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THE PLIGHT OF UNDERPREPARED STUDENTS IN HIGHER EDUCATION
The Role and Effect of Remedial Education*

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ABSTRACT

Remediation has become an important part of American higher education with over one-third of all students requiring remedial or developmental courses. With the costs of remediation amounting to over $1 billion each year, many policymakers have become critical of the practice. In contrast, others argue that these courses provide opportunities for underprepared students. Despite the growing debate on remediation and the thousands of underprepared students who enter the nation's higher education institutions each year, little research exists on the role or effects of remediation on student outcomes. This project addresses these critical issues by examining how higher education attempts 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, examines participation within the programs, and analyzes the effects of remedial education on student outcomes in college.

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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] Many remedial students are underprepared recent high school graduates. These students often leave secondary school without grade-level competency or the proper preparation for college-level material either due to poor high school course selection or the lack of a college-prep curriculum at their schools. There are also a large number of non-traditional students who require remediation, many of whom 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 more advanced college-level work, 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.

First, there is some disagreement about who should provide the service. Some policymakers 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

[1] Most scholars define "remediation" as courses students need to re-take while defining courses that are new material as "developmental." In this paper, we will refer to both types of courses as being remedial.

decision was made in November 1999 to phase out most remedial education at the system's four-year colleges beginning in 2000 (Hebel, 1999a).

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). Still other schools have refused to enroll underprepared students at all. During the fall of 2001, the 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).

As higher education takes on more of the responsibility to help underprepared students, many officials interpret the increasing role of remediation as a signal of the ineffectiveness of secondary school systems and suggest that efforts should instead be focused on high schools. Some 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 (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 contain 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, examines participation within remediation programs, and analyzes the effects of remedial education on student decisions and outcomes. In this way, it addresses a hole in the literature concerning remediation and reflects on how higher education attempts to assimilate underprepared students and prepare them for future college-level work and labor market success.

The paper examines three sets of questions. First, how does remediation vary across institutions (e.g. two- versus four-year schools; open and selective enrollment institutions)? Moreover, how do 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 and persistence of those in remediation compare to other students? Measuring the effects of remediation on student outcomes can be difficult since students attending remediation may not be comparable to other students. To avoid such selection bias, we exploit both exogenous variation in institutional remediation policies and college choice. We also examine the effects of remediation on other college outcomes such as grade point average, degree completion after three years (especially in the two-year colleges), and transfer behavior.[2]

To examine the supply, demand, and effects of remedial education, this paper presents evidence from data gathered by the Ohio Board of Regents (OBR). Since 1998, OBR has collected comprehensive information on college enrollment at Ohio's public colleges and universities. Through collaborative agreements, the OBR has linked college transcripts with information from FAFSA forms, standardized test scores and questionnaires, and employment records. 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, financial need, and postsecondary intentions (eventually it will provide information on labor market outcomes). In addition to the wealth of information available, the data allow one to distinguish between students who withdraw from school and those who transfer to other Ohio public colleges.[3] Therefore, these data do not have the shortcomings of other datasets and offer a level of detail not available elsewhere.

Although this paper focuses on remediation in the Ohio public higher education system, the results should also 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.[4] The only states with greater numbers of students in public higher education are

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[2] This version of the paper estimates the "intention to treat" effect. While this may be the paramter of most interest to policymakers, there are other parameters of interest that we hope to estimate in future versions of the paper. Most notably, since a significant number of students enroll but do not attend remediation classes, we hope to estimate the effect of the treatment on the treated. Also, as students start to get jobs, we hope to extend our analysis to include job market outcomes.

[3] While it is the case that we can not track students who transfer to private institutions or public out-of-state institutions, this is not likely to be a large group. The Integrated Postsecondary Education Data System (IPEDS) tracks the number of transfers at each institution but does not record the state of residence of transfer students although it does track the states of residence for incoming freshman. Assuming that transfer students are geographically representative of the incoming freshman class, then one would expect around 650 Ohio students to transfer to the non-Ohio schools with substantial Ohio enrollments. 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.

[4] 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

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.[5] 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 no 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 basic results, after controlling for selection bias, suggest that remediation has not improved the outcomes of students who enroll in the courses. While some types of campuses (e.g. University Branch Campuses) show no effect of remediation on college persistence, remedial students at non-selective four-year campuses are much more likely to dropout of college. At other institutions, remedial students are less likely to transfer to more selective schools and more likely to transfer to less selective schools. We also find that remedial students have lower GPA's and that community college students are less likely to attain a degree after three years.

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.

[5] 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).

The paper is organized in the following manner. Section 2 describes the data and summarizes the characteristics of the students and colleges in Ohio. Section 3 provides background and a review of the literature on the supply and demand for remediation. The organization, delivery, and placement process into remediation are reviewed along with the characteristics of students who take remedial courses. Section 4 explains the empirical methodology providing information and evidence about the validity of our identification strategy. Section 5 presents our empirical findings. Section 6 concludes.

II. Students and Colleges in Ohio

The Data

The data for this project come from the Ohio Board of Regents (OBR). Through an agreement with the OBR, we have gained access to anonymous student data for Ohio's public higher education system. The data are provided by the respective institutions to the OBR and include information on student demographics, enrollment, credit hours completed, and grade point averages. Furthermore, OBR has collaborative arrangements with other agencies that allow them to expand the data. For example, OBR links the student records to ACT and SAT records. Most Ohio students take the ACT exam, and the ACT records include the highest test score of the student and the most recent responses to the ACT survey, which includes important student-reported information on high school preparation and performance. OBR also links students to their respective FAFSA and employment records.

One limitation of the data is that they only include students attending Ohio public universities. Students from Ohio that attend universities in other states, including the nation's elite schools, and students that attend private schools in Ohio are excluded from the sample.[6] This exclusion is most likely not a serious weakness since reports suggest that remediation plays a smaller

[6]Miami University and Ohio State University are the top ranked public universities in Ohio. Miami University is the only university to be referred to as "highly selective" by the Barron's Guide to College (Barrons 1997). In the 2002

role in private institutions. According to the NCES (1996), less than two-thirds of private institutions offer remediation and only 13 percent of students take remediation at private, four-year colleges. Additionally, the schools included in the sample educate the majority of college students and are the places where the role remediation is likely most significant. Another concern related to the inclusion of only Ohio public institutions is the measurement of drop-out behavior. Students who transfer from Ohio public institutions to institutions located in other states are indistinguishable in the data from students who withdraw from Ohio public universities. This potential bias, however, should be very small since the percentage of students who likely transferred to private institutions or those outside of the state make up a small fraction of the total number of observed dropouts.[7]

The paper focuses entirely on the incoming freshman class of the 1998-1999 school year. This is the first cohort of students for whom the incidence of remedial course-taking is available through the OBR. We include students who enrolled in any college, including community colleges, for the first time in 1998 and track these students through the 2000-2001 school year. Future versions of the paper will extend this analysis as more data become available. We exclude four schools due to the inability to identify which courses were remedial in 1998-99. These excluded schools include University of Cincinnati, Hocking College, Kent State University, and Lima Technical College. Two-year technical colleges are also excluded as this time due to their special nature.

Higher Education in Ohio

Table 1 provides summary statistics for all first-time freshmen in the Ohio public higher education system during the 1998-99 school year. This study focuses on traditional college

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version of US News and World Reports' college rankings, Miami ranks in the second tier (53rd-131st) of national universities with doctoral programs. Other high ranking institutions in Ohio (e.g. Oberlin) are private colleges.

[7] The Integrated Postsecondary Education Data System (IPEDS) tracks the number of transfers at each institution but does not record the state of residence of transfer students although it does track the states of residence for incoming freshman. Assuming that transfer students are geographically representative of the incoming freshman class, then one would expect around 650 Ohio students to transfer to the non-Ohio schools with substantial Ohio enrollments. 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.

undergraduates and so limits the sample to students age 18, 19, or 20.[8] The summary statistics of this sample are displayed in Table 2. In addition, these students must have had valid zip code information to be used in the analysis.

III. The Supply and Demand of Remedial Education

The purpose of remedial education is to provide underprepared students the skills necessary to complete and succeed in college. 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).

The Organization and Delivery of Remedial Education in Ohio

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). The practice of focusing remediation at the community colleges is similar to the experience in other states, and recent developments suggest some systems are moving more towards this model. Several other states (Arizona, Florida, Montana, South Carolina, and Virginia) prohibit public universities from offering remediation education (Shedd, Redmond, and Lucy-Allen, 2002). Even though four-year colleges in Ohio offer remediation, some require students to take remedial courses at their satellite campuses.

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[8] In the future, we are also interested in investigating the impact of remediation on nontraditional, older students.

Institutional policy towards remedial courses varies. About 10 percent of higher educational institutions do not offer academic credit for remedial courses. 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 restrictions may restrict students' class schedules and may impede students' abilities to major in certain areas. 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. One college administrator claimed that frequently students needing remediation in their first year "have no possibility of completing an engineering degree and must choose other majors" (Dodd 2002). 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 universities 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, Ohio State University (OSU) is one of the most selective school in Ohio. Its remediation program should be different than the remediation program at Cuyahoga Community College (CYCC), the largest community college in Ohio. Students at OSU typically have higher test scores and more college preparation than students attending CYCC.

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 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 (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. Some colleges in Ohio (e.g. University of Toledo, Case Western Reserve University) use different placement exams or give different weight to high school background and preparation. The measurement error in the tests and the difference in weighting creates variation across similar students at different universities. Another reason remediation may differ across colleges is 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. Local colleges and universities repeatedly report the percent of students requiring remediation. Since students living nearby are more likely to attend a given college, the college by necessity must develop a relationship with nearby secondary schools. A more expansive remediation policy may be an indictment of the quality of local education and there may be political pressure to require less formal remediation.

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. The most widely used placement exams are the Computerized Adaptive Placement Assessment and

Support Systems (COMPASS) and the Assessment of Skills for Successful Entry and Transfer (ASSET), each published by the ACT, Inc. The tests consist of a variety of tests 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.[9] After taking the exam, the university assigns students to a specific math course, oftentimes a remedial course, based on their scores. Typically, universities 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 our sample, 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 3 provides describes the characteristics of students in remediation.

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. However, in both 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

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

those with a known core high school curriculum still required remediation in either math or English (OBR, 2002).

IV. Empirical Framework – Estimating the Effects of Remediation

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. This section discusses identification strategies designed to take advantage of variation in remediation. There are a number of sources of variation that may be exploited to identify the effects of remediation. For example, within each school there may be comparable students who the university did or did not assign to remediation respectively. There may also be comparable students at different universities who did or did not take remedial classes respectively. For reasons explained below, our empirical results take advantage of cross-university differences in remediation

Within-University Variation

As noted above, most institutions decide placement into remediation based on test scores and high school transcripts. Unfortunately, placement test scores are not available.[10] However, even if we could observe the data, there may be problems with this type of discontinuity analysis. In particular, students have multiple chances to pass the Asset or Compass exam. For example, at Cuyahoga Community College students can retake the exam twice while students cannot retake the exam Ohio State University. Because students have multiple opportunities to take the exam and their likelihood of doing so is not likely to be random, students who are barely below the cutoff may differ

[10] The Ohio Board of Regents has tried unsuccessfully to gather these data from Ohio's public colleges. Many of the colleges rely on different data fields and options from the test so the data do not facilitate comparisons across institutions (Sheehan 2002). See the Appendix for a discussion of how we would use this data if available in the future.

systematically from students slightly above the cutoff.[11] Because of these problems, we do not emphasize results based on discontinuity analysis. Instead, our identification strategies use variation across universities.

Across-University Variation

As in other state, the universities and colleges in Ohio have different remediation programs. As we show below, these remediation programs may differ in 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 may not. We exploit this variation to address the endogeneity related to who is assigned remediation.

There are a few potential problems with using this variation across universities to identify the effects of remediation. First, university attendance is an endogenous choice reflecting student ability. Students may choose a university (and remediation policy) that fits their abilities. As a result, students may not be perfectly comparable across schools. Additionally, variation in remediation across universities may be endogenous to the students attending the university. For example, Miami University, Ohio's most selective public, undergraduate university, attracts students who score on average 100 points higher than students who attend Bowling Green. These institutions may adopt different policies since their student bodies differ substantially. These institutional differences would be even more exaggerated when we compare selective four-year colleges to community colleges. Finally, using variation across different types of schools may reflect differences between students that may be due to things other than remediation such as variation in other campus-level interventions (e.g. advising or academic support). While these sources of variation are problematic, there are other reasons that variation across universities may exogenously exist. We discuss these possible sources below.

[11] For example, students below the cutoff may be people who consistently fail the exam and likely have less ability

In addressing the endogeneity of college choice, 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 university is to the students' residences (Rouse, 1995; Card, 1995). Students prefer to attend universities closer to their home. We also know that different universities have different remediation policies. As a result, if the university 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 close 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.

To address the differences that exist between different types of colleges, we restrict our sample to homogenous schools. Rather than comparing students who attend Miami University to students attending community colleges, we estimate models restricting the sample to homogenous schools. We group universities over a number of dimensions including type and selectivity of the campuses (non-selective four year colleges, university branch campuses, and community colleges).[12]

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 similar type of school. For example, among our group of students who attended a non-selective, four-year university, we estimate the conditional probability for each one of the schools in that group. In this case, a student who attended the University of Akron would be assigned the probability of attendance based on

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in math.

proximity for the University of Akron, Central State University, Cleveland State University, University of Toledo, Shawnee State University, and Wright State University.

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 school 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 available schools). 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 indivividual (indexed as ij to denote individual i and school j). 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:

[12] The selectivity groupings are from Barrons (1997).

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

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

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 can not be included independently in the estimation.[13] 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.[14]

Table 4 reports the conditional logit estimates for a variety of samples in our data. Each row in Table 4 represents a separate sample of colleges. Row 1, for example, shows the conditional logit results for the 12,943 who enrolled as freshman in 1998-99 at any of Ohio's six non-selective, four-year public four-year universities or any of the fifteen university branch campuses. The conditional logit suggests that the farther a student lives from a university the less likely he or she is to choose that institution. The relationship is statistically significant over a 99 percent confidence interval.

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[13] The j equations within a strata 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 can not be included within the model since they are individual-specific.

[14] Possible endogeneity in the choice set develops from the fact that colleges available to a student will depend upon the previous decision of where to apply. This application decision is based upon a student's ranking of the colleges, and therefore, the opportunity set that a student will ultimately face is partly endogenous. However, 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).

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.

As previously mentioned, our identification strategy relies on our ability to find homogeneous colleges. Since some four-year institutions are selective and others are not, we attempt other groupings of colleges to create more homogeneous sets of colleges. In the second row of Table 4, we report the coefficient on distance from college for the sample of students attending non-selective public colleges in Ohio. In row 3, we report the coefficient on distance for university branch campuses. In both of these cases, the coefficient shows a strong and statistically significant effect on college choice.

Table 4 also shows the relationship between distance and college choice for all community colleges, state-run community colleges, locally-run community colleges, and all colleges in the sample. In each case, distance has an effect on college choice. The relationship is particularly strong for students attending community colleges. The higher the quality of the school, the less important distance becomes although it always remains a statistically significant component of college choice.

Once we estimate the conditional logit, we save the predicted probabilities of attendance for each of the universities in this subsample conditional on the student attending one of the universities or colleges in this subsample. These predicted probabilities are determined solely on the basis of the distance students live from the universities and are an essential component of our instrumental variable strategy.

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. This section details how we measure and take advantage of variation in remediation across universities.

There are a number of reasons why variation exists across universities in their emphasis on remediation. The most widely recognized source of variation (and not the source of our variation) comes from differences in the quality of a student body. However, this type of variation is not useful to our identification strategy. 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. 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.

Variation in remediation policies among similar schools is the focus of this study. 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. We know the number and types of high school mathematics classes as well as the grades that students had in those classes. We also know students' ACT math scores which is highly related and in some cases used to designate placement. The predicted probabilities that we estimate are based on these data, and we still generate substantial variation for a single individual across universities.

Using ACT scores as a predictor of placement into remediation, Figure 1 demonstrates how homogeneous universities may have heterogeneous remediation policies. Each row corresponds to a different grouping of universities. Within each row, the left-hand graph shows the distribution of ACT scores at each of these universities. 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:

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

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 university. We then compare the likelihood functions generated by these 36 regressions. The right-hand graphs show these likelihood functions over for the various subsamples in our data.[15] To the extent that universities 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. Row 2 shows the results for non-selective colleges in Ohio. The ACT distributions of non-selective four-year colleges 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 20. The other rows in Figure 1 shows the distribution of test scores in all branch campuses and all community colleges. Each of these graphs shows a remarkable degree of homogeneity in the ACT distributions of these respective schools; however, the ACT cutoffs show a very heterogeneous relationship.

As a result of Figure 1, we do not focus on selective four-year colleges. As the figure shows, there is substantial variation across selective universities in the student populations and their underlying test scores. Since this variation may be the underlying cause of variation in remediation policies, we exclude such schools from additional analysis. Instead, we focus our discussion on non-selective four-year universities, branch campuses and community colleges.

To exploit the differences across each institution, we follow a two-step procedure. In the first step, we estimate the "University Remediation Rule" for each university. We model the likelihood of taking remediation at university ZZ as a probit.[16] We do so 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, general ACT score, math ACT score, high school GPA, family financial

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[15] A similar methodology is used in Kane (2002).
[16] 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.

background, students' high school math grades and number of classes taken, the type of high school that students attend, students post-secondary degree goal as stated when they take the ACT exam, and similar variables for SAT score. 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 university in our sample using data for students attending each institution.

The probit models generate 51 sets of coefficients or remediation "rules," one for each school. For each set of coefficients, we generate a predicted probability for every student in the sample. 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 5 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 an individual's maximum predicted probability across schools in the subsample and subtracting the same individual's minimum predicted probability across schools within the sample. We then compute the average of these ranges across individuals and report it in Table 5. For example, within non-selective four-year colleges, the average range is 39.4 percent with a standard deviation of 19.0 percent. Attending a different university can dramatically change the likelihood that an individual student attends remediation. In the other subsamples reported in Table 5, there remains substantial variation ranging from an average of 38 percent in the locally-run community colleges to 70 percent in the university branch campuses. In Column 2 of Table 5, 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 universities are the same. Clearly, substantial variation exists across the data.

We interpret these results as meaning that remediation policies vary substantially across universities. If this is the case, then our identification strategy should identify the effects of remediation. However, there remains the possibility that the results in Table 5 and Figure 1 simply mean the ACT math score is a poor predictor of the likelihood of remediation. As Figure 2 demonstrates, this is clearly not the case. Figure 2 plots the distribution of ACT math scores for four-year colleges in Ohio. In almost every case, the distribution of ACT math scores for remedial students is well below the distribution of ACT math scores for non-remedial students. Clearly, ACT math scores do predict remediation.

Building the Instrument

We combine the probabilities of attendance and of remediation to our instrument for remediation. From the conditional logit results, we have an estimate of the probability of attendance at any school within the subsample of schools conditional on attending one of them. From the remediation probabilities, we know the probability of remediation at an individual institution conditional on attending that university. We combine these estimates to get our first instrument:[17]

$$
\begin{aligned}
Z &= \Pr[\text{Remed}_{\text{i}} \mid \text{Attends any university } j \text{ where } j \in J] \\
&= \sum_{\text{j}\in\text{J}} \Pr[\text{Remed}_{\text{i}} \mid \text{Attends university } j\,]\Pr[\text{Attends university } j \mid \text{Attends any university } j \in J]
\end{aligned}
$$

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 universities' 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 ran similar regressions including our instrument, we could generate other 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.

[17] 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.

Table 6 reports the first-stage estimates for each subsample of universities. As mentioned earlier, we do not estimate the effects on selective universities given that significant heterogeneity exists across universities in these campuses. We focus instead on non-selective universities, university branch campuses, and community colleges. Each row of the table corresponds to one of these subsamples of universities. As mentioned, we include all of the covariates used in estimating the remediation probabilities in the first stage. We do not report these coefficients. We only report the coefficients and standard errors on our instrument in the respective models. The coefficients correct for heteroskedasticity. Row 1 shows the coefficient for the instrument based on distance and the different university rules for the sample of non-selective four-year colleges and university branches. The predicted probability of remediation has a coefficient of .668 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 show similar effects of our instrument on the likelihood of completing remediation.

V. The Effects of "the Intention to Treat" on College Outcomes

We estimate the effects of remediation on five related outcomes: drop-out rates, GPA, degree completion, and transfer behavior to both more selective and less selective institutions. We measure these outcomes at non-selective four-year universities, university branch campuses, and community colleges. As mentioned, we estimate the effects 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. As a result, we do not measure the effects of remediation on degree completion since students at four-year institutions have likely not graduated from college yet.

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. We report basic results using linear regression (OLS). We also report instrumental variable (IV) results using the instruments described in the previous section.

Table 7 reports our estimated effects of remediation on drop-out rates and transfer behavior to less selective colleges. The first row of the table shows the results for the combined sample of non-selective four-year colleges and university branch campuses while the second and third rows show the results for these groups respectively. The final row shows the results for community colleges.

In non-selective four-year colleges and university branch campuses, about 45 percent of students who initially enrolled in 1998 have withdrawn from school by 2002. This is slightly larger for university branch campuses (50 percent) than for non-selective four-year colleges (42 percent). About 68 percent of students at community college students have withdrawn from school without completing a degree.[18] Remediation also varies across these universities and colleges. Twenty-seven percent of students at non-selective universities attended remediation. Remediation rates are much higher at university branch campuses (40 percent) and community colleges (61 percent).

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 non-selective four-year colleges, the estimate is significant over a 95 percent confidence interval. This is driven largely by effects at the non-selective four-year colleges where the estimated effect (8 percentage points) is significant over a 90 percent confidence interval. Our IV estimates also suggest a significant effect of remediation on dropout rates at community colleges (6.6 percent) but not at university branch campuses.

The OLS estimates show a one to two percentage point effect although the estimated effects are not significant except in the combined samples of four-year colleges. Interestingly, the OLS

[18] 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 by Winter 2002. Students who transferred to other colleges are not considered dropouts in this study as they have been in other work on the subject.

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.

The rest of Table 7 shows the effects of remediation on "transferring down" or the likelihood that students transfer to a less selective college or university. The IV estimates do not show a significant effect of remediation on transferring "down." Although the IV and OLS coefficients are similar, the IV estimates are less precise and do not show any significant effects. While the point estimates suggest that remediation has "hurt" students involved in it, we cannot reject that remediation has had no significant effect. Incorporating data from other years may allow us to measure these effects more precisely. The results, thus far, however, do not show any significant effect of remediation.

Table 8 reports the IV and OLS estimates for the effects of remediation on grade point averages. In this case, both the IV and OLS estimates suggest that remediated students achieve lower grade point averages. For the IV estimates at the four-year colleges, it is about 0.3 points lower than other students from a base GPA of about 2.40. 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. As before, the estimated effects in the community college sample are not significant although the point estimates suggest that grade point averages are lower for remedial students.

Table 9 shows the IV and OLS estimates of the effects of remediation on degree completion and "transferring up" behavior. Students who started at university branch campuses do most of the transfer behavior. About 22 percent of these students transfer to either a selective or non-selective four-year college. Community colleges do not a significant number of students transfer to four-year colleges. About three percent of students at non-selective universities transfer to Ohio's most selective institutions by 2002.

Both the IV and OLS estimates do not suggest significant effects for non-selective universities and community colleges. The IV results, however, for university branches show remediation may reduce the likelihood that university branch students transfer to a "better" school by about 5 percentage points. This result is significant over a 90 percent confidence interval.

The other results in Table 9 show the likelihood of degree completion at two-year colleges. We only measure degree completion in the community colleges since students in the four-year colleges have only attended three years of school. In the community colleges, however, about 12 percent of students have finished at least an associate's degree by 2002. The IV estimate suggests that students who are remediated are far less likely to not have completed an associates degree by 2002. The IV estimates suggest that remediated students are 12 percentage points less likely to have completed a degree. The IV estimate is much stronger than the OLS estimate (6 percentage points). Both are highly significant.

As mentioned, one of the interesting features of Tables 7 through 9 is that the IV estimates are often higher than the OLS estimates. For example, in Table 8 the estimated IV effect on grade point average is almost twice that of the OLS estimate. 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 universities and the strength of their remediation policies that may lead OLS to be smaller than one might expect. Large universities 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 particular type of institution (e.g. Community Colleges), unobserved geographical heterogeneity within these students may still account for the estimates. We continue to investigate various reasons this relationship may exist.

VI. Conclusions

In summation, the IV estimates suggest negative effects of remediation for most students. 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. Although we have discussed reasons support these conclusions, we continue to investigate the validity of these assumptions and provide additional support for this framework.

One interesting interpretation of our results is a story about inefficient sorting across universities. Remediation may be a low cost way for students to "try out" a school that is of higher quality than what they may feel comfortable with. As our results indicate, many of these students at the four-year colleges transfer "down" after remediation. Unfortunately, many withdraw from college, especially among remedial students. This may indicate some inefficiency in the sorting mechanism. While with imperfect information, the sorting will be imperfect, it is hard to believe that "mis-sorted" students at four-year colleges are better off dropping out than transferring to a "lower" level college. A more efficient sorting mechanism would improve transfer rates for remediated students rather than exacerbating dropout rates. The community college results, particularly when disaggregated among state and local community colleges, suggest that at that level, remediated students may not perform significantly worse than their counterparts. We continue to investigate these hypotheses.

There are also several ways we intend to extend this work.

- Extension I – The Who completes remediation?
- Extension II – The Effects of the Treatment on the Treated on College Outcomes
- Extension III – Remediation at Two-year versus Four-year Colleges
- Extension IV – The Effects of Remediation on Labor Market Outcomes

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Figure 1

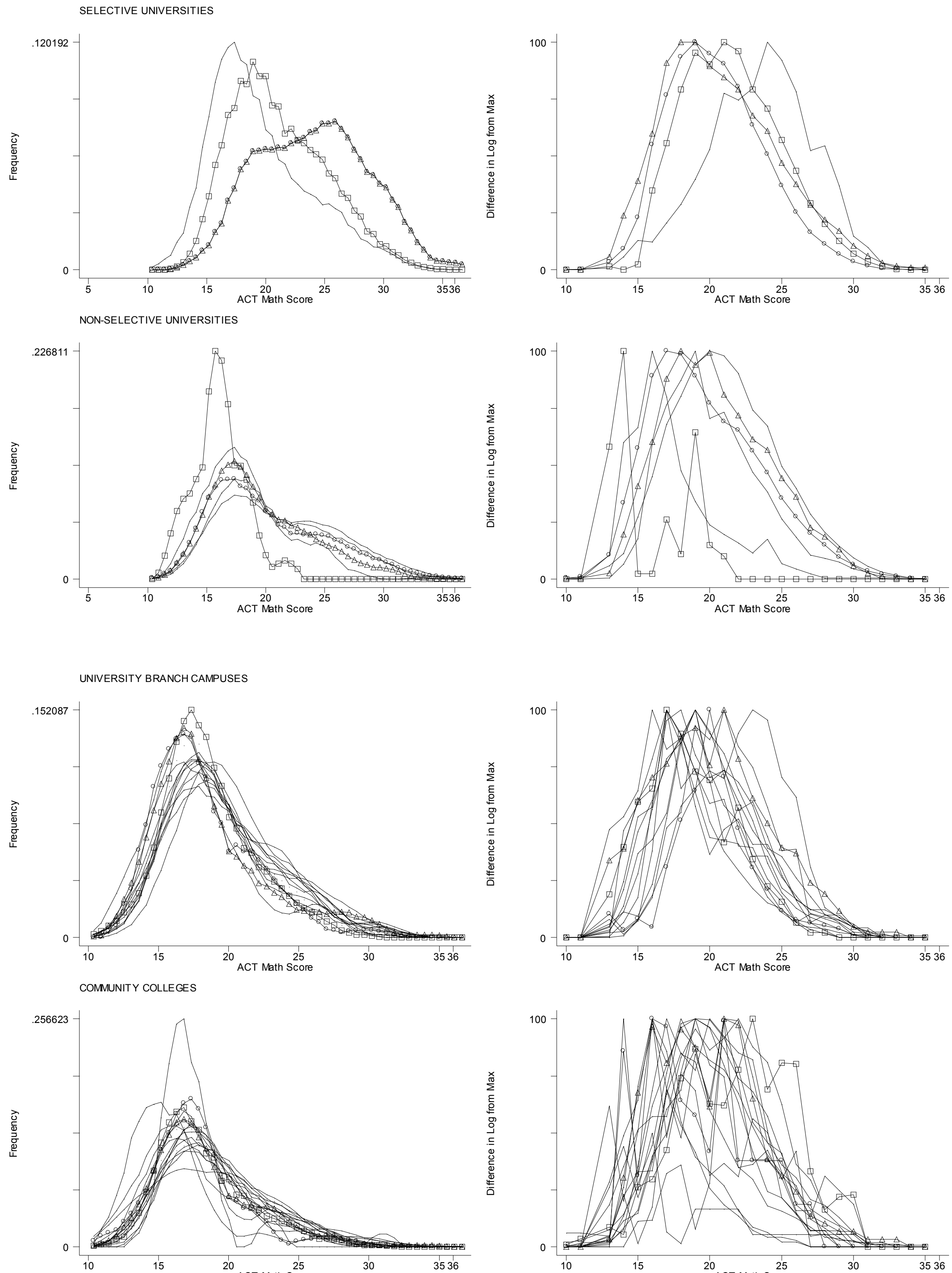
SELECTIVE UNIVERSITIES
.120192
0
Frequency
ACT Math Score
100
Difference in Log from Max
NON-SELECTIVE UNIVERSITIES
.226811
UNIVERSITY BRANCH CAMPUSES
.152087
COMMUNITY COLLEGES
.256623

Figure 2. ACT Test Score Distributions for Non-Selective 4-year Colleges by Remedial Status

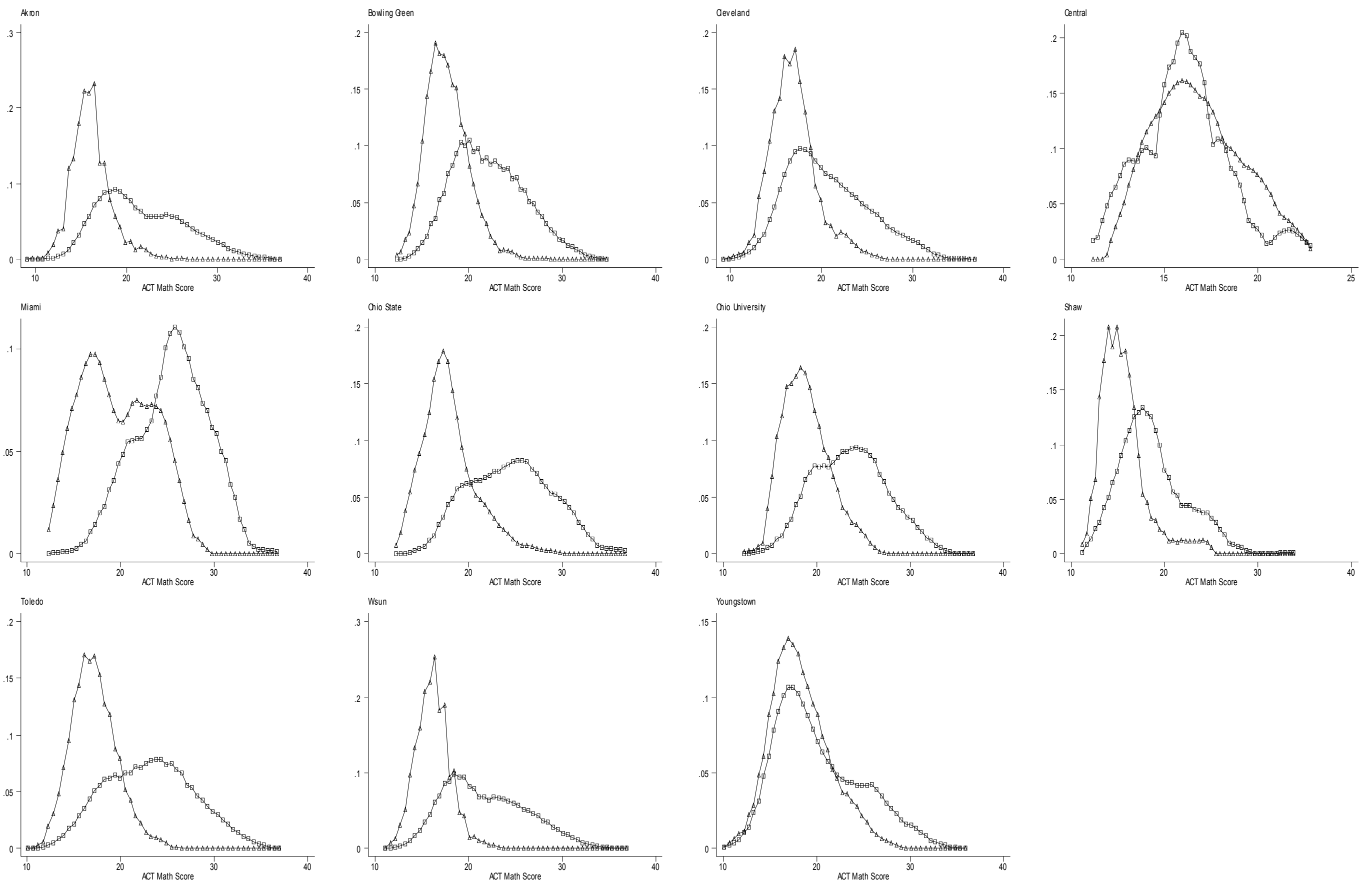

Table 1: Students in the Ohio Public Higher Education System

	Selective Four-year Colleges	Non-selective Four-year Colleges	Four-year University Branch Campuses	Community Colleges
Age in 1998	19.58 (2.05)	22.19 (6.90)	22.92 (8.37)	25.39 (9.67)
Female	0.549	0.534	0.550	0.505
Black	0.065	0.169	0.026	0.142
Hispanic	0.019	0.018	0.006	0.025
Asian	0.025	0.016	0.005	0.012
Ohio Resident	0.847	0.935	0.939	0.955
Intention to complete a College Degree	0.994 (0.077) [12,548]	0.993 (0.083) [5,530]	0.865 (0.342) [5,372]	0.707 (0.455) [20,111]
Enrolled in Remedial Math	0.120	0.263	0.375	0.457
Total Credit Hours (Fall98 – Winter02)	114.79 (59.84)	65.80 (54.32)	61.71 (58.81)	32.38 (33.70)
College GPA	2.82 (0.80) [17,803]	2.42 (1.05) 10,914	2.50 (0.99) [5,407]	2.23 (1.21) [10,566]
Dropped Out before Winter 2002	0.262	0.490	0.591	0.756
Completed at least Two-year degree	0.011	0.072	0.081	0.068
Took ACT	0.777	0.659	0.658	0.322
ACT Math Score (36 maximum)	23.00 (4.59) [13,995]	20.38 (4.70) 7,598	19.31 (3.90) [3,883]	18.75 (3.80) [7,272]
ACT Overall Score (36 maximum)	23.14 (4.00) [13,995]	20.63 (4.30) 7,598	19.66 (3.65) [3,883]	19.14 (3.76) [7,270]
Observations	18,004	11,505	5,905	22,557

Standard deviations are shown in the parentheses. The number of observations for variables with less than the total observations is shown in brackets. "Transferred Up" ("Down") is defined as going to a more (less) selective or higher level college (two-year to four-year) by the end of the period.

Table 2: Sample Descriptive Statistics - Traditional-aged, degree-seeking first-time students in 1998-99

	Selective Four-year Colleges	Non-selective Four-year Colleges	Four-year Univ. Branch Campuses	Community Colleges
STUDENT DEMOGRAPHICS				
Age in 1998	19.335 (0.482)	18.50 (0.63)	18.53 (0.62)	18.648 (0.685)
Female	0.552	0.521	0.528	0.522
Black	0.063	0.156	0.023	0.127
Hispanic	0.019	0.018	0.006	0.026
Asian	0.025	0.017	0.005	0.011
Ohio Resident	0.851	0.934	0.979	0.973
COURSE-TAKING BEHAVIOR				
In Remedial Math	0.113	0.268	0.396	0.606
Credits of Remedial Math attempted	0.881 (3.161)	1.72 (3.48)	2.97 (4.77)	5.669 (6.882)
Credits of Remedial Math Completed	0.554 (2.237)	0.89 (2.13)	1.98 (3.51)	3.493 (5.018)
Total Credit Hours (Fall98 – Winter02)	117.13 (58.72)	76.04 (55.40)	75.44 (59.33)	41.292 (34.578)
POSTSECONDARY OUTCOMES				
College GPA	2.83 (0.78) [17,208]	2.40 (1.01) [7,130]	2.41 (0.93) [3,458]	2.026 (1.087) [4,585]
Dropped Out before Winter 2002	0.246	0.420	0.500	0.683
Completed at least Two-year degree	0.010	0.058	0.099	0.092
Transferred Up	---	0.027	0.220	0.094
Transferred Down	0.060	0.088	0.090	---
ABILITY AND HIGH SCHOOL MEASURES				
Took ACT	0.796	0.774	0.798	0.484
ACT Math Score (36 maximum)	23.03 (4.58) [13,806]	20.64 (4.75) [5,662]	19.51 (3.87) [2,861]	18.780 (3.66) [4,119]
ACT Overall Score (36 maximum)	23.18 (3.99) [13,806]	20.80 (4.30) [5,662]	19.76 (3.60) [2,861]	19.122 (3.59) [4,119]
Average High School Math GPA	3.23 (0.67) [13,309]	2.89 (0.81) [5,662]	2.78 (0.80) [2,861]	2.642 (0.786) [4,119]
Number of years of Math in High School	7.59 (0.93) [13,277]	7.31 (1.18) [5,662]	7.15 (1.27) [2,861]	7.017 (1.297) [4,119]
Observations	17,353	7,311	3,583	8,503

Standard deviations are shown in the parentheses. The number of observations for variables with less than the total observations is shown in brackets. Sample is restricted to students ages 18-20 and those students who included valid zip codes on their applications.

Table 3: Students in Remediation

	Selective Four-year Colleges		Non-selective Four-year Colleges		Four-year University Branches		Community Colleges	
	No Remed.	Remed.	No Remed.	Remed.	No Remed.	Remed.	No Remed.	Remed.
Age in 1998	19.33 (0.48)	19.36 (0.48)	18.49 (0.62)	18.54 (0.64)	18.50 (0.60)	18.58 (0.65)	18.61 (0.68)	18.67 (0.69)
Female	0.548	0.588	0.498	0.583	0.504	0.564	0.486	0.545
Black	0.051	0.155	0.113	0.273	0.014	0.036	0.068	0.164
Hispanic	0.018	0.024	0.014	0.030	0.004	0.010	0.016	0.033
Asian	0.027	0.011	0.019	0.012	0.007	0.002	0.011	0.011
Ohio Resident	0.842	0.915	0.928	0.948	0.973	0.987	0.965	0.978
College GPA	121.66 (57.82)	81.60 (53.40)	2.55 (0.98) [5,258]	1.97 (0.98) [1,872]	2.55 (0.92) [2,079]	2.20 (0.90) [1,379]	2.23 (1.10) [1,792]	1.89 (1.06) [2,793]
Dropped Out before Winter '02	0.229	0.379	0.383	0.521	0.463	0.555	0.646	0.707
Completed at least two-year degree	---	---	---	---	---	---	0.147	0.056
Transferred Up	---	---	0.028	0.022	0.257	0.163	0.108	0.085
Transferred Down	0.056	0.090	0.078	0.117	0.078	0.110	---	---
Took ACT	0.790	0.843	0.801	0.702	0.829	0.751	0.539	0.449
ACT Math Score (36 max)	23.71 (4.36) [12,151]	18.08 (2.72) [1,655]	21.92 (4.64) [4,288]	16.67 (2.24) [1,374]	20.73 (3.98) [1,795]	17.44 (2.59) [1,066]	20.43 (3.95) [1,807]	17.49 (2.80) [2,312]
ACT Overall Score (36 max)	23.71 (3.80) [12,151]	19.27 (3.05) [1,655]	21.86 (4.16) [4,288]	17.50 (2.79) [1,374]	20.71 (3.66) [1,795]	18.16 (2.87) [1,066]	20.54 (3.70) [1,807]	18.01 (3.08) [2,312]
Average HS Math GPA	3.31 (0.63) [11,739]	2.64 (0.68) [1,570]	3.06 (0.75) [4,288]	2.35 (0.75) [1,374]	2.96 (0.77) [1,795]	2.48 (0.77) [1,066]	2.90 (0.75) [1,807]	2.44 (0.75) [2,312]
Number of years of Math in HS	7.67 (0.83) [11,695]	6.97 (1.27) [1,582]	7.45 (1.07) [4,288]	6.84 (1.36) [1,374]	7.28 (1.20) [1,795]	6.93 (1.36) [1,066]	7.20 (1.21) [1,807]	6.88 (1.34) [2,312]
Observations	15,390	1,963	5,354	1,957	2,164	1,419	3,351	5,152

Standard deviations are shown in the parentheses. The number of observations for variables with less than the total observations is shown in brackets. Sample is restricted to students ages 18-20 and those students who included valid zip codes on their applications.

Table 4: Conditional Logit & Distance

Sample	Coefficient on Distance from Conditional Logit	# Colleges	# Students
Non-selective four-year colleges & University Branch Campuses	-.0520 (.0005)	21	12943
Non-selective four-year colleges	-.0314 (.0005)	6	8605
University Branch Campuses	-.0807 (.0014)	15	4338
All Community Colleges	-.1028 (.0015)	19	9641
State Community Colleges	-.0905 (.0020)	11	4199
Local Community Colleges	-.1503 (.0037)	8	5442

Standard errors are in parentheses. Non-selective colleges include four-year colleges with a Barron's rating of "Less Competitive" or "Non-Competitive." Sample includes all students aged 18-20. Community colleges include only those students who declared an intent to pursue either associates or bachelors degrees.

Table 5: Ranges of Predicted Probabilities of Remediation within University Groupings

Sample	Mean Range of Predicted Probabilities within University Group	LR Test for Equality of Coefficients (Chi-sq df)
Non Selective 4-yr Colleges and Branch Campuses	68.7 (18.1)	1590.0 (60df)
Non-selective four-year colleges	39.4 (19.0)	501.8 (15df)
University Branch Campuses	70.1 (16.0)	881.4 (42df)
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)

Table 6: First-stage Estimates of Effect of Distance and Differences in Remediation Policies on Remediation Probabilities

Sample	Coefficient on Distance/Remediation Instrument
Non-selective 4-yr Colleges and University Branch Campuses	.668** (.016)
Non-selective 4-yr Colleges	.789** (.025)
University Branch Campuses	.710** (.019)
All Community Colleges	.711** (.018)

** Significant at the 5% level

Table 7: IV Estimates of Effect of Remediation on Dropout and Transfer Down Behavior

Sample	Pct in Remed.	Pct Dropout	Coeff on Remediation		Pct Transfer Down	Coeff on Remediation	
			IV	OLS		IV	OLS
Nonselective Four-year & University Branches (N=10894)	.3099	.4463	.1015** (.0297)	.0273** (.0110)	.0891	.0274 (.0177)	.0290** (.0066)
Nonselective Four-year (N=7311)	.2677	.4202	.0772* (.0407)	.0216 (.0141)	.0885	.0208 (.0244)	.0342** (.0085)
University Branches (N= 3583)	.3960	.5000	.0476 (.0337)	.0102 (.0182)	.0904	.0306 (.0202)	.0225** (.0109)
Community Colleges (N=8504)	.6060	.6826	.0660** (.0262)	.0091 (.0107)	---	---	---

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

Notes: "Dropout" is defined after three years. "Transfer Down" is defined for non-selective schools as a transfer to a branch campus or two-year college and for university branches as a transfer to two-year colleges.

Table 8: IV Estimates of Effect of Remediation on College GPA

Sample	Pct in Remed.	Mean College GPA	Coeff on Remediation	
			IV	OLS
Nonselective Four-year & University Branches (N=10588)	.3099	2.403	-.2353** (.0548)	-.1650** (.0205)
Nonselective Four-year (N=7130)	.2677	2.400	-.2907** (.0770)	-.2130** (.02694)
University Branches (N=3458)	.3960	2.411	-.2925** (.0600)	-.0916** (.0326)
Community Colleges (N=4585)	.6060	2.140	-.0848 (.0583)	-.1322** (.0241)

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

Table 9: IV Estimates of Effect of Remediation on Degree Completion and Transfer Up Behavior

Sample	Pct in Remed.	Pct Transfer Up	Coeff on Remediation		Pct Complete Degree	Coeff on Remediation	
			IV	OLS		IV	OLS
Nonselective Four-year & University Branches (N=10894)	---	.0903	.0314* (.0176)	.0143** (.0065)	---	---	---
Nonselective Four-year (N= 7311)	---	.0267	-.0099 (.0138)	.0047 (.0048)	---	---	---
University Branches (N= 3583)	---	.2202	-.0535* (.0278)	-.0259* (.0150)	---	---	---
Community Colleges (N= 8504)	.6060	.0941	.0216 (.0164)	.0082* (.0067)	.0929	-.1213** (.0162)	-.06234** (.0066)

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

Notes: "Transfer Up" is defined for non-selective four-year colleges as a transfer to a selective university, for university branches as a transfer to a selective or non-selective four-year college, and for community colleges as a transfer to any four-year institution.

APPENDIX

An Alternative Estimation Strategy: Using ACT Scores as proxy

There are two problems with using discontinuity analysis to identify the effects of remediation on students. First, the Asset/Compass test results are not available. Second, since students may retake the exam, students assigned to remediation may vary systematically from those not assigned. If Asset/Compass data were available, one plausible way to get around the problem of students retaking the Asset/Compass exam is to assign remediation based on a student's first attempt at the exam. This initial test can be an instrument for the likelihood that students eventually take remedial classes. Near the cutoff students may still be comparable.

While we do not have the first attempt at the Asset/Compass result, we do have results from another math diagnostic – the ACT Math Test – given prior to students' college enrollments. The same organization that publishes the ACT Math exam also publishes the Asset/Compass exam. The ACT Math exam can even be included as one of 12 subsections of the Asset exam. Moreover, the ACT offers consultation of how the ACT Math exam may be used to assign remediation for individual schools (ACT 2002). The ACT Math scores are noisy signals of students' abilities similar to the Asset exam, and similarly, these test scores might be usable to create comparable groups of students.

Figure 2 shows the distribution of ACT scores for both remedial and non-remedial students enrolled at the main campuses of Ohio's four-year universities. Each pane in the figure represents a different four-year college. For example, the graph in the first row of the first column shows the ACT distributions for remedial and non-remedial students at University of Akron. Clearly the remedial students score lower on average than the non-remedial students. However, there is a sizable overlap between these two distributions. Many students who scored low on their ACT math exam were able to avoid remediation. Similarly, many students who scored high on their ACT math exam still had to take remediation. For most universities, remedial students score much lower than non-remedial students; however, the distributions at Youngstown University and Central University seem to have overwhelming overlap. In these cases, students' ACT scores look like poor predictors of remediation.

While we know the remediation test score cutoffs for the Asset/Compass exam, it is not clear what similar cutoffs are in the ACT Math scores. We try to recreate these using the data. This is the same procedure used to estimate the right-hand side graphs in Figure 1. To estimate the most likely cutoff points, we first estimate the following probit models for each school:

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

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 university. We then compare the likelihood functions generated by these 36 regressions and choose the cutoff based on the highest likelihood function.

Figure 1 plots the likelihood functions for each school. The vertical axis is the difference between the likelihood function and the minimum likelihood function. The horizontal axis shows the possible cutoff values for each school. We have run similar models where we also include high school math variables (grades and number of years taken) and we estimate cutoffs similar to those in Figure 1.

One example may illustrate how we can use these figures. In the likelihood functions for the University of Akron, the likelihood function reaches its maximum when the ACT math score is equal to 18. This value of 18 appears to be the most likely point in predicting remediation in both specifications. We might assume that this is the ACT cutoff at Akron. However, we should note that the maximum likelihood plots do not always suggest a clear solution. Ideally, we would hope for a distinct spike only at the actual cutoff. But in the graphs depicted, there are multiple ACT values near the maximum. For example, in the graphs for the University of Akron, an ACT score of 19 has a high value in the likelihood function only slightly below the maximum.

One of the most interesting features of Figure 1 is the variance across schools. Within the four-year colleges, there is variance in the cutoff value across schools. For example, University of

Akron has a cutoff of 18 while Central University has a cutoff of 14. Ohio University has a cutoff of 21. Many of the changes across universities reflect differences in selectivity, but yet others reflect other differences across universities. We discuss these differences below.

If we were using a regression discontinuity method, we would select a range near the remediation cutoff and compare people on both sides of the cutoff. For example, in the case of Akron, we would compare students with ACT values of 17 or 18 to students whose ACT values were either 19 or 20. While the discontinuity is not perfect, the lower scoring students are much more likely to attend remediation. However, such comparisons may lead to bias. The students in the lower range would be more likely to perform poorly in college in the absence of remediation. The ACT math score may be evidence that these students have less ability. If we compared outcomes such as dropout behavior or grade point average, we would expect the lower scoring students to perform worse than the other students. This bias would cause us to overstate the effect of remediation.

Rather than use the regression discontinuity method, we focus on a difference in differences specification. Specifically, we compare the differences between students just around the remediation cutoff to differences between students well away from the remediation cutoff. For example, in the case of Akron, we first estimate the difference between students in the 17-18 range and in students in the 19-20 range. We then compare this difference to one of two other groups. The first group is a set of students scoring higher on the exam. For Akron, we create a second cutoff at 22 and compare students above and below this cutoff. The likelihood that a student attends remediation does not change dramatically for students who score 21 or 22 on the ACT math exam as compared to students who score in the 23-24 range. We can also create a similar comparison group of students who scored a lower range of the exam (range of 13-14 compared to a range of 15-16).

We use the following regression specification to estimate the model:

Outcome = a + b*(ACT below remed cutoff)

+ c*(2 above or 2 below ACT Cutoff +4)

+ d*(2 below ACT Cutoff or ACT 2 below ACT Cutoff+4) + e

The coefficient "b" is the difference-in-differences estimate. It shows how much more likely people are at the ACT cutoff to be enrolled in remedial classes. The parameter "c" reflects the difference between the group scoring near the ACT cutoff and the difference between the groups scoring 4 points higher. The parameter "d" shows the effect of being in the bottom part of the comparison. Assuming that the relationship between the outcomes and ACT scores is linear, the parameter "d" reflects the underlying slope of the relationship while the parameter "b" reflects the change in the slope at the remediation cutoff.

Appendix Table 1 presents difference-in-differences estimates of the effect of being around this discontinuity on outcomes. In Panel A, we present estimates based on Ohio's four-year universities. Panel B contains estimates for the sample of Ohio's community colleges. In Column 1 of Panel A, we present estimates of how the likelihood of remediation varies over these ACT ranges. Students who score just below the remediation cutoff are 15.1 percentage points more likely to take remediation than students just above the cutoff. Students who are well above the remediation cutoff are about 9.2 percentage points less likely to receive remediation, and students who score in the lower part of each comparison group (i.e. 2 below ACT Cutoff or 2 below ACT Cutoff+4) are about 2.3 percentage points more likely to take remediation. In Panel B, we present similar estimates for Ohio's community colleges. In these schools, scoring just below the ACT cutoff corresponds to a 17.7 percentage point decline in the likelihood that students take remediation. Students scoring well above the remediation cutoff are about 19.2 percentage points less likely to be enrolled in remedial classes, and students in the lower part of each comparison group are about 7.2 percentage points more likely to take remediation. All of these effects are statistically significant.

These results suggest strongly that students are much more likely to attend remediation if they are just below the ACT cutoff. This effect controls for the fact that students in this group are already more likely to attend remediation classes by virtue of their lower test scores. Students in the control group are much less likely to be enrolled in remedial classes.

Columns 2 and 3 of Appendix Table 1 estimate the effect of remediation on dropout behavior. In Column 2 of Panel A, the difference-in-differences estimate suggests that students who are below the remediation cutoff are about 3.4 percentage points more likely to withdraw from college altogether. Students with higher scores are less likely to dropout and there is not a discernible effect that students with lower scores are systematically more likely to withdraw. All of these effects are statistically significant. Column 3 shows the effect when we also include fixed effects for school of attendance. This is potentially important since there is variation across universities in their cutoff points and remediation policies. The estimated effect is now 2.9 percentage points. This result is significant over a 90 percent confidence interval.

The results for community colleges do not show any effect of remediation courses. While students below the cutoff are much more likely to attend remediation, they are not more likely to withdraw. The estimated effect when campus fixed effects are included is 1.6 percentage points with a standard error of 4.5 percentage points.

Overall these results suggest that students may be slightly more likely to withdraw from four-year colleges but not at two-year institutions. However, these estimated effects rely on the assumption that the relationship between students' ACT scores and dropout behavior behaves linearly. If this relationship is nonlinear, then the difference-in-difference estimator will not accurately measure the effect of remediation. For example, in the case of University of Akron, the above results suggest that even in the absence of remediation, students scoring an 18 on the math ACT exam are more likely to dropout than students scoring a 19. If this increased likelihood of a student dropping out is even larger than the difference between students who score 22 and students who score 23, then the estimates above are likely to overstate the effects of remediation.

We are uncomfortable with assuming that the relationship between ACT score and dropout behavior is nonlinear. We include these results in the appendix since under some assumptions, they may be correct. They also seem to be supportive of the general conclusions of the paper. If placement exam scores become available, we will develop these results more fully.

Appendix Table 1: Difference-in-Difference Comparisons of Effect of Remediation

Variable	Remediation Probability	Dropout Behavior	Dropout	Dropout w/ Lower Scoring Control Group	Remediation Probability w/ lower scoring control group
A. University Main Campuses					
Difference-in-Differences Estimate	.151 (.011)	.039 (.017)	.035 (.016)	-.012 (.021)	.080 (.021)
Scored 4 pts higher (lower in columns 4&5)	-.092 (.006)	-.053 (.012)	-.025 (.012)	.078 (.013)	.360 (.012)
Scored lower within the 2 grouping	.023 (.005)	-.002 (.012)	-.010 (.012)	.037 (.018)	.095 (.018)
Includes Campus FE	No	No	Yes	Yes	No
N	11559	11559	11559	9724	9724
B. Locally-run Community Colleges					
Difference-in-Differences Estimate	.177 (.043)	.011 (.049)	.015 (.048)	.008 (.037)	.167 (.037)
Scored 4 pts higher (lower in columns 4&5)	-.192 (.032)	-.060 (.037)	-.042 (.037)	.079 (.026)	.312 (.027)
Scored lower within respective grouping	.072 (.033)	.003 (.040)	.004 (.040)	.012 (.026)	.083 (.025)
Includes Campus FE	No	No	Yes	Yes	No
N	1899	1899	1899	2671	2671

Note that the samples in this table differ from the paper overall. This table includes selective campuses in Panel A and non-traditional students. Future versions of this paper will include samples of non-selective universities, university branch campuses, and all community colleges.