

The Effects of Structured Transfer Pathways in Community Colleges

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Most of the students who set out to earn degrees in community colleges never do. Interventions that simplify the complex organizational structures of these schools are promising solutions to this problem. This article is the first to provide rigorous evidence of the effects of structured transfer programs, one such intervention. Leveraging the phased rollout of transfer programs in California, I find large effects of the policy on degrees earned in treated departments. In the first 2 years, this growth was not coupled with growth in total degrees granted or in transfers, but in the third year, there is evidence of increased transfer. The analyses also show that the policy could affect equity; departments that offer transfer degrees became more popular and there is suggestive evidence that the highest achieving student groups enrolled in these classes at higher rates.

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Introduction

COMMUNITY colleges play an indispensable role in increasing and democratizing *access* to higher education. Their low rates of persistence, however, mean that they have not played a similar crucial role in increasing and democratizing *success and attainment* in higher education. Six years after first enrolling, two thirds of first-time community college students have not earned a credential or degree (National Center for Education Statistics [NCES], 2010, Table 2). These outcomes do not match students' educational goals when they start at a community college; more than 80% of first-time beginning community college students state that they aim to earn a bachelor's degree or above (NCES, 2011, Table 1-A).

These low rates of completion have obvious implications for both individuals and society. Individuals who have invested time and money in college but earn no degree do not accrue many of the labor market benefits associated with

college completion (Averett & Dalessandro, 2010; Belfield & Bailey, 2011; Jaeger & Page, 1996). Society also pays when completion rates are low. Taxpayers, who provide the majority of funding for community colleges, subsidize seats in classes for students who never earn the credentials needed to power the state's workforce, and students who do not complete degrees are much more likely to default on their student loans than students who graduate (Hillman, 2014).

Although there has recently been high-profile attention paid to college completion (notably in several of President Obama's State of the Union addresses) and concerns about educational attainment have led to increased scrutiny of and pressure on state systems and community colleges, focus on college persistence is not new. Colleges have long been concerned with low persistence rates and have searched for strategies to increase persistence and completion. One such effort, which is the focus of this article, is increased curricular structure and more well-defined pathways for students.

This study focuses on a piece of legislation in California that aimed to increase the efficiency in student transfer from community colleges to BA-granting public institutions and to increase the number of transfer-oriented students who earned associate degrees along the way. The legislation attempted to achieve this goal by smoothing the transition from California Community Colleges (CCCs) to the state's primary BA-granting schools by providing more programmatic structure and clearer information to students. The Student Transfer Achievement Reform Act (California Senate Bill [SB] 1440), passed in 2010, established Associate Degrees for Transfer (ADTs), a set of degrees that were to be jointly created by CCCs and California State Universities (CSUs). The degrees were composed of set coursework that was consistent across all CCCs and accepted by all CSUs in a range of majors. These degree agreements replaced previous unique bilateral campus-by-campus agreements. Students who earned an ADT were guaranteed admission to the CSU system, were admitted with junior standing, and were given priority consideration when applying to capacity-constrained programs.

I use a difference-in-differences-in-differences (DDD) framework to estimate the effect of the legislation on student and school behavior, leveraging the phased rollout of the program across departments, across campuses, over time. The legislation has had significant effects. The number of degrees granted in departments that offered ADTs increased notably; treated departments granted about seven more degrees per year, an increase of about 35%. The effects have increased over time. There is a marginally significant effect on the number of students who transfer from 2- to 4-year schools. These mixed effects seem to be indicative of multiple mechanisms through which the policy is affecting student behavior. It is partially a story of increased attainment; ADTs are inducing students to earn more associate degrees. It is also a story of student reshuffling; there is some evidence that students are moving from departments that do not offer ADTs to those that do. However, there is also suggestive evidence that the policy might have increased competition for seats in classes and that the policy could have negative effects on equity.

Background on Persistence and Transfer in Community Colleges

Curricular Structure in Community Colleges

Economic perspectives on educational persistence tend to focus on human capital theory and conclude that students will continue in higher education until the perceived costs exceed the discounted perceived long-term benefits (Becker, 1962; Turner, 2004). Costs can be defined quite broadly and can include direct economic costs associated with schooling, opportunity costs (foregone earnings), and psychic costs such as added stress or losses to quality of life. One source of psychic costs in community colleges is the time and stress associated with making repeated difficult choices. Students in community colleges face a string of complex decisions: which of the scores of potential credentials to pursue, how many courses to take at a time, which courses to take and in what order, which campus office to approach with what question, and so on.

The complexity and frequency of these decisions is often the direct result of schools' complex organizational structures, such as course schedules, awards offered, and mechanisms for sharing information (e.g., Bahr, 2013; Rosenbaum, Deil-Amen, & Person, 2006; Scott-Clayton, 2011; Scrivener & Weiss, 2013; Tinto, 1997).¹ Flexibility and choice are central to the identity of American community colleges, whose missions of democratization and access dictate that they serve students with an astoundingly wide variety of goals and preparation. Community colleges offer several potential outcomes (certificates, associate degrees, transferring to a 4-year school) in scores of disparate disciplines (from strictly vocational to purely academic).²

And as open-access institutions that aim to serve every student who could benefit from their services, community colleges are often loathe to direct all students toward any particular goal. Students are free to simultaneously explore certificates, associate degrees, and transfer pathways, and can take classes across a range of disciplines. Community colleges usually have relatively few required classes or core requirements. And while many schools have broad distributive requirements for particular degrees, most requirements can be fulfilled by a number

of classes. Core curricular pathways and common introductory classes are rare (Rosenbaum et al., 2006). In addition, because community college students typically are not required to declare an intended major or degree goal until they are ready to graduate, departments cannot track students in their programs to make sure that they are making progress (Jenkins & Cho, 2012). These decision environment features can increase the psychic costs associated with choosing a major or selecting courses, and these costs can grow over time.

Of all the outcomes available in community colleges, transferring to a 4-year school is arguably the most complex. It requires navigating at least two separate education systems: the academic system of the 2-year school and the transfer requirements of the 4-year school. With different course numbering systems and a separate set of courses needed to earn an associate degree and to meet transfer requirements at each 4-year school, this can be a complex task. Many community colleges have unique agreements with a number of 4-year schools, which means that a student transferring in a specific field from a specific community college would face a different set of transfer requirements at each 4-year school.

Student background characteristics, such as weak academic preparation, thin informational networks, and competing demands on time, can interact with these structural characteristics to compound the increased psychic costs associated with these complex decisions. Students often enroll part-time or discontinuously (often due to financial constraints and work obligations), which can reduce helpful social network effects, dampen positive peer effects, or limit opportunities to connect with services, faculty, and administrators. Similarly, community college students are less likely than their 4-year peers to have extensive information networks (Bailey, Jenkins, & Leinbach, 2005), which can make navigating complicated community college and transfer environments appear even more costly.

Humans are not decision-making machines. Evidence shows that people routinely exhibit bounded rationality—decisions we make are contingent on the available options and the decision framing—and that too many options can cause people to make bad decisions or even avoid

making a decision at all (Iyengar & Lepper, 2000; Simon, 1976). This abundance of options also reduces the likelihood that students will know other students following their same route, which can further increase the cost of collecting information.

Finally, arguably the most effective intervention to reduce the perceived psychic costs of complex decisions—individualized support from a knowledgeable adviser—is increasingly rare. Although studies have shown that proactive one-on-one advising can increase persistence and success, colleges typically offer little guidance to help students choose a program of study (Bettinger & Baker, 2014; Grubb, 2002). Counselor-to-student ratios of 1 to 1,000 are not rare in community colleges. In fact, one study found ratios of closer to 1 to 3,000 (Gallagher, 2014). Students often receive very little in the way of personalized guidance (Rosenbaum et al., 2006). When asked, students often report that they would like more guidance in selecting appropriate courses and that they are afraid they are making mistakes in choosing courses that lead to transfer (Moore & Shulock, 2014).

Interventions to Increase Persistence

There are a number of potential interventions, both at the institution and state level, that could improve persistence, graduation, and transfer rates by lowering perceived psychic costs by addressing structural concerns. Indeed, many of these interventions have been implemented and some have seen considerable success. Colleges could offer high-touch, proactive, one-on-one advising to students to create individualized course plans. Such an intervention could address informational barriers and provide students with a clear path to a goal and spell out course plans for each term (Karp, 2011). There is evidence that intrusive one-on-one advising can increase persistence and success (Bettinger & Baker, 2014). Mandatory orientations, career exploration workshops, or advising seminars could also serve to provide information and set norms (Derby & Smith, 2004; Zeidenberg, Jenkins, & Calgano, 2007). Schools, or outside vendors, could also leverage technology to help students navigate complex systems, such as degree requirements, financial aid, and transfer

pathways, and monitor progress (e.g., Bettinger & Baker, 2014; Bettinger, Long, Oreopoulos, & Sanbonmatsu, 2012). There is much promise in interventions aimed at increasing persistence by reducing the psychic costs associated with structural and informational barriers.

However, many such interventions are high cost or would require significant political will. State systems of higher education are facing increasing budget cuts that affect the number and kinds of support they can offer (Mitchell, Palacios, & Leachman, 2014). Transfer agreements and programs, on the contrary, are often relatively affordable, scalable, and politically feasible. Such policies, at the institutional or state level, aim to provide more structure and clearer information to students and can take many forms. Some state transfer agreements establish common general education requirements across all 4-year schools in a state—a student in a given community college who is planning on transferring will know exactly which general education courses will count for transfer at all state universities. Common course numbering systems are another example. By ensuring that English 101 at a community college covers the same content as English 101 at a 4-year school, transfer requirements are clearer and it is easier for students to create a complete 4-year course plan.

One comprehensive structural intervention aiming to smoothen the transfer process is a transfer degree program (Bers, 2013; Gross & Goldhaber, 2009). Such programs typically have a number of features. The courses needed to earn an associate degree in field x at the community college also fulfill the lower division courses required for a major in field x at the 4-year school. This set program of classes is generally relatively well structured; students do not have great latitude in choosing classes. The curriculum also applies to a number of 4-year schools; the requirements needed to transfer in field x are the same across all (or a clear subset of) the 4-year schools in the state. In addition to clearer structure, these transfer degrees are sometimes bundled with additional incentives such as guaranteed acceptance to a 4-year school, automatic junior standing, or special financial aid. As of 2011, at least 21 states had some sort of statewide transfer agreement and

eight states (Arizona, Florida, Louisiana, New Jersey, North Carolina, Ohio, Oregon, and Washington) had implemented robust transfer interventions: associate degrees with set curricula specifically for students intending to transfer to 4-year schools (Kisker, Wagoner, & Cohen, 2011; Roksa, 2009).

Although there is evidence that such program coherence and curricular structure can effectively promote persistence in K–12, we know relatively little about how and in what contexts increased programmatic structure can effectively promote persistence in higher education (Newmann, Smith, Allensworth, & Bryk, 2001; Scrivener & Weiss, 2013; Visher, Weiss, Weissman, Rudd, & Wathington, 2012). There is particularly little known about the effects of transfer programs on student outcomes. Longitudinal data on transfer rates, number of degrees, and course taking, from before and after transfer policies are enacted, are needed to persuasively assess the effect of transfer policies. Most states do not have such data; many data collection systems were enacted as the result of transfer policies (Roksa, 2009). As a result, much of the extant research has relied on leveraging variation across states in transfer policies. These types of studies cannot provide causal estimates, but they can provide suggestive evidence. Most studies of state articulation agreements have not found economically or statistically significant effects (Anderson, Sun, & Alfonso, 2006; Roksa, 2009), though there is some evidence that articulation agreements might affect certain subgroups (Gross & Goldhaber, 2009). However, it is hard to disentangle lack of effects from lack of adequate data.

More empirical evidence is also necessary because the consequences of increased structure, in the form of fewer choices, more rigid programs, or intrusive advising, are not always clear. Such structure might have unintended consequences for some groups of students. Perhaps some students would be turned off by having fewer curricular choices and would choose to enroll in a different college (for-profit or nondegree-granting) or not enroll at all. Or more rigid programs with fewer course choices might induce scheduling constraints or dissuade undecided students from enrolling. It is unclear in what ways, and for whom, these policies could have negative consequences.

Policy Context

CCCs

This article leverages a policy change in the CCC system to examine the effects of a structural intervention aimed at increasing degree receipt and transfer rates. The CCC system is the largest higher education system in the United States, educating more than 2.3 million students a year on 112 campuses. Nearly one third of community college students in the country are in the CCC system. Its integral role in California human capital production is clear: CCCs educate 70% of California's nurses and 80% of the state's firefighters, law enforcement personnel, and emergency medical technician (EMTs). Twenty-nine percent of University of California (UC) graduates and 51% of CSU graduates started at a CCC (Community College League of California, 2013).

Until recently, the CCC system provided archetypal examples of a number of the structural impediments that can affect student persistence. Within majors, each of the 112 CCCs set its own requirements for graduation and each CSU determined its own prerequisites for accepting CCC transfer students. Pairs of schools created individual campus-to-campus agreements that were complex and highly variable (Moore & Shulock, 2014). CCC students transferring to a CSU transferred with an average of 80 semester units when only 60 are required, and transfer students graduated with an average of 162 semester credits when the minimum requirement is 120 (California Community Colleges Chancellor's Office [CCCCO], 2010).³ Because requirements for associate degrees often did not align with transfer requirements, only one quarter of students who transferred had earned an associate degree (Moore & Shulock, 2010). As most moderately selective 4-year colleges, including many CSUs, have 6-year graduate rates below 70%, many community college students who transfer to these schools never earn a BA. Thus, transferring without first earning an AA increases the risk of investing a significant amount of time without ever earning a degree.

The Student Transfer Achievement Reform Act

In an effort to increase the magnitude and efficiency of student transfer and increase the number

of transfer-oriented students who earned associate degrees, the California State Legislature and Governor enacted the Student Transfer Achievement Reform Act (California SB 1440) in 2010 that established ADTs, a set of degrees that were to be jointly created by CCCs and CSUs. The legislation was meant to simplify and streamline the process of transfer and make it easier for transfer intending students to get an associate degree on their way to a bachelor's degree.

Although there were a number of bilateral transfer agreements at CCCs and CSUs prior to SB 1440, the ADT programs are different in a few key ways: (a) Students who complete an ADT are guaranteed admission to the CSU system (though not a specific program on a specific campus) and the course requirements are constant across all schools. (b) Students are given priority consideration when applying to a capacity constrained major that is similar to his or her ADT or to a capacity constrained CSU campus outside the student's local area. (c) Students are admitted with junior standing, and the CSU cannot require students to repeat classes that they have already taken as part of their ADT (so students should be more likely to earn a BA without accumulating extra credits).

Students do not need to apply to start an ADT program—it is just a matter of enrolling in the requisite classes. As with academic associate degrees in the CCC system, students do not need to declare that they are pursuing a particular degree until they apply to graduate. Some departments continued to offer their local (i.e., not systemwide) associate degrees when they started to offer ADTs, whereas others only offered an ADT. I explore the extent to which students double up on awards (i.e., earn two awards in the same department in the same year) in Appendix B (see online version of the journal).

In the fall of 2011 (the first term that the intervention was enacted), there were 133 ADT degree programs approved at 61 schools. That spring, roughly 1,500 students graduated with these degrees. By the fall of 2012, there were 450 approved ADT programs—at least one at each 112 CCCs. As of March 2016 there were 2,006 active ADTs in the CCCs and more than 20,000 students earned ADTs in the 2014–2015 school year. This gradual rollout of ADTs was a function of the process by which the degrees needed to be approved.

After the state approved a model curriculum in a subject, individual colleges could design their own specific curriculum in that field.⁴ After the community college department faculty approved the classes required for the major, the proposed degrees were vetted through the college's interdisciplinary curriculum committee. After that, the district's⁵ governing board had to approve the degree during a public hearing. Finally, the district had to submit the proposed degree to the state Chancellor's office for review. So, while all departments in any given field were eligible to offer ADTs starting at the same time, the variable timing of each of these steps produced a phased rollout of degrees.

SB 1440 was widely publicized by local media outlets and CCCs and CSUs. Numerous press releases were circulated, and CCCs were given help (text, logos, and forms) in publicizing the programs to students. In October 2012, a website detailing the degree program and offering accessible information for students was launched (*ADegreeWithAGuarantee.com*). Despite the existence of prior transfer initiatives and the fact that the ADT degree programs were, in some ways, more a repackaging of previously available courses than an entirely new program of study, the attention and communication from the media, the CCCCCO, and schools made these programs seem like an entirely new option for CCC students.

Data and Empirical Method

Data

To examine whether the introduction of ADTs affected course enrollment and the number of degrees granted in these fields, I use three sources of data: publically available department-level data from the CCCCCO, publically available school-level data on CCC to CSU transfers from the CSU Analytics website, and anonymized student-level data given to me by two community colleges in Northern California.

I use the CCCCCO data for the main analyses that examine degree granting rates in each department in each college each year from 2009 to 2014. Table 1 provides descriptive statistics on enrollments, degrees, and transfers in CCCs from 2009 to 2014. I use data from the CSU system Analytics Department to examine transfer rates to each CSU from each CCC each year from 2010 to 2015.

Data from the CSU system and the CCCCCO do not include enrollment information at the course level or demographic information at the course, department, degree, or transfer level. For an indication of how the introduction of ADTs affected student behavior and which students responded the most, I use student-level data from two community colleges. I use transcript data (course enrollments and grades) for all students in two community colleges in Northern California from Fall 2008 to Spring 2014 (approximately 2.3 million student-by-class observations). These data also include student demographic data from applications (gender, race, ethnicity, home zip code, self-reported education, and family income).

The student-level analyses from these two schools provide a preliminary indication of the student- and department-level responses that might be driving the broader system-level findings. However, it should be noted that these two schools do not necessarily represent the entire CCC system more broadly. Although system-level administrative policies and procedures ensure some level of implementation consistency across schools, the CCCs are a diverse group, both in terms of student inputs and in terms of outcomes (Kurlaender, Carrell, & Jackson, 2016). Table 2 presents some descriptive statistics on these two schools as compared with the CCC system more broadly. These schools are much more heavily Asian and much less heavily Latino than the state average. Their students are more likely to complete an award and/or transfer than students at other CCCs.

Method—Empirical Strategy, Primary Analyses

In attempting to determine whether the introduction of ADTs affected the number of degrees granted in a given department in a given college, there are three major sources of endogenous variation for which we need to account.

1. There are year-to-year trends in the number of degrees granted that are unrelated to the introduction of ADTs. Perhaps more community college students are completing degrees across all departments due to an increased institutional focus on degree completion. Or maybe broader economic trends (recessions, capacity constraints in

TABLE 1

California Community Colleges, 2008–2014

| | <i>M</i> | <i>SD</i> | <i>Mdn</i> |
|--|----------|-----------|------------|
| Headcount/semester/college | 38,033 | 22,359 | 34,465 |
| Sections offered/semester/college | 1,335 | 744 | 1,206 |
| Sections/department/semester/college | 13.7 | 24.8 | 6 |
| Number of certificates offered/college | 31.8 | 15.7 | 29 |
| Number of certificates granted/year | 457 | 411 | 351 |
| Number of certificates granted/department/year | 15.6 | 53.3 | 5 |
| Number of AAs offered/college | 47.3 | 17.2 | 48 |
| Number of AAs granted/year | 931 | 563 | 829 |
| Number of AAs granted/department/year | 20.4 | 62.8 | 5 |
| Number of students who transfer/college/year | 444 | 334.5 | 365 |

Note. All data come from the California Community Colleges Chancellor's office (CCCCO). Data cover the 2008–2009 to 2013–2014 academic years. AA = Associate of Arts.

4-year schools) are inducing students with the intention to earn a bachelor's degree to use community colleges as a point of entry to 4-year schools, thus shifting the demographic composition of community colleges.

2. There are differences between departments. Historical student interest was a primary factor in determining in which departments transfer curricula were developed (Moore & Shulock, 2014), so popular and fast-growing departments, such as business administration and early childhood education, were some of the first ADTs to be developed and implemented. Absent the introduction of ADTs, we would still expect these departments to be producing Associate of Arts (AAs) faster than other departments.
3. Finally, there are differences between colleges. Perhaps the schools that were experiencing the fastest growth introduced ADTs more quickly than slower growing schools.

The staggered introduction of ADTs degrees across CCCs, across departments, over time, allows me to account for all these potential confounding factors in one DDD model to identify the effects of the implementation of SB 1440 on CCC student degree earning. This estimation strategy essentially allows us to use comparison schools, comparison departments, and comparison years to construct a counterfactual for the

treatment group: what would have happened in these departments had they not been treated.

In essence, I am estimating the treatment effect as the difference between treated and control colleges in the difference in the change in the number of degrees granted in treated and control departments.

$$\begin{aligned} \bar{\delta} = & ((\bar{Y}_{c=1,d=1,y>2012}) - (\bar{Y}_{c=1,d=1,y<2012})) \\ & - [(\bar{Y}_{c=1,d=0,y>2012}) - (\bar{Y}_{c=1,d=0,y<2012})] \\ & - ((\bar{Y}_{c=0,d=1,y>2012}) - (\bar{Y}_{c=0,d=1,y<2012})) \\ & - [(\bar{Y}_{c=0,d=0,y>2012}) - (\bar{Y}_{c=0,d=0,y<2012})], \end{aligned} \quad (1)$$

where $\bar{Y}_{c=1,d=1,y>2012}$ is the number of degrees granted in department d that grants ADTs (treatment = 1) in college c that grants ADTs (treatment = 1) in the years *after* the policy takes place ($y > 2012$), with all other terms defined similarly.

In a regression framework, this analysis is written as:

$$\begin{aligned} Y_{cdy} = & \beta_0 + \beta_1 \Gamma_{cdy} + \alpha_{cd} + \delta_{cy} \\ & + \gamma_{dy} + \theta_y + \tau_c + \varphi_d + \varepsilon_{cdy}, \end{aligned} \quad (2)$$

where Y_{cdy} is the number of associate degrees granted in college c in subject d in year y , Γ_{cdy} is a treatment variable that is equal to one for treated departments at treated colleges in treated years and zero otherwise, α_{cd} is a vector of college-by-department fixed effects, δ_{cy} is a vector

TABLE 2

Two Focal Colleges Compared With CCC System

| | CCC | Two schools |
|--------------------------------------|-------|-------------|
| Enrollment, fall of 2014 | | |
| % female | 53.4 | 48.2 |
| % Asian | 10.9 | 30.8 |
| % Latino | 42.7 | 25.2 |
| % White | 28.1 | 26.1 |
| % withdrew | 13.8 | 10.4 |
| Student success (2008–2009 cohort) | | |
| Persistence ^a | 71.7% | 72.5% |
| Transfer rate ^b | 24.1% | 40.5% |
| Completion/SPAR ^c | 46.8% | 66.1% |
| Number of ADTs offered, January 2016 | 17.8 | 16 |

Note. All data, except for number of ADTs offered, come from the California Community Colleges Chancellor’s Office (CCCCO) Datamart. Data on the number of ADTs offered come from the CCCCCO division of Academic Affairs, which offers monthly reports on the numbers of ADTs offered at each CCC. CCC = California Community College; SPAR = Student Progression and Achievement Rates; ADT = Associate Degree for Transfer; UC = University of California; CSU = California State Universities; GPA = grade point average.

^aDefined as percentage of first-time students with minimum of six credits who attempted any math or English in the first 3 years and enroll in first 3 consecutive primary semester terms (four quarter terms) anywhere in the CCC system.

^bDefined as percentage of students who show “behavioral intent to transfer”—defined as (a) having completed at least 12 credit units and (b) attempting a transfer-level math or English course—and transfer within 6 years.

^cPercentage of first-time students with minimum of six credits who attempted any math or English in the first 3 years and achieve any of the following: (a) earned Associate of Arts/Associate of Science or credit certificate, (b) transfer to a 4-year institution, (c) achieve “Transfer Prepared” (successfully completed 60 UC/CSU transferrable units with a GPA ≥ 2.0).

of college-by-year fixed effects, γ_{dy} is a vector of subject-by-year fixed effects, and θ_y , τ_c , and φ_d are vectors of year, college, and department fixed effects. The main effects will drop out due to collinearity, but I include them in this model for purposes of clarity. This model provides full nonparametric control for college-specific time effects common across departments (δ_{cy}), year varying department effects (γ_{dy}), and college-specific department effects (α_{cd}). Thus, this model controls for anything that is particular to a given department in given school (perhaps computer science departments in schools in Silicon Valley are growing particularly quickly, for example), particular to a given department in a given year (maybe computer science departments grew more quickly after the Facebook’s initial public offering, for example) or particular to a given school in a given year (maybe community colleges in the Los Angeles area grew particularly quickly after the housing bubble burst, for example). The parameter of interest is β_1 which tells us the effect of being an SB 1440

active department, in a treated college in a treated year, holding all else constant.⁶

Differing Effects Over Time

There are reasons to believe that this policy might have differing effects over time. If ADTs are appealing options for students but it takes time for students to adjust their schedules to fit the required classes, we might see an increase in the treatment effect over the first couple of years that then plateaus. If ADTs increase student efficiency but do not induce students to change departments (a sort of “cannibalization of the future”), we might see a treatment effect for a few years that then dissipates. By including separate dummies for departments that are in their first, second, or third year of treatment, I can examine these hypotheses.

$$Y_{cdy} = \beta_0 + \beta_1 \Gamma_{cdy=1} + \beta_2 \Gamma_{cdy=2} + \beta_3 \Gamma_{cdy=3} + \alpha_{cd} + \delta_{cy} + \gamma_{dy} + \theta_y + \tau_c + \varphi_d + \varepsilon_{cdy}. \quad (3)$$

Effects on Number of Transfers

Increasing the number of associate degree granted was only one goal of the policy. Another goal was to increase the number of students transferring from CCCs to CSUs. I can test for this using a difference-in-differences (DD) model:

$$Y_{cy} = \beta_0 + \beta_1 \Gamma_{cy} + \theta_y + \tau_c + \varepsilon_{cy}, \quad (4)$$

where the outcome is the number of students who transfer from CCC c to any CSU in year y , Γ_{cy} is a treatment variable that is equal to one for treated colleges in treated years and zero otherwise. θ_y is a vector of year fixed effects, and τ_c is a vector of college fixed effects. Because these data are available only at the college, and not the department level, I cannot use a DDD model in this case. For these results, I use enrollment data from the CSU Analytics website.

We might expect there to be *dosage* effects for this outcome. Perhaps the introduction of only one ADT does not have significant effects on the number of students who transfer but having a critical mass of ADT programs does. Or, perhaps there is a lag—students do not transfer to a CSU directly after they graduate. To test these two hypotheses, I also estimate a model with non-parametric controls for dosage and time-varying effects:

$$Y_{cy} = \beta_0 + \beta_1 \Gamma_{cy,d=1-3,t=1} + \beta_2 \Gamma_{cy,d=1-3,t=2} + \beta_3 \Gamma_{cy,d=4+,t=1} + \beta_4 \Gamma_{cy,d=4+,t=2} + \theta_y + \tau_c + \varepsilon_{cy}, \quad (5)$$

where $\Gamma_{cy,d=1-3,t=1}$ is dummy variable that takes the value one if there are between one and three treated departments in their first year of treatment in a given college in a given year and zero otherwise. The dummy variable $\Gamma_{cy,d=4+,t=2}$ takes the value one if there are four or more treated departments in their second year of treatment in a given college in a given year and zero otherwise. The two other variables are similar combinations.

Mechanisms

The goal of this policy was both to encourage more, and more efficient, transferring and to induce more students with a transfer intent to

earn an associate degree. There are a number of behavioral and institutional mechanisms through which a structural intervention such as this could produce these results. It could operate at that student level (inducing changes in student behavior), the institutional level (causing structural changes), or both. I will examine a number of these potential mechanisms.

Disciplinary Cannibalization Versus Absolute Growth

One goal of SB 1440 was to increase the number of transfer students in CCCs who earn associate degrees. However, evidence of growth in treated departments in treated colleges in treated years is not necessarily evidence that the number of degrees granted *overall* increased—it could be that students who would have always earned an associate degree switched from untreated into treated majors—evidence of disciplinary “cannibalization.” This cannibalization of other departments would not necessarily produce a change in the overall number of associate degrees granted or in the transfer rate, but would produce significant increases in these outcomes in ADT departments. On the contrary, a perceived effect could also be due to a true effect; perhaps the introduction of SB 1440 increased the number of students who earned associate degrees (either by inducing students who were already planning to transfer in a certain major to “pick up” a degree along the way, or the structure and clarity of the program could provide support for students who would have otherwise dropped out).⁷

Each of these outcomes, cannibalization and a true increase in the number of degrees, has policy relevance, and we can empirically test to see whether we see evidence for either or both. I do this by estimating the number of degrees granted in a given school in a given year using college and year fixed effects and an indicator of being a treated college in a treated year.

$$Y_{cy} = \beta_0 + \beta_1 \Gamma_{cy} + \theta_y + \tau_c + \varepsilon_{cy}, \quad (6)$$

where the outcome is the number of degrees at a given college in a given year, Γ_{cy} is a treatment variable that is equal to one for treated colleges in treated years and zero otherwise. θ_y is a vector of year fixed effects, and τ_c is a vector of college fixed effects.

By estimating this model for all degrees granted in a given college in a given year, I have an estimate of how the presence of ADTs affected the number of degrees granted overall. I can also estimate this same outcome for two subsets of departments: treated programs ($Y_{cy,d=1}$) and untreated programs ($Y_{cy,d=0}$). These three models together paint a picture of the effect of ADT programs on overall degrees granted and can help us to examine whether a perceived treatment effect is evidence of an increase in the number of associate degrees granted overall or evidence that other degree programs are shrinking because of the policy.

Again, we might expect there to be differential effects over time (it might take a while for a policy like this, which involves students taking sequences of courses over time, to affect graduation patterns) or dosage effects (perhaps the introduction of only one ADT does not affect degrees granted overall or degrees granted in untreated programs, but having a critical mass of ADT programs does). To test these two hypotheses, I also estimate a model similar to Equation 6 with nonparametric controls for dosage and time-varying effects (similar to those found in Equation 5).

Changing Course-Taking Behaviors

If we see that the introduction of ADTs induced an increase in the number of degrees granted in treated departments, there a number of explanations for why this might be happening. It could be that these new programs induced students who were already planning to transfer to a bachelor's program in a certain department to pick up an associate degree in that department along the way—the policy would be having an effect by inducing already-trained students to file for a degree (which would imply no changes in human capital development). If this is indeed the mechanism at work, we would expect to see an increase in the number of associate degrees granted in treated departments, an increase in transfer rates in these departments, and no changes in student course taking (departments would experience the same rates of enrollment).⁸

The policy could also affect the number of degrees earned by inducing students who were already planning to transfer to switch into a treated department. In this case, we would expect

to see significant growth in enrollment for classes that lead to an ADT. We can test these hypotheses by estimating the same DDD specification presented in Equation 2 on *enrollment* in treated and untreated classes using data from two community colleges in Northern California.

If the policy is affecting student course-taking behavior, making students more efficient (collect fewer unnecessary credits) by streamlining the transfer process to all CSUs, we should also see a reduction in the number of credits that students have when they graduate. I examine this micro outcome for students in two community colleges using the same DDD specification and examining the average number of credits accumulated before graduation for a student graduating from department d in college c in year y .

Demand- Versus Supply-Side Shift

If we see an increase in the number of degrees granted in treated departments, coupled with an increase in enrollment in these departments, it could be that the introduction of ADTs induced increased *demand*—students were attracted to the programs for their simplicity, structure, or associated transfer benefits. However, it could also be that an estimated treatment effect is due to shifts on the *supply* side. Perhaps schools coupled the introduction of ADT programs with increased capacity by offering more sections of classes in the treated departments. This supply-side change in capacity could result in more students enrolling in these departments (which could be an indication that the school is now better meeting latent demand and might not be an indication of an increase in demand). Our same DDD specification allows us to examine this by estimating the number of sections offered in a department as a function of college-by-year, year-by-department, department-by-college fixed effects and a vector of dummies that indicate whether a department was treated in a particular college in a particular year, using a specification similar to Equation 2. I estimate the effects on sections of courses offered using data from the whole CCC system.

For Whom?

In addition to examining overall effects, it is also important to look at for whom these

policies are having an effect. It could be that the policies are ameliorating inequalities by inducing historically disadvantaged groups to earn more degrees and be more efficient. Conversely, it might be that the programs exacerbate inequalities by providing more efficient routes to already privileged groups. We can examine these hypotheses for students in two community colleges using the DDD specification and examining the average demographic characteristics (gender, age, race, number of terms in school, and average grade point average [GPA]) of students who are enrolled in courses in department d in college c in year y . This will indicate whether there are demographic shifts in enrollment associated with the ADT programs (controlling for anything particular about a particular departments, colleges, years and the interactions thereof).

Results

We start by examining the effects of the policy on the two main outcomes of interest: the number of associate degrees granted and the number of students who successfully transfer to CSUs. The DDD model estimates the effects of introducing ADTs on the number of degrees granted in treated departments in treated years in treated colleges. In Table 3, I present the results from two specifications, one which treats all treatment years the same way and one which separates treatment by year. The results are clear: The introduction of ADTs led to appreciable increases in the number of students graduating with associate degrees in these departments. The models indicate that treated departments experienced growth of about seven students—nearly 35% based on a mean of 20 degrees/department/year.⁹ Model 2 shows that the effects of the policy grew over time; treated departments granted significantly more associate degrees in their second and third years of offering ADTs than they did in their first.

In Appendix Table A1 (see online version of the journal), I provide 16 specifications of the model to account for a number of concerns that arise from the structure of these data. Each model produces very similar results.

Next, we turn to the other main outcome: the number of students who successfully transfer to CSUs, shown in Table 4. Here, we do not see

significant results; the policy does not seem to have had an effect on the number of CCC students who successfully transfer to CSUs. However, the point estimates for Years 2 and 3 at schools that offer four or more ADTs are large and marginally significant. There is suggestive evidence that the policy might have significant effects in later years.

Mechanisms

Significant growth in the number of degrees granted in treated departments could be because the policy induced students who otherwise would not have earned an associate degree to get a degree. In this case, we would expect to see that the overall number of degrees granted at a college increased. On the contrary, these ADT programs could induce students who would have otherwise earned a degree to switch into treated programs. In this case, we would not expect to see an increase in overall degrees granted. Table 5, which displays the results from Equations 4 and 5, allows us to examine these two hypotheses. The findings from the DDD model (Table 3) are clearly supported in these estimates, which show that the introduction of ADTs led to an increase in the number of degrees granted in treated departments in treated colleges in treated years. There is less conclusive evidence, however, to support whether this increase is due to cannibalization or an overall increase. There is weak evidence to support both hypotheses; in the first 2 years, the estimates for both colleges overall and untreated departments are nonsignificant but we see negative coefficients in untreated departments in the first year of treatment.¹¹ In the third year of treatment, there is evidence that the policy increased the number of degrees granted overall. These results are consistent with a story where some students are induced to switch majors and others are induced to earn a degree when they would not have otherwise. They might also represent the temporal component of the story. In the first few years of treatment, the students earning ADTs would be those who had already been enrolled and had accumulated credits toward their degrees; these students might have switched from other departments to more appealing ADT departments. Students graduating with ADTs in later years could be students who started after the programs

TABLE 3

DDD Estimate of the Effect of the Policy on Number of Degrees Granted per Department per Year

| | Outcome = number of degrees | |
|--|-----------------------------|-------------------|
| | (1) | (2) |
| Treated department, year, college | 6.886*** (0.785) | |
| Treated department, year, college, first year | | 5.597*** (0.676) |
| Treated department, year, college, second year | | 12.622*** (1.657) |
| Treated department, year, college, third year | | 19.693*** (3.381) |
| College × Year Fixed Effects | X | X |
| College × Department Fixed Effects | X | X |
| Department × Year Fixed Effects | X | X |
| <i>n</i> | 35,880 | 35,880 |
| Adjusted <i>R</i> ² | .864 | .864 |

Note. Data come from the California Community College Chancellor's Office and represent all departments in all 112 colleges from 2009 to 2014. Standard errors are clustered at the college-by-department level. DDD = difference-in-differences-in-differences.

†*p* < .10. **p* < .05. ***p* < .01. ****p* < .001.

TABLE 4

Effects of Policy on Number of Transfers per College per Year

| | Number of transfers from CCC to any CSU | Number of transfers from CCC to any CSU |
|--|---|---|
| Dummy: At least one ADT in college/year | -15.273 (13.152) | |
| Dummy: 1–3 ADTs in their first year in college/year | | -9.517 (11.888) |
| Dummy: 4+ ADTs in their first year in college/year | | -18.973 (21.262) |
| Dummy: 1–3 ADTs in their second year in college/year | | 7.392 (17.940) |
| Dummy: 4+ ADTs in their second year in college/year | | 31.649† (18.722) |
| Dummy: 1–3 ADTs in their third year in college/year | | 18.271 (29.393) |
| Dummy: 4+ ADTs in their third year in college/year | | 52.407† (27.814) |
| College dummies | X | X |
| Year dummies | X | X |
| Intercept | 341.199 (11.969) | 5.438 (0.030) |
| <i>n</i> | 667 | 667 |
| Adjusted <i>R</i> ² | .940 | .961 |

Note. Data come from California State University Analytics website (<http://www.calstate.edu/as/CCCT/index.shtml>), which uses data from the Student Enrollment file of the Enrollment Reporting System. Data are from 2009–2010 to 2014–2015 academic years from all California State Universities. Standard errors, presented in parentheses, are clustered at the college level. CCC = California Community Colleges; CSU = California State University; ADT = Associate Degree for Transfer.

†*p* < .10. **p* < .05. ***p* < .01. ****p* < .001.

were in place and made curricular decisions at the beginning of their career. Data from later years of treatment could provide evidence regarding the long-term effects of the program.

We can also examine the mechanisms underlying observed effects by examining whether the policy is inducing a shift in enrollments. The

DDD model presented in Table 6 shows this. An increase in enrollments in treated departments would indicate that students were being induced to switch into treated majors. However, we find a null effect, which could indicate one of a few things. It could mean that students were repackaging credits they had already earned—filing for

different degrees with the classes they already had or picking up degrees that they otherwise might have earned but not officially filed. But this null result could also be the result of capacity constraints. If classes in treated departments were already full before the treatment, we would not expect the number of students in these classes to change (assuming there is not an increase in the supply of seats), though we might expect the composition of students classes to change. I examine each of these possibilities below.

Table 6 also presents the results of the model to investigate how colleges reacted to the introduction of the ADT programs. This table shows the effect of ADT programs on the number of sections offered in a given department in a given term. If colleges were increasing supply by offering more classes in these departments, increases in enrollment or degrees granted could be a result of this supply shift and not indicative of increased demand. In Table 6, we see that this is not the case. On average, schools did not increase supply in these departments. As there is no increase in supply, the null result on increased enrollment could be due to capacity constraints.

This increased demand without increased supply could imply that there is a shift in the composition of students in these classes. I examine this in Table 7 which presents the effects on the characteristics of students who enroll in classes that count toward an ADT and relies on data from two colleges in Northern California. These results give some insight into if there is heterogeneity of response across different groups of students. In general, we do not see differential effects by student subgroup, with one important exception. Students who have been enrolled for more terms are more likely to enroll in classes that count for ADTs. This result fits with what we have seen already. If schools are not increasing supply and we are seeing increased numbers of degrees granted in these departments, it could be that the introduction of ADTs exacerbated capacity constraints in these departments. At the time of this study, the two focal schools used accumulated credits to determine registration priority. If classes were filling up, students who had been enrolled longer would have priority and would be able to enroll first. We seem to have evidence for this here.

There is one other finding in this table that I think merits discussion. Although it is

only marginally significant, the coefficient on the proportion of students who identify as Asian is positive and relatively large (3 percentage points). In these two schools, Asian students are the highest performing subgroup on all outcomes—graduation rates, GPA, and transfer rates. We thus have evidence that the highest performing subgroup is enrolling in ADT classes at increasingly high rates. As enrollment is a zero sum game, an increase in the proportion of students who identify as Asian necessarily means that other racial and ethnic groups must be enrolling at lower rates.

Finally, Table 8 presents the results from examining the number of credits that students had accumulated by the time they graduated, again using data from the two focal colleges. This is a direct test of one of the goals of the policy: to make students more efficient by providing guidance and pathways to earn degrees and transfer while accumulating fewer excess credits. There is suggestive, though not conclusive, evidence that the policy induced students to accumulate fewer credits over the course of their program. The results indicate that students earned more than 10 fewer credits, which equates to two fewer classes. If this in fact the case, it is strong evidence in support of the structure hypothesis. With clearer, more structured programs, students seem to be graduating with fewer excess credits.

Conclusion

Rates of persistence and completion in community colleges have long been a focus of policy and popular attention. Many of the students who set out to earn degrees never do, and this has consequences for both society and individuals. Of the many solutions to tackle this problem, strategies that address structural impediments present in community colleges (a profusion of potential pathways, uncoordinated scheduling, a lack of coordination between sectors, and insufficient information and support) are promising because they are affordable, scalable, and relatively easy to sell politically. Structured transfer programs, which smooth informational barriers and provide structured pathways for students, are one example of such an intervention. This article is one of the first to provide rigorous empirical evidence of these programs.

TABLE 5
Effects of Policy on Number of Associate's Granted per College per Year

| | Total degrees | Degrees in treated departments | Degrees in untreated department | Total degrees | Degrees in treated department | Degrees in untreated department |
|--|-----------------|--------------------------------|---------------------------------|-------------------|-------------------------------|---------------------------------|
| Dummy: At least one ADT in college/year | 0.569 (23.140) | 12.57 [†] (7.411) | -12.002 (20.146) | 11.845 (22.790) | 22.211*** (4.552) | -10.366 (22.052) |
| Dummy: 1-3 ADTs in their first year in college/year | | | | 22.318 (42.875) | 38.01** (13.167) | -15.687 (39.428) |
| Dummy: 4+ ADTs in their first year in college/year | | | | 41.804 (46.015) | 27.68* (10.874) | 14.129 (44.466) |
| Dummy: 1-3 ADTs in their second year in college/year | | | | 79.738 (58.757) | 88.64*** (13.290) | -8.902 (55.405) |
| Dummy: 4+ ADTs in their second year in college/year | | | | -67.589 (201.843) | 22.789 (17.323) | -90.378 (196.097) |
| Dummy: 1-3 ADTs in their third year in college/year | | | | 193.588* (88.755) | 165.62*** (28.768) | 27.967 (81.316) |
| Dummy: 4+ ADTs in their third year in college/year | | | | | | |
| College dummies | X | X | X | X | X | X |
| Year dummies | X | X | X | X | X | X |
| Intercept | 749.31 (17.741) | 51.857 (4.574) | 697.455 (17.209) | 749.312 (17.813) | 51.857 (4.023) | 697.455 (17.290) |
| <i>n</i> | 672 | 672 | 672 | 672 | 672 | 672 |
| Adjusted <i>R</i> ² | .887 | .744 | .883 | .89 | .801 | .882 |

Note. Data come from the California Community College Chancellor's Office and represent all 112 colleges from 2009 to 2014. Standard errors, presented in parentheses, are clustered at the college level. ADT = Associate Degree for Transfer.
[†]*p* < .10. **p* < .05. ***p* < .01. ****p* < .001.

TABLE 6

Effects of Policy on Enrollment and Number of Sections Offered

| | Ln (number of students enrolled), per department/college per year | Ln (number of Sections) |
|-------------------------------------|--|-------------------------|
| Treated department, college, year | 0.018 (0.014) | 0.013 (0.013) |
| College-by-term fixed effects | X | X |
| College-by-department fixed effects | X | X |
| Department-by-term fixed effects | X | X |
| <i>n</i> | 128,000 | 128,000 |

Note. Data come from the California Community College Chancellor's Office (CCCCO) Datamart and represent all departments in all 112 colleges from 2009 to 2014. Standard errors, shown in parentheses, are clustered at the college-by-department level. † $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

There are some very clear results that emerge from these analyses. The Student Transfer Achievement Reform Act had an effect on student behavior; the introduction of ADT programs led to a significant increase in the number of students earning associate degrees in the departments that offered ADTs. On average, these increases are appreciable: Treated departments saw graduation rates roughly 35% higher than before the introduction of ADTs. It appears that some of the students who earned ADTs were students who would have otherwise earned an associate degree in another field but decided to switch. There is also evidence that some students who earned ADTs might not have otherwise earned an associate degree—there is strongly suggestive evidence that the number of degrees being granted by schools is increasing over time as a result of this policy.

Absent any other effects of the policy, this outcome alone is important and worth highlighting. We have increasing evidence that people get few long-term returns from postsecondary credits that do not result in an award in academic (as opposed to vocational) fields (Bahr, 2014; Jacobson, LaLonde, & Sullivan, 2005; Jaeger & Page, 1996). However, the returns to a 2-year degree are generally large and significant in all student subgroups (Belfield & Bailey, 2011; Dadgar & Trimble, 2014; Jepsen, Troske, & Coomes, 2014; Stevens, Kurlaender, & Grosz, 2015). Even if this policy affected only associate degree receipt, and not transfer rates or transfer success, it could have real economic and societal implications.

As of now, the policy has not had a significant effect on the number of students who transfer

from CCCs to CSUs. It could be that not enough time has passed to examine this outcome; students who took advantage of the policy in the first years were likely students who would have transferred anyway and it may take time for some students to transfer after earning an ADT. There is suggestive evidence that we will see significant (statistically and substantively) effects on transfer in the years to come.

However, it could also be the case that the policy will not affect student transfer rates. There are a number of reasons why this could be. It may be that the policy has not reduced some important barriers for students—not all ADTs are accepted at all CSU campuses and the modest GPA bump given with the ADT might not be enough for students to get accepted to a local campus (Moore & Shulock, 2014). It is also possible that the policy might be unintentionally diverting students from 4-year degrees. If the introduction of ADTs creates an atmosphere that communicates the transfer process is complicated and difficult, this policy might be unintentionally “cooling out” marginal students (Clark, 1960). There are a number of explanations that could explain the increase in AAs without an associated increase in transferring, and future years of data will allow us to examine this question more closely.

Departments that offered ADTs did not experience significant increases in enrollment as a result of the policy, but this could be because they did not offer more sections of courses. Capacity was not increased in treated departments. There is evidence that these departments were facing more demand: Students who enrolled

TABLE 7
Effects of Policy on Characteristics of Students in Treated Classes

| | Prop. female | M_{age} | Prop. Asian | Prop. Latino | Prop. White | Prop. new students | Average number of terms enrolled | Prop. who earn an A | Prop. who withdraw | Overall GPA of enrolled students |
|---|------------------|------------------|------------------------------|-------------------|-------------------|--------------------|----------------------------------|---------------------|--------------------|----------------------------------|
| Treated class in treated school in treated year | 0.022 (0.017) | 0.011 (0.439) | 0.03 [†] (0.017) | -0.008 (0.015) | -0.025 (0.016) | -0.006 (0.009) | 0.548** (0.195) | 0.021 (0.027) | -0.006 (0.01) | 0.022 (0.034) |
| Intercept | 0.608 (0.006) | 26 (0.437) | 0.325 (0.009) | 0.215 (0.004) | 0.287 (0.005) | 0.018 (0.002) | 7.947 (-0.066) | 0.329 (0.008) | 0.08 (0.004) | 2.888 (0.021) |
| College-by-year fixed effects | X | X | X | X | X | X | X | X | X | X |
| College-by-department fixed effects | X | X | X | X | X | X | X | X | X | X |
| Department-by-year fixed effects | X | X | X | X | X | X | X | X | X | X |
| n | 1,451 | 1,303 | 1,451 | 1,451 | 1,451 | 1,451 | 1,451 | 1,451 | 1,451 | 1,451 |
| Adjusted R^2 | .873 | .694 | .796 | .642 | .682 | .477 | .833 | .666 | .55 | .692 |

Note. Includes all students who were enrolled in classes with Course Identification Numbers (CIDs) between 2008 and 2014 in two community colleges in Northern California. The analyses are limited to classes with CIDs because the identification strategy, DDD, relies on having the same class across schools. Only classes with CIDs have these direct counterparts. Standard errors, presented in parentheses, are clustered at the course-by-term level. Prop. = proportion; DDD = difference-in-differences-in-differences; GPA = grade point average.
[†] $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$.

TABLE 8

Effects of Policy on Number of Credits Earned by Graduating Students

| | Average number of credits earned, department, college, year |
|-------------------------------------|---|
| Treated department, college | -13.502 (8.840) |
| College-by-term fixed effects | X |
| College-by-department fixed effects | X |
| Department-by-term fixed effects | X |
| <i>n</i> | 1,108 |
| Adjusted <i>R</i> ² | .866 |

Note. Includes all students who graduated with associate's degrees between 2009 and 2012 from two community colleges in Northern California (averaged into department-by-college-by-year observations). Standard errors, presented in parentheses, are clustered at the college-by-department level.

†*p* < .10. **p* < .05. ***p* < .01. ****p* < .001.

in treated departments after the treatment was introduced had been enrolled, on average, for 0.5 terms longer than before the treatment started. As registration priority is determined by number of accumulated credits, this is consistent with a story where students with fewer credits are getting closed out of classes. As community colleges are open-access institutions meant to serve the masses, we must examine potential unintended consequences of policies to determine whether they are disadvantaging particularly vulnerable groups.

The estimated effects of the ADT policy on degree granting and transfer must be evaluated in this particular context: California higher education. It is unclear whether other states should expect larger or smaller effects from similar policies. In some ways, the public higher education system in California is uniquely poised to benefit from such a policy: It is large and geographically dispersed and the system is explicitly hierarchically structured. The few other state systems that are similar enough in these important dimensions (e.g., Florida, Texas, Ohio, and North Carolina) might expect equally large effects to those found in California, but most state systems are not structured to support such a policy and should not expect similar results.

At the same time, while some aspects of the California system should promote efficient transfer, California is below the national average both in terms of transfer-out rates and transfer-with-award rates (Jenkins & Fink, 2016). A large driver of these low rates is the significant capacity constraints at the 4-year schools, which make

transfer especially difficult to navigate. Thus, California tuition and admission policies, and the unique distribution of power in the system (e.g., due to constitutional restrictions the UC cannot be legislatively made to enact any policies), might dampen the effects and a comparable policy enacted in a similarly structured state might system find larger results. Although California is one of the few states to provide enough internal variation to provide causal estimates of a policy using a DDD analysis such as this, policymakers should think carefully about how these results might translate in other states.

Similarly, the effects of this program on student course taking (kinds of students enrolled in courses that lead to an ADT and number of credits students accumulate by graduation) must be situated in the two schools from which these data come. As I noted in the data section, and as highlighted in Table 2, the students in these schools are generally higher achieving than the average CCC student (they persist, transfer, and earn degrees at higher rates than the statewide average). Logically, with more high-achieving students, students in these schools are more likely to face competition for seats in ADT classes. The suggestive finding in this article, that students were closed out of classes, might not hold in other CCCs, let alone other school in other states. However, it is harder to explain how these compositional characteristics could affect efficiency (number of credits accumulated by graduating students). It seems reasonable that other schools, in California and in other states, might see similar effects of this policy for their students.

The Student Transfer Achievement Reform Act has only been active for three academic years, which is an especially exciting time to study it. Studying the policy early in its life allows us to examine early student behavior and could provide schools and administrators with early feedback for improvement. The early nature of these analyses also guides future research in this area—there are many potentially important questions that these analyses raise. Because the program is still in its infancy, the effects we are seeing now could prove to be long lasting and stable, or these effects could prove temporary as the system reaches a new equilibrium. If these early spikes in degrees are due to increase efficiency for this first cohort of treated students, we would expect the estimate of the effect of the treatment on the number of degrees granted to decline in the next few years, but the negative effect on the number of credits students have when they graduate should persist. As states look for ways to increase persistence, graduation, transfer (and efficiency in all these pursuits the face of tightening budgets), examining the effect of cheap, scalable interventions, such as the student transfer act in California, is important. This article provides early evidence of student response to structured articulation programs and offers avenues for future research.

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Notes

1. Structure can refer both to the observable institutional policies and practices that students encounter and also to the less evident “norms and nudges” that schools deliberately or tacitly promote (Scott-Clayton, 2011, p. 2).

2. The average school in the California Community College (CCC) system offers 111 distinct awards and almost one third of these schools offer more than 150 awards (author’s calculation using data from California Community College Chancellor’s Office [CCCCO]).

3. Although to be fair, many graduates who start at a California State University (CSU) also earn more credits than is strictly necessary. One report, using student-level CSU data, notes that the average CSU graduate earned 135 credits (Campaign for College Opportunity, 2014). The CSU acknowledges that acquiring more credits than necessary for graduation is not inherently undesirable and sets the threshold for officially “excess” units at 144. However, 162, the average number of credits earned by graduating transfer students, is substantially above even this generous interpretation.

4. To aid schools in creating transfer degree programs, the state facilitated the development of Transfer Model Curricula (TMC) through the academic senates of the CCCs and CSUs. Along with a common course numbering system, these guidelines made it clearer for schools to develop program curricula. CCCs were expected to create associate transfers for each of their majors that had an established TMC, though they were given some time to do so.

5. Community colleges in California are organized into districts, much like K–12 schools. There are between one and nine colleges per district. Some administrative decisions and functions happen at the district level.

6. One benefit of the difference-in-differences-in-differences (DDD) identification strategy is the ability to directly test the counterfactuals inherent in the design. The DDD model used in this article is built upon two separate difference-in-differences (DD) models: testing the effect of the policy in treated, as compared with untreated, departments in treated colleges and testing the effect of the policy in treated, as compared with untreated, colleges in treated departments. We can also test the effects in groups where we do not expect to find an effect (treated and untreated departments in untreated colleges and treated and untreated colleges for untreated departments) as an exercise to test comparison groups implicit in each of these models. In both of these falsification exercises,

if the coefficient of interest is not significantly different from zero, it provides evidence that we have valid comparison groups. I estimated these naïve DD models and did not find estimated effects significantly different from zero in either of the falsification tests (results not shown).

7. These models introduce an important statistical question. As I am working with the complete population of schools, the estimated error is by definition not due to sampling error. In each of the models for which I have the full population, I am proceeding with analyses as one would with a sample and treating this as a “super-population” problem, as per work by statisticians (Hartley & Sielken, 1975; Kish, 1995; Korn & Graubard, 1998). In essence, I am attempting to make inferences to a larger population that could include observations from future years or from other states. Under this framework, I am viewing these data as a simple random sample of all future years in California (or all other states) and I am assuming that the process generating the data is stable over time (so that each draw could be viewed as an independent draw from an underlying data generation process). This treatment is conservative and produces an upper bound of how large we estimate the standard error to be. Another option would be to view the population as fixed and apply a finite population correction ($fpc = \sqrt{(N-n)/(N-1)}$; Levy & Lemeshow, 1991). As I have sampled the full population, this would produce standard errors of 0. I am reporting the more conservative estimates.

8. In addition to highlighting policy-relevant questions, this analysis raises a statistically significant question. The main identifying assumption in the DDD model is that the observed outcomes for the control conditions (untreated departments, untreated colleges, and untreated years) provide enough information to estimate what would happen to the treated groups (treated majors in treated years in treated schools) in the absence of treatment. In this case, we might worry the causal warrant is not perfect because the counterfactual is not perfect: “control” subjects might also have been affected by the treatment, a classic violation of the stable unit treatment value assumption (SUTVA). This subanalysis allows us to interrogate this assumption and provides us with a clearer sense of the mechanisms through which apparent effects are taking place.

9. It is possible that a perceived effect of the policy on degrees granted could be due to students earning *multiple associate degrees in the same department in the same year*—I examine this empirically in Appendix B (see online version of the journal).

10. As I noted above, I use data from two community colleges to examine effects on course-taking and credits earned at the student level. Although these

schools are different from the average CCC in some important ways (as highlighted in Table 2), there is evidence that these two schools rolled out Associate Degrees for Transfer (ADTs) in a process similar to other CCCs and that the effects of the introduction of ADTs on degrees earned were similar at these two schools as they were across the system. In models estimating the effect of ADTs on degrees earned in these two schools, I find qualitatively similar effects to the effects seen in the whole system (results available upon request).

11. See Appendix C in the online version of the journal for a closer examination of the effects of ADTs on untreated departments. In online Appendix D, I examine the effects of ADTs on another class of untreated awards: certificates.

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