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The Returns to a Large Community College Program: Evidence from Admissions Lotteries[†]

By Michel Grosz*

This paper estimates the labor market returns to the associate's degree in nursing (ADN), which is one of the most popular community college programs. I use student-level academic and earnings records across two decades for all community college students in California. I leverage random variation from admissions lotteries to produce causal estimates of the effect of the ADN on earnings and employment at a single large ADN program. Enrolling in the program increases earnings by 44 percent and the probability of working in the health care industry by 19 percentage points. These estimates are similar to ones in models that do not use the lottery variation but do control for individual fixed effects and individual-specific linear time trends, which I also estimate in a wider set of institutions where lottery estimates are not possible. In light of concerns about nursing shortages, I estimate that the economic benefit of expanding an ADN program by one seat far outweighs the costs. (*JEL* D44, I11, I23, I26, J24, J31)

Community colleges have recently made a resurgence in debates about the future of public education. In 2015, for example, the Obama administration announced plans to make community college free for most students (Executive Office of the President 2015). There are a number of reasons for this increased attention. Community colleges are more accessible and affordable to students than four-year college, offering an alternative as post-secondary attainment lags behind demand for skilled workers (Goldin and Katz 2008; Cohen, Brawer, and Lombardi 2009). Community colleges also overwhelmingly enroll older, lower-income, and first-generation students, making them drivers of upward socioeconomic mobility (Belfield and Bailey 2011, Kane and Rouse 1999). Career technical programs,

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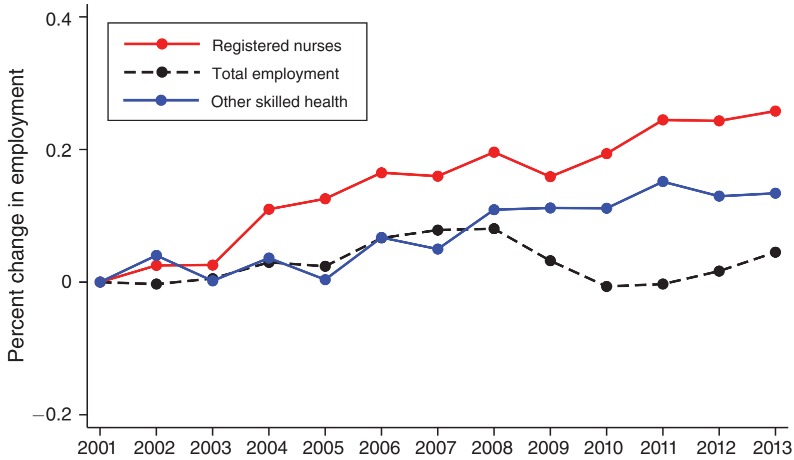

Figure 1. Employment Growth for Health care Occupations, 2001–2013

Notes: This graph shows employment growth relative to 2001 levels for health care occupations that require a sub-baccalaureate degree or certificate. Data come from the Occupational Employment Statistics. The category of other skilled health professions includes LPNs, radiologic technicians, dental hygienists, respiratory care therapists, and surgical technicians.

which represent half of community college enrollments, are especially important as the demand for skills in the labor force changes (Bailey et al. 2003, Acemoglu and Autor 2011).[1] In recent years, policymakers have focused additional attention on expanding career technical programs.

Career technical programs in health fields are of particular interest. As shown in Figure 1, the health care sector has seen rapid growth over the past two decades, with employment rising even during the Great Recession. Employment grew the most for health care workers with less than a bachelor's degree, who predominantly receive their training from community colleges (Van Noy et al. 2008; Ross, Svajlenka, and Williams 2014; Lockard and Wolf 2012). Health training programs are thus essential to provide workers the skills increasingly demanded in the labor market. Nevertheless, there is growing concern of shortages of skilled health care workers and of training programs not expanding their capacity to meet demand (Buerhaus et al. 2013). Given these concerns, it is crucial to quantify the role of existing programs in affecting the earnings and employment of students. Such evidence is limited, and to my knowledge, no study has yet used random variation to measure these effects.

In this paper I measure the labor market returns to enrolling in an associate's degree in nursing (ADN) program. I leverage the random lottery that assigns admission to a large ADN program in California and estimate causal effects of the program. Because of limited capacity and high demand from students, many colleges ration certain programs and courses through methods such as lotteries and wait lists (Gurantz 2015; Bohn, Reyes, and Johnson 2013; Bound and Turner 2007). This

[1] The terms "vocational" and "career technical" are largely interchangeable terms for programs and course work that train students for specific occupations.

paper is the first to use variation from admissions lotteries to study an existing community college program and one of very few in the context of higher education.

I rely on data that track community college students through their academic careers and into the labor market. I use detailed individual-level administrative records covering academic and earnings information for all students enrolled in California community colleges between 1992 and 2015. To these data I added information on the outcome of admissions lotteries to a large ADN program for cohorts since 2005. An important feature of this dataset is that I can track the academic and labor market trajectories of both admitted and rejected students before, during, and after they enroll in a community college.

This paper makes several contributions to the literature. First, I estimate the causal effect of an existing community college program on earnings and employment. The identifying variation comes from a random lottery, which is rare in studies of higher education though more common at other levels of education (Hanushek et al. 2007; Angrist, Pathak, and Walters 2013). There is a long history of experimental studies in the workforce development literature (Barnow and Smith 2016); however, few of these randomized demonstrations that study earnings are similar to existing career technical programs or even set within community colleges (Scrivener and Weiss 2013, Visher et al. 2012, Peck et al. 2018).

Second, I estimate two models of the returns to a program using the same sample. Recent estimates of the returns to community college programs leverage state administrative datasets, pooling the academic and earnings records of many thousands of students and using models that rely on pre-enrollment labor market experience and control for individual fixed effects. A key conclusion from this emerging literature is that the labor market returns to career technical programs, while generally positive, vary by subject and type of degree (Belfield and Bailey 2017; Stevens, Kurlaender, and Grosz 2019; Liu, Belfield, and Trimble 2015; Jepsen, Troske, and Coomes 2014; Cellini and Turner 2019). What remains unclear is how well the models typically used in these analyses, which exploit within-individual earnings changes, account for different types of bias. In this paper, I replicate the methods used in these studies and compare them to the results using the admissions lottery.

Third, I show that there is substantial heterogeneity in earnings effects even within a single degree and that this heterogeneity can be explained by regional economic opportunities and program characteristics. A growing literature documents variation in community college quality, measured by academic outcomes (Kurlaender, Carrell, and Jackson 2016; Calcagno et al. 2008; Clotfelter et al. 2013). Less is known about heterogeneity in labor market returns across colleges and especially within a particular field of study, especially at the sub-baccalaureate level (Cunha and Miller 2014, Dale and Krueger 2014).

I find that winning the admissions lottery substantially increases the likelihood that a student will enroll in and complete the ADN program relative to other applicants. There is also a positive effect on the chances that a student will complete any type of community college degree or certificate at any of the over 110 colleges in the state. This suggests that nursing applicants are on the margin of completing an ADN and no further post-secondary credential. This is especially striking since applicants must accumulate over half the certificates required for an associate's degree in order to even be eligible to apply for the ADN program.

Using the results of the lottery as an instrument for immediate enrollment, I find that the causal effect of enrolling in the lotteried program is a 44 percent increase in earnings 5 years after enrolling. This is a large effect, especially given standard estimates of the returns to a year of post-secondary education. I also find that students who immediately enrolled in the program were 19 percentage points more likely to work in the health care sector 5 years later. While I cannot explicitly attribute the large earnings effects to this employment effect, it is at least suggestive evidence that students gain by completing the program to enter careers as registered nurses. I also find that heterogeneity across programs is associated with local labor market opportunities in the health industry as well as program characteristics.

I also compare estimates from the randomized lottery to those that rely instead on individual fixed effects for identification. Results when using this alternative specification are broadly similar to those from the randomized lottery. Using the same sample of lottery applicants, the two methods yield almost identical results. While this similarity might be an artifact of the random selection of the lottery, I also show evidence that individual fixed effects estimates using samples of students at other California ADN programs account for bias in similar ways. This suggests that these types of models, used commonly in the literature, adequately account for selection bias and yield causal estimates of earnings effects.

I use the results of my analysis to inform recent policy discussions. In particular, as some commentators have written, colleges may not be adequately expanding their nursing program capacity to meet student interest and the rising demand for health care (Aiken, Cheung, and Olds 2009; Kavilanz 2018). I find that the private internal rate of return to enrolling ranges between 69 and 101 percent, and a lower bound on the social return is 17 percent. Nevertheless, because colleges in California and many other states are allocated funds based on overall enrollment, there is limited incentive for colleges to expand costly programs like nursing. Thus, an important policy implication of this study is that greater attention needs to be placed in developing strategies that make expansion more viable.

This paper proceeds as follows. Section I provides background on the institutional context. Section II describes the dataset and sample selection. Section III discusses the methodology for using the admissions lottery to estimate the effects of enrollment, and Section IV shows the results. Section V then compares the results using the lottery to results using individual fixed effects and also shows heterogeneity in these results across colleges in the state. Section VI translates the main estimates into internal rates of return and also incorporates information on the costs of program expansion, and Section VII concludes.

I. Background

In this paper, I focus on a program that awards an ADN, which is a requirement for work as a registered nurse (RN). As with most occupations in the health care sector, nursing is regulated by licensing boards and other regulatory institutions. The minimum requirement to become an RN is an ADN or bachelor's degree in nursing (BSN) from a program approved by a state licensing board. Graduates of these programs must also pass a national licensing exam, the National Council Licensure Examination (NCLEX-RN), that they may retake multiple times. There is some debate regarding whether aspiring RNs should pursue a two-year ADN or a four-year BSN, both of which are sufficient qualification for certification. There is little evidence, though, that BSNs do better in the labor market than ADNs (Auerbach, Buerhaus, and Staiger 2015).

My analysis is set in California, which has the largest system of community colleges in the country: 113 campuses and over 2.6 million students each year. By far the most popular career technical degree is in nursing: the state awarded 5,545 ADNs in 2013–2014, representing one in six vocational associate's degrees across 219 different fields.

Central College[2] is located in California's Central Valley, and its ADN program is among the largest in the state. The ADN program is highly structured and takes four semesters to complete.[3] Central College's ADN program has an admissions policy based on a random lottery. Of the 73 colleges in California that granted an ADN in 2014, 12 had admissions decided by a computerized lottery among eligible applicants, and an additional 12 had a lottery among students whose academic achievement surpassed a certain threshold. In order to become eligible for the Central College lottery, applicants must pass 36 units worth of college-level prerequisite courses, or slightly more than a full year's courseload.[4] One lottery is conducted each fall and spring semester, and results are posted online. If they are rejected, students may reapply to the next semester's lottery. Reapplication is easy: rejected applicants must simply click a button on the website within approximately a week of the result. Students who apply for a fifth consecutive time have a higher chance of admission, decided in a nonrandom process.

II. Data and Summary Statistics

A. *Data and Sample Construction*

I combine two sources of student-level administrative data for my analyses. The first consists of detailed statewide data that track all California community college students in their academic careers and the labor market. I use administrative records from the California Community College Chancellor's Office (CCCCO) for students enrolled over a two-decade time span, between 1992 and 2015. I observe term-level course work and grades for each student, academic outcomes such as the

[2] Anonymized for confidentiality reasons.

[3] Students take a set schedule of courses in a predetermined order consistent with standards set by the state's Board of Nursing. Students have access to academic and career support. Beginning in the first semester of the program, students gain hands-on experience, working under the supervision of nurses in nearby hospitals and clinics.

[4] These include nine courses in the fields of anatomy, physiology, chemistry, microbiology, and psychology. Some of the courses, such as intermediate algebra, also have prerequisites. The program prerequisites are determined by the state's accrediting body and vary little across colleges. Students may fulfill their prerequisites at another college, though most applicants take their prerequisites at Central College. It is difficult to determine when an applicant began the process of preparing to apply, but the median number of years between a student's first community college course and first lottery application is 5.5 years.

type and subject of each degree they earned or the four-year institution to which they transferred, financial aid information, and various demographic characteristics. The CCCCO matched these data to individual quarterly earnings and industry of employment information from the state's unemployment insurance system for 2000–2015.[5] The result is a dataset containing detailed information on each student's experience in the California Community College sytem as well as quarterly earnings and industry of employment before, during, and after their schooling.

I also use lottery data from Central College's ADN program for 4,726 applicants who applied in each lottery between spring 2005 and spring 2015. I can observe the semester and result of each lottery an applicant entered. I limit the sample to 1,919 applicants who first applied between spring 2005 (the first lottery in the data) and spring 2009 in order to have a consistent sample with which to observe long-run post-lottery outcomes. Since I have earnings records up to the last quarter of 2014, this yields 21 quarters of post-lottery earnings data for all applicants in the resulting sample and 20 quarters of pre-lottery earnings records. The lottery data include an applicant's name, gender, date of birth, and an internal identification number. Because the lottery is run at the college level, there is not a perfect match with the statewide academic data system. Instead, I match students in the lottery dataset to students in the statewide administrative dataset based on the few identifying characteristics that exist in both: the first three letters of their first and last name, their birth date, and their gender. I am able to match 1,730 of the 1,919 Central College ADN applicants to student records in the statewide data, for a match rate of 90 percent. A potential concern is that winning the lottery may affect a student's likelihood of being matched and thus of being in the analytic sample. However, because they must take so many prerequisites, few students are likely to have never enrolled in a community college class prior to applying. The difference in match rate between winning and losing applications is 1.1 percentage points with a p-value of 0.46. This suggests that lottery losers who never take any further community college class are matched based on community college enrollment prior to application. Online Appendix A.2 describes the matching process in more detail, as well as some additional checks.

In addition to the matched student-level dataset, I learned institutional details from visits to Central College, in which I interviewed administrators, attended an orientation presentation for incoming ADN students, and held a focus group with new students. I also gathered information on prerequisite course work, application requirements, admissions criteria, and graduation requirements directly from individual college websites and catalogs. This allows me to establish whether a student had taken prerequisites and whether they had enrolled in courses associated with the program.

[5] Approximately 93 percent of students in the college data are matched to earnings records. Students may be unobserved in the earnings records for several reasons apart from just a true lack of employment or earnings. The most likely other reasons for missing data include being self-employed over the period or having moved out of the state, never having earnings in California.

B. *Summary Statistics and Lottery Balance*

Column 1 of Table 1 shows summary statistics for all applicants in the analytic sample using characteristics determined before their first lottery. Applicants were 30 years old on average and predominantly female, which is common for most nursing programs. Most students received some form of financial aid, including a combination of tuition waivers, Pell Grants, state grants, and loans. Applicants had prior labor market attachment; 82 percent had ever been employed in the five years prior to applying. However, applicants were employed in low-paying jobs, with just an average of $4,740 per quarter. A large share, 40 percent, had previously worked in the health care industry, consistent with the idea that many applicants are nursing assistants, health aides, or licensed practical nurses looking to upgrade their skills. Online Appendix Table A1 shows that the student population of both Central College and its ADN program looks qualitatively similar to other colleges and ADN programs across the state.

Across the lotteries, 12 percent of applicants were admitted in each lottery, including 9 percent of first-time applicants. Column 2 of Table 1 shows the validity of the randomized lottery by reporting the difference in mean characteristics across admitted and rejected applicants within each lottery. These are coefficients of a regression of the baseline characteristic on an admissions dummy and lottery fixed effects. Since only students in their first through fourth lottery are among those chosen randomly, all fifth-lottery applications are excluded from the sample in this case. Winning applicants had slightly lower grade point averages (GPA) and were less likely to work in the food industry. However, overall the two groups look balanced, and there is no evidence of systematic selection across the two groups. The last column of Table 1 shows that the lottery is also balanced for first-time applicants. Online Appendix Table A2 provides further evidence of the randomization of the lottery and shows that an F-test of the joint significance of all the covariates has values of 0.706 ($p = 0.844$) for all lotteries and 0.594 ($p = 0.920$) for first-time lotteries.

III. Methods

I estimate the effect of enrolling in the ADN program on subsequent labor market outcomes. I assume the following relationship:

$$y_{ict} = \beta_0 + \beta_1 D_{ic} + X_i \beta_2 + \mu_c + \zeta_t + \varepsilon_{ict}, \tag{1}$$

where y_{ict} is the labor market outcome at time t for student i in application cohort c and D_{ic} is a dummy variable taking a value of one if the student enrolled as part of the cohort. Even controlling for observable student characteristics X_i and cohort fixed effects μ_c, the treatment is correlated with the error term, thus biasing estimates of β_1. I resolve this bias by exploiting the random variation produced by the admissions lotteries.

If students were only allowed to apply once, estimating the effect of the treatment on earnings would be straightforward. Admission through the lottery process

Table 1—Applicant Characteristics and Lottery Balance

		Admit-reject difference	
	Mean	All lotteries	First lottery
Female	0.786	0.0571	0.0788
		(0.0429)	(0.0762)
White	0.342	0.0412	−0.0186
		(0.0837)	(0.0936)
Hispanic	0.385	−0.00976	0.0481
		(0.0505)	(0.0558)
Asian	0.144	−0.0328	−0.0867
		(0.0459)	(0.0387)
Age	29.35	1.003	0.191
		(0.770)	(0.925)
GPA	2.793	−0.207	−0.214
		(0.0645)	(0.119)
Enrolled in other district	0.275	−0.0248	−0.0508
		(0.0616)	(0.0656)
Had Board of Governors (BOG) Waiver	0.540	−0.0294	−0.0192
		(0.0301)	(0.0361)
Had Pell Grant	0.327	−0.0494	−0.0568
		(0.0507)	(0.0620)
Cal Grant	0.139	0.00235	−0.0265
		(0.0276)	(0.0395)
Had loans	0.0540	−0.00168	−0.0231
		(0.0189)	(0.0190)
Employed > 1 quarter	0.818	−0.0416	0.0131
		(0.0354)	(0.0624)
Quarters employed	9.161	−0.352	0.353
		(0.508)	(0.693)
Employed > 8 quarters	0.626	−0.0322	0.0622
		(0.0436)	(0.0557)
Mean quarterly earnings	4,740.5	−65.66	282.3
		(629.5)	(1,019.8)
Industry is health	0.398	0.0577	0.115
		(0.0556)	(0.0615)
Industry is retail	0.198	0.0133	−0.00539
		(0.0332)	(0.0579)
Industry is administrative	0.104	−0.0152	0.00252
		(0.0258)	(0.0518)
Industry is education	0.0891	0.0108	0.00804
		(0.0257)	(0.0157)
Industry is food service	0.141	−0.0439	−0.0304
		(0.0244)	(0.0260)
Observations	1,730	4,082	1,730

Notes: The first column shows mean characteristics for applicants in the spring 2005 to spring 2009 Central College ADN lotteries, measured at term of first application. GPA measures grades in prerequisites prior to application. Enrollment at other district is defined as ever having taken a course at a community college outside Central College's district. BOG waiver is a full tuition waiver. Cal Grant is state-specific financial aid. Employment is defined as nonzero quarterly earnings. Quarters employed is defined as the number of quarters with nonzero earnings in the four years prior to application, with maximum 16. Mean quarterly earnings measured in four years prior to application. Employment by industry is defined by two-digit North American Industry Classification System (NAICS) industry codes: health is NAICS code 62; retail is NAICS codes 44 and 45; administrative is NAICS code 56; education is NAICS code 61; and food service is NAICS code 72. The second and third columns show results of regressing each characteristic on lottery admission and cohort fixed effects. The admission rate over all lotteries is 9.0 percent. The admission rate for applicants in their first lottery is 12.4 percent. The second column includes all applications that were decided by random lottery, including up to four lotteries per applicant. The final column only includes the first lottery a student entered. Standard errors are clustered at individual level.

is exogenous and also a strong predictor of enrollment, making it a valid instrument. However, the ability for losers to reapply necessitates a departure from this simple estimation strategy.

I estimate a first stage equation of the form

$$D_{ic} = \gamma_0 + \gamma_1 Admit_i + X_i \gamma_2 + \eta_c + e_{ic}, \tag{2}$$

where $Admit_i$ is the result of an applicant's first lottery. The coefficient γ_1 reflects the difference in enrollment among winning and losing compliers in their first lottery. The identifying assumption is that, conditional on X_i and η_c, the result of the first lottery is independent of e_{ic}. As shown earlier, admission seems random within lottery cohorts, supporting the identifying assumption.

The treatment D_{ic} is defined as enrollment in the cohort for which the applicant first applied. Thus, the coefficient γ_1 represents the fraction of compliers, for whom winning the first lottery leads to enrolling in the ADN program that semester. There are two main types of non-compliers. The first are students who are admitted but do not take up the offer.[6] The second consists of students who gain admission outside the lottery process, which is rare. I define the treatment narrowly as immediate attendance following a lottery win, as opposed to ever enrolling in the program. This is because first-time losers who ultimately enroll do so after a delay, either in a subsequent lottery or their fifth application. This means that the lottery affects earnings other than just through students enrolling in the program, which weakens the exclusion restriction. For completeness, I do show estimates of the effects of ever enrolling in online Appendix A.3; they essentially rescale the main effect by a smaller first stage, and thus yield larger estimates. This is similar to the approach taken by Ketel et al. (2016), who uses the result of an applicant's first lottery as an instrument for medical degree completion.

Panel A of Figure 2 shows quarterly mean earnings for first-time lottery winners and first-time lottery losers, net of age, year, and quarter effects. The panel is balanced: the same 1,730 students are represented at all points. The figure shows relatively flat earnings trajectories prior to application, with declines in the quarter immediately preceding application. The difference between the two curves represents the reduced form effect, which is large especially at later quarters. In fact, earnings for first-time lottery winners only begin to rapidly grow approximately 11 quarters after application, which corresponds to a few quarters after a student who enrolled in the program would be expected to have completed it. Panel B shows how the lottery affects the number of community college credits taken by applicants each quarter.

[6] In theory this would also include students who are admitted in their first lottery but take up the offer in a later cohort. Because students cannot defer admission, this is an empirically nonexistent group.

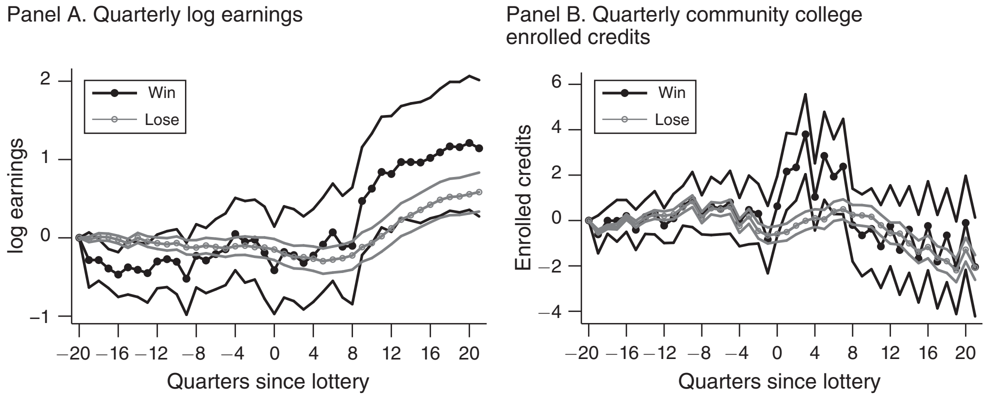

Figure 2. Earnings and Enrollment Trajectories, by First Lottery Result

Notes: The sample consists of 1,730 students who applied to Central College's ADN program between spring 2005 and spring 2009 separated by whether the student was admitted upon first lottery application. Point estimates come from a regression of log earnings or enrolled credits on dummies of quarter since first application (omitting quarter 20 prior to application), age dummies, and calendar time effects. Point estimates and 95 percent confidence interval shown, with standard errors clustered at individual level.

IV. Results

A. *First-Stage Results and Academic Outcomes*

Table 2 displays the effect of an applicant winning the first lottery on academic outcomes. The regressions control for cohort, demographics (age, gender, race), academic background (prior GPA, prior number of units), prior financial aid receipt (Pell Grants, tuition waivers), and labor market experience (mean prior earnings, any prior employment in health). Online Appendix Table A5 shows that these results are not sensitive to the inclusion of additional control variables, which is not surprising since the lottery is random.

On average, applicants submitted almost three applications; winning the first lottery reduces the number of applications by more than half that amount, or almost a year of waiting. Winning the first lottery increases the probability of enrolling in the Central College ADN program that semester by 0.49 percentage points. Few losing applicants enroll that semester, so the coefficient being lower than one is driven by admitted students choosing not to enroll. The result is highly statistically significant, with a large F-statistic. This is the first stage for the instrumental variables estimates of the effects on earnings. Because losing applicants can reapply and many are admitted on their fifth application, the effect of winning the first lottery on ever enrolling in the program is lower, only 20 percentage points. Approximately half of all applicants (46 percent) ever enroll in the program, though only 13 percent enroll after their first application.

There is also a strong first-stage effect on completing the ADN program. The Central College ADN lottery pushes students to complete an ADN at Central College, but it is not necessarily the case that it should have a strong effect on overall

Table 2—Effect of Lottery Result on Academic Outcomes

	Applications (1)	Enroll immediately (2)	Ever enroll (3)	Complete program (4)	Any health award (5)	Any award (6)	Transfer (7)
Win first lottery	−1.524	0.485	0.176	0.203	0.189	0.187	0.0326
	(0.0903)	(0.0676)	(0.0678)	(0.0741)	(0.0739)	(0.0735)	(0.0470)
F-statistic	285.2	51.42	6.716	7.473	6.569	6.469	0.480
Students	1,730	1,730	1,730	1,730	1,730	1,730	1,730
Y-mean	2.898	0.134	0.461	0.355	0.370	0.390	0.0936

Notes: Table shows estimates of the effect of a student being admitted to the Central College ADN on the first application. The sample consists of students who first applied between spring 2005 and spring 2009. Applications is the number of applications ever submitted. Enrolled immediately is enrollment in the Central College ADN program the following semester. Ever enrolled is ever having enrolled in the Central College ADN program. Complete program is earning an ADN from Central College. Any health award is earning any associate's degree or certificate in a health field from any California community college. Any award is earn any associate's degree or certificate in any field from any California community college. Transfer is whether the student ever later enrolled in a four-year college. Regressions control for calendar year, application cohort, demographics (age, gender, race), academic background (prior GPA, prior number of units), prior financial aid receipt (Pell Grants, tuition waivers), and prior labor market experience (mean prior earnings, any prior employment in health). Standard errors are clustered at the individual level.

community college completion. Losing the lottery might merely steer applicants away from nursing and into other health fields or even other non-health fields. In fact, by completing 36 units of prerequisites, ADN applicants are already more than halfway toward the typical requirement for an associate's degree. However, Table 2 shows that ADN admission has a strong effect on the receipt of any health-related degree or certificate at any California community college (column 5) as well as the receipt of any type of community college certificate or degree whatsoever (column 6).[7] Of course, lottery losers might instead decide to transfer to four-year colleges. If so, then the effect of the lottery on four-year college enrollment would be negative. Although I cannot observe four-year college completion, the final column of the table shows that the lottery has a slightly positive but not statistically significant effect on subsequent enrollment in four-year colleges. I cannot observe whether students enroll in for-profit colleges, which also offer programs in health. However, overall, these results support the idea that ADN program applicants are on the margin between pursuing an ADN and no further post-secondary credentials.

B. *Lottery Results for Labor Market Outcomes*

Panel A of Figure 3 shows quarter-by-quarter estimates of the effect of immediate enrollment on log earnings.[8] Online Appendix Table A3 shows the coefficients and standard errors of these results. Earnings effects in the first years following application—while enrolled students are still in school—are generally slightly positive but not statistically significant. However, starting in the tenth quarter after application

[7] Approximately a third of students (29 percent) who are never admitted to the program ultimately earn an ADN, presumably because they enroll at other colleges throughout the state. Only an additional 3 percent of these never-admitted students earn any type of degree or certificate.

[8] For log earnings regressions I impute $1 of earnings for students who have zero earnings. I show in a later section that results are robust to this imputation.

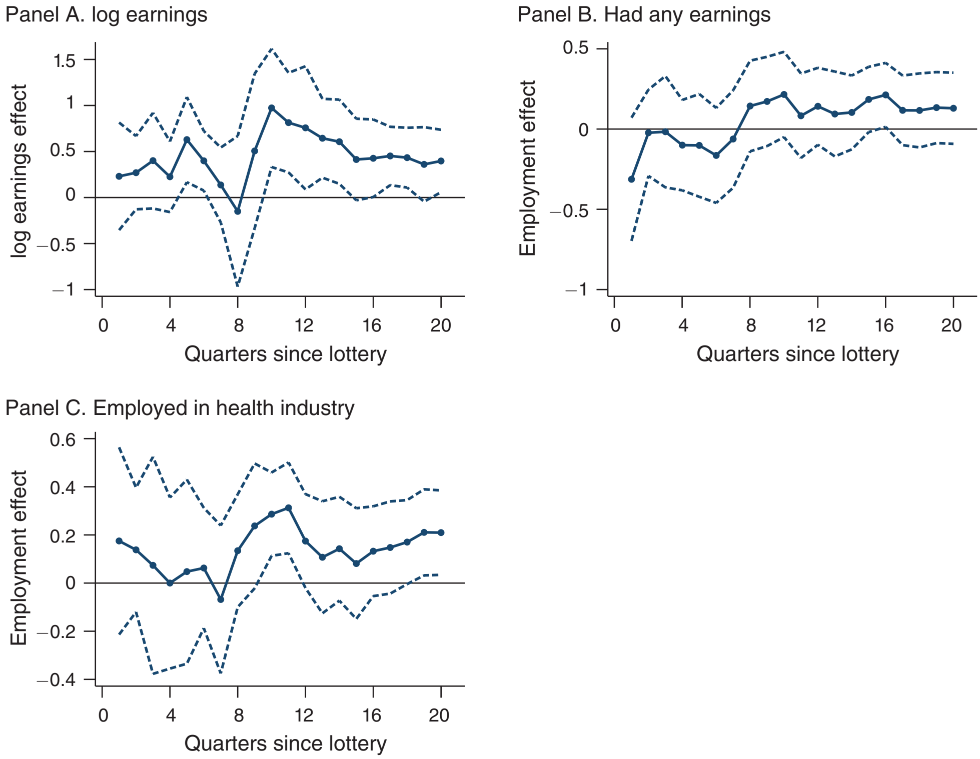

Figure 3. Instrumental Variables Estimates, Quarter-by-Quarter

Notes: This figure shows point estimate and the 95 percent confidence interval for instrumental variables estimates of immediate enrollment in Central College ADN program, instrumented with result of first lottery. Effects at each quarter come from a separate regression, with 1,730 students at each point. Outcomes are quarterly log earnings, having nonzero earnings, and employment in health professions. Employment in health is defined as employment in the two-digit NAICS industry code 62: health care and social assistance. Regressions control for calendar year, application cohort, demographics (age, gender, race), academic background (prior GPA, prior number of units), prior financial aid receipt (Pell Grants, tuition waivers), and prior labor market experience (mean prior earnings, any prior employment in health). Standard errors are clustered at the individual level.

the results become positive and statistically significant. The earnings effects stabilize at approximately 0.40 log points four years after application.

Because the estimates vary slightly quarter by quarter, Table 3 displays the main instrumental variables estimates for the eighteenth to twenty-first quarters after application, which are the last four quarters of earnings data I have available for all students. All the specifications control for calendar year and quarter effects, first application cohort, demographics, academic background, and prior financial aid receipt. For all these labor market outcomes, online Appendix Table A6 shows that the results are not sensitive to the incremental inclusion of individual controls. Column 1 of Table 3 shows that immediate enrollment following application leads to an earnings effect of 0.367 log points, or 44 percent.

As mentioned earlier, I do not instrument for degree completion, since doing so would assume that students who enroll in the program but do not complete it do not see any earnings impact. However, an estimate of the effect of completing an ADN

Table 3—IV Estimate of Effect of Enrollment on Labor Market Outcomes

		Earnings levels			Employment	
	log earnings (1)	All (2)	Winsorize (3)	Censor (4)	Any earnings (5)	Health industry (6)
Enroll	0.367	1,596.9	2,657.9	3,239.3	0.111	0.195
	(0.148)	(1,933.4)	(1,797.2)	(1,519.1)	(0.113)	(0.0848)
Observations	6,920	6,920	6,920	6,695	6,920	4,926
Students	1,730	1,730	1,730	1,706	1,730	1,316
Mean earnings	11,741.7	11,741.7	11,424.1	10,805.0	0.736	0.818
First stage F-stat	44.79	44.79	44.79	51.88	44.47	40.60

Notes: This table shows estimates of the effect of immediate enrollment in the Central College ADN program, instrumented with result of first application. The sample consists of students who first applied between spring 2005 and spring 2009. There are four quarters of data for each student, corresponding to quarters 18 through 21 following first application to the program. Winsorized earnings levels recoded quarters of earnings above $30,000, approximately the ninety-fifth percentile, as $30,000. Censored earnings levels drop these quarters of high earnings altogether. Health industry employment measures whether the individual had earnings in the two-digit NAICS code 62. Regressions control for calendar time, application cohort, demographics (age, gender, race), academic background (prior GPA, prior number of units), prior financial aid receipt (Pell Grants, tuition waivers), and prior labor market experience (mean prior earnings, any prior employment in health). Standard errors are clustered at the individual level.

on earnings is to scale the enrollment effect by the completion rate. The instrumental variables estimate of the effect of enrollment on completion is 0.498 (0.09), which implies that the completion effect is double the enrollment effect subject to this strong assumption.

The next three columns of Table 3 show the estimates for earnings levels in quarters 18 to 21 after application. The point estimate is an effect of $1,597 but is not statistically significant. One of the reasons for using log earnings is to avoid decreased precision due to outliers in quarterly earnings. Column 3 of Table 3 winsorizes quarterly earnings above the ninety-fifth percentile—approximately $30,000 in quarterly earnings—and column 4 drops these observations entirely. This leads to more precise estimates that are consistent with the log results.[9]

The large earnings effects may come from increased working hours or wages if the program provides students the skills and network connections to obtain stable employment in any occupation.[10] On the other hand, the program may steer graduates into high-paying jobs by conferring upon them the necessary credentials to enter registered nursing. The data I use do not contain information on occupation, wages, or work hours, so it is not possible to explicitly parse through these arguments. I draw some suggestive evidence, however, from detailed information on industry of employment.

Column 5 of Table 3 shows estimates of the effect of enrolling in the program on having nonzero earnings. The estimate suggests that enrolling in the program leads to an 11 percentage point increase in the likelihood of having nonzero quarterly

[9] I further test the sensitivity of the earnings levels results to winsorized and trimmed earnings data in online Appendix Table A7.

[10] In fact, nationwide, based on data in the 2014 American Community Survey, workers in the health care sector with an associate's or bachelor's degree were 20 percentage points more likely to work full time than health care workers without these credentials. Only 22 percent of workers employed as registered nurses worked part time.

earnings, but the coefficient is not statistically significant. Similarly, panel B of Figure 3 shows a quarterly effect on employment that is consistently positive but not statistically significant. Despite the fact that this result is not statistically significant, it is relatively large and economically meaningful.

The last column of Table 3, however, shows that there is a 19.5 percentage point effect of enrolling in the program on being employed in the health industry.[11] This is a large effect, especially since so many of the applicants had worked in the health industry prior to applying to the program.

These findings suggest that the large effects on earnings are mostly driven by earnings conditional on employment. That is, the program seems to lead to significant occupational sorting. This is evidence that the program drives participants to more lucrative occupations rather than increasing their likelihood of employment or improving their hours.

C. *Robustness Checks*

Table 4 shows a series of robustness checks for the main log earnings coefficient. Column 1 excludes students who enrolled in the program despite never winning a lottery. In conversations with program administrators I learned that these students are often military veterans or students with a special arrangement from a local hospital. In the main analyses I code these students as not winning the lottery. These students will be non-compliers because they are almost always admitted after their first application but do not win a lottery. Because they are a small enough group, however, excluding them from the analysis altogether does not significantly affect the estimates.

In the second column I limit the sample to students who had nonzero earnings prior to first application. This is similar to the set of students who will serve to identify the effects in the individual fixed effects specification in a later section. The estimated coefficient is similar to the preferred estimate.

One potential concern is that the cause of the large returns may be from students transferring to four-year colleges, making the ADN itself just an intermediary step. Column 3 excludes students who transferred to a four-year institution and still reveals a large and almost unchanged coefficient.

Column 4 excludes data points with missing earnings. In the specifications so far, I have taken the common practice of imputing \$1 where earnings are in fact zero. Taking these observations out of the analysis—that is, changing their earnings to \$0—has a negligible effect on the coefficient.

The last column of Table 4 is an attempt to investigate the mechanism by which the earnings effects accrue to students. I add controls for concurrent work in health, retail, administrative services, and education, which are the most popular industries for these students. Including these controls reduces the coefficient by 0.08 log points. While doing so is akin to conditioning on an outcome, this regression is at

[11] In the unemployment insurance earnings data, I can observe industry of employment, not occupation. I use the two-digit NAICS code 62 that indicates health care and social assistance. I express employment in health care not conditional on employment.

Table 4—IV Estimates: Robustness

	Excluding other admits (1)	Excluding no pre-earn (2)	Excluding transfer (3)	Excluding zeros (4)	Industry control (5)
Enroll	0.372	0.367	0.338	0.398	0.294
	(0.130)	(0.161)	(0.147)	(0.162)	(0.145)
Observations	6,060	6,164	6,532	5,109	6,920
Students	1,515	1,541	1,633	1,364	1,730

Notes: This table shows estimates of the effect of immediate enrollment in the Central College ADN program on log earnings, instrumented with result of first application. The sample consists of students who first applied between spring 2005 and spring 2009. There are four quarters of data for each student corresponding to quarters 18 through 21 following first application to the program. Column 1 omits students who were admitted to the program but not through the lottery (e.g. special programs for veterans). Column 2 omits students who had no quarters of nonzero earnings prior to first application. Column 3 omits students who ever transferred to a four-year institution at any time after the first lottery. Column 4 excludes all observations with zero earnings, which in the preferred estimates are coded as $1. Column 5 includes additional controls for concurrent industry of employment, measured at the two-digit NAICS code level. All regressions control for calendar time, application cohort, demographics (age, gender, race), academic background (prior GPA, prior number of units), prior financial aid receipt (Pell Grants, tuition waivers), and prior labor market experience (mean prior earnings, any prior employment in health). Standard errors are clustered at the individual level.

least suggestive evidence that the industry shift is not the sole driver of the large earnings effects.

Online Appendix A.2 discusses four additional specifications. In two specifications I leverage all the lottery information beyond just the first lottery. I also estimate the effects of ever enrolling in the ADN program. Finally, I combine the instrumental variables approach with a specification that includes individual fixed effects.

V. Individual Fixed Effects

A. *Method and Main Results*

The results so far suggest a large effect of the program on earnings. In this section I compare the estimates to individual fixed effects models, which Jacobson, LaLonde, and Sullivan (2005) notes can produce valid estimates when students have considerable pre-enrollment labor market experience. Recent work has applied this method at the community college level to estimate the returns to different career technical degree programs, credentials, and course work using state administrative datasets.

Because individual fixed effects models do not account for time-varying shocks that may affect individuals, there are lingering concerns about whether they produce causal estimates. Thus, I am in a unique position to investigate this issue by comparing the results to those from the Central College lottery.

I estimate a model of the form

$$y_{it} = \alpha_i + \gamma Enroll_{it} + \Phi Z_{it} + \mu_t + \xi_i \times t + u_{it}. \tag{3}$$

For student i in quarter t, $Enroll_{it}$ takes a value of one after enrolling in an ADN program. The matrix Z_{it} consists of time-varying individual characteristics, including

Table 5—Comparison of Lottery and Observational Estimates

	All Central College applicants			ADN program enrollers only		
	IV (1)	FE (2)	FE + trends (3)	Pre–post (4)	FE (5)	FE + trends (6)
Enroll	0.367	0.339	0.327	0.666	0.537	0.361
	(0.148)	(0.0351)	(0.0372)	(0.0397)	(0.0369)	(0.0372)
Observations	6,920	46,268	46,268	22,806	22,806	22,806
Students	1,730	1,595	1,595	754	754	754

Notes: Outcome is log earnings. The sample for the first three columns consists of students who first applied between spring 2005 and spring 2009. Column 1 shows estimates of the effect of immediate enrollment in the Central College ADN program instrumented with result of first application. There are four quarters of data for each student corresponding to quarters 18 through 21 following first application to the program. Regression controls for calendar time, application cohort, demographics (age, gender, race), academic background (prior GPA, prior number of units), prior financial aid receipt (Pell Grants, tuition waivers), and prior labor market experience (mean prior earnings, any prior employment in health). Column 2 shows estimates of equation (3); includes quarterly data 20 quarters prior and 21 quarters after enrollment; and controls for age dummies, concurrent community college enrollment, calendar time effects, and individual fixed effects. Column 3 repeats the column 2 specification and includes individual-specific linear time trends. Columns 4, 5, and 6 limit the sample to only students who enrolled in the Central College ADN program. Column 4 includes quarterly data 20 quarters prior and 21 quarters after enrollment and controls for demographics, academic background, financial aid receipt, age dummies, calendar time effects, and concurrent enrollment. Columns 5 and 6 add individual fixed effects and trends. Standard errors are clustered at the individual level.

dummies for age and whether the student was taking at least eight community college credits that quarter.[12] The individual fixed effect, α_i, accounts for time-invariant characteristics, so that the coefficient of interest, γ, is identified off within-individual changes in earnings. I also include calendar year and quarter fixed effects, μ_t. Individual-specific linear time trends $\xi_i \times t$ account for unobserved factors that may be correlated with enrollment and change at a constant rate over time.

Table 5 shows results of this exercise. The first column repeats the preferred lottery instrumental variables result. Columns 2 and 3 show estimates of equation (3) using the same sample of students.[13] I use data for each student from 20 quarters prior to their first application to 21 quarters afterward. Following the approach commonly used in the literature, I drop any quarters of earnings for students when they were under 18 years old. Column 3 adds individual-specific linear time trends. All three estimates—the instrumental variables and both with individual fixed effects—are quite similar in magnitude and statistically indistinguishable. Figure 4 shows estimates of equation (3), where γ is allowed to vary by quarter, and these coefficients are displayed in online Appendix Table A4.

The similarity between the instrumental variables and fixed effects estimates is perhaps not surprising since enrollment at Central College is driven in large part by the lottery process. In other words, if the lottery had perfect compliance, the lottery information would not be necessary to produce causal estimates; a simple comparison of earnings between enrollees and non-enrollees would suffice.

[12] In an online Appendix table, I show the main fixed effects results without controlling for concurrent enrollment, with almost identical results.

[13] One hundred and thirty-five students are dropped from the fixed effects estimates because they have zero earnings throughout the entire period and thus do not help identify the effect. As shown in the previous section though, the IV result is similar when dropping students with no pre-application earnings.

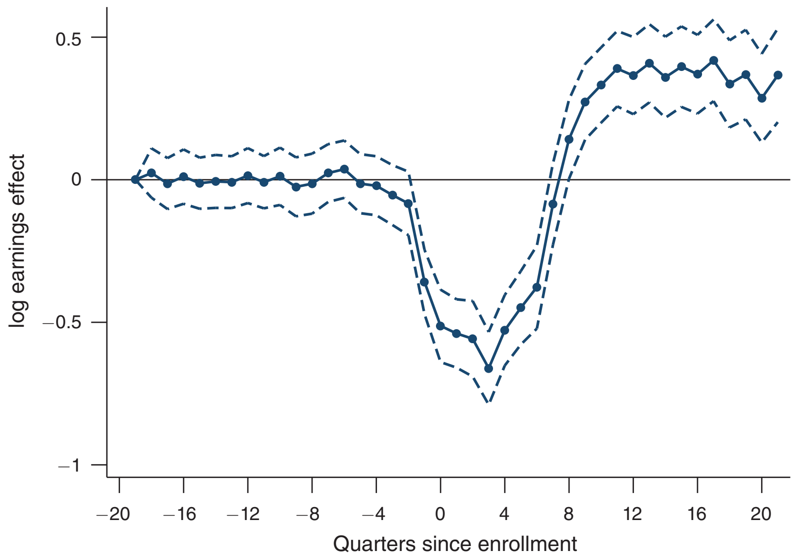

Figure 4. Quarterly Individual Fixed Effects Estimates, Central College

Notes: This figure shows point estimates and the 95 percent confidence interval for a single regression of log earnings effects at each quarter relative to enrollment at the Central College ADN program. The omitted category is quarter 20 prior to enrollment. The sample consists of 1,595 applicants to the Central College ADN program between spring 2005 and spring 2009. Regressions control for calendar time effects, age dummies, full-time community college enrollment, and individual fixed effects. Standard errors are clustered at the individual level.

In the next analyses, I benchmark the validity of the individual fixed effects approach in cases where admission is not based on a lottery. The challenge is that estimates that leverage random lotteries cannot be produced at colleges without lotteries. Instead I show that there is a pattern in the difference between fixed effects and OLS estimates that exists at Central College as well as other ADN programs in the state, including those that do not use lotteries for admissions.

First I limit the sample of Central College applicants to only those who ultimately enrolled in the Central College ADN program; the ability to identify applicants who never enroll is a unique feature of the Central College lottery data, and I do not have such information for other programs in the state. A sample limited to only students who enroll in the Central College program is sufficient, however, since the timing of the different enrolling cohorts helps identify the effects. Column 4 of Table 5 shows an estimate of equation (3) without controlling for individual fixed effects and trends. It is a naive estimate that merely compares earnings before and after enrollment, with added controls for time-invariant characteristics such as demographics, academic performance, and financial aid receipt. The estimate in column 5 adds individual fixed effects, and column 6 also adds trends. The difference in the coefficient between columns 4 and 6 shows the extent of the bias in the pre–post estimate. The specification with individual fixed effects and trends is also almost identical to the one in column 3. The results in columns 4 and 6 demonstrate two key points. First, the fixed effect estimate in a sample consisting only of enrolled students is similar to the lottery estimate in column 1. Second, the fixed effects estimate also accounts for a considerable amount of bias compared to pre–post regressions.

The point of benchmarking the pre–post and fixed effects estimates in Table 5 is to then estimate the effects at the other colleges that offer ADN programs and to comment on the adequacy of individual fixed effects models to estimate returns to community college programs in general. I have academic and earnings records but no application information for colleges other than Central College, so I can only observe who enrolls in nursing programs, not who applies. I construct the statewide sample in a parallel way as the Central College lottery sample: I limit the sample to students who started an ADN program at any California community college between the spring 2005 and spring 2009 cohorts. Again I use earnings data from 20 quarters prior to enrollment to 21 quarters after enrollment. Panel A of Table 6 shows estimates of equation 3, with and without individual fixed effects and trends, for Central College. A similar pattern exists as in the previous table: the estimates that do not control for individual fixed effects and trends are much larger than those that do.[14]

The other panels of the table help extrapolate this finding to other ADN programs beyond Central College. The key concerns are that the lottery and fixed effects estimates for Central College might be similar only because of the random variation from the lottery, and that patterns of selection into programs may differ across programs. The main challenge to addressing these concerns is that I cannot compare lottery and fixed effects estimates for colleges other than Central College. Panel B of Table 6 limits the sample to students at the 27 colleges where admission was decided by a random lottery.[15] There is a large drop in the coefficient when controlling for individual fixed effects and trends, which shows that patterns of selection are similar across colleges that use a lottery and the individual fixed effects models can account for this selection. Panel C limits the sample to students at all other colleges, where admission might be decided by a wait list or nonrandom selection process. There is, again, a similar drop in the coefficient when controlling for individual fixed effects. The similarity between panels B and C shows that individual fixed effects can account for selection even in programs without lotteries. While there is still the possibility that in non-lottery colleges the individual fixed effects models are still biased, the similarity across the two types of colleges suggests that the variation from the lottery is not the only reason that the lottery and fixed effects coefficients are similar in the Central College case. This suggests that models that control for individual fixed effects and trends to estimate returns are not only adequate in programs with lotteries but also programs without lotteries.

[14] The sample and estimates are different here than in previous analyses because I constructed the sample for this exercise in exactly the same manner as for other colleges. The sample in this table includes all ADN enrollees, not just those matched to the lottery data. It also includes students who may have first applied prior to 2005, while the lottery analyses limit the data to applicant cohorts since 2005. Nevertheless, the estimates for Central College in Tables 5 and 6 are quite similar.

[15] I categorized the admissions process of each of the programs that granted an ADN by reading about its policies in the course catalog and student handbook, available on program and college websites. Programs may change their admissions requirements across years, but I can only observe the policy for the years that college catalogs are available. I use the most recent year available. In recent years, more colleges in the state have moved toward admissions based on multiple screening criteria (Moltz 2010).

Table 6—Individual Fixed Effects Estimates at All California ADN Programs

	Pre–post (1)	Individual (2)	Fixed effects (3)
Panel A. Central College			
Start program	0.649	0.499	0.437
	(0.0305)	(0.0240)	(0.0221)
Observations	49,710	49,710	49,710
Students	1,535	1,535	1,535
Panel B. Colleges with lottery admissions			
Start program	0.342	0.173	0.107
	(0.0168)	(0.0123)	(0.0113)
Observations	234,096	234,096	234,096
Students	8,424	8,424	8,424
Panel C. Colleges with non-lottery admissions			
Start program	0.362	0.205	0.127
	(0.00835)	(0.00644)	(0.00570)
Observations	981,842	981,842	981,842
Students	36,292	36,292	36,292
Panel D. All colleges			
Start program	0.358	0.199	0.123
	(0.00748)	(0.00572)	(0.00509)
Observations	1,215,938	1,215,938	1,215,938
Students	44,716	44,716	44,716
Individual fixed effects		X	X
Individual-specific linear time trends			X

Notes: The sample consists of students who ever enrolled in an ADN program at any California community college between spring 2005 and spring 2009. Data include quarters between 20 quarters prior and 21 quarters after enrollment. Outcome is log earnings. Main coefficient is on a dummy variable with value of one after enrollment and zero otherwise. Column 1 controls for demographics, academic background, financial aid receipt, age dummies, calendar time effects, and concurrent enrollment. Column 2 adds individual fixed effects, and column 3 adds individual-specific linear time trends. Panel A is for students who ever enrolled in the Central College ADN program; panel B is for students who ever enrolled in an ADN program with lottery-based admissions; and Panel C is for students who ever enrolled in a program that did not have lottery-based admissions. Panel D includes all programs. Standard errors are clustered at the individual level.

Panel D shows the result across all ADN programs in the state. Across the three models, the estimates for Central College are much larger than for the state as a whole. A comparison in online Appendix Figure A1 shows that, while Central College and other California ADN students have similar earnings trajectories prior to enrollment, Central College students see a larger increase following enrollment. As I show below, however, there is a wide range of estimates across the 66 programs in the state, with Central College toward the top but not an outlier.

Figure 5 shows that the pattern between the pre–post and fixed effects estimates is apparent at almost all the colleges. Panel A of Figure 5 plots estimates of the return to enrollment in an ADN program from equation (3), calculated for each individual college, arranged in ascending order of the estimated coefficient. The dashed line gives the overall mean. The majority of estimates are large and positive, yet there is a considerable range. This is surprising, given that all ADN programs offer a similar curriculum, have similar prerequisites, and are overseen by a state board.

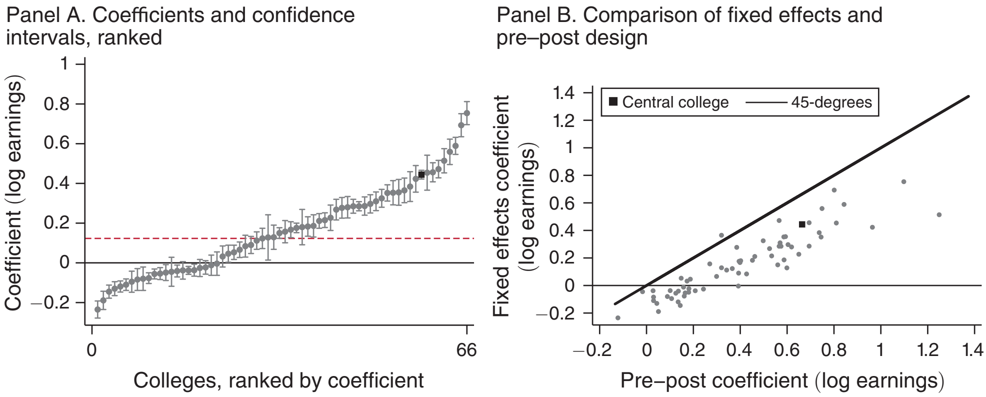

Figure 5. Individual Fixed Effects Returns, Heterogeneity by College

Notes: Panel A shows coefficients and 95 percent confidence intervals for college-specific regressions of log earnings on post-enrollment, controlling for individual fixed effects, individual-specific linear time trends, calendar year, age dummies, and concurrent full-time community college enrollment, clustering at the individual level. Sample consists of all students who enrolled in ADN programs at any community college in California between spring 2005 and spring 2009. Coefficients are shown in ascending order of point estimate. The dashed line shows the overall system-wide coefficient when aggregating all colleges together. Panel B shows the coefficients of the regressions from panel A on the vertical axis and the coefficient from an equivalent regression that does not control for individual fixed effects or trends on the horizontal axis. The black diagonal line is the 45-degree line. The large black square is the coefficient for Central College.

As mentioned earlier, the coefficient of 0.437 for Central College is larger than the average but not an outlier. Panel B of Figure 5 compares each college's coefficient controlling and not controlling for individual fixed effects and trends, with the Central College estimate highlighted as a larger black square. For all but one college the individual fixed effects coefficient is smaller, further providing support for the use of this approach.

B. *Heterogeneity in Individual Fixed Effects Results*

In this section I explore the heterogeneity across programs shown in Figure 5. In particular, I focus on characteristics of the program and of the surrounding labor market, defined as the college's county. Table 7 shows estimates of the difference in the coefficient from equation (3) when splitting the sample into groups based on demographic or college characteristics. In results not shown, I instead interact the main coefficient of interest with an indicator for membership in the particular group and find similar patterns of heterogeneity. It is important to note that the heterogeneity results presented here are correlational and meant to be exploratory, since selection into particular programs is likely not exogenous.

First, there may be differences in program quality. Quality is difficult to measure, especially since so many program inputs, such as curriculum and faculty-student ratios, are determined by the state board of nursing. The first row of panel A of Table 7 shows that students in programs that were above the median size, in terms of numbers of enrolled students, saw earnings increases 0.11 log points greater than students in small programs. The χ^2-statistic from a test of the equality of the two

TABLE 7—INDIVIDUAL FIXED EFFECTS, HETEROGENEITY

	Diff (1)	χ^2 (2)	p-value (3)	Students Group 1 (4)	Students Group 2 (5)
Panel A. Program characteristics (above median)					
Program size	0.11	110.83	0.00	27,034	17,682
Program completion rate	0.03	7.60	0.01	22,112	22,604
NCLEX first-time pass rate	−0.08	63.01	0.00	21,171	23,545
College's CTE share of awards	0.09	68.41	0.00	25,555	19,123
College's transfer rate	0.03	11.08	0.00	19,802	24,786
Panel B. County-level characteristics (above median)					
Number of hospital beds	0.09	72.51	0.00	24,911	19,677
Population share older than 60	−0.01	0.62	0.43	19,650	24,938
RN employment	0.03	8.81	0.00	21,941	22,775
Wage ratio of RN to medical assistant	0.07	33.64	0.00	13,352	31,364
Any other ADN programs	−0.05	15.7	0.00	33,856	10,732
Panel C. Admissions type					
Lottery	−0.02	2.57	0.11	8,424	36,292
Competitive	0.02	4.48	0.03	25,618	19,098
Wait list or first come, first served	−0.01	0.33	0.56	4,920	39,796
Panel D. Individual characteristics					
African American or Hispanic	−0.05	20.94	0.00	13,591	31,125
Older than 30	0.02	5.03	0.02	19,446	25,270
Female	0.04	8.18	0.00	34,870	8,409

Notes: The sample consists of students who ever enrolled in an ADN program at any California community college between spring 2005 and spring 2009. Data include quarters between 20 quarters prior and 21 quarters after enrollment. Outcome is log earnings. Each row shows the difference in the coefficient on enrollment from two separate regressions. Main coefficient is on a dummy variable with value of one after enrollment and zero otherwise. Column 1 shows the difference; columns 2 and 3 show the χ^2-test and associated p-value of the test of equality of the coefficients. Columns 4 and 5 show the number of students in groups one and two for the particular regression. In panel A, group one consists of students at colleges with above the median level of the listed attribute, and group two is below the median. Program size refers to the number of new students; program completion rate is the share of students who complete the program; NCLEX first-time pass rate is the share of students who pass the licensing exam on their first attempt; and college transfer rate comes from the CCCCO estimate of transfer velocity. In panel B, the groups are also high (group one) and low (group two) relative to the median. Information on hospital beds comes from the California Office of Statewide Health Planning and Development, 2014, and is expressed as a share of county population from the 2010 census. RN employment is the number of RNs as a share of total employment, and the wage ratio also comes from the 2010 census. The number of other ADN programs refers to whether the particular program was the only ADN community college program in the county. For panel C, lottery programs (27 programs) had randomization in their admission process. Competitive programs (43 programs) had admission based on student characteristics including but not limited to coursework, work experience, references, and essays. The rest of the colleges (nine programs) had wait lists or first-come, first-served lottery systems. For panel D, age is measured at first date of enrollment. Standard errors are clustered at the individual level.

coefficients is highly statistically significant. Similarly, students in programs with high completion rates also saw larger returns. Perhaps puzzlingly, students in programs that had high first-time pass rates on the NCLEX-RN, the national licensing exam, saw significantly lower earnings returns. However, this test is perhaps not a good indicator of program quality: first-time pass rates were high across almost all colleges, with more than 80 percent of colleges having pass rates above 80 percent. Following Gill and Leigh (2004), I also examine differences in earnings estimates across different types of colleges. Students at colleges that had an above-median share of their programs in career technical fields saw substantially larger earnings effects than other students. This is perhaps because these types of colleges are able to specialize in their connections with local labor market opportunities or because they might have better non-instructional supports for CTE students. Students at colleges with high transfer rates, as defined by the CCCCO, had slightly larger earnings increases.

Heterogeneity in earnings returns might also be due to differences in local conditions in the labor market for registered nurses. As a measure of the density of job opportunities for nurses, I compiled data from the California Office of Statewide Health Planning and Development on the capacity of hospitals in the state. Students in counties with a higher density of hospital beds per capita had earnings returns that were approximately 9 percent higher than other students. As another rough estimate of demand for health care, I categorized counties by median share of the population age 60 and over in the 2000 census. This measure was not correlated with the earnings return. Another important aspect of local labor markets that might affect the returns to an ADN are the employment prospects of workers who typically enter nursing programs, as well as the employment and earnings of other nurses. I created measures of the employment level and earnings of nurse assistants, medical assistants, and registered nurses relative to overall employment and earnings. Students in counties where medical assistants made lower wages relative to nurses saw higher returns. Students at colleges that were not the only nursing programs in the county saw substantially lower returns than students at college that were the only community college ADN program in the county.

Another key policy-relevant institutional characteristic is admission type. A common refrain when talking to ADN program administrators is that the lottery system does not allow them to admit the most qualified students. There were 12 programs whose policies featured a lottery among all eligible applicants, like at Central College. There were 40 "competitive" programs at which admission decisions were based in part on the applicant's qualifications. In an additional nine programs admission was based on a wait list or first come, first served.[16] Students in programs with lotteries saw earnings returns that were slightly lower than students in competitive and wait list programs, while students in competitive programs saw slightly larger earnings effects.

Panel D shows differences in the estimated returns by certain individual demographic characteristics. African American and Hispanic/Latino students have an earnings estimate 0.05 log points lower than other students. Estimates for women and older students are also slightly larger and statistically significant.

VI. Private and Social Returns to ADN Program Expansion

With ADN programs oversubscribed and a growing demand for health care workers, a crucial question is whether it is cost effective to increase capacity to ADN programs. In this section I calculate the internal rate of return (IRR) implied by the

[16] In the wait list setup, students add their names to the list whenever they complete their application requirements, and incoming cohorts are admitted from the top of the list. In the first-come-first-served setup, applications are only accepted in a narrow time window each semester, and spots are filled in the order the applications arrive.

estimates. I assume no general equilibrium effects, which would likely decrease the estimated return.

I calculate the IRR using both the quarterly lottery estimates from online Appendix Table A3 and comparable quarterly fixed effects estimates for all Central College applicants from online Appendix Table A4. I assume a 30 year career after enrollment. Because I only estimate effects up to 21 quarters (5.25 years) after application, I assume that the earnings effect stabilizes at the average of the final four quarters of estimated effects.[17] I convert the log earnings effect into a dollar amount by using the mean pre-application quarterly earnings of \$4,740. An important component of the IRR is the earnings growth rate of the comparison group. Empirically, I find that earnings of students who do not enroll in the program rise rapidly in the first few years and then level off, with overall growth rates of between 2 and 5 percent. In Table 8 I give a range of estimates of the IRR for assumed comparison group earnings growth rates of 0, 3, and 10 percent. Another important factor for the private return to enrollment is whether the student pays tuition. The program costs \$2,100 over six calendar year quarters, but approximately half of students have their tuition waived. I present estimates of the IRR for students who pay full tuition and students who do not. I assume that all students incur an up-front cost of \$5,700 in supplies, immunizations, and books, which is what the Central College catalog estimates.

The IRR estimates for the lottery estimates range from 69 to 101 percent, while those for the fixed effects specification are smaller. The difference between the estimates for lottery and fixed effects specifications is due in large part to the fixed effects estimates being negative in the early quarters after application. Nevertheless, all the IRR estimates are large, especially compared to standard estimates of the returns to a year of post-secondary education. I cannot measure non-earnings benefits, so these estimates are still likely a lower bound.[18]

An often cited reason for the lack of expansion of nursing programs is the prohibitive cost of adding a new seat. A reasonable empirical question, then, is to estimate the social return to expansion. There is no prior study to my knowledge that explicitly estimates expansion costs though. I compiled data from sources to separately estimate average variable and up-front capital costs. I obtained per-student operating costs from two nursing programs in the state that ranged from \$7,600 to \$9,200 per year per student. A similar estimate comes from a California legislature initiative that granted expansion funds from between \$6,500 and \$9,100 per new full-time equivalent student (CCCCO 2015, 2016). A conservative estimate, rounding up, is that variable costs are approximately \$10,000 per year per student. Much less information is available about capital, infrastructure, and equipment costs that a college would need to pay up front. Health care programs require specialized machinery and teaching equipment, and instruction often occurs in dedicated facilities. In the past

[17] Because the IRR is so large, changes in the assumptions about the earnings effects in later years and about career length have a negligible effect on the IRR. For example, assuming that the earnings effect decays by 20 percent each quarter after the twenty-first quarter only reduces the IRR by between 1 and 2 percentage points depending on the specification. Similarly, shortening or lengthening the assumed 30-year career length by 10 years has negligible effects.

[18] Online Appendix Table A9 repeats these calculations only over the time period I estimate, which is 21 quarters after application. The results are slightly smaller but still large.

Table 8—Internal Rate of Return Calculations for Central College

	No tuition waiver			Full tuition waiver		
	(1)	(2)	(3)	(4)	(5)	(6)
Control group earnings growth rate	None	3%	10%	None	3%	10%
Lottery instrument	69	72	84	84	91	101
Fixed effects	46	52	63	52	57	66

Notes: This table shows calculations of the internal rate of return, expressed as percentages. Lottery instruments use quarterly estimates from online Appendix Table A3, and fixed effects use estimates from onlineAppendix Table A4. Earnings benefits are the log estimate converted to a percent, multiplied by the counterfactual earnings mean. Counterfactual earnings in the first quarter are $4,740, and the columns of the table show whether there is 0, 3 percent, or 10 percent subsequent annual earnings growth. Earnings effects are calculated up to 30 years; log earnings effects after quarter 21 are assumed to remain consistent at the mean of quarters 18 to 21. The first three columns of the table show estimates where students are assumed to pay $350 in tuition each quarter for the first 6 quarters, while the second set of three columns assume the students have their tuition waived. All students are assumed to pay $5,700 up front in costs and supplies.

five years, two community colleges completed construction for new nursing buildings in California. Both projects cost approximately $8,000 per new student. In addition, I used one program's inventory list to estimate that teaching equipment, such as practice mannequins, costs $1,000 per additional student. Thus, the infrastructure and capital spending associated with adding an additional student is approximately $9,000.

To calculate a back-of-the-envelope estimate of the social return to program expansion, I include $9,000 in up-front costs and $10,000 in operating costs split over two years into the IRR calculations and omit tuition costs. The resulting social return ranges from 21 to 33 percent, depending on the specification and control group earnings growth rate. Not included in these calculations are the obvious spillover benefits to training new nurses and filling vacant positions. Dall et al. (2009) and Needleman et al. (2006) estimate that avoided adverse health outcomes and cost savings from an additional nurse are approximately $40,000 to $57,000. My estimates, while large, should thus be taken as a lower bound of the social return to expanding a nursing program.

Despite evidence that nursing programs are overwhelmingly cost effective, however, there are a number of reasons why colleges do not increase their capacity. In California, as in many other states, the incentive structure of college expenses and revenue is not aligned for expansion. Regardless of the program, colleges receive a set per-pupil allocation. At $4,900 in the most recent year, this per-pupil allocation is approximately half the cost of regular operating expenses for a nursing program. Colleges tend to recoup the costs of expensive programs by increasing enrollment in less costly programs or through external grants. Instead, capacity expansions have overwhelmingly occurred at the state level, if at all. Thus, it is perhaps not surprising that despite large earnings returns and concerns about nursing shortages, demand for seats in nursing programs still outpaces supply.

VII. Conclusion

In this paper I leverage the random assignment of admissions to a large community college ADN program to estimate the effect of enrollment on later earnings, thus providing one of the first estimates of the returns to a post-secondary degree using variation resembling an experiment. By taking advantage of a rich dataset describing the academic and labor market experiences of millions of students, I show that these estimates are consistent with methods that are more common in the literature.

I find large earnings effects and estimate that the value of expanding an ADN program far outweighs the costs. Despite the large economic benefit, there are limited incentives to community college administrators to expand enrollment. This is important in light of recent discussions and debates in the policy arena: my results suggest that state and federal efforts to address nursing shortages by expanding training programs are likely cost effective. It is also important in light of evidence that for-profit colleges do expand capacity in response to demand (Xia 2016). Potential solutions, adopted by many public institutions, include differential pricing or funding of programs, or performance-based funding schemes that allocate additional funds for increased graduation rates in certain costly fields (Stange 2015, Smith 2016, Long 2016).

My results also show that, for ADN applicants, the alternative to a degree in nursing seems to be no degree whatsoever. This is in line with growing work on differences in payoffs across college majors, where the differences may be driven in large part by selection into majors (Kirkeboen, Leuven, and Mogstad 2016). My findings suggest that selection into field of study can be highly specific and not necessarily driven by anticipated earnings returns. Rejected ADN applicants do not enter associate's degree programs in similar fields, such as dental hygiene or radiologic technology, even though these programs have similar starting wages, are less selective, and are often offered at the same college.

My findings also have implications for researchers using individual fixed effects models to estimate earnings returns to educational and training interventions. Starting with Jacobson, LaLonde, and Sullivan (2005), these methods have increasingly been used. This paper shows that these models produce estimates that are similar to those generated through a random lottery.

An open question is what the mechanism for the large earnings effects is. A large portion of this effect likely comes from restricting access to seats in programs. More generally, it is important to understand how community college career technical programs affect local labor supply. Recent work has explored inefficiencies from occupational licensing and credentialism (Kleiner 2016; Gittleman, Klee, and Kleiner 2015), but less is known about the effects of restricted educational supply on the local economy. On the other hand, part of the return is likely due to the highly structured nature of the program, which also has many nonacademic supports for students. A growing field of research has increasingly shown the benefits of a structured curriculum and nonacademic supports for community college students (Scott-Clayton 2015, Gardiner et al. 2017).

REFERENCES

Acemoglu, Daron, and David Autor. 2011. "Chapter 12—Skills, Tasks and Technologies: Implications for Employment and Earnings." In *Handbook of Labor Economics*, Vol. 4B, edited by David Card and Orley Ashenfelter, 1043–1171. Amsterdam: North-Holland.

Aiken, Linda H., Robyn B. Cheung, and Danielle M. Olds. 2009. "Education Policy Initiatives to Address the Nurse Shortage in the United States." *Health Affairs* 28 (4): w646–56.

Angrist, Joshua D., Parag A. Pathak, and Christopher R. Walters. 2013. "Explaining Charter School Effectiveness." *American Economic Journal: Applied Economics* 5 (4): 1–27.

Auerbach, David I., Peter I. Buerhaus, and Douglas O. Staiger. 2015. "Do Associate Degree Registered Nurses Fare Differently in the Nurse Labor Market Compared to Baccalaureate-Prepared RNs?" *Nursing Economics* 33 (1): 8–12.

Bailey, Thomas R., D. Timothy Leinbach, Marc Scott, Mariana Alfonso, Gregory S. Kienzl, and Benjamin Kennedy. 2003. *The Characteristics of Occupational Sub-baccalaureate Students Entering the New Millennium*. Washington, DC: National Assessment of Vocational Education, US Department of Education.

Barnow, Burt S., and Jeffrey Smith. 2016. "Employment and Training Programs." In *Economics of Means-Tested Transfer Programs*, Vol. 2, edited by Robert A. Moffitt, 127–234. Chicago: University of Chicago Press.

Belfield, Clive R., and Thomas Bailey. 2011. "The Benefits of Attending Community College: A Review of the Evidence." *Community College Review* 39 (1): 46–68.

Belfield, Clive, and Thomas Bailey. 2017. "The Labor Market Returns to Sub-baccalaureate College: A Review." https://ccrc.tc.columbia.edu/media/k2/attachments/labor-market-returns-sub-baccalaureate-college-review.pdf.

Bohn, Sarah, Belinda Reyes, and Hans Johnson. 2013. "The Impact of Budget Cuts on California's Community Colleges." http://www.ppic.org/content/pubs/report/R_313SBR.pdf.

Bound, John, and Sarah Turner. 2007. "Cohort Crowding: How Resources Affect Collegiate Attainment." *Journal of Public Economics* 91 (5–6): 877–99.

Buerhaus, Peter I., David I. Auerbach, Douglas O. Staiger, and Ulrike Muench. 2013. "Projections of the Long-Term Growth of the Registered Nurse Workforce: A Regional Analysis." *Nursing Economics* 31 (1): 13–17.

Calcagno, Juan Carlos, Thomas Bailey, Davis Jenkins, Gregory Kienzl, and Timothy Leinbach. 2008. "Community College Student Success: What Institutional Characteristics Make a Difference?" *Economics of Education Review* 27 (6): 632–45.

California Community College Chancellor's Office. 2015. *Nursing Educational Programs Report*. Sacramento: California Community College Chancellor's Office.

California Community College Chancellor's Office. 2016. *Nursing Educational Programs Report*. Sacramento: California Community College Chancellor's Office.

Cellini, Stephanie Riegg, and Nicholas Turner. 2019. "Gainfully Employed? Assessing the Employment and Earnings of For-Profit College Students Using Administrative Data." *Journal of Human Resources* 54 (2): 342–70.

Clotfelter, Charles T., Helen F. Ladd, Clara G. Muschkin, and Jacob L. Vigdor. 2013. "Success in Community College: Do Institutions Differ?" *Research in Higher Education* 54 (7): 805–24.

Cohen, Arthur M., Florence B. Brawer, and J.R. Lombardi. 2009. *The American Community College.* Hoboken, NJ: John Wiley and Sons.

Cunha, Jesse M., and Trey Miller. 2014. "Measuring Value-Added in Higher Education: Possibilities and Limitations in the Use of Administrative Data." *Economics of Education Review* 42: 64–77.

Dale, Stacy B., and Alan B. Krueger. 2014. "Estimating the Effects of College Characteristics over the Career Using Administrative Earnings Data." *Journal of Human Resources* 49 (2): 323–58.

Dall, Timothy M., Yaozhu J. Chen, Rita Furst Seifert, Peggy J. Maddox, and Paul F. Hogan. 2009. "The Economic Value of Professional Nursing." *Medical Care* 47 (1): 97–104.

Executive Office of the President. 2015. *America's College Promise: A Progress Report on Free Community College*. Washington, DC: Executive Office of the President.

Gardiner, Karen, Howard Rolston, David Fein, and Sung-Woo Cho. 2017. *Pima Community College Pathways to Health care Program: Implementation and Early Impact Report, OPRE Report 2017-10.* Washington, DC: Office of Planning, Research and Evaluation, Administration for Children and Families, US Department of Health and Human Services.

Gill, Andrew M., and Duane E. Leigh. 2004. *Evaluating Academic Programs in California's Community Colleges.* San Francisco: Public Policy Institute of California San Francisco, CA.

Gittleman, Maury, Mark A. Klee, and Morris M. Kleiner. 2015. "Analyzing the Labor Market Outcomes of Occupational Licensing." NBER Working Paper 20961.

Goldin, Claudia, and Lawrence F. Katz. 2008. *The Race between Education and Technology.* Cambridge, MA: Harvard University Press.

Gurantz, Oded. 2015. "Who Loses Out?: Registration Order, Course Availability, and Student Behaviors in Community College." *Journal of Higher Education* 86 (4): 524–63.

Hanushek, Eric A., John F. Kain, Steven G. Rivkin, and Gregory F. Branch. 2007. "Charter School Quality and Parental Decision Making with School Choice." *Journal of Public Economics* 91 (5–6): 823–48.

Jacobson, Louis, Robert LaLonde, and Daniel Sullivan. 2005. "Estimating the Returns to Community College Schooling for Displaced Workers." *Journal of Econometrics* 125 (1–2): 271–304

Jepsen, Christopher, Kenneth Troske, and Paul Coomes. 2014. "The Labor-Market Returns to Community College Degrees, Diplomas, and Certificates." *Journal of Labor Economics* 32 (1): 95–121.

Kane, Thomas J., and Cecilia Elena Rouse. 1999. "The Community College: Educating Students at the Margin between College and Work." *Journal of Economic Perspectives* 13 (1): 63–84.

Ketel, Nadine, Edwin Leuven, Hessel Oosterbeek, and Bas van der Klaauw. 2016. "The Returns to Medical School: Evidence from Admission Lotteries." *American Economic Journal: Applied Economics* 8 (2): 225–54.

Kirkeboen, Lars J., Edwin Leuven, and Magne Mogstad. 2016. "Field of Study, Earnings, and Self-Selection." *Quarterly Journal of Economics* 131 (3): 1057–1111.

Kleiner, Morris M. 2016. "Battling over Jobs: Occupational Licensing in Health Care." *American Economic Review* 106 (5): 165–70.

Kurlaender, Michal, Scott Carrell, and Jacob Jackson. 2016. "The Promises and Pitfalls of Measuring Community College Quality." *RSF: The Russell Sage Foundation Journal of the Social Sciences* 2 (1): 174–90.

Liu, Vivian Y.T., Clive R. Belfield, and Madeline J. Trimble. 2015. "The Medium-Term Labor Market Returns to Community College Awards: Evidence from North Carolina." *Economics of Education Review* 44: 42–55.

Lockard, C. Brett, and Michael G. Wolf. 2012. "Occupational Employment Projections to 2020." *Monthly Labor Review* (1): 84–108.

Long, Katherine. 2016. "New Funding Formula Will Mean Cuts at Some Community Colleges." *Seattle Times*, June 24. https://www.seattletimes.com/seattle-news/education/new-funding-formula-will-mean-cuts-at-some-community-colleges/.

Moltz, David. 2010. "Vying for Limited Slots." *Inside Higher Ed*, July 21. https://www.insidehighered.com/news/201%7/21/vying-limited-slots.

Needleman, Jack, Peter I. Buerhaus, Maureen Stewart, Katya Zelevinsky, and Soeren Mattke. 2006. "Nurse Staffing in Hospitals: Is There a Business Case for Quality?" *Health Affairs* 25 (1): 204–11.

Peck, Laura R., Alan Werner, Eleanor Harvill, Daniel Litwok, Shawn Moulton, Alyssa Rulf Fountain, and Gretchen Locke. 2018. *Health Profession Opportunity Grants* (*HPOG 1.0*) *Impact Study Interim Report: Program Implementation and Short-Term Impacts, OPRE Report 2018-16a*. Washington, DC: Research and Evaluation, Administration for Children and Families, US Department of Health and Human Services.

Ross, Martha, Nicole Svajlenka, and Jane R. Williams. 2014. *Part of the Solution: Pre-baccalaureate Health care Workers in a Time of Health System Change*. Washington, DC: Metropolitan Policy Program, Brookings Institution.

Scott-Clayton, Judith. 2015. "The Shapeless River: Does a Lack of Structure Inhibit Students' Progress at Community Colleges." In *Decision Making for Student Success: Behavioral Insights to Improve College Access and Persistence*, edited by Benjamin L. Castleman, Saul Schwartz, and Sandy Baum, Chapter 6. New York: Routledge.

Scrivener, Susan, and Michael J Weiss. 2013. *More Graduates: Two-Year Results from an Evaluation of Accelerated Study in Associate Programs* (*ASAP*) *for Developmental Education Students*. New York: Robin Hood Foundation.

Smith, Ashley A. 2016. "Funding Edge for Workforce Programs." *Inside Higher Ed*, July 6. https://www.insidehighered.com/news/2016/07/06/new-funding-approach-washington-incentivizes-workforce-programs-community-colleges.

Stange, Kevin. 2015. "Differential Pricing in Undergraduate Education: Effects on Degree Production by Field." *Journal of Policy Analysis and Management* 34 (1): 107–35.

Stevens, Ann Huff, Michal Kurlaender, and Michel Grosz. 2019. "Career Technical Education and Labor Market Outcomes: Evidence from California Community Colleges." *Journal of Human Resources* 54 (4): 986–1036.

Van Noy, Michelle, James Jacobs, Suzanne Korey, Thomas Bailey, and Katherine L. Hughes. 2008. *Noncredit Enrollment in Workforce Education: State Policies and Community College Practices*. Washington, DC: American Association of Community Colleges and Community College Research Center.

Visher, Mary G., Michael J. Weiss, Evan Weissman, Timothy Rudd, and Heather D. Wathington. 2012. *The Effects of Learning Communities for Students in Developmental Education: A Synthesis of Findings from Six Community Colleges*. New York: National Center for Postsecondary Research.

Xia, Xing. 2016. "What Explains the Rise of For-Profit Universities? Evidence from Dental Assistant Programs." Columbia University Job Market Paper 17207.