Admissions Policies, Cohort Composition, and Academic Success: Evidence from California

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Abstract

I study how postsecondary admission policies affect the composition and subsequent academic outcomes of new cohorts. I leverage the staggered replacement of admissions lotteries and waitlists at California's community college nursing programs with admissions that rely on prior grades and other measures. The change in admissions increased the average academic ability of incoming cohorts but also reduced the share of new students who were non-White. The change in admissions did not, however, improve completion rates and other academic outcomes. I conclude that the policy incurred costs in terms of equity without improving efficiency, and propose alternative strategies.

1 Introduction

Why do colleges use merit-based admissions? In most markets, prices adjust to allocate scarce resources between buyers and sellers. In some settings, however, it is undesirable to increase prices above a particular threshold, and other allocation strategies are used. For example, concerts and restaurants use first-come-first-served processes; charter schools and other public K-12 systems use

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lotteries; and one of the important factors in the allocation of donated organs is the candidate's wait time. In higher education, admissions at selective institutions rely almost exclusively on measures of merit, such as prior grades, performance on standardized tests, essays, recommendations, and interviews.

Merit-based admissions allow colleges and universities to select applicants that will add value along dimensions that they deem important. Better students, however the institution defines them, may increase graduation rates or generate positive peer effects, for example, which may also boost rankings. Administering merit-based admissions processes comes at a cost, however. For one, a student's academic preparation is correlated with socioeconomic factors, so admissions based on past academic performance may reduce diversity and the representation of certain groups on campus. Moreover, these types of admissions strategies may rely on imperfect tools and measures that do not reliably select the best students according to an institution's objective function. For example, there is mixed evidence on whether commonly used screening mechanisms, such as high school grades and standardized test scores, can effectively predict academic success in college (Rothstein, 2004; Bridgeman, McCamley-Jenkins and Ervin, 2000; Camara and Echternacht, 2000; Bulman, 2017; Geiser and Santelices, 2007). The selection process itself is also costly.

Despite the potential costs and uncertain benefits of merit-based admissions, there is little evidence comparing the outcomes of different admissions strategies (Smith, Hurwitz and Howell, 2015; Slonimczyk, Francesconi and Yurko, 2017). One reason is that admissions processes are typically opaque "black boxes" that may not follow strict guidelines. Moreover, even if the policies are explicitly defined, such as at state flagship universities that use high school GPA cutoffs, there is endogenous selection of strategies across institutions and little change over time, complicating any comparisons of the admission strategies themselves.[2]

In this paper I examine the effects of a large state-wide change in admissions rules. In 1991, the California Community Colleges instituted a policy restricting admissions to associate degree in nursing (ADN) programs to only "non-evaluative" admissions policies, such as waitlists and random lotteries. In 2007, though, the state legislature reversed this policy and allowed

[2]Notable exceptions include recent work showing that "standardized test optional" liberal arts colleges do not see changes in the diversity of incoming cohorts (Belasco, Rosinger and Hearn, 2015), as well as a growing literature on the effects of state-level bans of affirmative action policies (Naven, 2017; Hinrichs, 2014).

colleges to implement screening methods that included prior grades, work history, essays, and personal references. I leverage the incremental adoption of these new screening methods after 2007 across the state's many ADN programs to provide causal estimates of the effect of the new admissions systems. The identification strategy relies on differences in the timing of the adoption of evaluative admissions, which I show is not correlated to observable program or local labor market characteristics. I study how the new evaluative admissions processes affected the composition of new nursing cohorts as well as their subsequent academic attainment.[3]

This study of a large-scale natural experiment makes several contributions. First, much of the research has focused on which screening measure is the most reliable measure of potential ability (e.g. SAT, ACT, grades, etc.) or how to improve a particular screening instrument (Bettinger, Evans and Pope, 2013; Kobrin et al., 2008). This project, on the other hand, examines how a non-evaluative process such as a lottery or waitlist performs relative to evaluative measures. Staying on a waitlist long enough to be admitted to a program, for example, likely reflects an applicant's individual valuation of enrolling in the program. These revealed attributes may be enough to effectively screen applicants.

Second, this paper contributes new evidence on the effect of admissions strategies at a time of great policy interest in admissions at different levels of higher education. The "Varsity Blues" scandal at elite universities unleashed a torrent of commentary, including calls for doing away with merit-based admissions altogether (Kamenetz, 2019; Hess, 2019; Latinien, McCann and Fishman, 2019). A recent investigation into the University of Texas's archives added to this debate by showing that the university adopted standardized testing as a way to resist the integration of education brought about by *Brown vs. Board of Education* (Price, 2019). This new interest in admissions has also manifested itself in dramatic policy changes. In the past few years several elite liberal arts colleges have made standardized testing optional in order to increase student diversity, with scant empirical evidence to support these claims (Belasco, Rosinger and Hearn, 2015). Even more recently, a growing number of graduate programs have done away with requiring the GRE, making similar claims about diversity while also noting that the test is not a good predictor of a student's eventual success (Jaschik, 2019*a*,*b*). This paper investigates the validity of these types of claims,

[3] For the rest of this article I use the term "evaluative" to refer to admissions strategies that use inputs like GPA, work history, life experiences, etc. I use the term "non-evaluative" to refer to other systems, such as lotteries and waitlists.

which have been understudied despite the policy changes implemented in their name.

Studying admissions policies among community college nursing students rather than four-year colleges leads to new insights. The most related work in this area looks at elite four-year schools doing away with standardized test requirements (Belasco, Rosinger and Hearn, 2015). However approximately a third of postsecondary students attend a community college, and this sector is still relatively understudied. Applicants to nursing programs tend to be older, with substantial prior labor force attachment, and their likelihood of completing a degree or certificate program is lower (Calcagno et al., 2007). Moreover, because vocational programs teach students particular occupations and involve substantial hands-on training, academic preparation may not be a good indicator of a student's potential success in the particular occupation. For this reason, an admissions process that is based on grades, even in relevant coursework, may not predict success in the program. So, even if the policy change resulted in new cohorts with better academic background, it might not lead to higher completion rates.

I focus on outcomes in three broad areas. I first study whether the policy worked as intended: did programs that adopted these new admissions standards bring in cohorts with higher past academic performance? I find that a switch to evaluative methods leads to increases in the biology GPA of incoming students, as well as a decrease in the number of remedial courses students had taken. This is evidence that the new admissions rules succeeded in bringing in cohorts of students with better academic preparation.

I then examine the demographic composition of new cohorts. The reason that the colleges initially banned evaluative screening processes in the early 1990s was because of a lawsuit alleging that these policies unfairly excluded minority students. Thus, examining the effects of instituting evaluative admissions on the demographics of incoming cohorts is a way to test the initial lawsuit's claim of these unintended consequences. I find that colleges switching to an evaluative admissions rule increased their enrollment of white students while decreasing their share of Latino students. I also find that the mean age of students in the new cohort decreased, especially through increasing the share of students under 25. Thus, my results show support for the initial lawsuit: evaluative admissions policies decrease the likelihood that underrepresented groups gain admissions to nursing programs, even if these policies do not explicitly target these groups. This type of result has been the basis for affirmative action legislation and lawsuits in recent years, and motivation of the test-optional movement at four-year colleges.

Finally, I examine academic outcomes. The purpose of the 2007 legislation undoing the ban on evaluative admissions was to increase completion rates and pass rates on the national licensing exam. However, I find no evidence of improvements in first-year GPA, completion rates, or time to degree for students in cohorts accepted under the new admissions regimes. I also do not find any changes in pass rates on the national licensing exam. I do, however, find a large decrease in the number of years between when a student first started taking community college coursework and first enrolled in an ADN program. This is because the new admissions policies are a one-shot game, while old policies such as waitlists force students to wait. Thus, the new policies, while not improving academic outcomes, may improve labor market outcomes by moving students back into the labor market sooner.

Taken together, the findings show that evaluative admissions for ADN programs brought in better-prepared students, as intended, but without any meaningful change in outcomes. In addition, evaluative admissions reduced the racial and ethnic diversity of incoming cohorts, and skewed admissions towards younger students. However, the new admissions dramatically decreased the amount of time students had to wait before entering the cohorts. This suggests that certain aspects of the new systems, like doing away with waitlists, were more efficient relative to the old systems. Therefore, a clear policy implication would be to return to lotteries, perhaps even with increased odds of acceptance for first-time applicants. These policies would increase diversity at ADN programs while not changing completion rates. The policies would also allow losing applicants to move on to other pursuits without having to continue to wait, essentially helping them to not fall victim to sunk costs. Meanwhile, colleges could use other approaches to increasing completion rates, such as better mentoring, advising, and student supports.

The paper proceeds as follows. Section 2 outlines the policy setting and other background. Section 3 describes the data. Section 4 includes the methodology, sampling, and discussion of causal inference. Section 5 discusses the results, and section 6 concludes.

2 Background

The California Community Colleges system consists of 113 campuses and is the largest public higher education system in the country, with more than 2.5 million students enrolled each year. Approximately half of all degrees and certificates are awarded in career-technical fields, of which by far the most popular is the associate's degree in nursing (ADN). The ADN is the minimum qualification to work as a registered nurse. Registered nursing is one of the occupations with the highest projected demand (Bureau of Labor Statistics, 2015), yet the supply of new nurses has often struggled to keep pace.[4] These trends have led, nationwide, to ADN programs with more applicants than there are seats available. In turn, ADN administrators have had to institute admissions policies to ration seats.

ADN programs in California are regulated by the state's Board of Nursing. The Board establishes minimum standards for programs including guidelines on a program's courses, as well as academic and career support. The prerequisites for application to a program are fairly uniform across the state's community college ADN programs. Each program administers its own admissions process, so the format and particular requirements of an application vary slightly across the state.[5]

In California, there were no restrictions on the types of admissions policies that community college nursing programs could use until the early 1990s. However, in a 1988 lawsuit, the Mexican American Legal Defense and Educational Fund (MALDEF) claimed that admissions and prerequisite policies unfairly excluded Latino students. To avoid litigation, in 1991 the California Community College Chancellor's Office (CCCCO) instituted regulations forcing programs to adopt non-evaluative admissions methods, though they could still require prerequisite coursework (Hill, 2007). Programs adopted different types of non-evaluative methods. Some colleges began waitlists,

[4] Appendix Figure A1 shows the number of ADN completions, along with other health programs and career-technical programs in general. Despite the large growth in demand for registered nurses, there has not been a noticeable increase in ADN completions over the past decade. The lack of expansion of ADN programs is due in large part to the high cost of expanding programs, as well as a lack of financial incentives based on how community colleges are funded (Grosz, 2020; Stange, 2015).

[5] In general, programs require a C or C+ average (GPA of 2 to 2.5) in approximately 30 units—one year's worth of full-time work—in courses such as anatomy, physiology, chemistry, microbiology, psychology, and algebra. Some of the courses, such as algebra, might have their own prerequisites. Some programs have separate GPA requirements for a student's cumulative performance over all coursework and performance within the prerequisites themselves. Students may fulfill their prerequisites at certain other colleges within and outside the California Community College system, though the set of accepted courses varies by program. Programs also tend to require First Aid and CPR certifications, as well as other types of documentation such as high school diplomas and proof of eligibility to work.

where students who completed application requirements would be added to the end of the list, and each term's new cohort would consist of the longest-waiting applicants. Other programs adopted "first-come first-served" regimes, where a program would open applications for the following term's cohort during a pre-set window, accepting students in the order they submitted their applications. Finally, other colleges used random lotteries. Students could often reapply under lotteries and first-come-first-served regimes.

In October of 2007 the California Assembly, responding to concerns about low completion rates in ADN programs, passed AB-1559, which allowed community college ADN programs to adopt "multi-criteria screening" admissions policies, which I refer to in this article as "evaluative" admissions. Beginning January 1, 2008, ADN programs were now allowed to make admissions decisions based on a set list of criteria: prior academic degrees, diplomas, and certificates; GPA in relevant courses; work and volunteer experience; life experiences; and proficiency in certain other languages. Nursing program administrators favored the change, believing that having more control on the set of students to their programs would lead to increases in completion rates and pass rates on the NCLEX-RN exam, which are key contributors to a program's funding.

Despite the new regulations, programs did not immediately institute the new policies. The first program to take advantage of this new policy changed its admissions process to admit the cohort of fall 2008. As shown in Figure 1, by 2018, 41 colleges had changed their policies, accounting for approximately half of the ADN programs in the state (California Community College Chancellor's Office, 2016). The gradual adoption of multi-criteria screening processes since 2008 allows me to identify how these policies affect the composition of the incoming student body relative to the other admissions regimes. As I discuss in more detail in section 4, the timing of each program's adoption of the new processes does not seem to be related to observable program and local labor market characteristics.

3 Data

I use detailed individual-level administrative records from the California Community College Chancellor's Office (CCCCO) from 1992 to 2017. These records include course-taking behavior, information on degrees and certificates earned, and demographics. The data also contain information on the content of each course. This includes the title of each course (e.g. Introduction to Nursing 101) as well as its classification according to the Classification of Instructional Programs (CIP) codes, used by the National Center for Education Statistics to identify the programmatic content of courses and programs.

I create a sample that consists of the students who begin an ADN program at any California community college since 1992. In California, all ADN programs are oversubscribed, necessitating admissions processes.[6] This means that any student who enrolls in a course associated with an ADN program is a student who was admitted to the program. Based on a review of archival college catalogs, which describe the required coursework for the ADN at each college, I create a sample of all students who enrolled in a nursing program since 1992. I am not able to observe the set of applicants to nursing programs, since admissions processes are run by the individual programs rather than the CCCCO.

Table 1 shows summary statistics for new entrants to ADN programs in the fall of 2007, the last term before the California legislature passed the law allowing for evaluative screening processes. Column 1 shows the students who entered programs that would eventually adopt evaluative screening between 2008 and 2017. Over 80 percent of incoming students are women, and the racial and ethnic composition of new entrants are largely similar to that of California's community colleges in general. An important feature of ADN programs, and community college CTE in general, is that new students were 32 years old on average. A striking feature of the table is that, on average, students spent approximately six years between their first enrolled term at a community college to their first enrollment in a nursing program.[7] These are years that students spend enrolling in prerequisite coursework, and then waiting to win a lottery or have their name called off a waitlist. In general, students must enroll in 25-30 units worth of prerequisite coursework, or approximately a year of full-time coursework. This means that, on average, students who entered nursing programs spent five years longer than the minimum waiting to enter a program. Of course, because I cannot observe applications I cannot state with certainty

[6] This is the common wisdom, though it is difficult to empirically verify. I was also able to provide evidence for this claim by reviewing the application instructions on program websites, which all suggested that there were fewer seats available than eligible candidates. Conversations with program deans and system-wide administrators provided further support.

[7] The median is five years

that students spend all five of these years waiting; they may take time off from coursework in between. Table 1 also shows that half of all students earned some kind of degree or certificate within three years of starting the nursing program. Most completing students earned an ADN. Finally, although nursing programs usually consist of two years of full-time coursework, students who did earn an ADN took 2.9 years to complete their programs.

The sample I use for the main analysis consists only of students in programs that adopted a multi-criteria screening process. I do not use students in non-adopting programs. The event study design, which I describe in the next section, leverages differences in the timing of adoption of the new processes only among colleges that ultimately did adopt the new processes. Column 2 of Table 1 shows summary statistics for students in programs that had not, as of the 2017-2018 school year, changed their admissions policies. Students in these programs were similar in terms of their demographics and academic preparation. Where the two types of programs differ is in their outcomes: students in programs that adopted the new admissions policies had higher completion rates than programs that had not adopted. This difference is not statistically significant, however.

4 Methodology

4.1 Specification

I am interested in the causal effect of a program changing its admissions process. I use an event study design, which leverages the fact that, while many programs eventually adopted multi-criteria screening processes, there was variation in the timing of adoption.

The event study design helps resolve two primary concerns when estimating the effect of an event with a pre-period and post-period. The first of these is that other confounding events may have occurred in the same calendar year as the admissions rule change, which may have affected the outcomes I examine. Because different programs experienced the treatment in different calendar years, there is less concern about calendar year shocks affecting all the programs equally.

Second, a naive comparison group for colleges that adopted the new admissions rules would be the set of colleges that did not adopt. Table 1 showed that the set of adopters and non-adopters are similar on observable characteristics prior to the 2008 law change, but there may be unobserved differences in the colleges that adopted the new admissions rules. In the event study design I limit the sample to colleges that ultimately changed their rules, leveraging the difference in timing among colleges that ever adopted the new rules.

I estimate the following equation:

$$y_{ict} = \alpha_1 + \sum_{\substack{g=G_{min} \\ g\neq 0}}^{G_{max}} \beta_g \mathbf{I}(t - T_c = g) + \delta_c + \delta_t + \mu_c * t + e_{ict} \tag{1}$$

where y_{ict} is a characteristic or outcome for student i who starts in the ADN program at college c as a member of cohort t.[8] The subscript g refers to *event years*: the years since the program adopted its new evaluative screening admissions rules. The year where $g = 0$ is the year prior to the first one where a cohort would have been admitted based on the new rules, denoted as T_c. I omit this event year ($g = 0$), meaning that the coefficient β_g is expressed relative to the year prior to the change. The coefficients β_g give the difference between the outcome in event years g and event year 0. I also control for college effects δ_c and cohort effects δ_t. In this context it is important to also include program specific linear time trends $\mu_c * t$. These will account for any secular trends in each college, perhaps brought about by local demographic change. I cluster standard errors at the college level. In tables I also present differences-in-differences results, essentially imposing the restriction that all post-adoption coefficients are equivalent (i.e. that all β_g are equivalent for $g > 0$). This makes interpretation more straightforward.

4.2 Sample Definition

A key aspect of this analysis is how to construct the analytic sample, and in particular whether to use a balanced panel, with each college represented an equal number of times. A drawback of a balanced panel is that it cuts post-treatment years of data from the earliest adopting college, and also cuts pre-treatment years of data from the latest adopting college. These additional data points are crucial for identifying the time trends in the data. However, there are also drawbacks of using an unbalanced panel, in which all colleges are represented in each available calendar year. In an unbalanced panel the coefficient for each event year is identified off of different sets of colleges, which muddles the interpretation.

[8] Because some colleges have two cohorts per year (one each semester) and some have one, I consider cohorts as the set of students who start in each academic year.

In order to bridge this gap, I take a middle approach, adopted by Goodman-Bacon (2018) and Naven (2017). I identify the maximum set of event years possible when using a balanced panel. This corresponds to the number of pre-event years for the earliest adopting college and the number of post-event years for the latest adopting college.[9] Then, I include all available earlier and later years of data that would not be included in the balanced panel, using these to estimate one coefficient prior to the first event year and one coefficient after the last event year. This "loaded" approach is an unbalanced panel for which the coefficients of interest are identified with a balanced panel of colleges.

In the context I study, the first adopting college changed its rules in the Fall of 2008. Because the data go back to 1992, this means that the maximum number of pre-event years of data in a balanced panel is 16. Later adopters, like a college that changed its rules in the Fall of 2009, will have 17 or more years of pre-event data available. To create the "loaded" panel I code all event years greater than 16 as the 17th year of pre-event data. This allows me to use more years of data for some colleges to identify the trends, though the main coefficients are still identified with a balanced panel of colleges.

I use a similar approach for the post-event years. Because programs are still in the process of announcing plans to adopt the new admissions policies, there is no "last" adopter. Instead, I estimate up to four years of post-event coefficients given the data I have, which go up to 2017, and drop all adopters after 2017 from the analysis. By doing this, I can then "load" the fifth post-event coefficient with all event years after the fourth, in an analogous fashion as with the pre-event loading.

The "loaded" approach recovers unbiased estimates of the event year coefficients in the face of significant linear trends. Nevertheless, in robustness exercises I show the results using other sampling approaches.

4.3 Dependent Variables

The outcomes I study correspond to the three research questions. First, I am interested in the first stage effect of the policy: did the academic preparation of the incoming cohorts change? I

[9] In other words the minimum number of event years for which each college is represented the same number of times.

examine credit accumulation and GPA in the first two years a student is in the community college, before they enter the ADN program. I can also observe the number of basic skills courses in which they enroll in that same period. Changes in the academic preparation of new cohorts could be brought about by three mechanisms. Students could change their application patterns in response to the announcement of the new admissions rules. By changing the policy, admissions committees would also switch which applications they select. And finally, the change in policy might also affect matriculation rates among accepted students if the newly accepted students place a higher or lower value on the program than previously accepted students. I cannot differentiate between these mechanisms; nevertheless, the composition of the new cohorts is the policy-relevant outcome.

Next, because the original legal impetus came from a group claiming that evaluative screening admissions adversely affected Latino applicants, I am particularly interested in the racial and ethnic composition of the incoming students. I also look at the age composition of students.

In addition to the composition of the incoming new cohort, I also observe academic outcomes. The rationale espoused by supporters of the 2008 law change was that completion rates would increase and attrition rates would drop (Hill, 2007). I examine student GPA in the first year of the program as an intermediate outcome. I then look at two different completion outcomes. The first is whether a student completed an ADN and the second is whether a student completed any community college degree or certificate. I define both completion outcomes as occurring at any of the community colleges in the state.

The last type of outcome I study concerns the efficiency of the admission system. I have already shown that wait times for students entering nursing cohorts were high, requiring several years beyond the expected amount of time needed to complete prerequisite coursework. Replacing waitlists and other lengthy application systems with evaluative admissions might make the entire process more efficient and allow admitted students to more quickly complete the program and enter the labor force quicker. I operationalize this outcome as the number of years between a student's first term taking community college classes and first term of a nursing program.

4.4 Threats to Identification

There are two main potential threats to the identification strategy. First, there would need to be college-level shocks that are more likely to occur in the same event year. Because of the staggered adoption of the new admissions rules, any kind of calendar-year shock is accounted for. On the other hand, if colleges were hit with a particular type of shock in the second year following their adoption of the new rule, this would create a problem. It is unlikely that this type of coincidence would occur, however.

More worrisome is the potential that the timing of the adoption of the new criteria is endogenous. Although all colleges in the samples are eventual adopters, certain types of colleges may be more likely to adopt earlier relative to others. This could lead to biased results. From conversations with program administrators, I found that there were significant administrative hurdles to surpass in order to adopt the evaluative screening process allowed by the new policy. It is unclear how much heterogeneity there is in these costs, and whether that is related to the quality of the program or the outcomes I am interested in.[10] As a more formal test for the exogeneity of the timing, I regressed the semester of adoption on a variety of college and county characteristics, measured in 2007. This exercise is illustrated in Figure A2, which plots the month of adoption on the vertical axis and the 2007 program-level mean on the horizontal axis. The size of each marker represents the size of the program. Appendix Table A1 shows the coefficient estimates. There does not seem to be a systematic pattern relating the timing of adoption to these characteristics, and some are likely statistically significant merely by chance. Thus, there is less concern that the timing of the adoption of the new rules is endogenously determined.

5 Results

Figures 2-4 plot event study coefficients for characteristics and outcomes of incoming ADN cohorts.[11] Tables 2-4 display the post-treatment coefficients for each of these specifications, as well as the F-statistic and associated p-value on the hypothesis that all the post-treatment coefficients are zero. The tables also shows the results of an F-test on whether the *pre*-event coefficients are statistically significant. If the tests suggest that the coefficients on the pre-event dummies are zero, then this is support for the event study being well-identified. In a later section I present sensitivity

[10] While there are plenty of local news articles about colleges adopting the new rules, I did not find any related to how colleges decided whether to adopt or not adopt.

[11] For clarity, I only plot coefficients up to ten years prior to the policy change in the figures, although I estimate coefficients for 16 years prior.

checks showing where the specification fails to pass this test, which highlight the importance of controlling for these trends. Tables 2-4 also show the differences-in-differences coefficient for the entire post-intervention period. The differences-in-differences specifications still separately estimate coefficients for each of the 16 pre-period event years, but estimate one post-period coefficient rather than four.

5.1 Academic Preparation and Background

As discussed previously, the impetus for the 2008 legislation that allowed evaluative admissions was college administrators worrying that systems like lotteries and "first come first served" admissions do not admit the highest quality students. Since funding is often tied to completion rates and NCLEX-RN pass rates, student academic quality is of primary concern to administrators. At face value, changing admissions policies to accept students based on a set of agreed-upon variables should result in new cohorts of students having higher average composition along those variables. However, this might not occur for a few reasons. First, take-up rates of admissions offers are relatively low, around 50 percent, and there may be selection in takeup that counteracts the effects of the admissions decision (Grosz, 2020). More likely is that certain non-evaluative admissions policies do in fact serve to select students on certain attributes. "First come first served" policies, for example, reward the most proactive students, who apply the earliest. Waitlists reward applicants who are willing to wait. A final reason why the adoption of evaluative screening processes may not result in substantial changes in cohort quality is that there may be little variation to begin with. ADN program applicants must meet a high GPA standard in extensive prerequisites in order to be eligible to be considered for admissions.

Table 2 and Figure 2 show the event study estimates for a set of academic background variables. Overall GPA is flat in the pre-period as well as after the change in the policy. On the other hand, there is a large and positive effect on GPA in biology coursework, of approximately 10 GPA points over the four years following the admissions change. Many programs place great weight on performance in biology prerequisites, so it makes sense that applicant quality improved along this dimension. There is also an increase in math GPA in the event study graph, but the coefficient estimates are small and not statistically significant.

Another informative measure of a student's academic preparation prior to application in an

ADN program is whether they took remediation coursework. Table 2 and Figure 2 show that the share of students who took a basic skills course in their first year of community college dramatically dropped, by almost 5 percentage points, following the adoption of the new admissions rules. This amounts to an approximately 9 percent decrease in the share of students who had taken remedial coursework. Taken together, these results show that the change in admissions procedures does seem to affect the academic preparation of incoming students, as intended by the legislation.

5.2 Demographics

The purpose of the original ban on evaluative admissions processes was, as claimed by the group that brought forth a lawsuit, to counteract adverse acceptance rates for minority students. Figure 3 and Table 3 examine the effects of switching to an evaluative admissions policy on demographic characteristics.

Recruitment of male nurses has been a priority in recent years in an occupation that has historically been primarily female (Evans, 2013), and one way to increase the number of male nurses would be to accept more men into nursing programs.[12] Panel a) of Figure 3 shows no discernible effect on the share of male students following implementation of evaluative admissions.

There does seem to be an effect, however, on the racial and ethnic composition of the new cohorts. After the implementation of new rules, new cohorts were 2.3 percentage points more likely to be white. Compared to a pre-implementation average of 36.2 percent, this amounts to a 6.3 percent increase in the share of new students who are white. The F-statistic reported in Table 3 suggests that all four coefficients are jointly statistically different from zero. The next two columns of Table 3, as well panels c) and d) of Figure 3, show that I cannot determine with any precision which racial and ethnic groups declined in representation as the share of white students increased. However, the sign for Latino students is negative, though not statistically significant. Thus, this analysis does lend credence to the argument that multi-criteria screening processes do crowd out minority students.

The final column of Table 3 and panel d) of Figure 3 show the effect on mean age of new ADN students upon admission. The figure shows a downward and sizeable effect in positive event years,

[12] According to the legislation, of course, admissions committees are not allowed to use gender as a basis for admissions.

suggesting that new students were between one and three years younger following implementation of evaluative admissions. The joint test of significance for the four post-treatment coefficients has a p-value of 0.12, however, so I cannot reject the null that they are all zero. Appendix Table A2 and Figure A3 examine subcategories of age. Although not precisely estimated, the results suggest that the declines in mean age come predominantly from an increase in the share of students under 25 and declines in the shares of students over 40, with no discernible changes in the share of students between 25 and 40 years old. The skewing of the new cohorts towards younger students perhaps shows how admissions committees weight competing criteria that can be used for admissions. On the one hand, younger students have better academic preparation in terms of GPA. On the other hand, older students likely have stronger work history, which is an allowable criterion for admissions purposes but which I cannot observe in the data. My results suggest that admissions committees value the academic criteria more than the employment criteria.

Overall, my results support the claims that MALDEF made to the CCCCO in the early 1990s. Relative to non-evaluative admissions, evaluative admissions seem to select fewer minority students as well as younger students. My results are, of course, not normative: the California legislature presumably weighed the benefits of potentially increasing completion rates against the cost of decreasing enrollment of certain demographic groups. The next subsection explores whether there were, in fact, improvements in completion rates due to the evaluative admissions policies.

5.3 Academic Outcomes

The demographic effects of evaluative admissions policies were the basis for the original ban. However, the potential benefit of evaluative admissions, in the form of improved academic outcomes, was the reason for their reinstatement. Although I find small effects on certain measures of academic preparation, evaluative admissions also involved essays and other components, which committees could be using to choose students better posed for academic success. To analyze whether evaluative admissions as a whole led to improved outcomes I observe the effect of the admissions rule changes on cohort academic performance.

The first column of Table 4 shows the number of years between a student's first course in a community college and first semester in an ADN program. There is a pronounced decline following the implementation of the new admissions policies. Over the four years, the average student under the new regime waited 0.36 years less, a five percent decline. This drop is meaningful, and is not surprising given the fact that the new admissions policies have less room for reapplication. In fact, later cohorts face even larger declines, of more than half a year. This result suggests that multi-criteria screening processes can reduce inefficiencies inherent in waitlist and repeated lottery systems. Although I cannot observe the behavior of rejected applicants, the shortening of their wait likely leads them to return to the labor market sooner or to apply to other programs.

Earlier I showed evidence of whether the new policies affect student quality: the mean overall GPA of incoming students does not seem to change, but fewer take remediation classes and biology GPA improves. Table 4 and Figure 4 show that completion rates did not increase following the policy change. There is a positive coefficient on student first-year GPA, but it is not statistically significant. The share of students who completed any degree is unchanged, and the coefficients even have a negative sign. Likewise, the share of students who complete an ADN is unchanged. There is an increase in ADN completion rates in the fourth year following the policy change, but this coefficient is statistically insignificant and small.[13]

The final subfigure in Figure 4 shows the effect of changing admissions on the college's pass rates on the National Council Licensure Examination (NCLEX), which is required of nursing program graduates in order to work as nurses. Data on program-level pass rates are available from the CCCCO at the program level, but not at the individual level, going back to the 2003-2004 academic year. I cannot match individual students to their NCLEX score, nor do I know for certain how many students from each cohort take the exam each year. Because ADN programs supposedly take 2 years to complete I match the NCLEX pass rates to the cohort two years prior. Thus I can estimate at most three post-2008 coefficients and seven pre-2008 coefficients. I weight the regressions by the number of students who sit for the exam, which is also provided in the data. Pass rates are already high, 88 percent, meaning that there is little room for upward movement in any event. I find no change in the pass rate due to the policy.

A lingering question is whether the negligible effects I find of the policy on outcomes is merely due to an underpowered study design. On the other hand, the measures of academic quality used for admissions, especially grades, may not good predictors of student success in the

[13]Taken at face value, the coefficient amounts to only a 3.8 percent increase in completions.

program. Community college vocational students are more likely to be older, work part-time, and have families to take care of, so failure to complete is often a result of "life getting in the way" (Goldrick-Rab, 2010) rather than a lack of academic preparation. One way to answer this question is to ask what increase in completion rates an admissions officer designing an evaluative admissions policy would expect given the changes in the composition of the new cohorts. That is, if these characteristics predict success in the program, then they can be used to estimate the potential effects of the new admissions policy on completion.

Table 5 shows this relationship between the observable inputs of new cohorts prior to 2008—the first year of evaluative admissions—and their eventual ADN and overall degree completion. These are linear probability models that control for college, calendar year, and college-specific trends, and are not meant to have a causal interpretation. Rather, Table 5 demonstrates that these characteristics, which are observable to the admissions officer, strongly predict completion; they can help relate the main estimates of the effects of changing admissions strategy on inputs to those on outcomes.[14]

In particular, Table 3 showed that changing admissions policy increased the share of new students who were white by 2.3 percentage points. According to the results in Table 5 these additional white students would have a 5.5 percentage point higher likelihood of earning an ADN, implying that overall completion rates would increase by 0.1 percentage points. This is a small effect. A similar calculation shows that the increase in Biology GPA of incoming students would only increase competion rates by 0.7 percentage points.[15] The effects are comparable for the other inputs.

These estimates of the effect of the policy on completion rates are within the confidence intervals shown in Table 4, where I explicitly estimate the effect of the policy on completion rates, so I cannot rule them out. Still, these are small effect sizes for a policy expressly intended to boost completion, especially when compared to the relatively large reductions in the diversity of the student body.

In sum, I find no evidence that changing admissions policies improved completion rates. This

[14] Appendix Table A3 shows that these results are robust to the inclusion of college fixed effects and trends.

[15] Using the upper bound of the confidence intervals for the estimates on the share of students who are white would only give an increase in the completion rate of 0.3 percentage points. Similarly, taking the upper bounds of the confidence intervals for GPA in biology, the completion rate increase would be 1.4 percentage points.

lack of effect comes in spite of increases in measures of student ability, which suggests that the screening variables used by these programs may not be ones that predict student success.

5.4 Previous Admissions Type

The main results may differ by the type of admissions the programs used prior to the change. The effects of evaluative admissions might be most pronounced at programs with random lotteries, where endogenous selection on student characteristics would be the least pronounced. On the other hand, the improvement in wait time might be concentrated among programs with waitlists. Of the 44 programs in the sample that switched their admissions, 12 had waitlists, 28 had lotteries, and 4 had first-come-first-served. The collection of the admission type data is complicated, though, by the fact that the available archival college catalogs do not fully describe the lottery process: some lotteries are not purely random and give additional weight to certain applicants. For these reasons, I separate the programs into the 12 waitlist programs and the 32 other programs that include some amount of randomness. Tables A8-A10 show these results.

The main results are almost all the same, qualitatively, with a few notable exceptions. Switching to evaluative admissions improved the incoming math GPA of former waitlist programs, and also led to programs with a slightly higher share of men.

Most notably, though, waitlist programs that switched to evaluative admissions had the most pronounced drops in wait time between starting community college and enrolling in an ADN program. By eliminating waitlists, these programs reduced the wait time by almost 80 percent of a year. Lottery and first-come-first-served programs, on the other hand, had much smaller drops in wait time.

5.5 Robustness and Sensitivity

I perform a few different specification tests to assess the sensitivity of the estimates to sampling and modeling choices. The fully specified model relies on the "loaded" sampling approach, described earlier, and include cohort dummies, institution dummies, and institution-specific linear trends. Tables A4-A7 show the implication of changing these specifications. The first few columns include various combinations of fixed effects and trends and display the resulting coefficients. Column 5 is the main specification. Most interesting is the test that pre-event coefficients are zero. The test fails in most cases without controlling for institution-specific trends as well as academic year cohort and institution. Nevertheless, the qualitative results of the post-event coefficients are largely unchanged.

The final two columns of Tables A4-A7 use two different sampling strategies. In the balanced panel I limit the data so that all institutions are represented the same number of times: one observation per event year per college. This leads to a large drop in the number of observations, and the analysis does not perform as well: in some cases the pre-event coefficients are jointly significantly different than zero. The final column uses a sampling approach similar to the main specification, but instead of loading all the unbalanced event years onto one coefficient it separately identifies each one. This leads to an unbalanced number of observations per college, but only the coefficients on the balanced set of event years is reported. These results are similar to the preferred approach, likely because the pre-event period is long, so that including more or fewer years of pre-event data for certain colleges does not add important information.

5.6 Changes relative to non-adoping colleges

The event study design only uses data from colleges that eventually adopted the new admissions policies within the time period. However, non-adopting colleges may also see the composition of their new cohorts chnage if other colleges change their admissions. Colleges implementing new evaluative admissions might attract better students by drawing them away from colleges with lotteries. Or, the new admissions might just be a way for colleges to change the selection from among their own pool of applicants. Without information on the applicant pool, however, I cannot answer these questions in a causal way.

Figure A4 shows mean characteristics of incoming students, net of college fixed effects and college-specific linear time trends, at colleges that did not have evaluative admissions. In none of the figures is there a clear break in trend before and after 2008. Of course, this analysis is limited by being just a pre-post design, but still does not show evidence of any changes in the composition of the incoming cohorts and non-adopting colleges.

As another test, I ask whether a college sees its cohort composition change if nearby colleges change their admissions. The intuition is that the market for nursing school applicants might be local to smaller geographic areas. So, if changing admissions merely reshuffles the applicant pool across colleges, then colleges that did not change their admissions should see declines in white students and declines in academic preparation. Specifically, I implement an event study similar to that in equation 1. The event, in this case, is the earliest year that a nearby college switched its admissions, and I limit the sample to colleges that never changed their admissions. I define the set of local colleges in three ways: colleges in the same county, colleges within a 25 mile radius, and colleges within a 100 mile radius. Approximately 75 percent of colleges had at least one other college within 25 miles, and all colleges had at least one college within 100 miles.[16]

Table 6 shows the results. If colleges that changed their admissions were diverting students from non-adopting colleges, then the results in the table would have the opposite sign as in the main results in previous tables. Instead, I find results that are not statistically significant, but of the same sign. The results are robust to the three different definitions of the local area. Thus, this is additional support for the idea that colleges are not diverting students from other colleges, but instead are changing selection patterns from within their own set of applicants.

6 Conclusion

In this paper I measure how a change in a community college ADN program's admissions policy affects the composition of its incoming cohorts as well as the eventual academic outcomes of its students. I leverage a statewide policy in California that led many of the states ADN programs to switch their admissions from lotteries and waitlists to ones that relied on evaluative measures such as grades and work experience.

I find that admissions strategies at ADN programs that are based on evaluative measures do not lead to improved completion rates for students. ADN completion rates are low already, but more intensive admissions requirements do not seem to be a way to improve them.

There are two potential explanations for this result. First, the allowable types of measures may not contain valuable information for screening applicants to ADN programs. Nursing programs involve difficult coursework, but the most demanding aspects of the program are often the field placements at local hospitals, the clinical labs on site, and outside responsibilities.[17] For this reason,

[16] Results are not sensitive to different lengths of the radius between 25 and 100 miles. Definitions of a smaller radius drop many colleges. For example, only half the colleges had another college within 10 miles.

[17] I gained this information from a focus group and semi-structured interviews with program administrators and new

GPA in biology or math may not be a useful way to determine who will successfully complete an ADN program.

Second, even if the components included in the new admissions policies were useful in predicting success among applicants, there may not be enough variation among applicants for these components to be useful. In other words, the pool of applicants might already be sufficiently small that there is no usefulness for a screening mechanism. This is the argument made by Kamenetz (2019) and others in response to the Varsity Blues admissions scandal: the pool of applicants to elite four-year colleges like Yale and Stanford are so selective already that an admissions committee may not be able to accurately predict their subsequent academic success.

Although academic outcomes do not improve, I do find that the demographic composition of the new cohorts changes. I find that switching away from lotteries and waitlists leads to cohorts that are more likely to be composed of young and non-minority students. This effect of admissions policies, even those that do not explicitly target certain demographic groups, was the reason for the initial ban on evaluative measures imposed in the late 1980s.

These two categories of findings have a clear policy implication: admissions strategies that rely on evaluative measures are not an improvement over lotteries or waitlists in terms of the academic outcomes of the students and the diversity of the incoming cohorts. So, what is to be done? This is where the final finding is important: moving away from lotteries and waitlists leads to drastic improvements in the time that applicants spend waiting to enter programs. Thus, an implication of this work is to combine the two approaches. ADN programs could implement strategies that do not use evaluative measures but also do not force students to wait longer than one semester to learn if they are accepted. These would involve one-shot lotteries and first-come-first-served designs, as opposed to waitlists and other methods where students have increased probability of being accepted the longer they wait.

students, performed in 2015.

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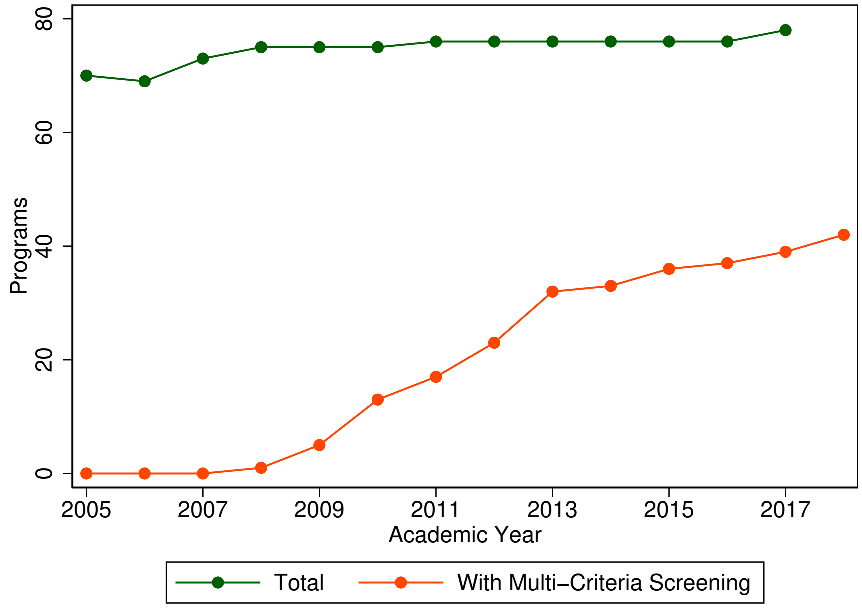
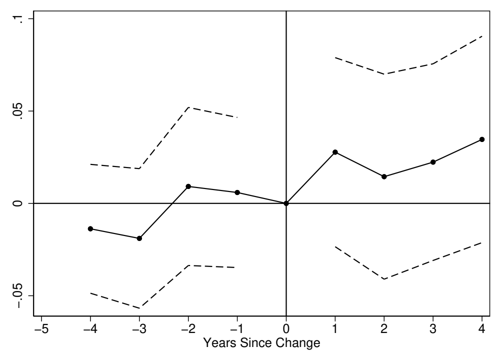
Figure 1: Adoption of Multi-Criteria Screening Processes

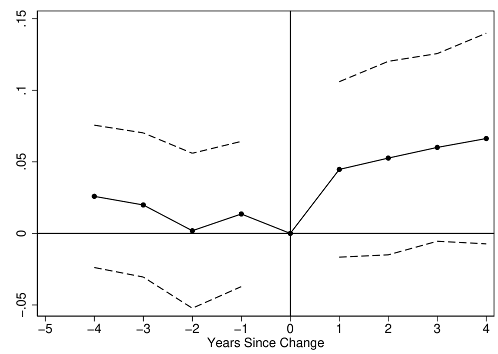


Notes. This figure shows the number of total ADN programs as well as the number of programs with multi-criteria screening processes. The number of ADN programs is based on data from the California Community College Chancellors Office (CCCCO) up to the 2015-2016 academic year. The number of programs with multi-criteria screening processes is based on publications of the CCCCO, including for years in which there are not yet data.

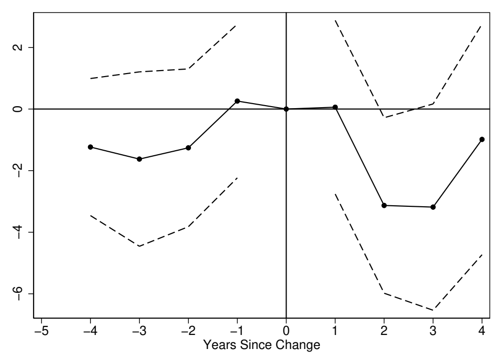
Figure 2: Academic Background, Loaded Panel, College Fixed Effects and Trends



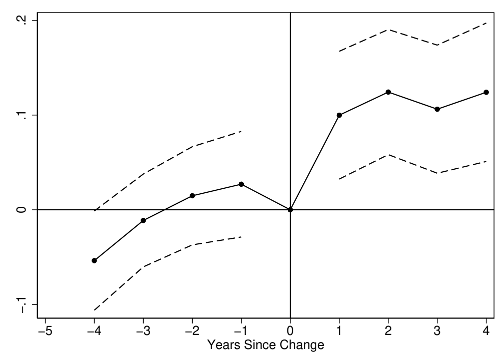
a) GPA



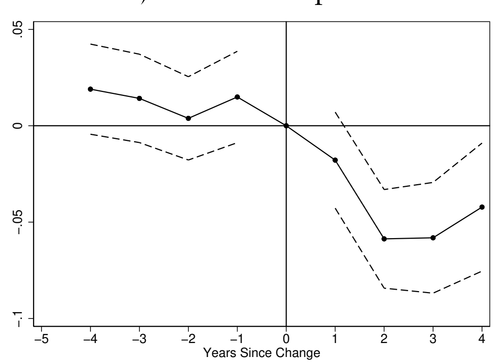
b)Math GPA



c) Units Attempted



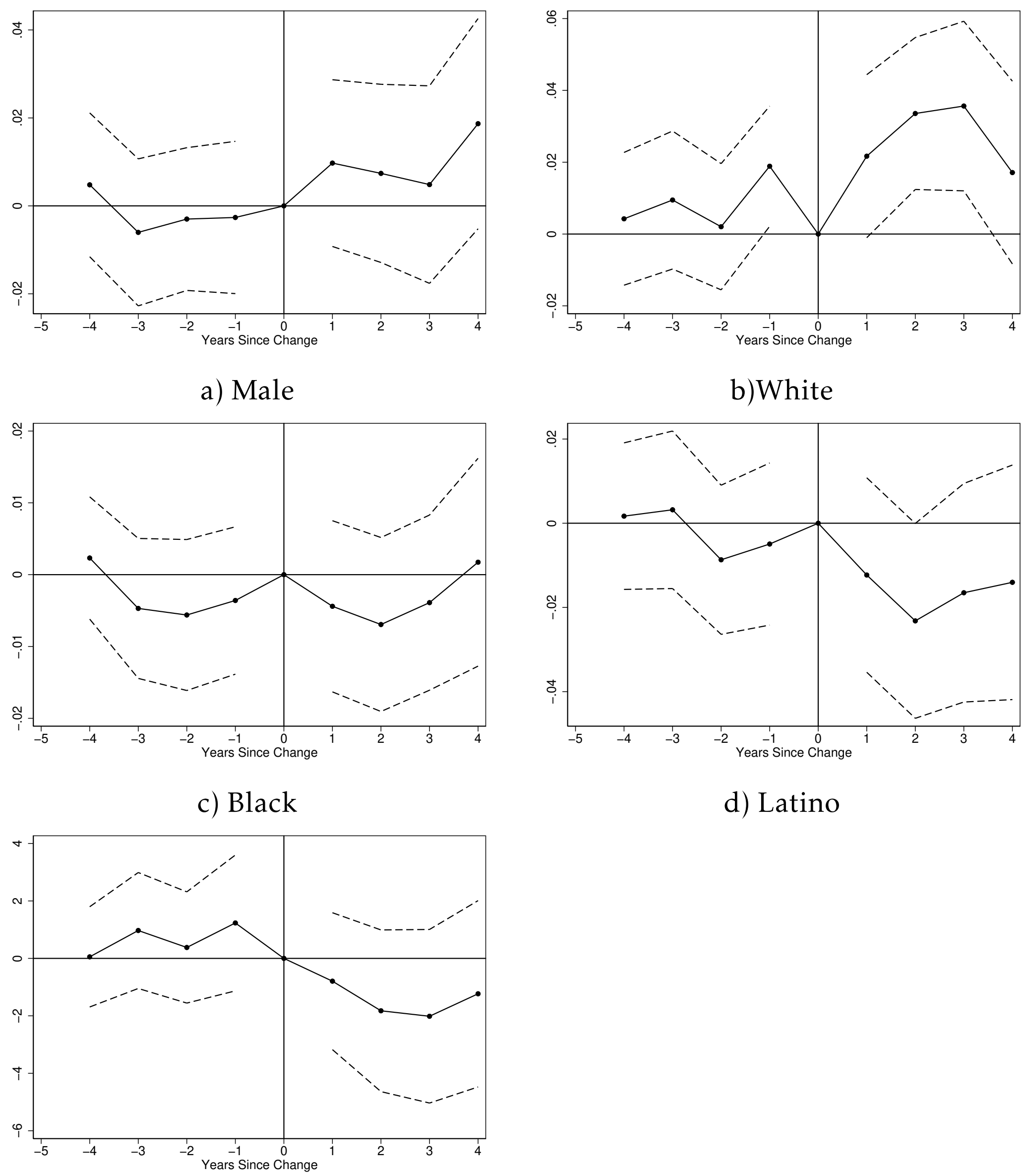
d) Biology GPA



e) Basic Skills Courses

Notes. Figures show point estimates and 95 percent confidence intervals of results from regressions estimating 16 years prior and four year post change of admissions policy. Regressions control for calendar year, program, and program-specific linear time trends. Standard errors clustered at the program level.

Figure 3: Demographics, Loaded Panel, College Fixed Effects and Trends



a) Male

b)White

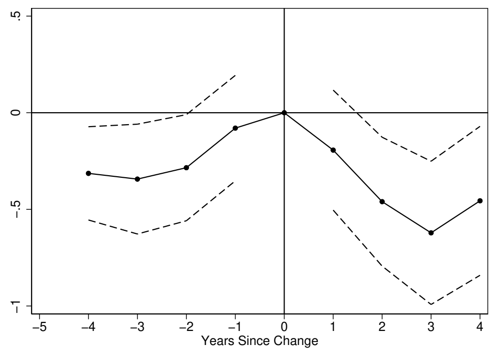
c) Black

d) Latino

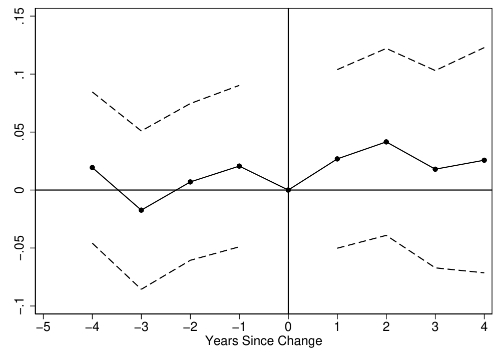
e) Age

Notes. Figures show point estimates and 95 percent confidence intervals of results from regressions estimating 16 years prior and four year post change of admissions policy. Regressions control for calendar year, program, and program-specific linear time trends. Standard errors clustered at the program level.

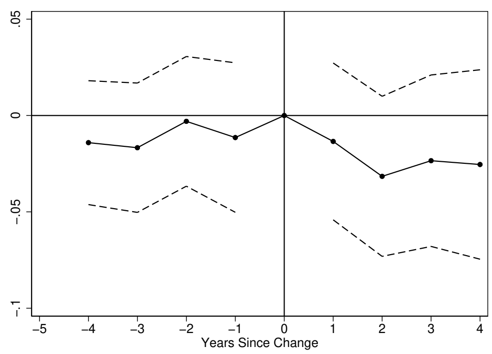
Figure 4: Outcomes, Loaded Panel, College Fixed Effects and Trends



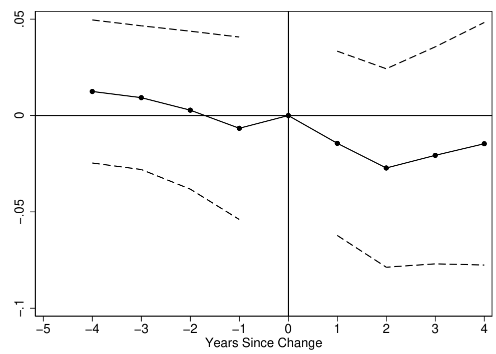
a) Time to Start



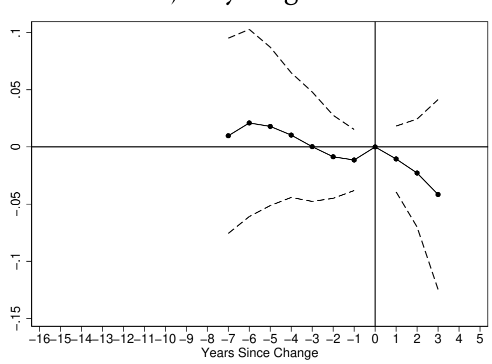
b) First-Year GPA



c) Any Degree



d) Complete ADN



e) NCLEX-RN Pass Rates

Notes. Figures show point estimates and 95 percent confidence intervals of results from regressions estimating 16 years prior and four year post change of admissions policy. Regressions control for calendar year, program, and program-specific linear time trends. Standard errors clustered at the program level.

Table 1: Summary Statistics for Students of Fall 2007 Cohort, by Whether Program Ever Switches to Multi-Criteria Screening

	(1) Ever Adopt	(2) Never Adopt
A. Demographics		
Male	0.198	0.181
	(0.399)	(0.385)
White	0.419	0.375
	(0.493)	(0.484)
Black	0.0786	0.110
	(0.269)	(0.313)
Hispanic	0.249	0.250
	(0.433)	(0.433)
Asian/Other	0.253	0.265
	(0.435)	(0.442)
Age	32.36	31.50
	(51.97)	(54.20)
B. Academic Preparation		
GPA	2.979	2.885
	(0.750)	(0.825)
GPA in Math	2.791	2.672
	(1.001)	(1.099)
GPA in Biology	2.930	2.802
	(0.823)	(0.942)
Units Attempted	57.72	49.14
	(40.87)	(41.14)
Basic Skills Courses	0.468	0.439
	(0.499)	(0.496)
Time to Enrollment	6.331	5.852
	(4.871)	(5.016)
C. Academic Outcomes		
Any Degree, 3 Years	0.555	0.407
	(0.497)	(0.491)
Any Nursing Degree, 3 Years	0.398	0.234
	(0.490)	(0.423)
Time to degree	1.108	1.271
	(3.630)	(3.953)
Time to Nursing Degree	2.873	3.209
	(1.301)	(1.743)
First-Year GPA	3.052	3.115
	(0.878)	(0.962)
Observations	6221	6079

Table 2: Main Results, Academic Background

	(1) GPA	(2) Math GPA	(3) Bio GPA	(4) Units	(5) Basic Skills
A. Event Study					
Event Year +1	0.0250	0.0356	0.100**	-0.210	-0.0218
	(0.0258)	(0.0304)	(0.0336)	(1.398)	(0.0125)
Event Year +2	0.0123	0.0453	0.127***	-3.398*	-0.0620***
	(0.0279)	(0.0335)	(0.0330)	(1.414)	(0.0129)
Event Year +3	0.0215	0.0549	0.113***	-3.503*	-0.0610***
	(0.0269)	(0.0325)	(0.0339)	(1.670)	(0.0144)
Event Year +4	0.0361	0.0640	0.136***	-1.276	-0.0446**
	(0.0281)	(0.0365)	(0.0363)	(1.864)	(0.0166)
F-test: pre-years	0.485	0.545	1.643	0.779	0.440
p-value: pre-years	0.901	0.859	0.088	0.649	0.927
F-test: post-years	0.489	0.886	4.523	2.502	7.285
p-value: post-years	0.744	0.471	0.001	0.040	0.000
B. Differences in Differences					
Post Change	0.0231	0.0424	0.115***	-1.916	-0.0430***
	(0.0219)	(0.0270)	(0.0284)	(1.215)	(0.0110)
Y-Mean	3.006	2.762	2.958	63.290	0.490
N	232372	143125	158185	254335	254335

Notes. Both panels shows estimates from regressions estimating 16 years prior and four year post change of admissions policy. Regressions control for calendar year, program, and program-specific linear time trends. Panel A estimates each post-event change separately, while Panel B constrains all post-event coefficients to be equivalent. The F-tests are a test that all the pre-event or post-event coefficients are jointly zero. Standard errors clustered at the program level.
$*p < 0.05, **p < 0.01, ***p < 0.001$

Table 3: Main Results, Demographics

	(1) Male	(2) White	(3) Black	(4) Latino	(5) Mean Age
A. Event Study					
Event Year +1	0.00675	0.0187	-0.00508	-0.0126	-0.511
	(0.00941)	(0.0107)	(0.00573)	(0.0114)	(1.212)
Event Year +2	0.00808	0.0269*	-0.00652	-0.0208	-1.558
	(0.0101)	(0.0106)	(0.00564)	(0.0114)	(1.428)
Event Year +3	0.00435	0.0351**	-0.00449	-0.0145	-1.784
	(0.0110)	(0.0119)	(0.00610)	(0.0128)	(1.526)
Event Year +4	0.0240*	0.0141	-0.00163	-0.00543	-1.028
	(0.0117)	(0.0122)	(0.00664)	(0.0147)	(1.627)
F-test: pre-years	0.694	1.057	0.859	1.546	1.508
p-value: pre-years	0.731	0.392	0.571	0.117	0.130
F-test: post-years	1.279	2.833	0.482	1.005	0.485
p-value: post-years	0.276	0.023	0.749	0.404	0.747
B. Differences in Differences					
Post Change	0.00883	0.0234**	-0.00520	-0.0149	-1.029
	(0.00836)	(0.00863)	(0.00484)	(0.00971)	(1.110)
Y-Mean	0.199	0.362	0.073	0.249	33.677
N	254335	254335	254335	254335	254002

Notes. Both panels shows estimates from regressions estimating 16 years prior and four year post change of admissions policy. Regressions control for calendar year, program, and program-specific linear time trends. Panel A estimates each post-event change separately, while Panel B constrains all post-event coefficients to be equivalent. The F-tests are a test that all the pre-event or post-event coefficients are jointly zero. Standard errors clustered at the program level.
$*p < 0.05, **p < 0.01, ***p < 0.001$

Table 4: Main Results, Outcomes

	(1) Wait Time	(2) First-Year GPA	(3) Any Degree	(4) Finish ADN
A. Event Study				
Event Year +1	-0.186	0.0284	-0.0124	-0.0176
	(0.152)	(0.0381)	(0.0206)	(0.0241)
Event Year +2	-0.453**	0.0423	-0.0301	-0.0306
	(0.164)	(0.0399)	(0.0209)	(0.0259)
Event Year +3	-0.617***	0.0173	-0.0217	-0.0246
	(0.183)	(0.0421)	(0.0224)	(0.0283)
Event Year +4	-0.445*	0.0235	-0.0214	-0.0179
	(0.190)	(0.0483)	(0.0248)	(0.0315)
F-test: pre-years	1.339	1.472	0.418	0.403
p-value: pre-years	0.203	0.143	0.939	0.946
F-test: post-years	3.444	0.335	0.537	0.380
p-value: post-years	0.008	0.855	0.708	0.823
B. Differences in Differences				
Post Change	-0.370**	0.0295	-0.0204	-0.0228
	(0.133)	(0.0337)	(0.0177)	(0.0214)
Y-Mean	7.015	3.055	0.547	0.351
N	254002	183400	254335	254335

Notes. Both panels shows estimates from regressions estimating 16 years prior and four year post change of admissions policy. Regressions control for calendar year, program, and program-specific linear time trends. Panel A estimates each post-event change separately, while Panel B constrains all post-event coefficients to be equivalent. The F-tests are a test that all the pre-event or post-event coefficients are jointly zero. Standard errors clustered at the program level.
$*p < 0.05, **p < 0.01, ***p < 0.001$

Table 5: Student Background Characteristics and Eventual Degree Attainment, pre-2008 Cohorts

	(1)	(2)
	Complete ADN Program	Complete Any Degree
Male	-0.0430***	-0.0398***
	(0.00839)	(0.00515)
White	0.0548***	0.0382***
	(0.00851)	(0.00625)
Black	-0.00375	0.0251**
	(0.00906)	(0.00841)
Hispanic	0.0149*	0.0240***
	(0.00626)	(0.00663)
Age	-0.00320***	-0.00160***
	(0.000662)	(0.000454)
GPA	0.0912***	0.165***
	(0.0111)	(0.00784)
GPA in Math	0.00829**	-0.00315
	(0.00277)	(0.00260)
GPA in Biology	0.0689***	0.0290***
	(0.00722)	(0.00524)
Units Taken	0.00109***	0.00436***
	(0.000157)	(0.000218)
Basic Skills Courses	-0.0413***	-0.0333***
	(0.00622)	(0.00441)
Time to Enrollment	0.00522***	0.00251*
	(0.00114)	(0.00107)
N	62423	62423
Y-Mean	0.401	0.643
R-Squared	0.316	0.261
Cohort FE	X	X
College FE	X	X
College Trends	X	X

Notes. Table shows results of OLS regressions of student characteristics on completion of an ADN or of any community college program. Regressions also control for the square of age. Standard errors clustered at the program level.
$*p < 0.05, **p < 0.01, ***p < 0.001$

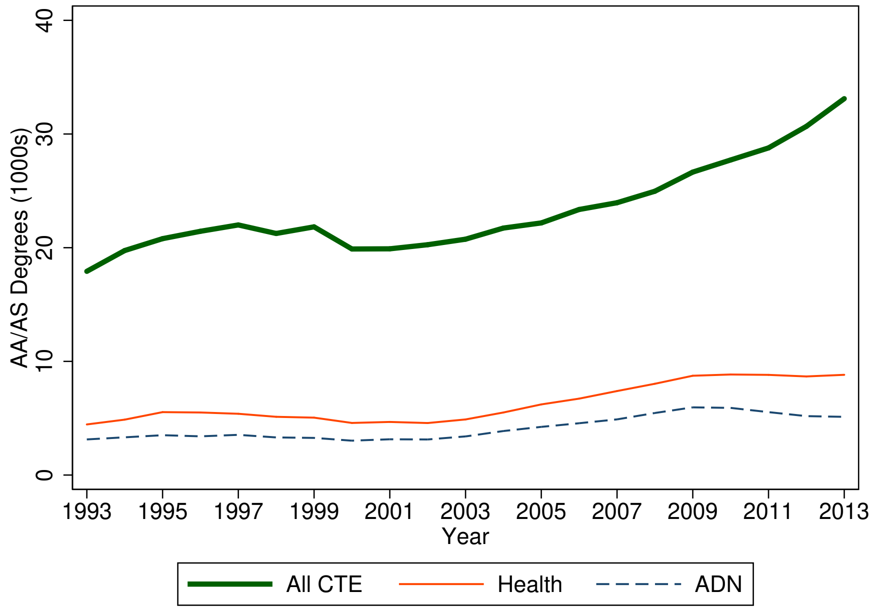
Table 6: Effect of Switches at Other Colleges on Non-Adopting Colleges

	(1) Male	(2) White	(3) Latino	(4) Black	(5) Mean Age	(6) GPA	(7) Bio GPA
A. In Same County							
Post Change	0.0172	0.0272	-0.0261	0.00701	1.255	-0.00754	0.00401
	(0.0152)	(0.0175)	(0.0180)	(0.0118)	(1.929)	(0.0386)	(0.0445)
Y-mean	0.213	0.263	0.322	0.116	33.025	2.913	2.867
N	115515	115722	115722	115722	115521	104233	66971
B. Within 25 Miles							
Post Change	0.0203	0.0295	-0.0251	0.00938	-1.054	-0.0396	-0.0193
	(0.0146)	(0.0163)	(0.0172)	(0.0111)	(2.080)	(0.0384)	(0.0420)
Y-mean	0.208	0.243	0.285	0.120	32.380	2.940	2.889
N	115515	115722	115722	115722	115521	104233	66971
C. Within 100 Miles							
Post Change	-0.00362	0.0222	-0.0118	0.00701	0.144	-0.0386	-0.0171
	(0.0126)	(0.0158)	(0.0118)	(0.00943)	(1.306)	(0.0317)	(0.0356)
Y-mean	0.182	0.351	0.256	0.117	31.456	2.857	2.784
N	115515	115722	115722	115722	115521	104233	66971

Notes. Panels shows estimates from regressions estimating 16 years prior and four year post the earliest year that other colleges in the specified geographic area changed admissions policy. Regressions control for calendar year, program, and program-specific linear time trends. Standard errors clustered at the program level. $*p < 0.05, **p < 0.01, ***p < 0.001$

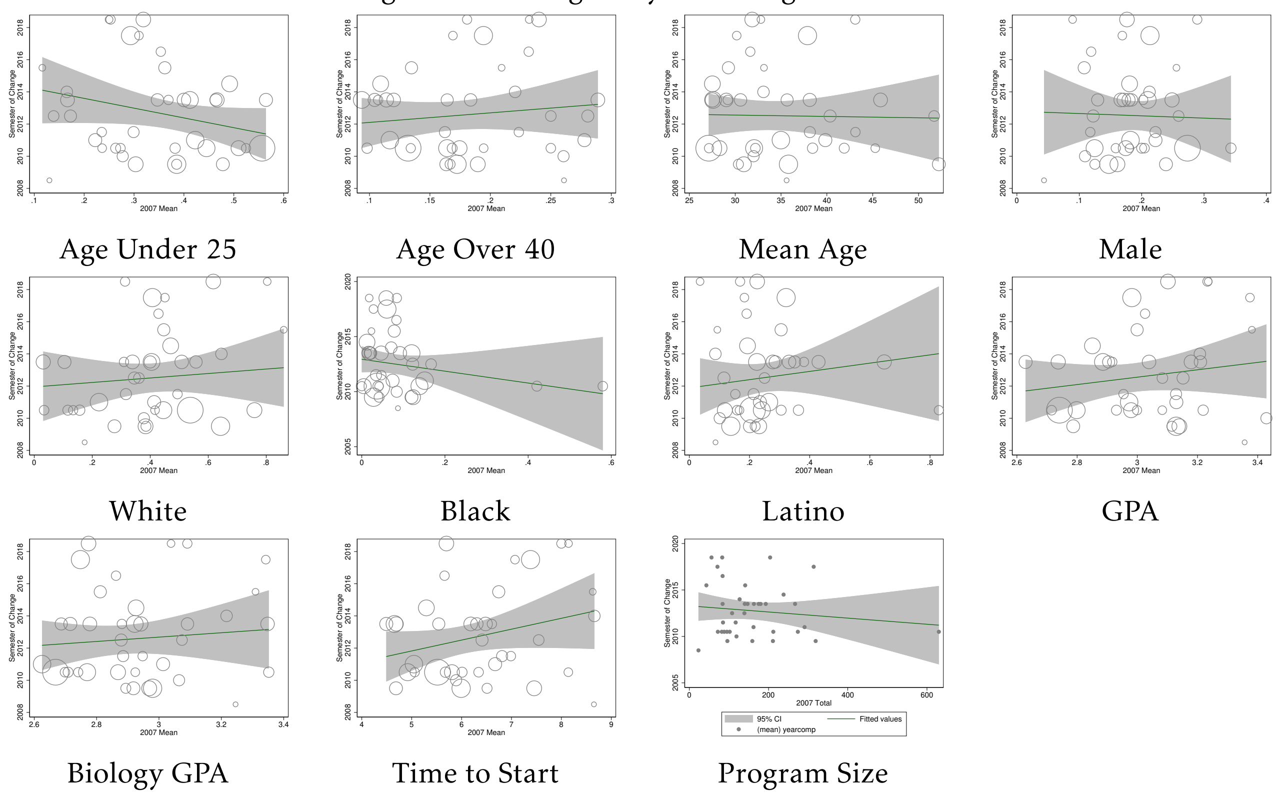
A1 Appendix Tables and Figures

Figure A1: CTE, Health, and ADN Completions Since 1993



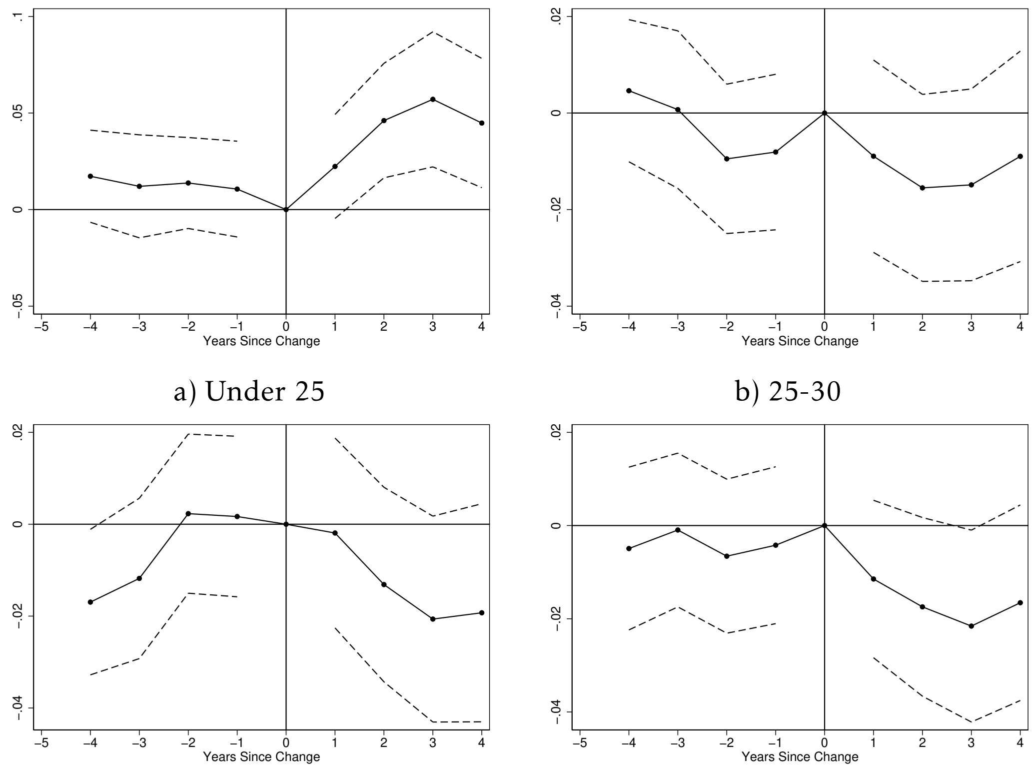
Notes. This figure shows the total number of associate degrees in career-technical education (CTE) programs since the 1992-1993 academic year; the number of associate degrees in all health programs; and the number of associate degrees in nursing (ADN).

Figure A2: Endogeneity of Timing



Notes. These figures show scatterplots of mean characteristics for each program in 2007 (horizontal axis) and year of implementing evaluative admission (vertical axis). The size of each bubble is proportional to the number of students in the 2007 cohorts. The figures also show a best fit line, weighted by the number of students, and associate 95 percent confidence interval.

Figure A3: Age Categories, Loaded Panel, College Fixed Effects and Trends



a) Under 25

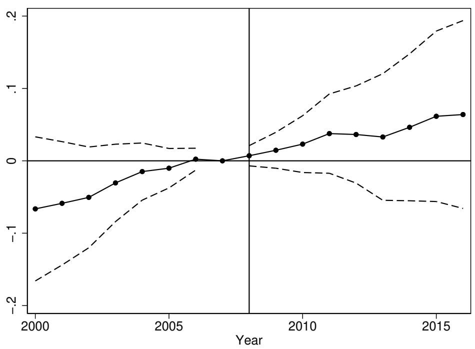
b) 25-30

c) 30-40

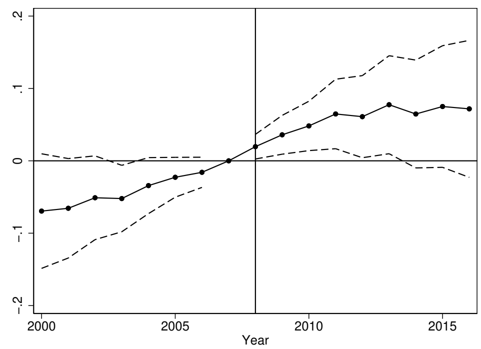
d) 40 and over

Notes. Figures show point estimates and 95 percent confidence intervals of results from regressions estimating 16 years prior and four year post change of admissions policy. Regressions control for calendar year, program, and program-specific linear time trends. Standard errors clustered at the program level.

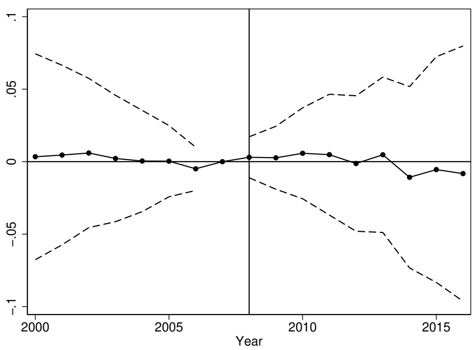
Figure A4: Cohort Characteristics at Colleges with Non-Evaluative Admissions



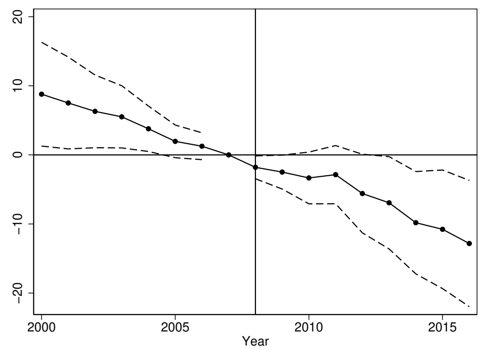
a) Male



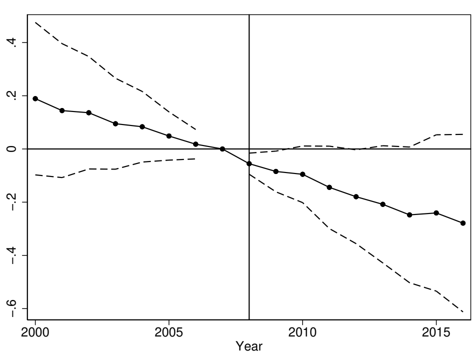
b) White



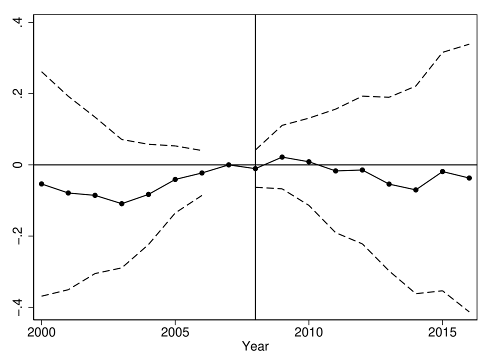
c) Latino



d) Age



e) GPA



f) Bio GPA

Notes. Figures show point estimates and 95 percent confidence intervals of results from regressions estimating 16 years prior and four year post change of admissions policy. Regressions control for calendar year, program, and program-specific linear time trends. Standard errors clustered at the program level.

Table A1: Test for Endogeneity of Timing

	(1) Unweighted	(2) Weighted
Male	0.250	-0.459
	(1.880)	(1.742)
White	0.545	0.811
	(0.888)	(0.905)
Black	-0.648	2.091
	(2.336)	(2.332)
Hispanic	-0.868	-1.402
	(1.001)	(1.056)
Age	-0.00359***	-0.00348***
	(0.000551)	(0.000590)
GPA	1.268*	1.381*
	(0.468)	(0.528)
GPA in Math	0.447	0.590
	(0.355)	(0.371)
GPA in Biology	0.488	-0.398
	(0.958)	(0.924)
Units Attempted	-0.00864	-0.0122
	(0.0128)	(0.0143)
Basic Skills Courses	0.225	0.759
	(1.038)	(1.028)
Time to Enrollment	-0.0213	0.0344
	(0.140)	(0.170)
Any Degree, 3 Years	-0.171	-0.369
	(0.993)	(1.093)
Any Nursing Degree, 3 Years	0.355	0.297
	(0.931)	(0.946)
Unemployment Rate	-2.679	5.635
	(15.73)	(22.56)
UI Benefits (log)	-0.978*	-0.689
	(0.376)	(0.504)

Notes. Each cell shows results from a regression of year of adoption of evaluative measures on college mean characteristics in 2007, the year prior to the policy change. Column 1 does not weight, while Column 2 weights by the size of the incoming cohort. Standard errors clustered at the program level. $*p < 0.05, **p < 0.01, ***p < 0.001$

Table A2: Main Results, Age Detail

	(1) Under 25	(2) 25-29	(3) 30-39	(4) Over 40
A. Event Study				
Event Year +1	0.0197	-0.00957	-0.000822	-0.00930
	(0.0133)	(0.00992)	(0.0102)	(0.00836)
Event Year +2	0.0445**	-0.0163	-0.0124	-0.0158
	(0.0147)	(0.00961)	(0.0105)	(0.00951)
Event Year +3	0.0574***	-0.0162	-0.0205	-0.0207*
	(0.0174)	(0.00989)	(0.0111)	(0.0102)
Event Year +4	0.0464**	-0.0107	-0.0196	-0.0161
	(0.0166)	(0.0108)	(0.0118)	(0.0104)
F-test: pre-years	0.531	0.830	1.240	1.037
p-value: pre-years	0.870	0.600	0.260	0.409
F-test: post-years	3.782	0.939	1.340	1.153
p-value: post-years	0.004	0.440	0.252	0.330
B. Differences in Differences				
Post Change	0.0363**	-0.0128	-0.00995	-0.0135
	(0.0117)	(0.00778)	(0.00852)	(0.00780)
Y-Mean	0.375	0.223	0.246	0.157
N	254002	254002	254002	254002

Notes. Both panels shows estimates from regressions estimating 16 years prior and four year post change of admissions policy. Regressions control for calendar year, program, and program-specific linear time trends. Panel A estimates each post-event change separately, while Panel B constrains all post-event coefficients to be equivalent. The F-tests are a test that all the pre-event or post-event coefficients are jointly zero. Standard errors clustered at the program level.
$*p < 0.05, **p < 0.01, ***p < 0.001$

Table A3: Student Background Characteristics and Eventual Degree Attainment, pre-2008 Cohorts

	(1)	(2)	(3)	(4)	(5)	(6)
	Complete ADN Program			Complete Any Degree		
Male	-0.0558***	-0.0438***	-0.0430***	-0.0469***	-0.0403***	-0.0398***
	(0.00965)	(0.00841)	(0.00839)	(0.00659)	(0.00511)	(0.00515)
White	0.0918***	0.0560***	0.0548***	0.0652***	0.0390***	0.0382***
	(0.0180)	(0.00834)	(0.00851)	(0.0117)	(0.00607)	(0.00625)
Black	-0.0226	-0.00488	-0.00375	-0.00824	0.0239**	0.0251**
	(0.0241)	(0.00970)	(0.00906)	(0.0136)	(0.00852)	(0.00841)
Hispanic	0.0477**	0.0147*	0.0149*	0.0372**	0.0232***	0.0240***
	(0.0152)	(0.00621)	(0.00626)	(0.0111)	(0.00670)	(0.00663)
Age	-0.000365	-0.00308***	-0.00320***	0.0000240	-0.00157***	-0.00160***
	(0.000890)	(0.000657)	(0.000662)	(0.000606)	(0.000453)	(0.000454)
GPA	0.0966***	0.0909***	0.0912***	0.163***	0.167***	0.165***
	(0.0157)	(0.0116)	(0.0111)	(0.0118)	(0.00804)	(0.00784)
GPA in Math	0.0209***	0.00990**	0.00829**	0.00491	-0.00290	-0.00315
	(0.00558)	(0.00308)	(0.00277)	(0.00464)	(0.00264)	(0.00260)
GPA in Biology	0.0847***	0.0700***	0.0689***	0.0389***	0.0287***	0.0290***
	(0.00916)	(0.00771)	(0.00722)	(0.00639)	(0.00543)	(0.00524)
Units Taken	0.00267***	0.00121***	0.00109***	0.00528***	0.00442***	0.00436***
	(0.000251)	(0.000170)	(0.000157)	(0.000244)	(0.000221)	(0.000218)
Basic Skills Courses	-0.0470**	-0.0409***	-0.0413***	-0.0354**	-0.0309***	-0.0333***
	(0.0155)	(0.00610)	(0.00622)	(0.0107)	(0.00437)	(0.00441)
Time to Enrollment	0.00624**	0.00545***	0.00522***	0.00272	0.00265*	0.00251*
	(0.00185)	(0.00121)	(0.00114)	(0.00137)	(0.00107)	(0.00107)
N	62423	62423	62423	62423	62423	62423
Y-Mean	0.401	0.401	0.401	0.643	0.643	0.643
R-Squared	0.126	0.295	0.316	0.183	0.254	0.261
Cohort FE	X	X	X	X	X	X
College FE		X	X		X	X
College Trends			X			X

Notes. Table shows results of OLS regressions of student characteristics on completion of an ADN or of any community college program. Regressions also control for the square of age. Standard errors clustered at the program level.
$*p < 0.05, **p < 0.01, ***p < 0.001$

Table A4: Specification Checks: Academic Background

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Unbalanced Panel, Ends Loaded				Balanced	All Data
A. GPA							
Post Change	0.126***	0.140***	0.113***	0.117***	0.0231	0.00134	0.0254
	(0.0157)	(0.0126)	(0.0175)	(0.0217)	(0.0219)	(0.0269)	(0.0221)
F-test: pre-years	4.096	6.576	1.371	5.503	0.485	1.214	0.424
p-value: pre-years	0.000	0.000	0.187	0.000	0.901	0.277	0.936
Y-Mean	3.006	3.006	3.006	3.006	3.006	2.989	3.006
N	232372	232372	232372	232372	232372	60984	232372
C. Math GPA							
Post Change	0.0336	0.0653***	0.0905***	0.132***	0.0424	0.0662*	0.0558*
	(0.0185)	(0.0148)	(0.0202)	(0.0264)	(0.0270)	(0.0325)	(0.0276)
F-test: pre-years	2.745	3.803	0.647	4.931	0.550	0.988	0.952
p-value: pre-years	0.002	0.000	0.774	0.000	0.855	0.452	0.484
Y-Mean	2.762	2.762	2.762	2.762	2.762	2.742	2.762
N	143125	143125	143125	143125	143125	41682	143125
C. Biology GPA							
Post Change	0.266***	0.290***	0.139***	0.216***	0.115***	0.0725*	0.114***
	(0.0188)	(0.0150)	(0.0196)	(0.0303)	(0.0284)	(0.0350)	(0.0294)
F-test: pre-years	10.88	17.38	1.970	12.26	1.665	1.190	1.437
p-value: pre-years	0.000	0.000	0.033	0.000	0.083	0.293	0.157
Y-Mean	2.958	2.958	2.958	2.958	2.958	2.958	2.958
N	158185	158185	158185	158185	158185	44931	158185
D. Units							
Post Change	0.420	-0.00825	-0.158	2.172***	-0.301	1.180	0.881
	(0.409)	(0.343)	(0.443)	(0.547)	(0.543)	(0.757)	(0.593)
F-test: pre-years	4.671	8.643	1.409	7.708	1.638	2.162	1.458
p-value: pre-years	0.000	0.000	0.169	0.000	0.090	0.018	0.150
F-test: post-years							
p-value: post-years							
Y-Mean	28.74	28.74	28.74	28.74	28.74	28.41	28.74
N	248267	248267	248267	248267	248267	44914	79815
E. Basic Skills							
Post Change	0.0810***	0.115***	-0.0236**	-0.154***	-0.0430***	-0.0224	-0.0325**
	(0.0117)	(0.00980)	(0.00885)	(0.0169)	(0.0110)	(0.0124)	(0.0111)
F-test: pre-years	12.36	19.66	0.440	6.289	0.463	1.585	1.191
p-value: pre-years	0.000	0.000	0.927	0.000	0.914	0.106	0.291
Y-Mean	0.490	0.490	0.490	0.490	0.490	0.491	0.490
N	254335	254335	254335	254335	254335	65053	254335
College FEs		X	X	X	X	X	X
Cohort FEs			X		X	X	X
College Trends				X	X	X	X

Notes. All panels shows estimates from regressions estimating 16 years prior and four year post change of admissions policy, on the listed outcome. The first five columns have the ends "loaded, where all available years of data are included, but only coefficients for the 16 years prior and four years afterwards are estimated. Column 6 includes data for only the 16 years prior and four years afterwards. Column 7 estimates coefficients for all years of data, and includes all years of available data. The F-tests are a test that all the pre-event or post-event coefficients are jointly zero. Standard errors clustered at the program level. $*p < 0.05, **p < 0.01, ***p < 0.001$

Table A5: Specification Checks: Demographics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Unbalanced Panel, Ends Loaded				Balanced	All Data
A. Gender							
Post Change	0.0299***	0.0381***	-0.00903	0.0147	0.00853	0.0168	0.0104
	(0.00625)	(0.00444)	(0.00563)	(0.00793)	(0.00836)	(0.0113)	(0.00854)
F-test: pre-years	2.311	3.036	2.610	1.815	0.729	0.771	0.493
p-value: pre-years	0.011	0.001	0.004	0.053	0.698	0.657	0.896
Y-Mean	0.196	0.196	0.196	0.196	0.196	0.196	0.196
N	253991	253991	253991	253991	253991	64975	253991
B. White							
Post Change	-0.133***	-0.145***	0.0307***	0.0534***	0.0299***	0.0447***	0.0313***
	(0.0139)	(0.00714)	(0.00746)	(0.00884)	(0.00875)	(0.0116)	(0.00873)
F-test: pre-years	7.942	38.15	1.217	4.657	1.236	1.946	1.283
p-value: pre-years	0.000	0.000	0.274	0.000	0.262	0.036	0.234
Y-Mean	0.401	0.401	0.401	0.401	0.401	0.398	0.401
N	254335	254335	254335	254335	254335	65053	254335
C. Latino							
Post Change	0.131***	0.151***	-0.0156*	-0.00960	-0.0201*	-0.0109	-0.0137
	(0.0103)	(0.00657)	(0.00713)	(0.0102)	(0.00968)	(0.0124)	(0.00997)
F-test: pre-years	6.632	23.17	1.354	4.837	1.342	0.773	1.671
p-value: pre-years	0.000	0.000	0.196	0.000	0.201	0.655	0.082
Y-Mean	0.286	0.286	0.286	0.286	0.286	0.274	0.286
N	254335	254335	254335	254335	254335	65053	254335
D. Black							
Post Change	-0.0211**	-0.0362***	-0.0117**	-0.0199***	-0.00301	-0.0104	-0.00640
	(0.00664)	(0.00309)	(0.00432)	(0.00468)	(0.00510)	(0.00687)	(0.00514)
F-test: pre-years	0.773	6.256	1.271	3.147	1.016	1.963	1.125
p-value: pre-years	0.655	0.000	0.241	0.001	0.427	0.034	0.338
Y-Mean	0.0777	0.0777	0.0777	0.0777	0.0777	0.0891	0.0777
N	254335	254335	254335	254335	254335	65053	254335
E. Age							
Post Change	-1.441*	-0.806	2.451**	0.751	-1.029	-1.305	-0.792
	(0.614)	(0.620)	(0.838)	(1.091)	(1.110)	(1.319)	(1.036)
F-test: pre-years	0.723	1.244	2.267	2.054	1.594	1.043	1.497
p-value: pre-years	0.703	0.257	0.012	0.025	0.102	0.405	0.134
Y-Mean	33.68	33.68	33.68	33.68	33.68	33.36	33.68
N	254002	254002	254002	254002	254002	64995	254002
College FEs		X	X	X	X	X	X
Cohort FEs			X		X	X	X
College Trends				X	X	X	X

Notes. All panels shows estimates from regressions estimating 16 years prior and four year post change of admissions policy, on the listed outcome. The first five columns have the ends “loaded, where all available years of data are included, but only coefficients for the 16 years prior and four years afterwards are estimated. Column 6 includes data for only the 16 years prior and four years afterwards. Column 7 estimates coefficients for all years of data, and includes all years of available data. The F-tests are a test that all the pre-event or post-event coefficients are jointly zero. Standard errors clustered at the program level. $*p < 0.05, **p < 0.01, ***p < 0.001$

Table A6: Specification Checks: Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Unbalanced Panel, Ends Loaded					Balanced	All Data
A. Wait Time							
Post Change	4.473***	4.898***	-0.0539	-1.234***	-0.370**	-0.544**	-0.366*
	(0.132)	(0.130)	(0.100)	(0.142)	(0.133)	(0.175)	(0.143)
F-test: pre-years	77.42	124.6	1.103	4.911	1.278	11.46	1.166
p-value: pre-years	0.000	0.000	0.355	0.000	0.236	0.000	0.309
Y-Mean	7.015	7.015	7.015	7.015	7.015	6.500	7.015
N	254002	254002	254002	254002	254002	64995	254002
B. First-Year GPA							
Post Change	0.153***	0.151***	0.0351	0.0522	0.0295	-0.0696	0.00742
	(0.0234)	(0.0193)	(0.0254)	(0.0314)	(0.0337)	(0.0416)	(0.0340)
F-test: pre-years	1.802	3.357	2.104	1.806	1.491	4.315	1.858
p-value: pre-years	0.055	0.000	0.021	0.054	0.136	0.000	0.046
Y-Mean	3.055	3.055	3.055	3.055	3.055	3.012	3.055
N	183400	183400	183400	183400	183400	47763	183400
C. Any Degree							
Post Change	0.0502**	0.0614***	0.00430	0.0501*	-0.0204	-0.00572	-0.0162
	(0.0160)	(0.0125)	(0.0145)	(0.0202)	(0.0177)	(0.0194)	(0.0177)
F-test: pre-years	1.304	4.121	0.324	3.336	0.418	3.758	0.261
p-value: pre-years	0.222	0.000	0.975	0.000	0.939	0.000	0.989
Y-Mean	0.547	0.547	0.547	0.547	0.547	0.527	0.547
N	254335	254335	254335	254335	254335	65053	254335
D. Finish ADN							
Post Change	-0.0527**	-0.0205	0.0101	0.0418	-0.0228	0.00237	-0.00959
	(0.0192)	(0.0160)	(0.0171)	(0.0248)	(0.0214)	(0.0232)	(0.0214)
F-test: pre-years	0.724	3.096	0.986	3.295	0.404	1.879	0.597
p-value: pre-years	0.703	0.001	0.453	0.000	0.945	0.044	0.818
Y-Mean	0.351	0.351	0.351	0.351	0.351	0.336	0.351
N	254335	254335	254335	254335	254335	65053	254335
College FEs		X	X	X	X	X	X
Cohort FEs			X		X	X	X
College Trends				X	X	X	X

Notes. All panels shows estimates from regressions estimating 16 years prior and four year post change of admissions policy, on the listed outcome. The first five columns have the ends "loaded, where all available years of data are included, but only coefficients for the 16 years prior and four years afterwards are estimated. Column 6 includes data for only the 16 years prior and four years afterwards. Column 7 estimates coefficients for all years of data, and includes all years of available data. The F-tests are a test that all the pre-event or post-event coefficients are jointly zero. Standard errors clustered at the program level. $*p < 0.05, **p < 0.01, ***p < 0.001$

Table A7: Specification Checks: NCLEX-RN Pass Rates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Unbalanced Panel, Ends Loaded				Balanced	All Data
Post Change	0.0310*	0.00768	0.0149	-0.000904	-0.00741	0.0187	0.000236
	(0.0152)	(0.0115)	(0.0144)	(0.0116)	(0.0118)	(0.0206)	(0.0239)
F-test: pre-years	0.818	0.690	1.450	0.737	0.981	0.950	2.684
p-value: pre-years	0.578	0.680	0.212	0.642	0.458	0.490	0.022
Fe							
pe							
Y-Mean	0.879	0.879	0.879	0.879	0.879	0.910	0.879
N	556	556	556	556	556	219	350
College FEs		X	X	X	X	X	X
Cohort FEs			X		X	X	X
College Trends				X	X	X	X

Notes. All panels shows estimates from regressions estimating 16 years prior and four year post change of admissions policy, on the listed outcome. The first five columns have the ends "loaded, where all available years of data are included, but only coefficients for the 16 years prior and four years afterwards are estimated. Column 6 includes data for only the 16 years prior and four years afterwards. Column 7 estimates coefficients for all years of data, and includes all years of available data. The F-tests are a test that all the pre-event or post-event coefficients are jointly zero. Standard errors clustered at the program level. $*p < 0.05, **p < 0.01, ***p < 0.001$

Table A8: Main Results, Academic Background, by Previous Admissions Type

	GPA	Math GPA	Bio GPA	Units	Basic Skills
A. Waitlist					
Post Change	0.0576	0.156**	0.221***	-1.764	-0.0624**
	(0.0395)	(0.0545)	(0.0639)	(2.374)	(0.0220)
Y-Mean	2.985	2.759	2.835	65.117	0.490
N	38520	23674	26222	41878	41878
B. Lottery and FCFS					
Post Change	0.0543	0.0505	0.112**	-0.957	-0.0333*
	(0.0307)	(0.0374)	(0.0384)	(1.636)	(0.0145)
Y-Mean	3.030	2.782	2.976	61.276	0.454
N	105518	66832	73666	115451	115451

Notes. All panels shows estimates from regressions estimating 16 years prior and four year post change of admissions policy, on the listed outcome. Panel A consists of 12 programs that had waitlists prior to changing their admissions, while Panel B consists of 32 programs that had various types of lotteries and first-come-first-served regimes. Standard errors clustered at the program level. $*p < 0.05, **p < 0.01, ***p < 0.001$

Table A9: Main Results, Demographics, by Previous Admissions Type

	Male	White	Black	Latino	Mean Age
A. Waitlist					
Post Change	0.0241	0.0436*	-0.0150	0.00338	0.458
	(0.0176)	(0.0203)	(0.0123)	(0.0216)	(1.928)
Y-Mean	0.198	0.284	0.108	0.221	38.119
N	41878	41878	41878	41878	41842
B. Lottery and FCFS					
Post Change	0.00192	0.0148	-0.00263	-0.0164	-0.981
	(0.0133)	(0.0119)	(0.00549)	(0.0132)	(1.719)
Y-Mean	0.203	0.401	0.038	0.261	32.097
N	115451	115451	115451	115451	115325

Notes. All panels shows estimates from regressions estimating 16 years prior and four year post change of admissions policy, on the listed outcome. Panel A consists of 12 programs that had waitlists prior to changing their admissions, while Panel B consists of 32 programs that had various types of lotteries and first-come-first-served regimes. Standard errors clustered at the program level. $*p < 0.05, **p < 0.01, ***p < 0.001$

Table A10: Main Results, Outcomes, by Previous Admissions Type

	Wait Time	First-Year GPA	Any Degree	Finish ADN
A. Waitlist				
Post Change	-0.698*	-0.0990	0.0492	0.0273
	(0.292)	(0.0678)	(0.0301)	(0.0346)
Y-Mean	7.221	3.025	0.618	0.407
N	41842	29734	41878	41878
B. Lottery and FCFS				
Post Change	-0.147	0.0716	-0.0581*	-0.0407
	(0.168)	(0.0485)	(0.0260)	(0.0321)
Y-Mean	6.795	3.059	0.502	0.299
N	115325	85382	115451	115451

Notes. All panels shows estimates from regressions estimating 16 years prior and four year post change of admissions policy, on the listed outcome. Panel A consists of 12 programs that had waitlists prior to changing their admissions, while Panel B consists of 28 programs that had various types of lotteries and 4 programs that had first-come-first-served regimes. Standard errors clustered at the program level. $*p < 0.05, **p < 0.01, ***p < 0.001$