I Z A Institute
of Labor Economics
Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 14075

Minding the Gap: Academic Outcomes from Pre-college Programs

Phoebe Kotlikoff
Ahmed S. Rahman
Katherine A. Smith

JANUARY 2021

IZA Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 14075

Minding the Gap: Academic Outcomes from Pre-college Programs

Phoebe Kotlikoff
United States Navy

Ahmed S. Rahman
Lehigh University and IZA

Katherine A. Smith
USNA

JANUARY 2021

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Minding the Gap: Academic Outcomes from Pre-college Programs*

This paper analyzes the effects of assignment to a one-year college preparatory program on academic performance in college. To measure the value added from pre-college programs, we use a large dataset of United States Naval Academy students from the 1988 to 2018 graduating classes, of which a little over 22% received post-high school remediation. Given the Academy's unique admissions criteria that members of each incoming class originate from an even distribution of congressional districts, we instrument for pre-college treatment using the number and quality of other applicants originating from the same district. After incorporating these instruments as well as a wide range of outcome measures and background characteristics, we find that preparatory programs have positive but limited effects for human capital development for undergraduate students. Specifically, these pre-college programs promote significant but short-lived improvements in academic grades. They also can encourage students to choose STEM-oriented majors, and promote retention by lowering voluntary exits.

JEL Classification: I20, J24

Keywords: human capital, remedial education, higher education, liberal arts college

Corresponding author:
Ahmed Rahman
Economics Department
College of Business
Lehigh University
621 Taylor Street
Bethlehem, PA 18015
USA

E-mail: asr418@lehigh.edu

* The authors would like to acknowledge that the data used in this study has been approved for use according to HRPP# USNA.2012.0006 – IR – EM4 – A. We appreciate the help and counsel of the U.S. Naval Academy's HRPP Office and Institutional Research Office in this process. Many thanks to participants in the microeconomics brownbag at Brown University and the in-house workshop at the Center for Naval Analysis for their helpful feedback.

1 Introduction

College kids need our help, or so we keep hearing. Graduation and performance rates at U.S. colleges and universities continue to decline, and world education rankings place the U.S. at new all-time lows.[1] A potential contributing factor to this decline is that students are arriving on college campuses across the country ill-prepared for college level courses. According to the National Center for Education Statistics, in 2011-2012 roughly one third of all students take remedial (developmental) courses in college.[2] Even at the most selective colleges and universities, 13.3 percent of students take a least one remedial course.[3] A number of programs designed, either explicitly or implicitly, to aid potentially struggling students have sprung up around the nation. These include community college systems which can help students transition into 4-year bachelor programs and remedial programs which feed incoming students into specific colleges (Bowen et al. 2009). Due to high demand for these developmental courses, roughly 80% of four year institutions offer remedial courses which do not count towards an undergraduate degree.

But do they work? Remedial education is expensive, costing over $3 billion in 2011 (See Alliance for Excellent Education, 2011) and their effectiveness remains an open question. These costs are borne not only by the students in terms of increased tuition and fees (increasing student debt burdens) but also are often subsidized by the schools or state and federal funds. The high costs of remedial provision at undergraduate institutions have prompted at least eight states to ban remedial courses at 4-year institutions, forcing students that need remediation to first attend community colleges.[4] At an annual cost of over one billion dollars for U.S. public colleges alone, critics of remediation wonder if such programs should be offered at all (Breneman and Haarlow 1997). Measuring effectiveness is complicated by heterogeneity in student selection and program implementation — in some cases students are prescribed remediation, in other cases students enroll themselves. For example in 2007 the Texas Higher Education Coordinating Board created a summer bridge program aimed at selecting students across 22 Texas colleges and enrolling them in remedial math and reading courses.[5] In other circumstances, the

[1] From OECD report "Education at a Glance 2014."

[2] The term "remedial" describes coursework that students should have mastered before entering college. Of note are programs expressly intended to improve performance for minority students, such as the Meyerhoff Scholarship Program at the University of Maryland – Baltimore County, the CARE program at Florida State University, the African American Male Initiative at the University of Georgia, and the Black Male Initiative at City University of New York (Bowen et al. 2009).

[3] Statistics in Brief (January 2013), National Center for Educational Statistics.

[4] The National Center for Public Policy and Higher Eduction, *Crosstalk* Fall 2005

[5] "Bridging the Gap- An Impact Study of Eight Developmental Summer Bridge Programs in Texas",Barnett et al, June 2012.

responsibility of remediation falls on the students.

One approach is to complete remediation requirements in high school, as done in Tennessee. Kane et al. (2019) report that this approach yielded no impacts on students' math achievements. Remediation can also occur in college itself — Scott-Clayton and Rodríguez (2012) find that such programs simply divert students away from college-level courses toward remedial courses. Perhaps the most widely-used approach is to impose a delay, or "gap-year," between high school graduation and college entrance. Miller and Birch (2007) show positive impacts from this method although note there are important selection issues conflating their results.[6]

The overall effects on students from remedial programs may be numerous and complicated. Proponents of such programs imagine they can help students acclimate to dormitory life and college culture, get an important head-start on the curriculum, or foster solidarity and kinship with fellow struggling students. Detractors may worry about the negative consequences of spoon-feeding material and "teaching to the test," or about the possibility of stigmatizing groups of students with remediation.

This paper examines the impact of participation in post-graduate education on student preparation for undergraduate success. We use a large cross-sectional dataset of students from the United States Naval Academy graduating classes of 1988–2018, and analyze the effects from two types of pre-college programs — the Naval Academy Preparatory School (henceforth NAPS) and an assortment of other independent post-graduate programs (henceforth Foundation schools). Students who are not admitted to USNA directly from high school may be offered a one year appointment to either one of these programs. On average, over 20% of each graduating class attends some type of pre-college program. The NAPS program is a USNA-run, tuition-free preparatory school designed to ease students into the rigors of higher education. Students at NAPS attend college level courses for an entire academic year before matriculating into USNA. The NAPS program is modeled from the top preparatory schools around the United States. NAPS students must take courses in English, math, chemistry, and physics. Students are given an assessment at the beginning of the academic year and placed in courses according to their current level in each subject. Similar to preparatory schools around the country, NAPS students are housed in a single dormitory, in this case located in Newport, Rhode Island. The environment away from home gives students a taste of the independence they will experience as first-year college students. Alternatively, applicants may be offered the chance to enroll in an independent preparatory program

[6] Such "red-shirting" strategies have also been studied for very young students (see for example Deming and Dynarski 2008, and Elder and Lubotsky 2009).

that is sponsored by the Naval Academy Foundation. This is a need-based system, but students are asked to pay at least 40% of tuition (a list of these schools appears in Appendix 6.1).[7]

There are a number of advantages to analyzing students from USNA to assess the effectiveness of pre-college/post secondary school programs. The Naval Academy is a highly-ranked liberal arts college that admits a wide range of students from all parts of the country and all ranges of socio-economic levels and academic abilities. Looking at *two* types of pre-college programs (NAPS and Foundation) allows us to contrast different effects from different approaches. More critical for statistical inference, upon matriculation students at USNA take very similar courses during their freshman year, allowing for an unusual degree of comparability of academic performance. Students have 100% of their tuition paid and are not permitted to hold jobs outside of school, removing heterogeneity in terms of outside non-academic employment. Finally, USNA is a college that has remained remarkably consistent in terms of curriculum and school policy relative to most undergraduate institutions, allowing us to exploit three decades of student educational history.[8]

Of course the principle challenge in such studies is typically selection bias (students are prescribed either by others or themselves). Without an explicit experiment, or some clearly-defined cutoff for admissions to exploit a discontinuity, assessing the marginal impacts from any educational program is extremely difficult. We infer causal impacts by employing an instrumental variables strategy. Our data consists of all students who were admitted to the Naval Academy *either* directly or indirectly (through the NAPS or Foundation program). Any instrument we employ should not be designed to capture variation in the likelihood between pre-college admission and no admission. Rather it should be designed to capture variation between pre-college admission and direct admission. The instrument is valid if it can help predict someone's selection to pre-college who would have otherwise been chosen for direct admission, based on factors unrelated to his or her individual academic merits.

To this end we exploit information on the congressional district from where the student originates. The admissions process to the Naval Academy is unique in that every applicant must be nominated. There are a variety of nomination sources such as the President of the U.S., Superintendent of the Academy, but the bulk (roughly three fourths) of nominations come from Senators and Congress-

[7]Given students are living independently at both NAPS and the Foundation schools we cannot identify separately the impacts on academic exposure and social exposure. This may limit our ability to extrapolate our findings to remedial programs where students are commuting from home and not experiencing a social setting similar to a residential college or university.

[8]As one indication of this, our inclusion of year fixed effects in the empirical specifications we will perform barely alter any of our empirical results.

men/women; this is to ensure relatively equal representation across the United States for each graduating class. Each member of Congress can have five constituents attending the Naval Academy at any time. We employ up to two instruments that use district-level variation in direct placement to the Naval Academy. The first of these is the time-averaged total number of applicants to the Naval Academy from each district. This measure captures to a large extent the spatial importance of certain regions of the United States to naval operations generally and the Academy in particular. Rahman (2020) documents the historic importance of naval personnel originating from specific regions of the U.S. in establishing the military industrial complex during the Second World War. This geographic variation in military "representation" persists to the present day.[9] Such variation produces different degrees of competition for direct admittance to the Academy for reasons unrelated to academics. So for two individuals with like academic and demographic backgrounds, the one originating from the more "USNA-inclined" district may have a higher likelihood of being selected for pre-college instead of direct admittance.

The second instrument we use is the lowest Admissions score among the *other* students admitted directly to the Academy from an individual's congressional district during that academic year. Admissions allocates each applicant a score based on a variety of academic and extra-curricular accomplishments. Thus for any two students with the same Admissions' score, the one whose congressional district has admits with higher scores that year is facing stronger competition for the direct slots and is therefore more likely to be selected for pre-college instead of direct admittance. By using the lowest score of those directly admitted, we capture an implicit quality threshold associated with that district that year.

What we find is that these preparatory programs have positive but rather short-lived effects for human capital development for undergraduate students. The effects are strictly confined to the NAPS program, where the curriculum is designed to line up with the follow on courses taken during freshman year at USNA. For Foundation school participants we find no academic impacts at all. The results suggest that programs that are tightly linked academically and socially to the follow-on college experience can go beyond simply teaching to the test. But while academic outcomes are improved into students' sophomore year, these programs do little to facilitate deeper learning that comes with major-specific courses later in one's college tenure. Further, given that the impacts dissipate, pre-college exposure does not seem to reduce academic-related exit but does limit voluntary exit leading more students to

[9]For example there is a strong correlation between the counties where naval operations developed during WWII documented in Rahman (2020), and the regions from where current applicants to the U.S. Naval Academy originate documented here.

stick with the college experience. In short, pre-college programs appear to boost academic performance enough to reduce exit and can serve as a tool to promote technical education for under-represented groups. Funding for such programs warrants greater debate.

2 Related Literature

2.1 Literature

Remediation for high school graduates that are under-prepared for undergraduate education typically occurs directly before or directly after matriculation. While the cost and interest in pre-matriculation programs has been on the rise, a greater proportion of research has focused on the benefits of remediation in post-matriculation coursework. In this case, colleges assess student preparedness during the admissions process and often encourage some students to enroll in remedial classes during their freshman year.

Results from these programs are mixed. Attewell et al. (2006) finds remediation programs for students during their first year in college decrease the likelihood of graduating on time by 6%, mainly because students tend to fall behind their peers. Adleman (1999) on the other hand finds no relationship between remediation and graduation. Lavin et al. (1981) study remedial coursework at CUNY where students ostensibly enroll on a voluntary basis, finding slightly positive effects on graduation rates. Bettinger and Long (2009) analyze remedial coursework in mathematics, suggesting some positive effects on both retention and grades in follow-on math courses.

Many studies have addressed the question of effectiveness of remediation by using regression discontinuity design techniques. This works well when students can easily be compared who are placed just above and below the cutoff for remedial courses (Calcagno and Long 2008; Lesik 2007; Martorell and McFarli, 2008). Students scoring above the specified cutoff score are not assigned to remedial-level courses, while students scoring below the cutoff are assigned. Given that students who score around the placement cutoff are similar in ability, causal estimation of the local average treatment effects of remedial education on long run educational outcomes is possible.

A major limitation in this literature is that remediation-program studies are typically administered in-house and post-matriculation. As such whether students are chosen or self select academic help remains unclear, as does the extent to which remediation crowds out college study (as students typically must take remedial and regular coursework simultaneously — see Scott-Clayton and Rodriguez 2012).

Our study produces a much cleaner analysis on the academic effects of prescribing remedial education to college students. We study the pre-college remediation effects on students of various academic backgrounds who are all chosen by the Admissions Board of the Naval Academy. The measured effects are also more comparable across cohorts, as all students have very similar course and service obligations, especially during the post-treatment freshman year.

The U.S. Naval Academy is a liberal arts college with a STEM-based education comparable to moderate-to-top academic programs around the country. It is also a service academy — these institutions have long generated a well-spring of insightful research in the economics of education.[10] Further, USNA is the only service academy employing tenured and tenure-track faculty — students interact with faculty of similar caliber to faculty in other liberal arts colleges. The student body is drawn from the same pool as other selective academic institutions around the U.S. The results of this study have implications that apply to all types of remedial education outside of USNA.

3 Data

The data covers the USNA graduating classes of 1988 through 2018, a total of over thirty-five thousand students and nearly twenty-eight thousand graduates.[11] The full sample includes 28,068 students who entered directly from high school, 6041 who went through NAPS, and 2234 who went to another independent preparatory school. Along with distinguishing between students who enter the Academy directly and those who first attend NAPS or another independent preparatory school, the data contain a rich assortment of student characteristics. In terms of background information, the data identify each individual's age, race, gender, SAT scores, high school name and location, and median income of residential area. In terms of potential educational outcome measures, the data include each individual's grades for all courses, name of declared major, aptitude grades, and academic, military and overall orders of merit. Summary statistics including a breakdown of treated and control groups by type of pre-college program are displayed in Tables 1 and 2.[12]

[10] A small representative sample would include Brady et al. (2017), Carrell, Hoekstra & West (2011a), Carrell, Hoekstra & West (2011b), Carrell, Fullerton & West (2009), Carrell & West (2010), Insler et al. (2020), Lyle (2009) and Lyle (2007).

[11] These include those who are admitted but ultimately do not graduate. We do not observe the background characteristics of those applicants who are flatly rejected.

[12] Note that a potential selection issue may exist as we do not have data on rejected students or those that are accepted but choose not to enroll. However, we do know that of those students that are accepted to NAPS and those that accepted directly, the yield rates are nearly the same. Of those applicants that were offered an indirect slot (yield to NAPS) 89% accepted. This is very close to yield for direct admits which is 87% over for the class of 2015-2019. So roughly the same number decline the Naval Academy either directly or indirectly.

Table 1: Means and Standard Errors for
Key Background Variables

Variable	Direct Admission n=28,068	NAPS n=6041	Foundation Schools n=2234
Verbal SAT	657.38	579.89	630.29
	(64.02)	(67.55)	(63.12)
Math SAT	677.80	599.11	650.53
	(60.45)	(60.54)	(56.96)
HS_Rank	592.94	450.32	484.39
	(118.43)	(119.02)	(112.15)
Age (upon matriculation)	18.43	19.79	19.33
	(.64)	(1.01)	(.47)
Female (indicator)	.176	.143	.115
	(.381)	(.350)	(.319)
African-American (indicator)	.039	.192	.016
	(.193)	(.393)	(.125)
Hispanic-American (indicator)	.069	.180	.025
	(.254)	(.384)	(.157)
Asian-American	.043	.045	.019
	(.204)	(.209)	(.137)
Varsity athlete (indicator)	.371	.467	.410
	(.483)	(.499)	(.492)
Regional_median_income	58330.8	58646.3	63039.5
	(15868.1)	(16368.8)	(16725.6)
HS_graduation_rate	79.25	78.18	79.95
	(7.96)	(8.22)	(7.94)
Admissions' Score	67181.11	60243.8	62429.6
	(4815.30)	(3007.05)	(3323.26)

Standard errors reported in parentheses.
See Appendix 6.3 for variable descriptions.

Table 1 includes information on student background profiles. Verbal SAT is a record of the student's highest reported verbal SAT score. Math SAT is a record of the student's highest reported math SAT score. High School Standing is a standardized rank of each student within his or her respective high school class. A score of 800 means the student was ranked top in his/her graduating high school class; a score of 500 means the student was ranked in the very middle of his/her class. The variable Age gives an accurate measure of a student's age on the day he/she reported with the rest of his/her class to Induction Day (matriculation) at USNA.[13]

To incorporate district impacts we include a measure of district level median household income as well as high school quality. The median income data comes from ProximityOne Data Services. These are at the congressional district level and were measured for 2010. This serves as an important district-level control, particularly as we exploit other district-level information in our IV strategy. Note that the income-of-residence levels are on average noticeably higher for attendees of other preparatory programs than for attendees of the NAPS program. This makes sense, as NAPS is a fully funded program, while those agreeing to attend alternative prep programs must pay tuition, at least in part. Our second district effect measures regional high school graduation rates within congressional districts. This data comes from the National Center for Educational Statistics.

We also utilize an admissions' score, an index produced by the USNA admissions office that incorporates not just SAT scores and high school standing, but also many background variables unobserved by us such as extra-curriculars, strength of recommendation letters, and athletic performance. We label these *soft skills* — those qualitative factors that conceivably shape both admission decisions and subsequent college performance. We wish to isolate these factors for use as an additional control variable. We thus construct a *soft skills* measure by running the following regression:

$$ascore_i = \phi_0 + \phi_1 vsat_i + \phi_2 msat_i + \phi_3 hss_i + \lambda_t + \epsilon_i \tag{1}$$

where $ascore_i$ is an index for student i constructed by the admissions offce, $vsat_i$ and $msat_i$ are student i's SAT scores, and hss_i is the student's standardized high school standing. Our soft skills index for each student i is $\widehat{\epsilon}_i$, the portion of the score left unexplained once we account for basic observable measures

[13]Inclusion of age is important given that many more schools are offering a deferment option with the idea that with a short one year delay students that matriculate have better academic outcomes. Members of the treated group all must take an extra year and will therefore by and large be older. In addition many students are prior enlisted service members and may be older. There is a mandated age minumum and maximum for matriculating students. A student must be 17 but cannot have turned 24 by July 1st of their admissions year to the Naval Academy.

of student quality. Factors such as quality of essay and interview are captured in the index, leaving us with the same (though more aggregative) set of information that the admissions office itself has when it assigns students to enter directly or take a pre-college year. Also note the inclusion of class-year fixed effects λ. Since admissions personnel were very likely to adjust the relative weights on the inputs to the multiple, inclusion of such shift terms will likely give us a more accurate index measure. To our knowledge no other study has exploited this level of academic student background in assessing the effects of an educational program.

We shall also use the admissions' score to construct a measure of relative competitiveness within one's congressional district as one of our two instruments. For student i originating from district j applying to join the Class of t, this measure can be calculated as

$$\text{Min.Admit.Score}_{it} = \min[ascore_{1jt}, ascore_{2jt}, ..., ascore_{njt}] \tag{2}$$

for an individual applying when there are n direct admits (not including i) from i's congressional district j during year $t-4$. For those who are admitted directly, they will be on track to graduate for the Class of t. For those selected for pre-college, they will be on track to join the Academy in year $t-3$ and graduate for the Class of $t+1$.

Table 2 includes information on performance variables for student assessment while at USNA. Graduation refers to the graduation rate of each cohort (for a full list of USNA's majors by group see Appendix 6.2). We include major selection information for different cohorts (students take the same coursework during freshman year and declare majors only at the end of that year). Grade Semester 1 through 4 are measures of academic course GPAs during the first four semesters at USNA. Academic grades include all academic coursework but exclude military and professional course grades.[14] The variables Voluntary dropout and Academic dropout are binary variables that indicate whether or not the student left USNA voluntarily, and whether or not the student was dismissed from the USNA due to academic deficiencies.[15]

Considering the summary statistics from Table 2, note that average differences between treated and non-treated groups for variables such as SAT scores and high school rank are quite large. For example, the average math SAT scores for incoming high school students is 70 points higher than those of students

[14] Military "coursework" includes things like physical education courses and professional conduct.

[15] Students may exit the Academy before the start of their junior year without monetary penalty. Students who exit after this point must provide backpay for all tuition and other incurred fees. As a result there are almost no voluntary exits after the 4th semester.

Table 2: Means and Standard Errors for College Performance Variables

Variable	Direct n=28,068	NAPS n=6041	Foundation Schools n=2234
Graduated (indicator)	.806	.777	.848
	(.395)	(.416)	(.358)
Sophomore Engineering Majors	.328	.200	239
	(.469)	(.400)	(.427)
Sophomore Math & Science Majors	.229	.269	.203
	(.420)	(.443)	(.402)
Sophomore Humanities/ Social Science Majors	.310	.432	.461
	(.462)	(.495)	(.498)
Senior Engineering Majors	.313	.182	.230
	(.463)	(.386)	(.421)
Senior Math & Science Majors	.209	.230	.187
	(.406)	(.421)	(.390)
Senior Humanities/ Social Science Majors	.283	.363	.429
	(.450)	(.481)	(.495)
Grades Semester 1	2.81	2.41	2.60
	(.707)	(.609)	(.610)
Grades Semester 2	2.82	2.31	2.52
	(.671)	(.603)	(.590)
Grades Semester 3	2.96	2.38	2.63
	(.683)	(.634)	(.620)
Grades Semester 4	2.97	2.41	2.68
	(.671)	(.600)	(.578)
Overall GPA	2.89	2.47	2.67
	(.734)	(.522)	(.576)
Voluntary dropout	.125	.078	.079
	(.331)	(.268)	(.270)
Academic dropout	.033	.076	.045
	(.178)	(.266)	(.207)

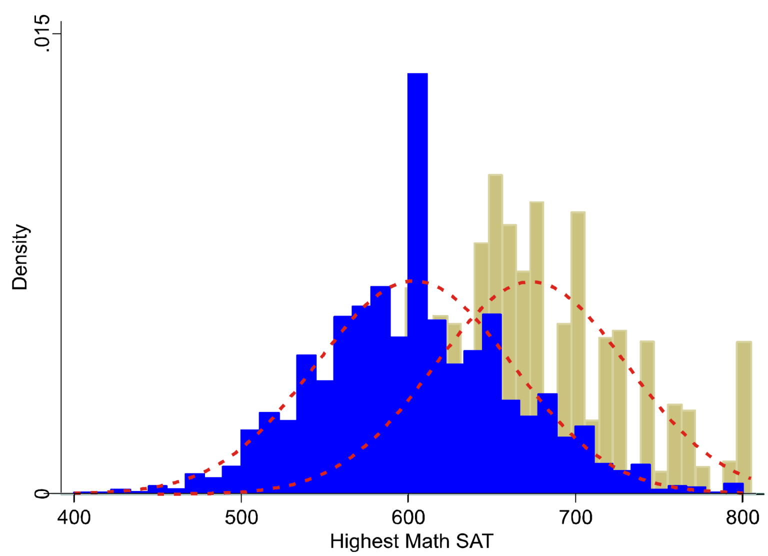
Standard errors reported in parentheses.

See Appendix 6.3 for variable descriptions.

who first attend NAPS. Tables 1 and 2 display key differences in both background characteristics and performance metrics between treated and control groups. Simply looking at the averages for background characteristics, we find that there appears to be a dramatic difference in the magnitude and spread of the high school percentile variable across student backgrounds. We also see a significant difference in the means of performance variables like academic course grades. The difference in means and large overlap in terms of standard deviation motivates our use of IV estimation.

Figure 1 illustrates the overlap in Math SAT scores among those students first attending NAPS and direct entry. This degree of overlap between direct entry students and pre-college students also holds for verbal SAT scores and for high school percentile rank (not illustrated). The significant overlap suggests that factors other than just academics may play a role in selection to pre-college. This helps us isolate the marginal impacts of such programs.

Figure 1: Distributions of Math SAT Scores for NAPS (Blue) and Direct (Gold) Students



Because a student leaving a four year institution prematurely can be costly for the institution, the students themselves and society as a whole, it is important to better understand the characteristics of those that do complete their four year degree versus those that do not. Table 3 shows the average background characteristics and performance variables for those that finish relative to those that do not.

Students that leave college tend to have weaker academic backgrounds reflected in lower test scores

Table 3: Summary Statistics Between Graduates and Non-Graduates

Variable	Graduates n=27,902	Non-Graduates n=6809
Verbal SAT	642.73	635.34
	(69.32)	(71.66)
Math SAT	664.64	650.24
	(65.91)	(66.41)
HS_Rank	565.57	547.34
	(129.00)	(130.56)
Age (upon matriculation)	18.73	18.76
	(.895)	(.958)
Varsity athlete (indicator)	.416	.261
	(.493)	(.439)
Admissions' Score	65790.4	64128.4
	(5118.8)	(4791.0)
Regional_median_income	65790.4	57031.8
	(5118.8)	(15600.1)
Grades Semester 1	2.81	2.15
	(.616)	(.883)
Grades Semester 2	2.77	2.17
	(.625)	(.814)
Grades Semester 3	2.895	2.21
	(.648)	(.904)
Grades Semester 4	2.899	2.18
	(.632)	(.941)

Standard errors reported in parentheses.
See Appendix 6.3 for variable descriptions.

and class ranks. Despite not having to pay tuition at the Academy, drop-outs tend to come from lower-income regions. Not surprisingly, those that do not graduate have lower grades on average. Students that attend NAPS and then proceed to drop-out have even lower pre- and post-matriculation academic performance than the direct admits.

3.1 Empirical Strategy and Identification

The objective of this type of study is to compare differences in outcomes between "treated" and "non-treated" individuals. In this case outcomes are measures of educational achievement, and treatment is enrollment in a pre-college program. Specifically, the untreated group of students in the study is the direct admissions group, and the treatment group is the group of students that attended NAPS or an independent preparation school through the Foundation program.

Having two different "treatments" provides us a unique robustness check. The students that are assigned to NAPS are typically offered a very narrow selection of courses. The ten-month course of instruction at NAPS emphasizes preparation in English Composition, Mathematics, Chemistry, Physics, and Information Technology, precisely those courses standard to the first two academic years of Naval Academy instruction. At the same time students are completing their course work they are also participating in military, physical, and character development programs. Students attending Foundation schools on the other hand are typically taking the most advanced courses their prep school offers in various (and sometimes quite different) subject areas, and are not exposed to the same extra-curriculars.

The selection to a one year pre-college program is non-random. As a baseline to compare our results to previous literature, we first estimate an OLS model. As previously mentioned, many studies on this subject (U.S. Department of Education 1996, Fitzpatrick 2001) utilize simple ordinary least squares regression, or some close variation. With non-random selection other empirical techniques will be necessary.

To address selection bias, we run a 2SLS generalized instrumental estimation. The analysis requires both excluded and non-excluded instruments. Non-excluded instruments are those background variables which may influence both treatment and outcome, such as math and verbal SAT scores, and rank in one's high school graduating class. We also include some variables that can be excluded from the primary regressions. These are the number of district-level applicants (to proxy for competitiveness based on quantity of applicants) and the minimum admissions score among all direct admits from one's congressional district (to proxy for competitiveness based on perceived quality of applicants). We include these individually in separate first-stages, as well as employ both in an over-identified model or just-identified model, depending on the specification.[16] Both of these excluded instruments capture the geographical admissions constraints unique to USNA that impact selection to pre-college treatment but not follow-on academic outcomes.

3.2 Model Estimation

As a baseline we start with simple OLS regressions. We then turn to our IV strategy to isolate exogenous variation in treatment on academic outcomes. We explain the details of each procedure below.

3.2.1 Ordinary Least Squares Estimation

Equations for the OLS model shows the correlations between the binary treatment variable (either NAPS or Foundation schools) and a range of academic performance variables. The OLS regressions take the following form:

$$ap_i = \beta_0 + \beta_1 prep_i + X_i'\gamma + \alpha_j + \lambda_t + \varepsilon_i \tag{3}$$

for each student i originating from state j of the class-year t. The academic performance variables, ap, include grades and relative class rank. $prep$ is an indicator that the student participated in NAPS or another independent preparatory school. X includes controls such as math and verbal SAT scores, high school standing, the soft skills index, and other non-academic factors. Effects from these controls are captured by the vector of coefficients γ. We include state and class-year fixed effects (α_j and λ_t) for all specifications.

3.2.2 IV Estimation and Internal Validity

The IV estimation uses up to two exogenous variables that captures district-level variation in direct placement to the Naval Academy. The first of these is the time-averaged total number of applicants to the Naval Academy from each district (Direct.App). The unique admissions process both requires but limits congressional nominations. Each Congressman/woman can have a maximum of five students attending the USNA at any point in time. Each year for an open slot within a district, congressional

[16]Tests of over-identifying restrictions support the inclusion of these instruments. Results remain quite consistent with alternate specifications.

representatives can nominate up to ten students. Therefore, each candidate's direct competition tends to be from those within their district. However, there is no specific geographic constraint on NAPS or Foundation programs.

For the second exogenous variable we use the minimum admissions score assigned to the *other* students admitted directly to the Academy from an individual's congressional district during that academic year (Min.Admit.Score). Admissions allocates each applicant a score based on a variety of academic and extra-curricular accomplishments. Thus for any two students with the same Admissions' score, the one whose congressional district has a higher minimum score among all other direct admits may be considered relatively less qualified and is therefore more likely to be selected for pre-college instead of direct admittance.

We estimate

$$ap_i = \beta_0 + \beta_1 \tilde{\text{prep}}_i + X_i'\gamma + \alpha_j + \lambda_t + \varepsilon_i \tag{4}$$

where $\tilde{\text{prep}}_i$ are the predicted values of the likelihood of attending pre-college.

As our instruments are modeled for binary outcomes (selection to pre-college or selection to direct admission), we utilize the IV approach in D'Ignazio and Menon (2020) and outlined in Wooldridge (2002).[17] This involves using the nonlinear fitted values as an additional instrument in an otherwise conventional 2SLS procedure.[18] Our compliers have a fairly wide range of measured academic ability that helps us identify the average treatment effect of pre-college.[19]

The exogenous treatment propensity is estimated using a Probit regression:

$$P(\text{prep}_i = 1|\mathbf{X}) = \Phi(\text{Direct.App}_i, \text{Min.Admit.Score}_i, X_i, \alpha_j, \lambda_t). \tag{5}$$

The estimated propensity score from (5) is then used as a generated instrument along with all other exogenous variables in a 2SLS estimation.[20]

[17]Wooldridge(2002) suggests that this procedure is best to produce the average treatment effect, and is more efficient than the standard 2SLS model. We also perform standard 2SLS as Angrist(2001)suggests (reported in the appendix 7), and GMM as suggested by Cameron and Trivedi (2005) (available upon request).

[18]Specifically, we first estimate a Probit, regressing a binary variable of whether the student is chosen for a preparatory program on the instruments and all exogenous student background characteristics. We then use the predicted values as an additional generated instrument using 2SLS estimation, making sure to adjust all the standard errors.

[19]As we demonstrate below, the Academy did not impose a strict cutoff for selection, rendering regression discontinuity approaches inappropriate, and giving us the potential to estimate something broader than a local average treatment effect.

[20]Note that we use bootstrapped standard errors for all estimates produced from this procedure.

Like all IV approaches, one might question its internal validity. Specifically, can we be reasonably confident that the average number of applicants, or the degree of competition within an applicant's congressional district, are unrelated to unobservables that may relate to academic success? We are for a variety of reasons. In terms of our first instrument, Figure 2 for example shows the average number of applicants per congressional district for 2009. We see a highly skewed distribution — some districts tend to have many applicants to the Naval Academy than average. Which districts these are appear to be random — they are in different districts all around the country, with no seeming relationship to district median income, average educational quality or other district-level attributes. We find no correlation between the number admits from the student's district to background observables.[21] In terms of the second instrument, the degree of competition at the district level could be driven by better schools and higher family incomes within those districts that contribute to students' academic success. To explicitly control for this (thus removing it from the error term), we include district level effects captured in median household income and regional high school graduation rates in all stages of the estimation.

Finally note that we include class year and state fixed effects in all specifications.

4 Results

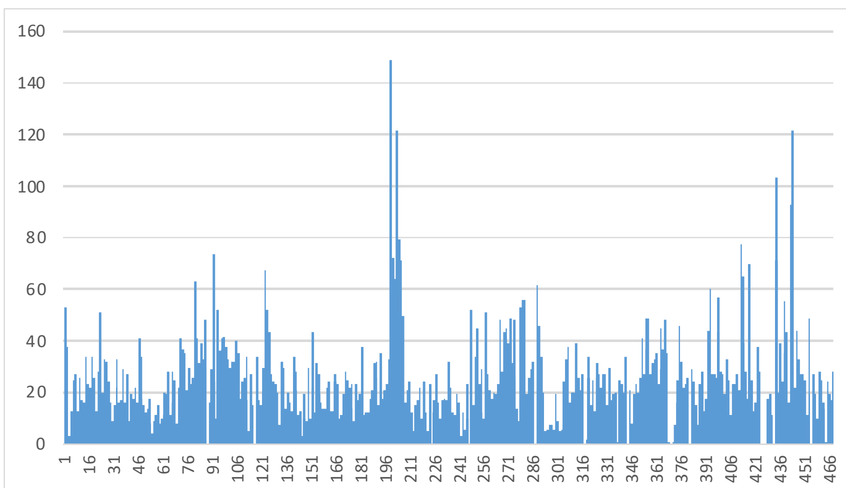
Across our methods of analysis, empirical results hold consistently. To summarize, remedial programs appear to promote modest and temporary improvements in academic grades, encourage students to choose STEM-oriented majors, and promote retention by lowering voluntary exits. They do not appear to help lessen exits due to academic trouble. Effects on grades diminish rapidly over each semester; by one's junior year we detect no effect. Thus, these programs appear to help with academic performance mainly in areas already covered in pre-college, not in follow-on applied coursework. The type of remedial program also seems to matter. Being run and controlled by the Naval Academy, NAPS, delivers much stronger results than the Foundation program, where content and social environments may vary significantly from that at USNA. Specific results are described below.

4.1 Ordinary Least Squares Estimation

It is useful to first examine how ordinary least squares regressions suggest returns to educational outcomes based on participation in a preparatory school program. Table 4 illustrates the relationship

[21] Specifically, all four academic background traits have correlation coefficients with the instrument lower than 0.01 in absolute value.

Figure 2: Average Number of Applicants Across Congressional Districts (Alphabetized by State) for 2009



between participation in a pre-college program as well as other controls on academic performance.

Estimated coefficients on the pre-college indicator paint an interesting picture. Once we control for measurable background academic characteristics, precollege participation is associated with positive average academic grades *only* during the first semester. These diminish and turn negative during the second semester, remaining negative and statistically significant for all subsequent semesters.[22]

The coefficients on the independent variables Math SAT, Verbal SAT and High School Standing have the expected signs and magnitudes. Higher math and verbal SAT scores, and higher high school standing, are associated with positive returns for all semesters of academic grades. Interestingly, our soft skills index also appears to significantly matter for academic performance. As one might suspect, factors such as letters of recommendation and extra-curriculars are positive predictors for college success.

In terms of the district level effects, median household income of the student's congressional district also strongly relates to academic performance. Likewise district average high school graduation rates are associated with better academic performance. In both cases more resources at the district level are related to better educational outcomes at the collegiate level for students from those districts. Finally, minority students as well as women tend to earn lower scores across all semesters.[23]

The OLS results here suggest an intuitive story. Pre-college programs may generate some positive grade effects early on, but these quickly peter out as one progresses in one's college career. However, we of course suspect that pre-college selection is based on factors correlated with college success, including the ones employed here as explanatory variables. The negative (and significant) estimated impacts for every semester after the first might suggest there are issues with selection bias. Thus we turn to an instrumental variable strategy.

[22]Note that the first two semesters are the most comparable across cohorts, as almost all freshman at USNA take the same courses. By the third semester, students have declared their majors and begin to take more specialized course work, although they still take many of the same engineer- and math-oriented classes as well.

[23]Without richer data on students' socioeconomic backgrounds as well as data regarding their experience at the Naval Academy we only consider race and gender as control variables.

Table 4: OLS Estimates of Pre-college on Academic GPA

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1st Sem	2nd Sem	3rd Sem	4th Sem	5th Sem	6th Sem	7th Sem	8th Sem
Pre-college	**0.0786*****	**-0.0347****	**-0.0506*****	**-0.0639*****	**-0.0775*****	**-0.0787*****	**-0.0579*****	**-0.0777*****
	(6.29)	**(-2.88)**	**(-3.86)**	**(-5.00)**	**(-5.58)**	**(-6.06)**	**(-4.52)**	**(-6.15)**
SAT Math	2.071***	2.044***	2.412***	1.880***	1.301***	1.276***	1.126***	1.021***
	(34.98)	(36.58)	(40.98)	(30.77)	(19.68)	(21.05)	(18.79)	(17.15)
SAT Verbal	1.067***	0.869***	0.811***	0.851***	0.849***	0.819***	0.687***	0.518***
	(19.69)	(16.62)	(14.78)	(14.83)	(13.73)	(14.29)	(12.17)	(9.25)
HS Rank	1.359***	1.311***	1.191***	1.121***	1.045***	1.015***	0.978***	0.954***
	(45.65)	(46.15)	(39.37)	(36.24)	(31.68)	(32.68)	(32.59)	(31.86)
Soft Skills	0.0264***	0.0253***	0.0214***	0.0198***	0.0134***	0.0127***	0.0111***	0.0123***
	(16.62)	(16.18)	(13.14)	(11.71)	(7.45)	(7.38)	(6.82)	(7.28)
Regional median income	0.0918***	0.0841***	0.117***	0.0995***	0.0919***	0.0885***	0.0549**	0.0420*
	(4.83)	(4.65)	(6.05)	(5.11)	(4.20)	(4.50)	(2.84)	(2.24)
HS graduation rate	0.00224*	0.000753	0.000549	0.000867	0.000886	0.000458	0.00131	0.000991
	(2.52)	(0.89)	(0.61)	(0.95)	(0.87)	(0.50)	(1.42)	(1.09)
Female	-0.104***	-0.134***	-0.120***	-0.0214*	0.0167	0.0367***	0.0594***	0.0605***
	(-9.59)	(-12.82)	(-10.92)	(-2.00)	(1.44)	(3.31)	(5.46)	(6.10)
Black	-0.156***	-0.168***	-0.209***	-0.189***	-0.187***	-0.179***	-0.169***	-0.198***
	(-9.88)	(-10.83)	(-11.48)	(-10.94)	(-10.36)	(-10.10)	(-9.87)	(-11.03)
Hispanic	-0.0827***	-0.0782***	-0.0874***	-0.0916***	-0.107***	-0.0989***	-0.113***	-0.0987***
	(-5.52)	(-5.46)	(-5.52)	(-5.69)	(-6.23)	(-6.26)	(-6.99)	(-6.51)
Asian	-0.0338*	-0.0836***	-0.105***	-0.120***	-0.114***	-0.100***	-0.116***	-0.0964***
	(-1.97)	(-4.74)	(-5.80)	(-6.32)	(-5.73)	(-5.32)	(-6.13)	(-5.56)
Athlete	0.0869***	0.0319***	0.00848	-0.00489	-0.0136	-0.0143	-0.0114	-0.0224**
	(10.18)	(3.84)	(0.97)	(-0.54)	(-1.40)	(-1.57)	(-1.26)	(-2.58)
Blue Chip	-0.137***	-0.0982***	-0.0465***	-0.0339**	-0.0212	-0.0202	-0.0180	-0.0600***
	(-10.98)	(-8.26)	(-3.71)	(-2.72)	(-1.61)	(-1.57)	(-1.44)	(-4.85)
Age on I-Day	0.0933***	0.0739***	0.0434***	0.0300***	0.0233***	0.0124*	0.00870	0.0171**
	(16.65)	(13.67)	(7.49)	(5.15)	(3.77)	(2.15)	(1.56)	(3.04)
R^2	0.344	0.358	0.350	0.309	0.247	0.265	0.239	0.263
N	23618	23085	22474	21973	21056	20104	19895	19027

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

All specifications include state and year effects

We start by estimating the likelihood of being selected into a pre-college program, as opposed to being admitted directly to the Academy, using probit regressions. Results are presented in Table 5. Not surprisingly, stronger measures of academic ability, including our measure of soft skills, imply a lower likelihood of selection to a pre-college program.

It also appears that median residential income is an important control in participation. Even though income level is associated with stronger academic performance, it is also a positive predictor of pre-college attendance (when controlling for other predictors of academic success). This makes sense; essentially only those of a certain prosperity level can afford to take an entire year off to prepare for college. Surprisingly, this is also true for those attending NAPS, even though it is a fully funded program.[24] As we will see, this will be even more important for other preparatory programs that are only partially funded. From the data we can see pre-college programs are also apparently used to promote underrepresented ethnic (though not gender) diversity.

Note our inclusion of age upon matriculation as an additional control. Causation obviously runs the other way here — participation in pre-college delays the date of matriculation. Its inclusion however is potentially important in that delayed entrance to school may help with academic performance simply because students are older and more mature. In addition, there tends to be a higher proportion of prior enlisted service members at NAPS that tends to raise average age.[25]

The final two variables are used as excluded instruments that capture district level effects that are crucial to pre-college assignment. The first one, the average number of district-level applicants, suggests that districts that submit more applications to USNA tend to send more students to NAPS. Likewise, higher admissions' scores for other applicants from a particular district tends to be associated with a higher likelihood of being assigned to a pre-college program. We therefore include the lowest direct admit admission score. From both of these instruments we capture the fact that competitive districts have lots of qualified candidates but a limited number of direct admit spots, so the Academy can use the pre-college assignment to bring in more qualified students and thereby relax to some degree these geographical constraints. Given these variables may be correlated with congressional district educational quality, we include district level school quality (measured by graduation rates) in the subsequent stage.

[24]Students at NAPS receive a stipend and receive free room and board. In the NAPS brochure for 2019-2020, the financial checklist suggest students bring only $200.00 in small bills for incidental expenses.

[25]Miller and Birch (2007) show positive impacts from delaying college although they note there are important selection issues conflating their results.

Table 5: Selection into pre-college

	(1)	(2)	(3)
dependent variable:	pre-college	pre-college	pre-college
Direct Applications (average)	**0.00139***		**0.00299*****
	(2.14)		**(4.40)**
Direct Min Admissions Score		**0.118*****	**0.119*****
		(26.00)	**(26.19)**
SAT_Math	-5.533***	-6.232***	-6.223***
	(-27.03)	(-28.03)	(-27.97)
SAT_Verbal	-3.899***	-4.245***	-4.241***
	(-21.41)	(-21.62)	(-21.59)
HS_Rank	-2.991***	-3.729***	-3.749***
	(-31.77)	(-34.75)	(-34.88)
Soft_Skills	-0.150***	-0.185***	-0.185***
	(-27.39)	(-29.85)	(-29.87)
Regional_median_income	0.271***	0.513***	0.414***
	(4.15)	(7.69)	(5.88)
HS_graduation_rate	-0.00697*	-0.00253	-0.00384
	(-2.50)	(-0.84)	(-1.26)
Female	-0.00281	0.00470	0.00463
	(-0.08)	(0.12)	(0.12)
Black	0.256***	0.200***	0.201***
	(5.82)	(4.16)	(4.17)
Hispanic	0.157***	0.118*	0.122**
	(3.71)	(2.56)	(2.65)
Asian	-0.113	-0.131	-0.130
	(-1.80)	(-1.95)	(-1.94)
Athlete	0.0808**	0.0604	0.0583
	(2.81)	(1.96)	(1.89)
Blue_Chip	-0.400***	-0.353***	-0.352***
	(-10.85)	(-8.91)	(-8.88)
AgeonIDay	0.689***	0.650***	0.648***
	(48.88)	(43.17)	(42.96)
Pseudo R^2	0.499	0.529	0.530
N	25101	23786	23786

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
All specifications include state and year effects

4.2 IV Estimation

Results for academic effects once selection to pre-college is instrumented are displayed in Table 6. For these we estimate an over-identified model using a probit model.[26] We use the propensity scores generated from the probit (along with other exogenous instruments) to estimate the causal effect of pre-college selection on college outcomes using 2SLS estimation.[27]

As we can see, these results change the story told by OLS regressions. In short, pre-college participation appears to boost student grade performance during the early part of their college tenure. Unsurprisingly, the biggest effect is during the first semester, where on average pre-college produces a third of a letter grade improvement (say from a B to a B+ average). These estimated effects diminish over subsequent semesters but remain positive and statistically significant through the second year at USNA (see Figure 3, which demonstrates estimates across all semesters).

[26] Second-stage results are very consistent when we use an exactly-identified model in the first stage using either instrument.

[27] Stock-Yogo tests suggests we do not suffer a weak-instrument problem (first-stage F-statistics are reported in the tables). Given our IV strategy, the compliers are those who would have been admitted directly were it not for district-level competition. We thus face some limitation in concluding whether or not pre-college would help those at the ultimate bottom of the academic distribution. However, we observe a fair amount of overlap in measured academic abilities across treated and untreated. Further, Wooldridge (2002) proposes a 2SLS generalized instrumental estimation can best capture the average treatment effect.

Table 6: IV Estimates of Pre-college on Academic GPA

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1st Sem	2nd Sem	3rd Sem	4th Sem	5th Sem	6th Sem	7th Sem	8th Sem
Pre-college	**0.290*****	**0.170*****	**0.108*****	**0.0694***	**0.0606**	**0.00792**	**0.0130**	**-0.0329**
	(11.18)	**(7.04)**	**(3.63)**	**(2.07)**	**(1.93)**	**(0.28)**	**(0.48)**	**(-1.58)**
SAT Math	2.228***	2.227***	2.555***	1.953***	1.408***	1.346***	1.222***	1.074***
	(34.81)	(32.68)	(51.68)	(29.70)	(20.60)	(24.50)	(19.14)	(15.35)
SAT Verbal	1.214***	1.003***	0.927***	0.976***	0.920***	0.873***	0.695***	0.524***
	(20.67)	(22.50)	(18.43)	(17.90)	(11.74)	(15.33)	(11.12)	(7.33)
HS Rank	1.463***	1.402***	1.260***	1.180***	1.111***	1.050***	1.005***	0.970***
	(42.64)	(44.22)	(38.11)	(32.31)	(26.95)	(29.13)	(34.44)	(28.31)
Soft Skills	0.0313***	0.0299***	0.0253***	0.0230***	0.0171***	0.0149***	0.0131***	0.0139***
	(18.64)	(17.63)	(16.11)	(13.83)	(7.67)	(8.20)	(5.96)	(8.25)
Regional median income	0.0803***	0.0749***	0.116***	0.107***	0.0968***	0.0984***	0.0795***	0.0850***
	(4.16)	(3.36)	(5.73)	(5.42)	(5.28)	(5.37)	(5.04)	(4.89)
HS graduation rate	0.00235*	0.000887	0.000720	0.000469	0.00299***	0.00161**	0.00219***	0.00163**
	(2.32)	(1.33)	(0.84)	(0.46)	(5.07)	(2.82)	(4.15)	(3.24)
Female	-0.111***	-0.139***	-0.126***	-0.0269*	0.0170	0.0389***	0.0625***	0.0620***
	(-8.97)	(-12.86)	(-13.62)	(-2.14)	(1.33)	(3.63)	(5.57)	(5.97)
Black	-0.177***	-0.194***	-0.230***	-0.208***	-0.217***	-0.203***	-0.189***	-0.220***
	(-11.47)	(-11.81)	(-11.12)	(-10.93)	(-11.01)	(-12.77)	(-11.46)	(-14.71)
Hispanic	-0.0904***	-0.0824***	-0.0926***	-0.0973***	-0.121***	-0.111***	-0.130***	-0.112***
	(-5.75)	(-6.42)	(-6.51)	(-6.01)	(-6.50)	(-7.22)	(-8.46)	(-8.18)
Asian	-0.0295	-0.0821***	-0.105***	-0.118***	-0.110***	-0.0968***	-0.122***	-0.0988***
	(-1.73)	(-4.69)	(-5.45)	(-5.94)	(-5.92)	(-4.19)	(-7.25)	(-6.37)
Athlete	0.0898***	0.0351***	0.00935	-0.00419	-0.00869	-0.0118	-0.00982	-0.0211**
	(10.95)	(4.16)	(0.96)	(-0.41)	(-0.83)	(-1.21)	(-0.82)	(-2.69)
Blue Chip	-0.124***	-0.0884***	-0.0338*	-0.0229	-0.0125	-0.0223	-0.0206	-0.0651***
	(-10.17)	(-6.70)	(-2.50)	(-1.79)	(-1.04)	(-1.70)	(-1.54)	(-7.26)
Age on I-Day	0.0557***	0.0376***	0.0150*	0.00644	-0.000257	-0.00299	-0.00228	0.0102
	(8.11)	(6.34)	(2.10)	(0.71)	(-0.04)	(-0.41)	(-0.32)	(1.36)
Adjusted R^2	0.336	0.351	0.344	0.303	0.235	0.258	0.231	0.223
N	22395	21895	21316	20847	19983	19068	18878	18035
First-stage F-stat	355.4***	347.6***	337.3***	329.8***	310.9***	296.4***	293.0***	277.8***

Following Wooldridge (2002, section 18.1) we use 2SLS accounting for the endogenous dummy.

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

All specifications include state and year effects

All standard errors are boot-strapped

These results suggest that our OLS estimates on NAPS's influence on average grades are biased downwards. It suggests that negative correlations between pre-college and college outcomes are mostly due to selection. When we attempt a true randomization of selection, these negative effects go away. On the other hand, these results still suggest that academic gains are only achieved during the first few semesters when pre-college and college courses are most similar.

Note that the procedure used here and advocated Wooldridge (2002, section 18.1) is to address the fact our endogenous variable is a dummy. To compare results with a standard 2SLS approach we redo the analysis using both exogenous instruments but not including the generated instrument. Results are reported in the Appendix.[28] Standard errors are larger in this case, and estimated positive grade effects dissipate faster. Nonetheless the results echo the notion that pre-college boosts grades in the short run.

To further unpack the effects of pre-college, we look at a few other measures of academic performance beyond grades. Results are presented in Table 7. Pre-college treatment induces more students to pick STEM majors. Having gone through a pre-college program, students are roughly 20% more likely to choose a STEM major. This could be driven by several factors. First, to graduate in four years with a STEM major one must have all prerequisite math courses completed upon matriculation. Pre-college treatment satisfies prerequisites, widening the pool of students that can choose STEM. Second, better performance in freshman year math courses encourages students to choose STEM majors.

Pre-college treatment also appears to reduce voluntary exits. Specifically, pre-college treatment leads to a fall in voluntary exits by roughly 36% a year. Beyond USNA this is an important finding given individual and societal costs arising from students financing a bachelors degree with student loans but not getting the degree and therefore the future income benefits. The mechanism behind the fall in voluntary exits however is unclear. Perhaps the better grades freshman year motivate students to stay. Following the major choice discussion above, perhaps students are able to pick from a wider choice set of majors that better match their interests. Finally, perhaps students are falling for the sunk-cost fallacy — they may feel they have invested too much time to abandon the Academy. While establishing the mechanism may be beyond the scope of this paper, the finding that pre-college treatment significantly lowers voluntary exits suggests an important benefit from treatment unrelated to grade performance.

In contrast to the voluntary exits, attendance in a pre-college program appears to have no effect on academically-induced exits. In order to graduate from USNA, students must have a 2.0 GPA.

[28] We also run IV-GMM. Estimates are nearly identical to those in the Appendix.

Table 7: IV Estimates of Other Effects of Pre-college

	(1)	(2)	(3)
Dependent variable:	Voluntary Exit	Academic Exit	Stem Major
Pre-college	**-0.358*****	**-0.00293**	**0.196****
	(-4.30)	**(-0.03)**	**(2.98)**
SAT Math	-0.585**	-1.327***	5.811***
	(-3.19)	(-4.86)	(36.90)
SAT Verbal	-0.199	0.210	-2.780***
	(-1.18)	(0.85)	(-19.42)
HS Rank	-0.207*	-1.719***	0.987***
	(-2.20)	(-12.61)	(12.93)
Soft Skills	-0.0258***	-0.0467***	0.0297***
	(-5.00)	(-6.26)	(7.15)
Regional median income	-0.0341	-0.180*	-0.128**
	(-0.59)	(-2.18)	(-2.67)
HS graduation rate	0.00159	-0.00579	-0.000492
	(0.59)	(-1.56)	(-0.22)
Female	0.375***	-0.101*	-0.117***
	(12.67)	(-2.10)	(-4.59)
Black	-0.0512	0.344***	0.158***
	(-0.98)	(6.24)	(3.83)
Hispanic	-0.0284	0.235***	0.000395
	(-0.65)	(4.33)	(0.01)
Asian	-0.188**	0.0961	0.0875
	(-3.23)	(1.21)	(1.91)
Athlete	-0.880***	-0.115**	0.0107
	(-28.19)	(-3.00)	(0.49)
Blue Chip	0.633***	0.0403	-0.235***
	(16.48)	(0.80)	(-7.62)
Age on I-Day	0.0472*	-0.0519	0.00878
	(2.29)	(-1.83)	(0.52)
Wald χ^2	1413.6***	659.8***	2606.3***
N	23786	23786	20821

Following Wooldridge (2002, section 18.1) we account for the endogenous dummy.
t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
All specifications include state and year effects
All standard errors are boot-strapped

Throughout the four years at the Academy students that are below that threshold are reviewed and exit if it becomes evident they cannot improve their grades enough to compensate for a bad semester or sequence of semesters. Pre-college therefore seems to not be able to help the students that are far behind academically. Pre-college attendance lowers attrition but not for the very weakest students.

Table 8: IV Estimates of Pre-college on Academic GPA – Comparing same cohorts across semesters

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	1st Sem	2nd Sem	2nd Sem	3rd Sem	3rd Sem	4h Sem	4th Sem	5th Sem	5th Sem	6th Sem
Pre-college	**0.266*****	**0.169*****	**0.166*****	**0.106*****	**0.0808****	**0.0680***	**0.0965*****	**0.0611***	**0.0779****	**0.0186**
	(9.35)	**(7.48)**	**(6.27)**	**(4.48)**	**(3.07)**	**(2.53)**	**(3.65)**	**(2.18)**	**(2.79)**	**(0.76)**
Adjusted R^2	0.377	0.353	0.367	0.344	0.359	0.303	0.332	0.236	0.241	0.258
N	21883	21883	21300	21305	20839	20839	19965	19972	19060	19060
χ^2 test of coef. dif.	30.08***		6.99***		7.11***		1.12		8.99**	

	(11)	(12)	(13)	(14)
	6th Sem	7th Sem	7th Sem	8th Sem
Pre-college	**0.04**	**0.021**	**0.036**	**-0.028**
	(0.028)	**(0.028)**	**(0.026)**	**(0.028)**
Adjusted R^2	0.269	0.230	0.234	0.254
N	18853	18864	18021	18021
χ^2 test of coef. dif.	2.76		6.76*	

Following Wooldridge (2002, section 18.1) we use 2SLS accounting for the endogenous dummy.

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

χ^2 test based on GMM estimates excluding year and state fixed effects.

All specifications include state and year effects. All additional controls included but not reported.

All standard errors are boot-strapped

Given the potential influence of pre-college treatment on attrition, we perform two exercises. First, we analyze and compare pre-college effects across the same cohorts of students in semester pairs. In this way we can observe the diminishing influence of pre-college on the same group of students who remain in college up to different specified points in their tenure. Results are displayed in Table 8. We observe a similar trend as reported earlier. We also can see that the *decline* in pre-college effects over semesters is statistically significant.

We also examine academic impacts conditional on students graduating. The results on Table 9 indicate that even though less pre-college attendees leave the Academy, the academic effects are not considerably different between our treated and non-treated group. Less attrition by pre-college attendees has only slight impacts on academic performance. The minimal effects are likely driven by the fact that treatment primarily affects voluntary exits rather than academic exits.

Table 9: IV Estimates of Pre-college on Academic GPA — Graduates Only

	(1) 1st Sem	(2) 2nd Sem	(3) 3rd Sem	(4) 4th Sem	(5) 5th Sem	(6) 6th Sem	(7) 7th Sem	(8) 8th Sem
Pre-college	**0.274*****	**0.170*****	**0.0922*****	**0.109*****	**0.0703***	**0.0232**	**0.0266**	**-0.0397**
	(9.20)	**(6.14)**	**(3.42)**	**(3.50)**	**(2.15)**	**(0.83)**	**(0.99)**	**(-1.73)**
Adjusted R^2	0.357	0.352	0.354	0.328	0.236	0.265	0.236	0.272
N	17910	17906	17911	17903	17910	17901	17909	17905
First-stage F-stat	282.7***	282.5***	282.7***	282.5***	282.7***	282.5***	282.7***	282.5***

Following Wooldridge (2002, section 18.1) we use 2SLS accounting for the endogenous dummy.

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

All additional controls included but not reported

All specifications include state and year effects

All standard errors are boot-strapped

4.3 Variation across pre-college programs

How robust are these findings to differences in type of pre-college program? To answer we analyze academic performance from two separate pre-college programs — the Naval Academy Preparatory School, and Foundation schools where students attend a post graduate year at select private high schools. The former program is run by USNA itself. The later program is influenced by USNA in that Foundation schools are handpicked by the Academy, but the curriculum is left to the discretion of the schools themselves. The social environment is also different — NAPS is run as a military prep school like some of the Foundation schools (such as the Hargrove Military Academy) but not all (such as the Kent School). Comparing academic outcomes of these two types of treatment allows us to explore whether it is simply additional exposure to college-level material, or is it the way the material is taught or other non-academic factors. If it is the later then control of taught material or the social environment that USNA has over NAPS may potentially be of great importance.

The Foundation school program

Students who do not attend NAPS and are not admitted directly to USNA may be offered appointment to a "Foundation school." Foundation students have up to 60% of their tuition covered by the Foundation Program and have a 95% guarantee of transfer to the Academy. Families are expected to contribute resources to pay for at least 40% of tuition based on their income level. Students offered the opportunity to go to an independent preparatory school have the option to apply to 15 civilian and 4 military preparatory schools including Hargrave Military Academy, the Kent School, Peddie, and various other civilian and military preparatory schools. A full list of current Foundation preparatory schools is included in Appendix 6.1.

This program differs significantly from the NAPS program. Rather than being offered a place at a specific institution like NAPS, students may choose their desired preparatory school, introducing variation in location, cost, and quality of education. Other independent preparatory school students make up a smaller cohort of pre-college entrants at 6% of each entering USNA class. The Foundation program provides a different perspective on returns to investment in pre-college education.

Similar to the NAPS program, the other independent preparatory school program is designed as a preparatory year for students who are qualified to matriculate but seen as deficient in a specific area. Foundation students participate in what is known as a post-graduate or "PG" year. At preparatory school, they enroll in courses that include at a minimum English, Science, and Math. Foundation schools fall into one of three categories: military preparatory schools, preparatory schools affiliated with a college or university, or independent preparatory schools.

The range of schools that participate in the Naval Academy Foundation program includes schools across all of the U.S. They are a cross-section of typical preparatory school programs. Like other preparatory schools, Foundation schools place high emphasis on academic performance, athletic performance, and college matriculation. Taken together, conclusions from the treatment groups described above can be extrapolated to broader national education given the level of detail of the USNA dataset.

Table 10 displays the results from probit regressions on selection to NAPS and other pre-college programs separately. Estimated coefficients on background academic variables vary in magnitude but maintain the same signs. Selection into either pre-college program is in large part driven by perceived academic weakness.

Yet in other ways selection is very different compared with NAPS. Residential income is a stronger

Table 10: Selection into pre-college broken down by type

	(1)	(2)
Dependent variable:	NAPS selection	Foundation selection
Direct Applications (average)	**0.00274*****	**0.00113**
	(3.61)	**(1.44)**
Direct Min Admissions Score	**0.100*****	**0.0309*****
	(21.45)	**(6.94)**
SAT Math	-7.022***	-0.972***
	(-27.51)	(-4.08)
SAT Verbal	-4.805***	-0.651**
	(-21.64)	(-2.96)
HS Rank	-3.178***	-2.020***
	(-27.03)	(-17.00)
Soft Skills	-0.160***	-0.102***
	(-23.32)	(-14.85)
Regional median income	0.138	0.418***
	(1.72)	(5.11)
HS graduation rate	-0.00470	-0.000239
	(-1.35)	(-0.07)
Female	0.103*	-0.0871
	(2.40)	(-1.87)
Black	0.602***	-1.003***
	(12.12)	(-10.60)
Hispanic	0.674***	-0.910***
	(13.91)	(-11.37)
Asian	0.379***	-0.703***
	(5.35)	(-6.98)
Athlete	0.0467	0.0608
	(1.32)	(1.73)
Blue Chip	0.00481	-0.532***
	(0.11)	(-10.54)
Age on I-Day	0.645***	0.175***
	(39.20)	(10.33)
Pseudo R^2	0.564	0.188
N	23786	23786

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
All specifications include state and year effects

predictor of pre-college attendance here. This makes sense, as these pre-college programs are only partially funded, compared with the fully-funded NAPS program. Students from these programs will on average come from more affluent backgrounds.

Further, it is clear that unlike the NAPS program, these alternative pre-college programs are not designed to produce diversity. Indeed, minorities appear to have less likelihood to being admitted to an alternative pre-college program than being admitted directly. We would like to see if pre-college produces different effects for less diverse and more affluent groups of students.

Concerning the two instruments, we see that the congressional district's minimum admissions' score for direct admits is a strong exogenous predictor of either pre-college selection. The more competitive the district applicant pool the more likely someone from that district may be qualified but did not got a direct admit slot given geographic constraints. However, our district-level measure of popularity measured by the number of applicants appears not to provide as much explanatory power for Foundation selection. This perhaps is due to the fact that students from more affluent congressional districts may have lots of choice in colleges and therefore the Naval Academy doesn't receive as large of a pool of applicants from those congressional districts.

Table 11: IV Estimates of NAPS and Foundation on Academic GPA

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1st Sem	2nd Sem	3rd Sem	4th Sem	5th Sem	6th Sem	7th Sem	8th Sem
Pre-college (NAPS)	**0.293*****	**0.201*****	**0.135*****	**0.0899***	**0.0729**	**-0.00393**	**0.0508**	**-0.00554**
	(7.81)	**(5.74)**	**(3.60)**	**(2.52)**	**(1.73)**	**(-0.10)**	**(1.04)**	**(-0.13)**
Pre-college (Foundation)	**0.0403**	**-0.0136**	**-0.163**	**-0.127**	**-0.0780**	**-0.255**	**0.0580**	**0.0621**
	(0.28)	**(-0.11)**	**(-1.05)**	**(-0.82)**	**(-0.42)**	**(-1.52)**	**(0.34)**	**(0.40)**
Adjusted R^2	0.338	0.348	0.343	0.301	0.234	0.257	0.216	0.249
N	22395	21895	21316	20847	19983	19068	18878	18035
First stage F-stat (NAPS)	350.0***	341.6***	330.6***	325.5***	305.9***	291.5***	287.3***	277.7***
First stage F-stat (Foundation)	26.6***	26.1***	25.6***	25.3***	25.0***	25.0***	25.0***	24.5***

Following Wooldridge (2002, section 18.1) we use 2SLS accounting for the endogenous dummy.

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

All specifications include state and year effects. All standard errors are boot-strapped.

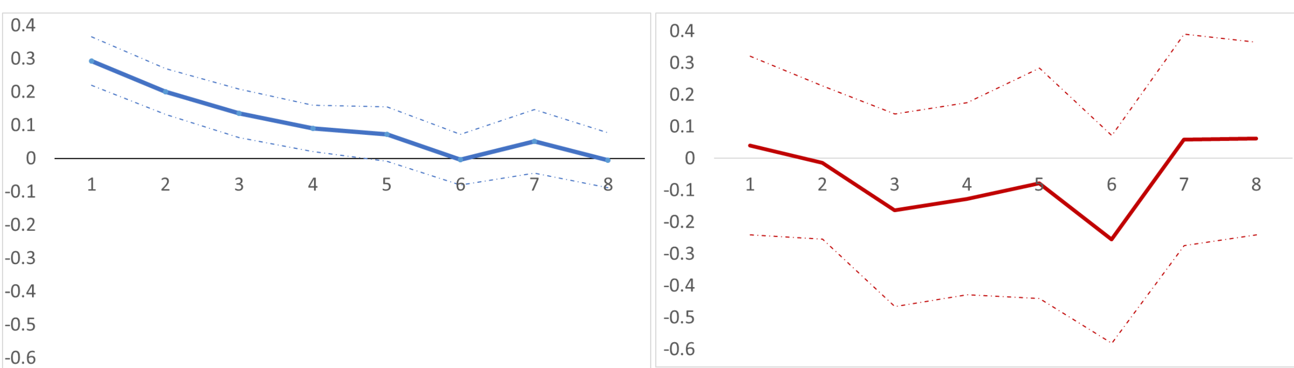
All additional controls included but not reported.

Table 11 displays the results where treatment is now broken down between the two types of treatment, NAPS and a variety of non-USNA prep schools. The results are dramatically different. For NAPS students grade effects are strongest in the first semester and linger for two academic years before dissipating. Foundation schools on the other hand do not seem to show any significant impact on GPA. We also observe that the decrease in voluntary exits and increase in STEM major choice come solely from NAPS participation, not though Foundation schools (results not reported). As there are many different types of schools that make up the Foundation program, this is prehaps not so surprising.

The results suggests that programs that are tightly linked academically and socially to the follow-on college experience can improve academic outcomes, but the impacts are not universal to all programs. The NAPS program is able to boost student grades by familiarizing students with core content that they will again experience as freshmen and sophomores. However once students take specialized courses more specific to academic majors, the gains even from NAPS disappear. Further, there is no apparent academic gains from Foundation school participation, where taught material may not directly replicate material at USNA, and non-academic aspects may be very different from students' follow-on college experience.

Figure 3 plots estimates coefficients for both NAPS and Foundation schools across all eight semesters (with dashed lines marking confidence intervals). Here we see effects dissipate for NAPS over one's college tenure, becoming essentially zero. We also see that Foundation programs have no discernible effects at all.

Figure 3: Estimated effects of NAPS (left diagram) and Foundation programs (right diagram) on GDP across eight semesters



5 Conclusions

College graduation rates and overall college performance measures have been declining, in part due to lack of student preparation. Can prescribing remediation help stem this trend? Of course the answer from economists will be as always, it depends. Mainly, it depends on how we define college "success." In contrast to the findings of Adleman (1999) and Attewell et al. (2006), we suggest that remedial education prior to matriculation can indeed improve college grade performance, lower voluntary attrition, and increase STEM majors. Empirical findings imply pre-college programs may endeavor to improve college-level representation among underrepresented groups without damaging academic outcomes. On the other hand, pre-college does not produce *lasting* academic gains, nor do they help with the most struggling students in danger of failing out. Whether by providing students the confidence to choose STEM fields, or merely by serving as powerful commitment devices, these programs appear capable of helping some students. Such programs might be effective in promoting academic performance among the traditionally disadvantaged. But we should also be realistic in terms of longer-run educational effects. These programs are expensive, so administrators should carefully weigh the costs with the specific goals that such programs are designed to achieve.

References

Angrist, Joshua D. 2001. "Estimation of Limited Dependent Variable Models with Dummy Endogenous Regressors: Simple Strategies for Empirical Practice." *Journal of Business and Economic Statistics* 19(1): 2–16.

Attewell, P. A., D. E. Lavin, T. Domina and T. Levey. 2006. "New Evidence on College Remediation." *Journal of Higher Education* 77(5): 886–924.

Bettinger, Eric and Bridget Long. (2009). "Addressing the Needs of Under-Prepared Students in Higher Education: Does College Remediation Work?" *Journal of Human Resources* 44(3): 736–771.

Bowen, William G., Matthew M. Chingos and Michael S. McPherson. 2009. *Crossing the Finish Line — Completing College at America's Public Universities.* Princeton, NJ: Princeton University Press.

Brady, Ryan R., Michael Insler, and Ahmed S. Rahman. 2017. "Bad Company — Reconciling Negative Peer Effects in College Achievement." *European Economic Review* 98: 144–168.

Breneman, David and William Haarlow. 1997. "Remedial Education: Costs and Consequences." *Remediation in Higher Education.* Washington D.C.: Thomas B. Fordham Foundation.

Calcagno, J. C., & Long, B. T. 2008. "The impact of postsecondary remediation using a regression discontinuity approach: Addressing endogenous sorting and noncompliance "(NBER Working Paper. No. 14194). Cambridge, MA: National Bureau of Economic Research.

Cameron, A. C. and P. K. Trivedi. 2005. *Microeconometrics: Methods and Applications.* Cambridge University Press, New York, NY.

Carrell, Scott, M. Hoekstra and J. West. 2011a. "Is Poor Fitness Contagious? Evidence from Randomly Assigned Friends," *Journal of Public Economics* 95(7): 657–663.

Carrell, Scott, M. Hoekstra and J. West. 2011b. "Does Drinking Impair College Performance? Evidence from a Regression Discontinuity Approach," *Journal of Public Economics* 95(1): 54–62.

Carrell, S., Maghakian, T., and West, J. 2010. "A's from Zzzz's? The Causal Effect of School Start Time on the Academic Acheivment of Adolescents." *American Economic Journal: Economic Policy* 3(3): 62–71.

Carrell, Scott, Richard Fullerton and James West. 2009. "Does Your Cohort Matter? Measuring Peer Effects in College Achievement." *Journal of Labor Economics* 27(3): 439–464.

Deming, David and Susan Dynarski. 2008. "The Lengthening of Childhood," *Journal of Economic Perspectives* 22(3): 71–92.

D'Ignazio, Alessio and Carlo Menon, 2020. "Causal Effect of Credit Guarantees for Small- and Medium-Sized Enterprises: Evidence from Italy," *Scandinavian Journal of Economics*, vol. 122(1), pages 191-218, January.

Elder, Todd E. and Darren H. Lubotsky. 2009. "Kindergarten Entrance Age and Children's Achievement." *Journal of Human Resources* 44(3): 641–683.

Fitzpatrick, Brian S. 2001. "The Performance of Preparatory School Candidates at the United States Naval Academy." unpublished manuscript, Naval Postgraduate School.

Insler, Michael, Alexander F. McQuoid, Ahmed S. Rahman and Katherine A. Smith. 2020. "Fear and Loathing in the Classroom: Why Does Teacher Quality Matter?" IZA discussion paper no. 14036.

Kane, Thomas J., Angela Boatman, Whitney Kozakowski, Christopher Bennett, Rachel Hitch, and Dana Weisenfeld. 2019. "College Remediation Goes Back to High School: Evidence from a Statewide Program in Tennessee." NBER working paper no. 26133.

Lavin, D.E., Alba, R.D., and Silberstein, R.A. 1981. *Right Versus Privilege: The open access admission experiment at the City University of New York*. New York: The Free Press.

Lesik, S. 2007. "Do developmental mathematics programs have a causal impact on student retention? An application of discrete-time survival and regression-discontinuity analysis." *Research in Higher Education*, 48(5), 583–608.

Lyle, David S. 2009. "The Effects of Peer Heterogeneity on the Production of Human Capital at West Point." *American Economic Journal: Applied* 1(4): 69–84.

Lyle, David S. 2007. "Estimating and Interpreting Peer and Role Model Effects from Randomly Assigned Social Groups at West Point." *Review of Economics and Statistics* 89(2): 289–299.

Martorell, Paco and Isaac McFarlin Jr. 2011 "Help or Hindrance? The Effects of College Remediation on Academic and Labor Market Outcomes", *The Review of Economics and Statistics* 2011 93:2, 436-454.

Miller, Paul, and Elisa Birch. 2007. "The Characteristics of 'Gap-Year' Students and Their Tertiary Academic Outcomes." *Economic Record* 83(262): 329–344.

U.S. Department of Education. 1996. National Center for Education Statistics. *Digest of Education Statistics, 1996*, NCES 96-133, by Thomas D. Snyder. Production Manager, Charlene M. Hoffman. Program Analyst, Claire M. Geddes. Washington DC.

Rahman, Ahmed S. 2020. "Officer Retention and Military Spending — The Rise of the Military Industrial Complex during the Second World War." *Economic History Review* 73(4): 1074–1096.

Scott-Clayton, Judith and Olga Rodriguez. "Development, Discouragement, or Diversion? New Evidence on the Effects of College Remediation." NBER working paper no. 18328.

Wooldridge, JM. 2002. Econometric Analysis of Cross Section and Panel Data. MIT Press.

6 Appendix — Institutional Specifics

6.1 Foundation Schools

Naval Academy Foundation Schools 1. Avon Old Farms School, Avon, Connecticut 2. Blair Academy, Blairstown, New Jersey 3. Greystone Preparatory School at Schreiner University, Kerrville, Texas 4. Hargrave Military Academy, Chatham, Virginia 5. The Hill School, Pottstown, Pennsylvania 6. The Hun School of Princeton, Princeton, New Jersey 7. Kent School, Kent, Connecticut 8. The Kiski School, Saltsburg, Pennsylvania 9. The Marion Military Institute, Marion, Alabama 10. The Mercersburg Academy, Mercersburg, Pennsylvania 11. New Mexico Military Institute, Roswell, New Mexico 12. Northfield Mount Hermon School, Northfield, Massachusetts 13. Northwestern Preparatory School, Crestline, California 14. The Peddie School, Hightstown, New Jersey 15. Portsmouth Abbey School, Portsmouth, Rhode Island 16. Salisbury School, Salisbury, Connecticut 17. Valley Forge Military Junior College, Wayne, Pennsylvania 18. Western Reserve Academy, Hudson, Ohio 19. Wyoming Seminary, Kingston, Pennsylvania

6.2 United States Naval Academy Majors by Group

- Group 1 – Engineering and Weapons:
  - Aerospace Engineering
  - Computer Engineering
  - Electrical Engineering
  - General Engineering
  - Mechanical Engineering
  - Naval Architecture
  - Ocean Engineering
  - Systems Engineering
- Group 2 – Mathematics and Science:
  - Chemistry
  - Computer Science
  - Cyber Operations

  - General Science
  - Information Technology
  - Mathematics
  - Oceanography
  - Operations Research
  - Physics
  - Quantitative Economics
- Group 3 – Humanities and Social Sciences:
  - Arabic
  - Chinese
  - Economics
  - English
  - History
  - Political Science

6.3 Variable Descriptions

- Background Characteristics
  - African American- Binary variable indication whether a student classifies themselves as African American
  - Asian American- Binary variable indication whether a student classifies themselves as Asian American
  - Caucasian- Binary variable indication whether a student classifies themselves as Caucasian
  - Hispanic- Binary variable indication whether a student classifies themselves as Hispanic
  - Age on IDay- A student's age on their first day at the Naval Academy, Induction Day/ Matriculation
  - Central- A binary variable indicating whether a student is from Illinois, Indiana, Iowa, Kentucky, Michigan, Minnesota, Missouri, Ohio, or Wisconsin

- Northern- A binary variable indicating whether a student is from Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, or Vermont
- Pacific- A binary variable indicating whether a student is from Alaska, Arizona, California, Hawaii, Nevada, Oregon, Utah, or Washington
- Southern- A binary variable indicating whether a student is from Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, North Carolina, South Carolina, Tennessee, Virginia, or West Virginia
- Western- A binary variable indicating whether a student is from Colorado, Idaho, Kansas, Montana, Nebraska, New Mexico, North Dakota, Oklahoma, South Dakota, Texas, or Wyoming
- Verbal SAT- A student's highest reported SAT score for the verbal section
- Math SAT- A student's highest reported SAT score for the math section
- Sex- A binary variable indicating gender where 1=female
- High School Quality Measure- A measure of the academic quality of individual high schools on the same scale as the SAT: from 200 to 800
- High School Rank (Percent)- A student's percent rank in their high school class where .99 signifies being in the top 1% of high school graduating class
- Military Father- Binary variable indicating whether the student's father was in the military
- Military Mother- Binary variable indicating whether the student's mother was in the military
- Ascore- an index that incorporates not just SAT scores and high school standing, but also many background variables unobserved by us such as extra-curriculars, strength of recommendation letters, and athletic performance.

• Performance Variables

- AC grades1- First semester academic grade point average
- AC grades2- Second semester academic grade point average
- AC grades3- Third semester academic grade point average
- AC grades4- Fourth semester academic grade point average

- Academic Average- Average course GPA in all academic courses for the first four semesters excluding professional and military coursework
- AOM- Normalized class rank based on eight semesters of academic grades
- Graduated (indicator)- A binary variable indicating whether a student graduated
- Major Switch- A binary variable indicating whether a student changed their major while at USNA
- MajorGrade3- Third semester majors courses grade point average
- MajorGrade4- Fourth semester majors courses grade point average
- Majorgrade5- Fifth semester majors courses grade point average
- MajorGrade6- Sixth semester majors courses grade point average
- Class Rank- Normalized class rank based on combined AOM and MOM, eight semesters of academic grades and military performance grades
- Freshman dropout- A binary variable indicating whether a student left USNA during their first year
- Sophomore dropout- A binary variable indicating whether a student left USNA during their sohpomore year
- Start Group 1- A binary variable indicating whether a student elected a major in group 1 during their first year
- Start Group 2- A binary variable indicating whether a student elected a major in group 2 during their first year
- Start Group 3- A binary variable indicating whether a student elected a major in group 3 during their first year
- STEM grades1- First semester STEM grade point average
- STEM grades2- Second semester STEM grade point average
- STEM grades3- Third semester STEM grade point average
- STEM grades4- Fourth semester STEM grade point average
- Tutor- A binary variable indicating whether a student was involved in the student-tutor program while at USNA

– Varsity Athlete- (indicator) A binary variable indicating whether a student was a varsity athlete while at USNA

7 Appendix — Robustness

Table 12: IV Estimates of Pre-college on Academic GPA – Comparing same cohorts across semesters

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	1st Sem	2nd Sem	2nd Sem	3rd Sem	3rd Sem	4h Sem	4th Sem	5th Sem	5th Sem	6th Sem
Pre-college	**0.176****	**0.121***	**0.0937**	**0.116**	**0.0386**	**-0.0226**	**0.0190**	**-0.0125**	**-0.0471**	**-0.120***
	(3.24)	**(2.08)**	**(1.38)**	**(1.96)**	**(0.54)**	**(-0.32)**	**(0.28)**	**(-0.15)**	**(-0.60)**	**(-2.08)**
N	22451	22451	21854	21859	21381	21381	20491	20498	19569	19569
Adjusted R^2	0.380	0.352	0.368	0.343	0.359	0.305	0.334	0.239	0.246	0.259

	(11)	(12)	(13)	(14)
	6th Sem	7th Sem	7th Sem	8th Sem
Pre-college	**-0.049**	**-0.074**	**-0.077**	**-0.023**
	(-0.69)	**(-0.87)**	**(-1.08)**	**(-0.37)**
Adjusted R^2	0.271	0.232	0.237	0.256
N	19365	19376	18531	18531

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

All specifications include state and year effects. All additional controls included but not reported.

All standard errors are boot-strapped