree-seeking students have dropped out of the system without any award. The last two columns separate the sample by age group.[3] Traditional college students are more likely to want a four-year degree, and therefore, intend to transfer to a four-year college. The younger students are also more likely to have taken the ACT and be placed in remediation.

In Ohio, there are two kinds of community colleges: state and local. Table 1b displays the summary statistics of the students at each type of college. While the oldest community college was founded in 1887, most were established in the 1960s by county governments or local school boards (Education Commission of the States, 2003). Today, each community college services a geographic area made up of several counties. However, as shown in the table, there is a slight difference in the student bodies attracted to each type. Students at the local community colleges are more likely to be pursuing a four-year degree. Their ACT scores are also slightly higher. For this reason, we break the analysis down by type of college.

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[2] Two-year technical colleges are excluded due to their special nature and the differences in the academic intent of their students.

[3] As is common in the literature, we refer to younger students who enter college within two years of graduate as "traditional" college students (i.e. ages 18, 19, or 20). Nontraditional students are defined as being any other age.

One limitation of the data is that they only include students attending Ohio public colleges and universities. Students from Ohio that attend colleges in other states or that attend private schools in Ohio are excluded from the sample. This omission could affect the measurement of dropout rates because students who transfer from community colleges to institutions located in other states or private colleges are indistinguishable in the data from students who withdraw from higher education completely. This potential bias, however, should be very small since this group makes up a small fraction of the total number of observed dropouts.[4] Furthermore, this data is a large improvement over other sources which do not allow one to track students across any schools.

Although this paper focuses on remediation in Ohio community colleges, the results should have external validity for several reasons. First, Ohio is a significant state in terms of size and diversity. It has three large cities as well as rural areas and so it reflects the complete spectrum of communities and labor markets that exist across the nation. In addition, Ohio is the sixth largest state in terms of its number of college students and seventh in terms of population.[5] The only states with greater numbers of students in public higher education are California, Texas, New York, and Illinois. Second, the array of public choices in Ohio also reflects the options students face in many other states. Ohio has a mixture of selective and nonselective four-year institutions as well as two-year community and technical colleges spread geographically across the state.

Another compelling reason to study Ohio is that its college enrollment and remediation rates are similar to national patterns. The percentage of Ohio public students that graduate from high school and the percent that enter higher education the following fall are near the national averages.[6]

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[4] While it is the case that we cannot track students who transfer to private institutions or public out-of-state institutions, this is not likely to be a large group. Using data from the Integrated Postsecondary Education Data System on the number of transfers at each institution and assuming that transfer students are geographically representative of the incoming freshman class, then one would expect around 650 Ohio students to transfer to non-Ohio schools each year. If we further assume that *all* 650 transfer students just finished their first year of school, then about 4.3 percent of observed dropouts are actually transfer students.

[5] Source on college enrollment: *Digest of Education Statistics* (2000). Ohio is the fifth largest state in terms of students at public institutions. Source on population information: Population Division, U.S. Census Bureau, Table ST-2001EST-01 - Time Series of State Population Estimates. The only states larger than Ohio in 2000 population are California, Texas, New York, Florida, Illinois, and Pennsylvania.

[6] The percent that graduate from high school is 69.6 in Ohio compared to the national average of 66.1. The percent that continue on to college is 56.1 percent compared to a national average of 56.7 (Mortenson, 2002). However, in

Furthermore, while the NCES reported that 20 percent of all first-time freshmen in 1995 enrolled in remedial reading and 25 percent enrolled in remedial writing, the OBR found one-fifth of Ohio students did so during the summer or fall of 2000. Nationally 27 percent enrolled in remedial math in 1995 while 29 percent did so in the state. Finally, Ohio is an exemplary case because it is confronting the many concerns highlighted above in the debate about remediation. In 2000, Ohio public colleges spent $15 million teaching 260,000 credit hours of high school-level courses to freshman; another $8.4 million was spent on older students. These courses, which do not count towards a college degree, cost the 20,000 remedial freshman students an additional $15 million. The magnitude of the number of students involved and the costs of remediation have parents, students, and policymakers in Ohio concerned (Sternberg and Thomas, 2002).

The Organization and Delivery of Remedial Education at Community Colleges

The purpose of remedial education is to provide underprepared students the skills necessary to succeed in college and gain skilled employment in the labor market. This practice has been around as early as the 17th century when Harvard College assigned tutors to underprepared students studying Latin (IHEP, 1998). However, during the 20th century, the increased demand for higher education by students from all backgrounds accelerated the need for remediation in higher education. By 1995, 81 percent of public four-year colleges and 100 percent of two-year colleges offered remediation (NCES, 1996).

With the exception of two campuses (Miami University and Central State University), all public colleges in Ohio offer remedial courses to entering freshmen. However, most remedial students take their courses at the community colleges. For example, about 55 percent of traditionally-aged, first-time freshman at community colleges enroll in remedial courses (OBR, 2001). In additional to their traditional students, half of two-year colleges provide remedial or developmental courses to local business and industry (NCES, 1996). As noted above, the practice of focusing remediation at the community colleges is similar to the experience in other states.

Ohio, fewer students enter the two-year rather than four-year public system than is found nationally (38 percent in

Institutional policy towards remediation varies. However, often remedial courses do not count toward degree or certification credits. Therefore, remediation frequently lengthens the time necessary to complete a degree, and this can have implications on financial aid due to time limitations. Moreover, remedial courses are often the gateway for students to enroll in upper level courses. About two-thirds of campuses nationally restrict enrollment in some classes until remediation is complete (NCES, 1996). This is also the case in Ohio where, similar to national trends, campuses vary in the extent to which they require versus suggest that under-prepared students enroll in remedial or developmental work (OBR, 2002). Often institutional rules prevent students from taking college-level classes until they have completed remedial education. These requirements may restrict students' class schedules and impede students' abilities to transfer to four-year institutions. To the extent that remediation affects the classes that students can take, it may also influence what major students can select. For example, some majors are extremely demanding in terms of required credit hours and have little leeway for students to enroll in non-required classes. In turn, students' labor market outcomes may worsen compared to other students.

The Selection Process into Remedial Education

While there are statewide standards in Ohio to distinguish between remedial and college-level work, institutions differ in how they interpret these standards at the campus level. There is also a great deal of variation across colleges as to what constitutes a remedial course and how students are selected into remedial courses. Institutional rules on placement into remediation might differ for several reasons. Schools may differ in their rates of remediation due to differences in their student bodies. For example, due to their localized nature, one community college may cater more to nontraditional, older students than another school or may have students interested in particular fields due to the demands in the local labor market.

Across schools with similar student bodies, there may be variation in remediation policies for a myriad of reasons. First, the preferences of the administration are likely to influence the role of

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Ohio compared to 48 percent nationally).

remediation at a school. For example, the University of Toledo recently decided not to offer remediation courses due a change in the college leadership. Students requiring remediation are now referred to Owens Community College, which has had to cope with the increase in students (Sheehan 2002). The preferences of the departments responsible for remediation courses are also likely to be important in determining an institution's view of remediation. Colleges may use different placement tests or decide to weight various criteria differently in determining remediation. For example, high school background and preparation often play a role in placement into remediation. The measurement error in the tests and the difference in weighting procedures create variation across similar students at different universities. Remediation may also differ across colleges due to costs. If the cost of remediation differs across schools, then colleges will vary in their placement policies. Particularly over time, as college budgets become more or less stringent, institutions may be more or less willing to spend money on remediation. Finally, the political economy of the surrounding area could explain differences in remediation if some communities are more or less likely to support remediation in college.

Selection into remediation is usually determined with a combination of measures. While most students are identified using placement exams in reading, writing, and mathematics, some schools also use standardized test scores and high school transcripts to make assignments. Interestingly, the Ohio Board of Regents records that 36 percent of first-year students age 19 or younger attending any public Ohio campus graduated from high school without a college prep curriculum. This is exactly the same proportion of students who enrolled in at least one remedial course in their first year of college (OBR 2001).

At most schools, the placement exam is taken at the beginning of students' freshman years. All community colleges in Ohio use the Computerized Adaptive Placement Assessment and Support Systems (COMPASS) as a placement exam with some also using the Assessment of Skills for Successful Entry and Transfer (ASSET), each published by the ACT, Inc. The tests consist of a variety of sections to measure students' skill level. For example, the Asset exam is a written exam with as many as 12 subsections, including in depth assessment of students' writing, numerical, and reading skills.[7] As noted above, colleges vary in which parts of the COMPASS and ASSET they use. After taking the exam, the college assigns students to a specific math course, oftentimes a remedial course, based on their scores. Typically, colleges make these designations based on “hard” cutoffs – students scoring below a given threshold are assigned to a remedial course.

Participation in Remedial and Developmental Education

The first major group of students in remedial education is underprepared, recent high school graduates, many of whom exit secondary school without grade-level competency or the proper preparation for college-level material. In Ohio, 37 percent of first-year students under the age of 19 fit into this category having graduated from high school without a college-prep curriculum (OBR, 2002). In addition, a substantial number of adult students enroll in developmental courses. Many of these workers were displaced by structural shifts in the labor market and seek developmental courses to acquire the skills necessary for re-employment. Others are often recent immigrants or welfare recipients. Nationally, about 27 percent of remedial students are over the age of 30 (IHEP, 1998), and this is similar to the pattern in Ohio. Table 2 provides describes the characteristics of students in and out of math remediation. As suspected, students placed in remediation have lower ACT scores. Moreover, they are more likely to be female and African-American. Not surprisingly, a simple tabulation of college outcomes also suggests that remediated students have lower college GPAs, are more likely to drop out, and less likely to complete a degree or transfer to a four-year school. The rest of the analysis will attempt to control for the ability bias plaguing these correlations.

Past research has found that the need for remediation in college is closely tied to the high school course of study of a student. A 2002 study by the Ohio Board of Regents found that students who had completed an academic core curriculum in high school were half as likely to need remediation in college when compared to students without this core. Hoyt and Sorensen (1999) found a similar pattern when examining the need for remediation at Utah Valley State College. Similar evidence is presented in Table 2. Students in remediation report lower high school GPAs in

[7] Complete information on both the Asset and Compass exams is available at http://www.act.org.

math and fewer years of math courses. However, in previous studies, many students who had successfully completed upper level math courses still required remedial math courses or needed to repeat subjects in college. In Ohio, 25 percent of those with a known core high school curriculum still required remediation in either math or English (OBR, 2002).

III. Estimating the Impact of Remediation using Across-College Variation

To assess the effects of remedial education, we use regression analysis to compare the outcomes of remedial students to each other as well as to non-remediated students. However, since students who take remedial education differ systematically from other college students, additional effort is necessary to deal with selection issues. There are a number of sources of variation that may be exploited to identify the effects of remediation. For example, there may be comparable students at *different* universities who did or did not take remedial classes respectively. In addition, *within* each school there may be comparable students who the university did or did not assign to remediation respectively. This section discusses an identification strategy designed to take advantage of the first kind of variation.[8] It involves exploiting differences across colleges using an instrumental variable approach.

Across-College Variation

As in other states, community colleges in Ohio have different remediation programs in terms of the types of classes offered, the method of assignment, the cutoff point on placement test, and so on. Because of this variation across institutions, similar students attending different universities might have different remediation experiences. In some cases, a student might attend remedial courses at one college while similar students at other institutions do not. However, a straightforward comparison of similar students across schools is problematic for several reasons. First, community college attendance is an endogenous choice reflecting among other things student ability. Students may choose a college (and remediation policy) that fits their abilities. As a result, students may not be perfectly comparable across schools. Additionally, variation in remediation across colleges may be endogenous to the students attending the college. For example, students attending a community college in one part of the state may be better prepared than students in another city. Finally, using variation across schools may reflect differences that are due to things other than remediation such as other campus-level interventions (e.g. advising or academic support).

To address the endogeneity of college choice and placement in remediation, we employ an instrumental variable approach. Since the key endogenous, right-hand-side variable is whether students take remediation or not, one needs an instrument that is related to the likelihood of taking remediation but not related to students' outcomes (e.g. persistence, grade point average) in college. We use an instrument that combines both the likelihood of a student choosing a given institution and the likelihood of taking remediation at this college. Previous research has shown that students are more likely to attend one school over another depending on how close the college is to a student's residence (Rouse, 1995; Card, 1995). In essence, students prefer to attend colleges closer to their home. Coupled with the fact that colleges have different remediation policies, the likelihood of remediation will depend on the policies of nearby colleges. If the college closest to a student tends to do more remediation, then the student is more likely to be remediated than a similar student who happens to live closer to a school, which does very little remediation. In short, if distance exogenously predicts the college of attendance and each college has a different remediation policy (which for the moment we will assume to be exogenous), then the interaction of these variables exogenously predicts remediation.

Estimating College Choice

To approximate the likelihood that an individual will attend a specific college, we estimate the probability of attendance conditional on that individual attending a community college. For

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[8] To best exploit within-college variation, it would be necessary to have information on students' placement test scores, but unfortunately, these data are not available at this time.

example, a student who attended Cuyahoga Community College would be assigned 19 different probabilities each corresponding to a different community college.

The conditional logistic regression model is well-suited for this framework since it both allows for multiple alternatives and can be used to exploit match-specific information such as distance. Also known as McFadden's choice model (1973), the conditional logit has been used to study choice behavior with such applications as choice of travel mode and occupation. While the form of the likelihood function is similar to that of the multinomial logistic regression, the variables are choice-specific attributes rather than individual-specific characteristics. If the independent variables were instead attributes of the individuals rather than alternatives, then the models would be the same.

For this model, the data are organized as pair-wise combinations of each student i with each community college j so that there are a total of $i \times j$ observations. These observations are stratified by individual into groups of j with each stratum constituting all possible college matches with one individual. Using these combinations, the conditional logit model is made up of j equations for each individual i, with each equation describing one of the alternatives. The conditional logit model then calculates the probability of enrollment at each of the colleges in the stratum (i.e. it considers the probability of a person attending any one of the community colleges). It does this by computing the likelihood of enrollment at each school relative to all alternatives so that the probabilities sum to one for each individual (or within one stratum).

The format of the conditional logit allows for a variable that describes the distance to each college for each individual (indexed as ij to denote individual i and school j).[9] The dependent variable, signifying the choice of the individual, equals one for the alternative that was chosen. Under the assumption that the ε_{ij}'s are independent and identically distributed with the extreme value distribution, we get the conditional logit functional form:

[9] Distance is calculated using the zip code on the student's college application and the zip code of the institution.

$$\Pr(Y_i = j) = \frac{e^{B'X_{ij}}}{\sum_j e^{B'X_{ij}}}$$

$$B'X_{ij} = \alpha + \beta S_j + \gamma D_{ij} + \varepsilon_{ij}$$

where S_j is a series of fixed effects for each school, and D_{ij} is the distance that student *i* lives from university *j*. The format allows for maximum likelihood estimates of the coefficients, and the probability of any particular choice can be calculated using the conditional logit specification.

Since the likelihood of attendance at each college is calculated relative to the alternatives within each stratum, there must be variation within the strata for estimation purposes. For this reason, student characteristics cannot be included independently in the estimation.[10] The estimation does not identify the causal effect of a student's attributes on enrollment. Instead, the estimates indicate how school characteristics affect the likelihood of a particular individual to enroll at the school. If the Independence of Irrelevant Alternatives (IIA) condition is met, the estimates will be consistent even if the decision to attend college at all is endogenous.[11]

Table 3 reports the conditional logit estimates for the 19 community colleges in our data. Each row represents a separate sample of colleges. Row 1, for example, shows the conditional logit results for the 9,641 who enrolled as freshman in 1998-99 at any of Ohio's 19 community colleges. The conditional logit suggests that the farther a student lives from a college the less likely he or she is to choose that institution. The relationship is statistically significant over a 99 percent confidence interval. The reported coefficient is not the marginal probability of distance on choice, but it clearly reflects the sign of the relationship between distance and college choice. The other rows of Table 3 show conditional logit estimates for state and local community colleges respectively. In both of

[10] The *j* equations within a stratum are not independent, and a person's gender, for example, would difference out of all the equations within one stratum since each contains data on only one individual. Therefore, unlike the multinomial regression model, non-college alternatives such as local labor market conditions cannot be included within the model since they are individual-specific.

[11] As long as students apply to schools that they determine to be most preferred, estimation will retain good statistical properties due to the IIA property. See Manski and Wise (1983) for further discussion. Also see Luce (1959) and McFadden (1979).

these cases, the coefficient shows a strong and statistically significant effect on college choice. Once estimating the conditional logit, we save the predicted probabilities of attendance at each community college conditional on the student attending one of the community colleges. These predicted probabilities are determined solely on the basis of the distance students live from a college and are an essential component of our instrumental variable strategy.

The Probability of Remediation

Our identification strategy uses distance as a predictor of college of attendance and uses variation in remediation policies across universities to predict the likelihood of remediation at any given institution. Variation in remediation policies among similar types of schools is the focus of this study to avoid unwanted variation due to differences in the quality of a student body.[12] As discussed above, these differences may be due to the preferences of the administration or department providing remediation, differences in the costs of remediation from school to school, or the political economy of the surrounding community. We use this variation to identify and compare similar students with different remediation experiences. The first-best solution would be to observe the placement exam that universities use to assign remediation, but we do not have the data to do this. However, we do have information on a substantial number of measures that help to predict that test score. For students who took the ACT, we know their scores, which is highly related and in some cases used to designate placement. Additionally, we have information from the student questionnaire that accompanies the ACT and details the types of high school classes taken as well as the grades received. The predicted probabilities that we estimate are based on these data, and we generate substantial variation for a single individual across colleges.

Using ACT scores as a predictor of placement into remediation, Figure 1 demonstrates how similar colleges have heterogeneous remediation policies. While the focus of this paper is on community colleges, for comparison we show ACT distributions and remedial cutoffs for both four-

[12] Variation arising from differences in the types of students attending the respective institutions is problematic since the remediation policies may simply identify different types of students making comparisons difficult to interpret.

year and two-year campuses. Each row represents a different type of college. In each row, the left-hand graph shows the distribution of ACT scores at each community college. The right-hand graph shows the likelihood functions for ACT cutoffs. These likelihood functions come from a series of regressions we use to estimate the likely cutoff points. For each possible ACT score, we estimate the following probit model:

$$\Pr(\text{Remediation}) = f(a + b * I(ACT>J) + e)$$

where I(ACT>J) is an indicator for whether the ACT score of student *i* is greater than J, and J varies over the possible range of the ACT math score (1-36). We estimate this model for each possible cutoff point within each college. Then we compare the likelihood functions generated by these 36 regressions. The right-hand graphs show these likelihood functions.[13] To the extent that community colleges use the ACT score to assign remediation, these likelihood plots should show a spike next to the most likely cutoff value used by an individual school.

The first row shows the test score distributions for selective four-year, public institutions in Ohio. There is a good deal of heterogeneity in the ACT test score distributions and not surprisingly, more heterogeneity in the likely ACT remediation cutoffs. Schools have different test score distributions as well as differences in the most likely cutoff value used by the schools. The other rows show the ACT distributions and remedial cutoffs other types of colleges. Row 4 shows the results for community colleges in Ohio. Similar to these other rows, the ACT distributions look more homogeneous while the remediation cutoffs in the right-hand column show much greater heterogeneity. ACT cutoffs vary across these institutions between 14 and 24.

To exploit the differences across each institution, we follow a two-step procedure. First, we estimate the "Community College Remediation Rule" for each community college. To do this, we model the likelihood of taking remediation at a particular community college as a probit.[14] We do so

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To avoid this type of variation, we estimate the effect of remediation by comparing students from one institution with students from other institutions with similar students attending.

[13] A similar methodology is used in Kane (2002).

[14] We also estimate the model using a linear probability model. We did this because we did not want identification of the endogenous parameter to be made by the non-linearity in the model.

with two separate models. In the first, we control for both students' overall and math ACT scores. In the second, we include controls for race, gender age, students post-secondary degree goal, general ACT score, math ACT score, high school GPA, family financial background, students' high school math grades and number of classes taken, the type of high school that students attend, and similar variables for SAT score.[15] To control for non-linearities, we saturate the model with dummy variables. Students' test scores enter the model linearly. We run this model for each community college in our sample using data on students who attend each institution.

The probit models generate 19 sets of coefficients or remediation "rules," one for each community college. For each set of coefficients, we generate a predicted probability of remediation for each student in the sample. In the end, for each student and for every school, we obtain estimates of the likelihood that the student would have taken remediation at that specific school.

Within subsamples of schools, there is substantial variation across these probabilities. Table 4 reports the average range of these probabilities for the first of our two models and the standard deviation of these ranges. We compute this by taking the difference in an individual's maximum and minimum predicted probability across the community colleges. For example, while an individual might have a 20 percent chance of remediation at one community college, they may have a 90 percent chance at another. We then compute the average of these ranges across individuals and report it in Table 4. For example, at state community colleges, the average range is 75.2 percent with a standard deviation of 9.8 percent. Attending a different university can dramatically change the likelihood that an individual student attends remediation. Local community colleges have less variation with an average range of 38.1 and a standard deviation of 5.2. In Column 2 of Table 4, we report likelihood ratio tests where we test whether the coefficients in our individual rules are equal. For every subsample, the likelihood ratio rejects the hypothesis that the coefficients across colleges are the same. Clearly, substantial variation exists across the data.

We interpret these results as meaning that remediation policies vary substantially across colleges. If this is the case, then our identification strategy should identify the effects of remediation.

[15] Because some community college students do not take the ACT or SAT, we create a dummy variable equal to one

However, there remains the possibility that the results simply mean the ACT math score is a poor predictor of the likelihood of remediation. As Figures 2A and 2B demonstrate, this is clearly not the case. Figure 2A plots the distribution of ACT math scores for state community colleges in Ohio. In almost every case, the distribution of ACT math scores for remedial students is below the distribution of ACT math scores for non-remedial students. Clearly, ACT math scores are correlated with the likelihood of remediation. Figure 2B presents similar results for all of the community colleges in Ohio.

Building the Instrumental Variable

We combine the probabilities of attendance and of remediation to build our instrument for remediation. From the conditional logit results, we have an estimate of the probability of attendance at any particular community college conditional on attending one of them. From the remediation probabilities, we know the probability of remediation at an individual institution conditional on attending that community college. Therefore, our instrument is calculated:[16]

$$\begin{aligned} Z &= \Pr[\text{Remed}_i \mid \text{Attends any community college}] \\ &= \sum_{j \in J} \Pr[\text{Remed}_i \mid \text{Attends CC } j\,]\Pr[\text{Attends CC } j \mid \text{Attends any community college}] \end{aligned}$$

Since we created the probabilities of remediation conditional on students' backgrounds, we include all of the variables used in the probability estimation as covariates in our instrumental variables. As a result in our first stage regressions, the instrument picks up the portion of the remediation probability that varies according to distance and differences in colleges' remediation policies.

Intuitively, our instrument is a correction in the probability of remediation based on distance to schools with different remediation policies. If we were to estimate a regression of the likelihood of taking remediation on all covariates, we could generate predicted values for every person. If we

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if the score is missing so that we may keep them in the analysis.

[16] We have also estimated results using a second instrument based on the remediation probability at the school nearest to a given student as the instrument for that student. The results are similar.

ran similar regressions including our instrument, we could generate a second set of predicted values. The difference between these two predicted values is the correction based on distance and different remediation policies. This procedure is similar mathematically to what the first-stage does and may be more intuitive.

Table 5 reports the first-stage estimates for each subsample of universities reporting the coefficients and standard errors on our instrument in the respective models. The coefficients correct for heteroskedasticity and show the coefficient for the instrument based on distance and the different community college remediation rules. Among community colleges, the predicted probability of remediation has a coefficient of .711 and is highly significant. The closer that a student lives to a school with an expansive remediation policy, the more likely the student is to take remediation. Each of the subsamples shows similar effects of our instrument on the likelihood of completing remediation.

IV. The Effects of Remediation using Across-University Variation

We estimate the effects of the "intention to treat" on four related outcomes: drop-out rates, GPA, degree completion, and transfer behavior to four-year institutions. The effects are estimated using administrative data covering students' college experiences through the end of the winter semester 2002. Since these students initially enrolled in fall 1998, these students should have completed three years of college.

To measure the effects of remediation, we run the following regression model

$$\text{Outcome}_i = \alpha + \beta \,\text{Remed}_i + \gamma X_i + e$$

where X is a matrix of individual characteristics that may influence both assignment to remediation and students' outcomes. Remediation enters the model as a dummy variable equal to one if the person enrolled in any remedial math course.[17] We report basic results using linear regression (OLS) and the instrumental variable (IV) approach to deal with ability bias.

Tables 6a and 6b report the estimated effects of remediation on drop-out rates for traditional and non-traditional students respectively.[18] At all community colleges, about 61 percent of traditional students and 50 percent of non-traditional students attended remedial courses. About 68 percent of traditional students who initially enrolled in 1998 have withdrawn from school by 2002. About 79 percent of non-traditional students have also withdrawn.

The OLS estimates show at most a one percentage point effect although the estimated effects are not significant. By contrast, the IV estimates suggest that remediated students are more likely to withdraw from college than their counterparts. Since these estimates are due to exogenous variation in college choice and institutional rules, this effect should not be due to selection issues. Across all community colleges, the estimate is significant over a 95 percent confidence interval. This effect is driven largely by the local community colleges where the estimated effect (13 percentage points) is significant over a 95 percent confidence interval.

Interestingly, the OLS estimates are smaller in magnitude than the IV estimates. Since the estimates are insignificant across most samples, this is not troubling; however, as will be seen below, this is a consistent trend in our estimation strategy. We discuss possible reasons for it below.

Table 7a and 7b report the IV and OLS estimates for the effects of remediation on grade point averages of traditional and non-traditional students.[19] In this case, both the IV and OLS estimates suggest that remediated students achieve lower grade point averages. The OLS estimates suggest significant differences ranging from one-tenth of a GPA point to as much as four-tenths of a GPA point. In every case, the OLS estimates are significant. For the IV estimates, the results are similar in magnitude but insignificant. The estimated impact (0.2 points lower) is marginally

[17] We focus on math remediation at this time. Later analysis will attempt to differentiate between students with varying amounts of remediation and include those in remedial writing or reading courses.

[18] Students are considered "drop-outs" if they are no longer at any public, Ohio college at the end of the time period and have not received a degree. Since our data allows us to track students across public colleges in Ohio, we are confident that most of these students have indeed left higher education. Students who transferred to other colleges are not considered dropouts in this study as they have been in other work on the subject.

[19] The GPA measure includes all courses taken at Ohio public institutions since Fall 1998.

significant in the sample of non-traditional students. This is roughly equivalent to non-remediated students achieving one letter grade higher in one three-credit class in each of the six semesters that these students attended.

Table 8a and 8b show the IV and OLS estimates of the effects of remediation on degree completion while Tables 9a and 9b show the estimates for "transferring up" behavior. The OLS and IV results suggest that traditional-age, remediated students are significantly less likely to complete a degree within the period studied in this paper than non-remediated students. The estimated effect in the IV specifications suggests an overall effect of 12 percentage points. The IV results also suggest that non-traditional students in remediation are less likely to complete a degree than non-remediated students. The estimates in Tables 9a and 9b suggest that remediation may lead to a small increase in student transfer rates. Traditional-age students at both state and local community colleges are significantly more likely to transfer to a four-year campus than non-remediated students.

As mentioned, one of the interesting features of Tables 6 through 9 is that the IV estimates are often higher than the OLS estimates. For example, in Table 6 the estimated IV effects on drop-out rates is much higher than the OLS estimates. Given that the possible selection bias is thought to be negative (i.e. remediated students are more likely to perform worse than others), one might have thought that the IV estimates would be smaller than the OLS estimates. There are several possible reasons for this result.

One reason that IV may be greater than OLS is based on the fact that we are using cross-university variation in remediation policies. For example, when examining the effect of remediation on drop out behavior, the IV estimate is related to both the strength of the relationship between these policies and dropout rates and the relationship between differences in remediation policies and student characteristics. The weaker the latter relationship, the larger in magnitude the IV estimate should be. Moreover, there may be compositional issues related to the size of community colleges and the strength of their remediation policies that may lead OLS to be smaller than one might expect. Large community colleges that unnecessarily remediate a large number of students may in part drive the OLS estimate. The more that schools unnecessarily remediate students, the smaller the OLS estimate.

Another reason that the OLS results may be smaller in magnitude than the IV results relates to our instrument. Our instrument uses geographical variation to identify the probability of remediation. The OLS estimates are largely based on comparisons of students *within* geographical areas while the IV estimates are based on comparisons *across* geographical areas. If differences in students across geographical areas are larger than differences within geographical areas, then IV estimates may be larger than OLS estimates. While our analysis limits the sample to students who are attending a community college, unobserved geographical heterogeneity within these students may still account for the estimates.

Table 10 attempts to control for some of the heterogeneity between students. As mentioned earlier, community college students at their initial enrollment declared whether or not they wanted to attempt a degree. The analysis in this paper focuses on the set of students who declared that they wanted to complete any degree – whether two-year or four-year. In Table 10, we control more differences that may exist between students who intend to get different degrees. Specifically, we estimate the following specification:

$$\text{Outcome}_i = \alpha + \beta_1 \text{Remed}_i + \beta_2 (\text{Intent=2yr}) + \beta_3 \text{Remed}_i *(\text{Intent=2yr}) + \gamma X_i + e.$$

The specification controls for existing differences between students with different degree intentions and allows remediation to affect them differently. The reported estimates are based on an IV specification where our instrument is also interacted with the degree intent variable to create a second instrument. The sample sizes are identical to those reported in other tables.

As Table 10 shows, the effect of remediation on stop-out behavior is largely focused on students who intended to complete a two-year degree. The estimated effect is much larger and suggests that remediation may derail their plans. The estimated effects on degree completion show similar results. While remediation does decrease the likelihood that students finish a degree within 3.5 years of their initial enrollment it is event stronger for those students whose degree intention was only two years. There are little significant differences in the effect of remediation on GPA or on transfer behavior when comparing students with different degree intentions..

V. Conclusions

In summation, the IV estimates based on across-college variation suggests that students in remediation at community colleges are more likely to withdraw from college and more likely to fail to complete a degree within 3.5 years of their initial enrollment. Traditional-age students may be as much as 12 percentage points less likely to graduate within 3.5 years if they took remediation. There is mixed evidence on the effects of remediation on college GPA's. The IV estimates are all negative but are not significant. Once we control for additional student heterogeneity, we find that remediated students tend to have GPA's that are about 0.1 GPA points lower than non-remediated students. The estimates for non-traditional students are similar. Finally, we do find some evidence remediation improves the likelihood that traditional students transfer to four-year campuses. These IV estimates depend on the assumptions that colleges are exogenously located and that they adopt remediation policies that are unrelated to the geographic region where they are located.

Interestingly, the results are much weaker when we control for student heterogeneity in degree intent. The observed negative effects are strongest for students who had an intention of completing a two-year degree. While there are still some negative effects for other degree-seeking remedial students (e.g. lower GPA and less degree completion), there is no increase in stop-out rates for students who intended to complete a four-year degree. Remediation appears to discourage students seeking two-year degrees but not students attempting four-year degrees.

These results contrast previous work (Bettinger and Long 2002) where remediation was found to generate negative effects for students at four-year institutions. Students in remedial courses at public four-year colleges in Ohio on average were more likely to drop-out, less likely to graduate, and had lower college GPAs. This may suggest that while remediated students at four-year colleges "mis-sorted" into the four-year system and then performed poorly, community college students do not have the same problem. However, a story about negative peer effects in remedial courses could explain the negative impact of remediation on some student outcomes at both four- and two-year institutions.

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Figure 1: ACT Distributions and the Probability of Remediation

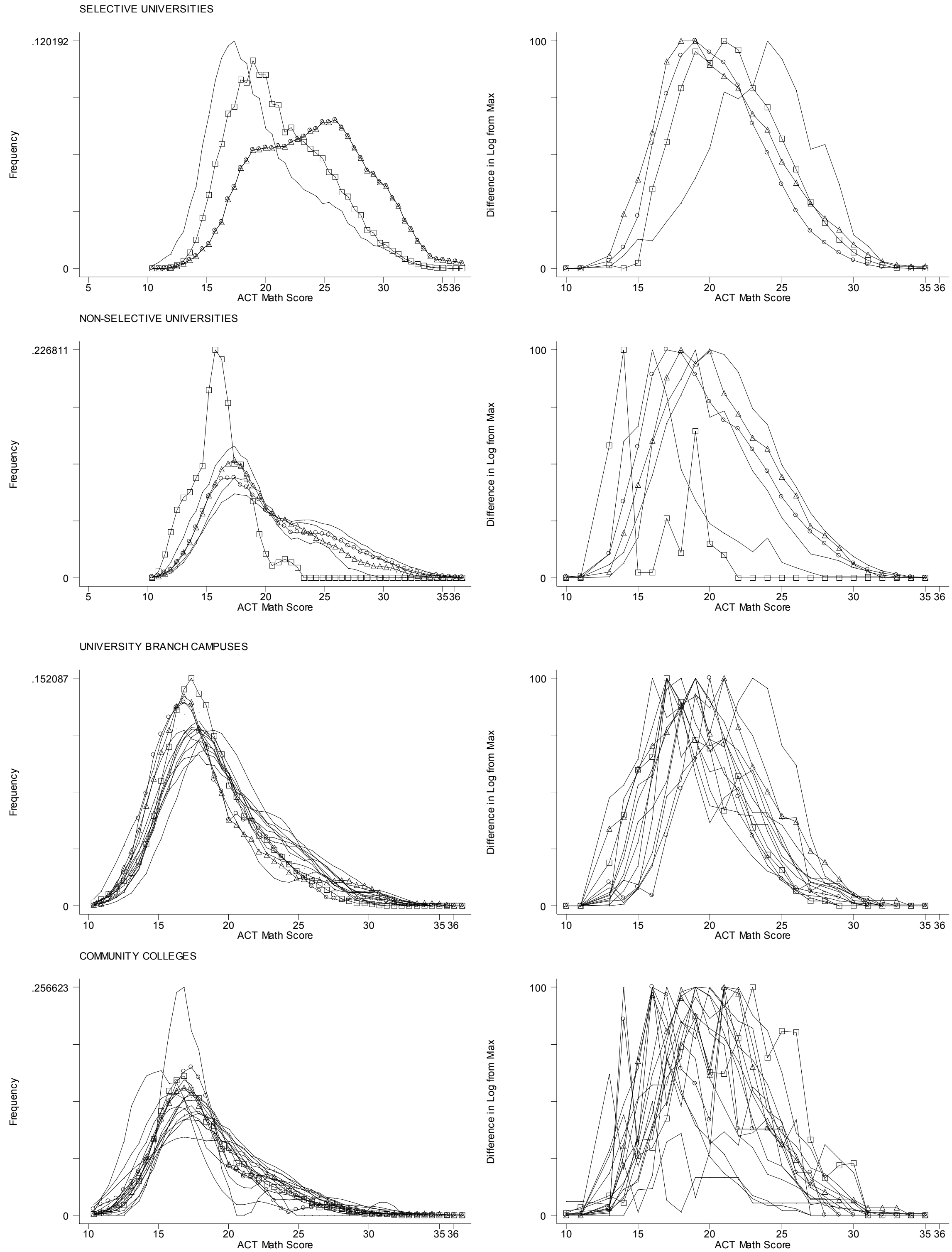

Figure 2A. ACT Test Score Distributions by Remedial Status, State Community Colleges

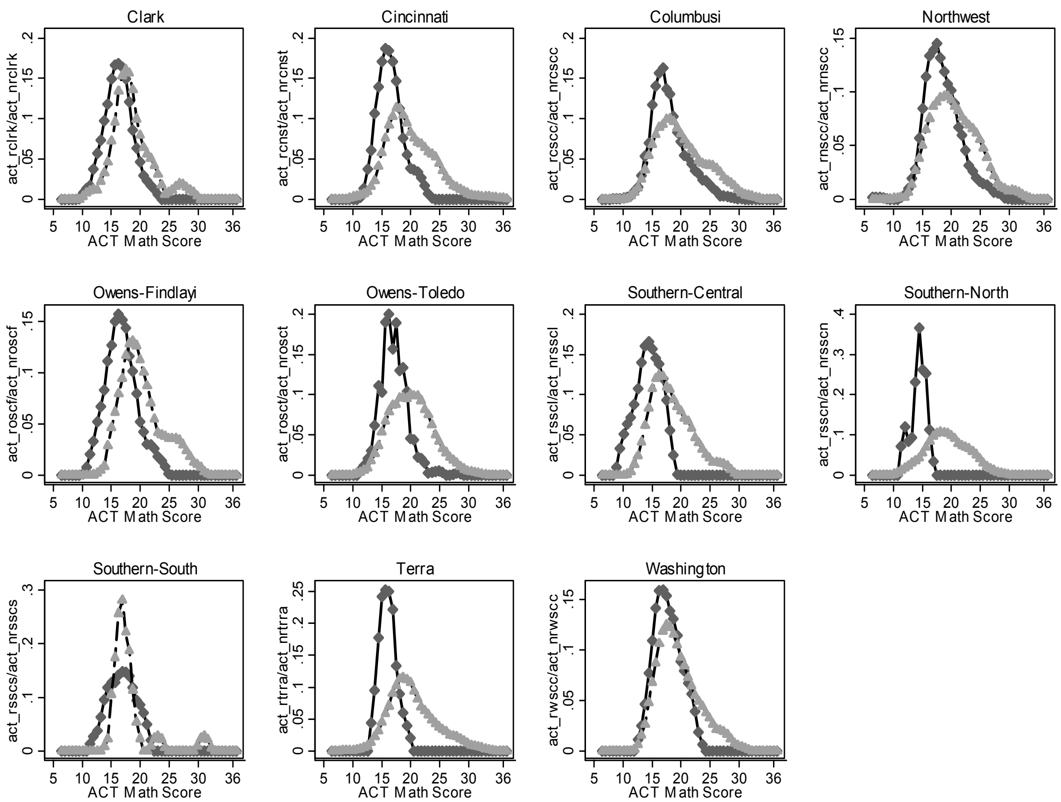

Figure 2B. ACT Test Score Distributions by Remedial Status, Local Community Colleges

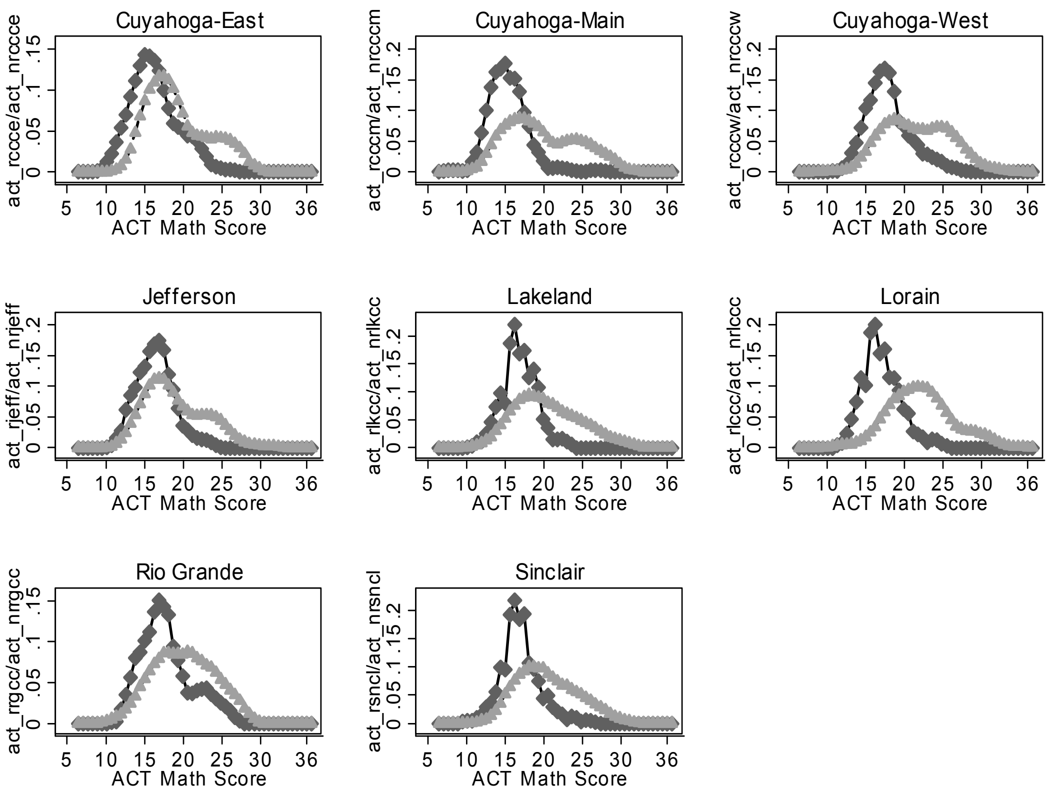

Table 1a: Students in the Ohio Community College System

	All Students	All degree-seeking students	Traditional-aged degree-seeking students	Nontraditional degree-seeking students
Age in 1998	24.39 (9.67) [22,380]	21.53 (6.58) [14,189]	18.63 (0.68)	27.88 (8.87)
Percent Female	50.5	53.8	52.5	56.7
Percent Black	14.2	14.4	12.5	18.4
Percent Hispanic	2.5	2.7	2.5	2.9
Percent Asian	1.2	1.2	1.0	1.6
Percent Ohio Resident	95.5	97.3	97.6	96.5
Intention to complete a Two-year Degree	28.6	45.3	39.1	59.0
Intention to complete a Four-year Degree	34.4	54.7	60.9	41.0
Enrolled in Remedial Math	45.7	57.2	60.9	49.1
Credits of Remedial Math attempted	4.175 (6.29)	5.33 (6.75)	5.71 (6.87)	4.52 (6.42)
Credits of Remedial Math Completed	2.55 (4.52)	3.29 (4.93)	3.54 (5.02)	2.75 (4.69)
Total Credit Hours (Fall98 – Winter02)	32.38 (33.70)	38.73 (34.86)	41.85 (34.72)	31.95 (34.19)
College GPA	2.23 (1.21) [10,566]	2.13 (1.15) [7,258]	2.04 (1.08) [5,230]	2.35 (1.28) [2,021]
Dropped Out before Winter 2002	76.1	70.9	67.5	78.4
Completed a Two- or Four-year degree	6.1	8.1	9.2	5.6
Transferred Up	6.1	8.3	9.8	5.1
Percent Took ACT	32.2	42.5	55.0	15.2
ACT Math Score (36 maximum)	18.75 (3.80) [7,270]	18.78 (3.82) [6,040]	18.61 (3.66) [5,358]	20.14 (4.65) [676]
ACT Overall Score (36 maximum)	19.14 (3.76) [7,270]	19.18 (3.76) [6,040]	18.97 (3.62) [5,358]	20.85 (4.40) [676]
Observations	22,557	14,213	9,742	4,447

Sample: First-time students entering the Ohio community college system in fall 1998.
Notes: Standard deviations are shown in the parentheses. The number of observations for variables with less than the total is shown in brackets. “Degree-seeking” students denoted on their applications a desire to get an Associates or Bachelor degree or transfer to another institution (presumably a four-year institution). “Traditional” college students began when they were age 18, 19 or 20. Individuals without valid zip code information from their applications were dropped.

Table 1b: Students in State versus Local Community Colleges

	All Degree-seeking Students		Traditional-aged degree-seeking students		Nontraditional degree-seeking students	
	State CC	Local CC	State CC	Local CC	State CC	Local CC
Age in 1998	21.99 (6.89) [6,601]	21.14 (6.28) [7,588]	18.65 (0.69)	18.62 (0.67)	28.17 (8.72)	27.57 (9.02)
Female	52.9	54.7	51.8	53.1	55.1	58.5
Black	12.5	16.1	10.7	14.0	15.8	21.3
Hispanic	2.6	2.7	2.3	2.8	3.2	2.6
Asian	1.1	1.3	1.2	0.9	1.0	2.2
Ohio Resident	95.6	98.7	95.9	99.0	95.0	98.1
Intention: Two-year Degree	60.1	32.5	54.1	27.3	71.2	45.9
Intention: Four-year Degree	39.9	67.5	45.9	72.7	28.8	54.1
Took ACT	43.3	41.8	58.8	52.0	14.7	15.8
ACT Math Score (36 max)	18.63 (3.59) [2,866]	18.91 (4.01) [3,174]	18.54 (3.49) [2,523]	18.67 (3.81) [2,835]	19.35 (4.24) [339]	20.93 (4.91) [337]
ACT Overall Score (36 max)	18.97 (3.52) [2,866]	19.36 (3.96) [3,174]	18.83 (3.41) [2,523]	19.09 (3.79) [2,835]	20.02 (4.10) [339]	21.67 (4.53) [337]
Enrolled in Remedial Math	57.9	56.6	60.8	61.0	52.7	45.2
Observations	6,618	7,595	4,290	5,452	2,311	2,136

Sample: First-time, degree-seeking students entering the Ohio community college system in fall 1998.
Notes: Standard deviations are shown in the parentheses. The number of observations for variables with less than the total is shown in brackets. "Traditional" college students began when they were age 18, 19 or 20. Individuals without valid zip code information from their applications were dropped.

Table 2: Students in Remediation at Ohio Community Colleges

	All Degree-seeking Students		Traditional-aged degree-seeking students		Nontraditional degree-seeking students	
	No Remediation	Enrolled in Remediation	No Remediation	Enrolled in Remediation	No Remediation	Enrolled in Remediation
Age in 1998	22.04 (7.48) [6,070]	21.15 (5.80) [8,119]	18.60 (0.67)	18.66 (0.68)	27.83 (9.79)	27.93 (7.80)
Female	50.2	56.6	48.7	55.0	52.7	60.9
Black	8.9	18.5	6.6	16.4	12.9	24.2
Hispanic	2.1	3.1	1.5	3.2	3.1	2.7
Asian	1.3	1.1	1.0	1.0	1.7	1.4
Ohio Resident	96.5	97.8	96.9	98.1	95.9	97.0
Intention: Two-year Degree	46.6	44.4	41.8	37.3	54.5	63.7
Intention: Four-year Degree	53.4	55.6	58.2	62.7	45.5	36.3
Took ACT	45.3	40.4	59.4	52.2	21.7	8.5
ACT Math Score (36 max)	20.50 (4.13) [2,756]	17.33 (2.82) [3,284]	20.34 (3.98) [2,262]	17.34 (2.80) [3,096]	21.25 (4.67) [491]	17.18 (3.06) [185]
ACT Overall Score (36 max)	20.72 (3.91) [2,756]	17.88 (3.09) [3,284]	20.49 (3.75) [2,262]	17.86 (3.07) [3,096]	21.80 (4.37) [491]	18.32 (3.33) [185]
Average HS Math GPA	2.91 (0.75) [2,584]	2.43 (0.76) [2,967]	2.89 (0.75) [2,112]	2.44 (0.76) [2,783]	3.00 (0.78) [469]	2.30 (0.83) [181]
Number of years of Math in HS	7.16 (1.25) [2,635]	6.80 (1.40) [3,094]	7.17 (1.24) [2,162]	6.82 (1.40) [2,915]	7.10 (1.30) [471]	6.57 (1.41) [176]
Total Credit Hours (Fall98 – Winter02)	39.38 (37.07)	38.25 (33.09)	44.54 (37.27)	40.13 (32.87)	30.80 (35.10)	33.15 (33.18)
College GPA	2.36 (1.16) [3,136]	1.95 (1.10)	2.26 (1.09) [2,031]	1.91 (1.05) [3,199]	2.55 (1.26) [1,102]	2.11 (1.25) [919]
Dropped Out before Winter 02	68.4	72.8	64.1	69.7	75.7	81.3
Completed at least 2yr degree	11.5	5.5	14.7	5.7	6.2	5.0
Transferred Up	9.7	7.3	11.0	9.1	7.5	2.6
Observations	6,086	8,127	3,806	5,936	2,264	2,183

Sample: First-time, degree-seeking students entering the Ohio community college system in fall 1998.
Notes: Standard deviations are shown in the parentheses. The number of observations for variables with less than the total is shown in brackets. "Traditional" college students began when they were age 18, 19 or 20. Individuals without valid zip code information from their applications were dropped.

Table 3: Conditional Logit & Distance

Sample	Coefficient on Distance from Conditional Logit	Number of Colleges	Number of Students
All Community Colleges	-.1028 (.0015)	19	9,641
State Community Colleges	-.0905 (.0020)	11	4,199
Local Community Colleges	-.1503 (.0037)	8	5,442

Standard errors are in parentheses. Sample includes all students aged 18-20 who declared intent to pursue either an associates degree or transfer and get a bachelors degree.

Table 4: Ranges of Predicted Probabilities of Remediation within University Groupings

	Mean Range of Predicted Probabilities within College Group	LR Test for Equality of Coefficients (Chi-sq df)
All Community Colleges	74.5 (9.8)	1254.8 (54df)
State Community Colleges	75.2 (9.8)	939.2 (30df)
Local Community Colleges	38.1 (5.2)	288.2 (21df)

Notes: The mean range is computed by taking the difference in an individual's maximum and minimum predicted probability across the community colleges. For example, while an individual might have a 20 percent chance of remediation at one community college, they may have a 90 percent chance at another. The average of these ranges across individuals is reported. The likelihood ratio tests whether the “remediation rules” for each college are equal.

Table 5: First-stage Estimates of Effect of Distance and Differences in Policies on Remediation Probabilities

	Coefficient on Distance/Remediation Instrument	
	Traditional Students	Nontraditional Students
All Community Colleges	.711** (.018)	.593** (.028)
State Community Colleges	.778** (.024)	.644** (.038)
Local Community Colleges	.675** (.028)	.574** (.047)

** Significant at the 5% level

Table 6a: IV Estimates of Effect of Remediation on Dropout – *Traditional Students*

Sample	Percent in Remediation	Percent Dropout	Coefficient on Remediation	
			OLS	IV
Community Colleges (N=8503)	.6060	.6826	.0091 (.0107)	.0660** (.0262)
State Community Colleges (N=3721)	.6031	.6348	.0115 (.0167)	.0515 (.0346)
Local Community Colleges (N=4782)	.6081	.7200	.0035 (.0141)	.1335** (.0423)

** Significant at the 5% level * Significant at the 10% level

Notes: “Dropout” is defined as not being part of the Ohio public higher education system after three and a half years.

Table 6b: IV Estimates of Effect of Remediation on Dropout – *Nontraditional Students*

Sample	Percent in Remediation	Percent Dropout	Coefficient on Remediation	
			OLS	IV
Community Colleges (N=4325)	.4969	.7896	.0015 (.0129)	.0842** (.0409)
State Community Colleges (N=2252)	.5311	.7722	.0081 (.0186)	.0572 (.0524)
Local Community Colleges (N=2073)	.4597	.8085	.0041 (.0179)	.2228** (.0689)

** Significant at the 5% level * Significant at the 10% level

Notes: “Dropout” is defined as not being part of the Ohio public higher education system after three and a half years.

Table 7a: IV Estimates of Effect of Remediation on College GPA– *Traditional Students*

Sample	Pct in Remediation	Mean College GPA	Coefficient on Remediation	
			OLS	IV
Community Colleges (N=8030)	.6060	2.140	-.1322** (.0241)	-.0848 (.0583)
State Community Colleges (N=3445)	.6031	2.291	-.1509** (.0355)	-.1275* (.0722)
Local Community Colleges (N=4585)	.6081	2.026	-.1117** (.0330)	-.1390 (.0972)

** Significant at the 5% level * Significant at the 10% level
Notes: Outcome is defined three and a half years after college entry.

Table 7b: IV Estimates of Effect of Remediation on College GPA – *Nontraditional Students*

Sample	Percent in Remediation	Mean College GPA	Coefficient on Remediation	
			OLS	IV
Community Colleges (N=3952)	.4969	2.4318	-.2786** (.0389)	-.214* (.122)
State Community Colleges (N=1991)	.5311	2.5261	-.3665** (.0535)	.0295 (.1495)
Local Community Colleges (N=1961)	.4597	2.3360	-.0671* (.0353)	-.5773** (.2139)

** Significant at the 5% level * Significant at the 10% level
Notes: Outcome is defined three and a half years after college entry.

Table 8a: IV Estimates of Effect of Remediation on Degree Completion– *Traditional Students*

Sample	Pct in Remediation	Pct Complete Degree	Coefficient on Remediation	
			OLS	IV
Community Colleges (N=8503)	.6060	.0929	-.06234** (.0066)	-.1213** (.0162)
State Community Colleges (N=3721)	.6031	.1174	-.0944** (.0110)	-.1804** (.0229)
Local Community Colleges (N=4782)	.6081	.0721	-.0353** (.0081)	-.0832** (.0242)

** Significant at the 5% level * Significant at the 10% level

Notes: The outcome measures whether a students has received an Associates or Bachelor degree and is defined three and a half years after college entry.

Table 8b: IV Estimates of Effect of Remediation on Degree Completion – *Nontraditional Students*

Sample	Percent in Remediation	Pct Complete Degree	Coefficient on Remediation	
			OLS	IV
Community Colleges (N=4325)	.4969	.0569	-.0074 (.0075)	-.0952** (.0240)
State Community Colleges (N=2252)	.5311	.0644	-.0087 (.0111)	-.0828** (.0315)
Local Community Colleges (N=2073)	.4597	.0487	-.0097 (.0102)	-.0700* (.0381)

** Significant at the 5% level * Significant at the 10% level

Notes: The outcome measures whether a students has received an Associates or Bachelor degree and is defined three and a half years after college entry.

Table 9a: IV Estimates of Effect of Remediation on Transfer Behavior– *Traditional Students*

Sample	Pct in Remediation	Pct Transfer Up	Coefficient on Remediation OLS	Coefficient on Remediation IV
Community Colleges (N=8503)	.6060	.0941	.0082* (.0067)	.0216 (.0164)
State Community Colleges (N=3721)	.6031	.0989	.0200* (.0104)	.0315** (.0125)
Local Community Colleges (N=4782)	.6081	.0901	.0017 (.0089)	.0519* (.0266)

** Significant at the 5% level * Significant at the 10% level
Notes: "Transfer Up" is defined as a transfer to any four-year institution within three and a half years of college entry.

Table 9b: IV Estimates of Effect of Remediation on Transfer Behavior – *Nontraditional Students*

Sample	Percent in Remediation	Pct Transfer Up	Coefficient on Remediation OLS	Coefficient on Remediation IV
Community Colleges (N=4325)	.4969	.0462	-.0053 (.0061)	-.0259 (.0193)
State Community Colleges (N=2252)	.5311	.0435	-.0093 (.0083)	-.0283 (.0234)
Local Community Colleges (N=2073)	.4597	.0492	-.0030 (.0085)	.0185 (.0316)

** Significant at the 5% level * Significant at the 10% level
Notes: "Transfer Up" is defined as a transfer to any four-year institution within three and a half years of college entry.

Table10: Differences in the Effect of Remediation by Degree Intent (Two- or Four-year Degree)
Sample: All Community Colleges

Dependent Variable	Stop-out Behavior	College GPA	Degree Completion	Transfer Behavior
	(1)	(2)	(3)	(4)
Remediated Student	.0207 (.0309)	-.1171* (.0683)	-.0843** (.0191)	.0226 (.0193)
Intent to Get a Two-Year Degree (relative to Four-year Degree)	-.0951** (.0282)	.0343 (-.0629)	.1019** (.0175)	-.0364** (.0177)
Remediated * Two-Year Degree Intent	.1665** (.0432)	-.0646 (.0956)	-.1143** (.0267)	-.0158 (.0270)