Economic Studies at BROOKINGS

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Predicting the Impact of College Subsidy Programs on College Enrollment

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Model Description

Initialization

For each scenario of the model, we generate J colleges with m available seats per year (for the sake of simplicity, m is constant across colleges). During each year of the model run, a new cohort of N students engages in the college application process. Initial college quality (Q) is normally distributed, as are race-specific distributions of student achievement (A) and student resources (R). We allow for race-specific correlations between A and R. The values used for these parameters, and their sources, are specified in Supplementary Table 1. We select these values to balance computational speed and distribution density (e.g., for number of colleges and students), real-world data (e.g., for achievement and resource distributions), and based on work with previous versions of the model (Reardon et al., 2016; Reardon et al., 2018).

Dynamics

Application. During this stage of our model, students generate an application portfolio, with each student selecting n_s colleges to which they will apply. Every student observes each college's quality (Q_c) with some amount of uncertainty (u_{cs}), which represents both imperfect information and idiosyncratic preferences.

$$Q_{cs}^* = Q_c + u_{cs};\ u_{cs} \sim N(0, \tau_s). \tag{C.1}$$

The error in students' perceptions of college quality has a variance that depends on a students' resources in that students from high-resources families have better information about college quality. Specifically,

$$\tau_s = \mathrm{Var}(Q_c)\left(\frac{1-\rho_s^Q}{\rho_s^Q}\right), \tag{C.2}$$

where ρ_s^Q, the reliability of student perceptions of college quality, is a function of student resources and bounded between 0.5 and 0.7, as described in Table 1.

Students then use perceived college quality (Q_{cs}^*) to evaluate the potential utility of their own attendance at that college (U_{cs}^*), based on the quality of that college and a perceived cost of attending college that is dependent on resource percentile (R_s^*)[1]:

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1. Resource percentiles are used here for greater ease of manipulation and interpretation.

$$U_{cs}^{*} = Q_{cs}^{*} - \left(a + b * R_{s}^{*} + c * R_{s}^{*2} + d * R_{s}^{*3}\right).$$

(C.3)

Values that determine the cost function are given in Table 1, and the calibration process used to obtain them is discussed below.

When present in a given simulation run, subsidy programs are activated for the appropriate colleges after year 15 of model runs, allowing college quality and enrollment behavior (i.e. colleges' enrollment yields) to stabilize first. At this point, colleges' binary subsidy statuses (S_c)—which had previously all been 0—are set based on model parameters that determine which schools will be subsidized and remain constant through the remainder of the model run. Utility is then calculated as:

$$U_{cs}^{*} = Q_{cs}^{*} - ((1 - S_{cs} * L) * \left(a + b * R_{s}^{*} + c * R_{s}^{*2} + d * R_{s}^{*3}\right)),$$

(C.4)

where S_{cs} indicates whether a student receives a subsidy at a college and L is a subsidy magnitude, implicitly placing subsidies in terms of the utility function cost element; the value is presented in Table 1 and the calibration process that was used to obtain it is discussed below.

Students may augment their own achievement, and they perceive their own achievement with noise. Thus, their assessment of their achievement, for purposes of deciding where to apply, is

$$A_{s}^{*} = A_{s} + \alpha_{s} + e_{s};\ e_{s} \sim N(0, \sigma_{s}),$$

(C.5)

where α_s represents enhancements to perceived achievement that are unrelated to achievement itself (e.g., strategic extracurricular activity participation or application essay consultation) and e_s represents a student's error in his or her perception of his or her own achievement. The values that are used for these parameters and their relationships with student resources are listed in Table 1. As above, the error in a student's assessment of his or her own achievement has a variance that depends on his or her family resources:

$$\sigma_{s} = \mathrm{Var}(A)\left(\frac{1 - \rho_{s}^{A}}{\rho_{s}^{A}}\right),$$

(C.6)

where ρ_s^A, the reliability of student perceptions of their own achievement, is a function of student resources and bounded between 0.5 and 0.7, as described in Table 1.[2]

Based on their noisy observations of their own achievement and college quality, students estimate their probabilities of admission into each college:

$$P_{cs} = f(A_s^* - Q_{cs}^*), \tag{C.7}$$

where f is a function based on admission patterns over the prior 5 years. In each year f is estimated by fitting a logit model predicting the observed admissions decisions using the difference between (true) student achievement and college quality for each submitted application over the past 5 years. We set the intercept to 0 and the slope to $\beta = -0.015$ for the first 5 years of our simulation (since there are no prior estimates to use). These values were selected based on observing the admission probability function over a number of model runs. The starting values do not influence the model end-state, but do influence how quickly the function (and the model itself) stabilizes.

Each student applies to a set of at most n_s colleges, where n_s is determined by the student's resources, as described in Table 1. Given n_s, a student applies to the set of n_s colleges that maximize his or her overall expected utility. To determine the expected utility of an application portfolio, we do the following. Let $E_s^*\{C_1, C_2, \dots, C_{n_s}\}$ indicate student s's expected utility of applying to the set of n_s colleges $\{C_1, C_2, \dots, C_{n_s}\}$, where the colleges in the set are ordered from highest to lowest perceived utility to student s: $U_{C_1 s}^* \geq U_{C_2 s}^* \geq \cdots \geq U_{C_n s}^*$. Define $E_s^*\{\emptyset\} = 0$. Let P_{cs}^* indicate student s's perceived probability of admission to college c. Then the expected utility of applying to a given set of colleges is computed recursively as

$$E_s^*\{C_1, C_2, \dots, C_{n_s}\} = P_{C_1 s}^* \cdot U_{C_1 s}^* + \left(1 - P_{C_1 s}^*\right) \cdot E_s^*\{C_2, \dots, C_{n_s}\}. \tag{C.8}$$

In our model, each student applies to the set of colleges $\{C_1, C_2, \dots, C_{n_s}\}$ that maximizes $E_s^*\{C_1, C_2, \dots, C_{n_s}\}$, excluding colleges with perceived utility less than or equal to zero. In principle, this means that a student needs to compute the expected utility associated with applying

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2. The intercept value, minima, maxima, and linear relationships with resources used for the reliabilities with which students perceive their own achievement and college quality, as well as the intercept and slope values used for students' evaluation of the utility of attending colleges, are based on those used in previous work (Reardon et al., 2016). Briefly, the resource relationships are based on experimentation into the role of differential information quality in the observed sorting of students into colleges by SES (Reardon et al., 2016). In the absence of available empirical evidence, the other values used are plausible estimates: The average student has moderately high, but not perfect, perception of college quality (e.g., familiarity with college rankings) as well as his or her own achievement (e.g., knowledge of their SAT® scores). Because of resource, effort, and opportunity costs the utility of attending a very low-quality college is less than 0 (i.e., lower than not attending college). Extensive model testing suggests that our selections of these specific parameter values did not affect the overall interpretation of our results.

to every possible combination of n_s colleges in the model and then chooses the set that maximizes this expected utility. The model developed by Reardon et al. (2016) uses a fast algorithm for this maximization. We use the same algorithm here.

Although the model assumes all students are rational, utility-maximizing agents with enormous computational capacity, this is moderated by the fact that the student agents in the model have both imperfect information and idiosyncratic preferences, both of which are partly associated with their family resources. This means that there is considerable variability in student application portfolios, even conditional on having the same true academic records, and that high-resource students choose, on average, more optimal application portfolios than lower-resource students. Both of these features mimic aspects of actual students' empirical application decisions (e.g., Hoxby & Avery, 2012). More generally, the assumption of rational behavior is an abstraction that facilitates focus on the elements of college sorting that we wish to explore. We recognize that real-world students use many different strategies to determine where they apply.

Admission. Colleges observe the apparent achievement ($A_s + \alpha_s$) of applicants with some amount of noise (like the noise with which students view college quality, this also reflects both imperfect information as well as idiosyncratic preferences):

$$A_{cs}^{**} = A_s + \alpha_s + w_{cs};\ w_{cs} \sim N(0, \Phi). \tag{C.9}$$

As described in Table 1, colleges assess students' achievement with a reliability of 0.8. Given that true achievement has a variance of 2002 in the population, this implies that the error variance colleges' assessments of student achievement is

$$\phi = \mathrm{Var}(A)\left(\frac{1-0.8}{0.8}\right) = .25 \cdot 200^2 = 100^2. \tag{C.10}$$

Thus, in the model, colleges' uncertainty and idiosyncratic preferences have the effect of adding noise with a standard deviation of 100 points (half a standard deviation of achievement) to each student's application.3

Affirmative action policies (like subsidies) are activated in "elite" colleges after year 15 of model runs. At this point, colleges' binary affirmative action statuses (T_c) —which had previously all been 0—are set based on model parameters that determine which schools will use affirmative

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3. As with the parameter values that describe student perception, the means, minima, and maxima used for the reliability with which colleges perceive student achievement is based on what was used in previous work (Reardon et al., 2016). Although there is a lack of extant empirical evidence to inform these values, we made estimates that seem sensible: collectively, college admission officers have quite a bit of experience evaluating students and thus colleges have a highly accurate (but also not perfect) perception of student achievement. Extensive model testing suggests that our selections of these specific parameter values did not affect the overall interpretation of our results.

action (e.g. the top 8 colleges) and remain constant through the remainder of the model run. Perceived student achievement adjusted by race affirmative action (G) and resource affirmative action (H) magnitude values is given by:

$$A_{cs}^{***} = A_{cs}^{**} + T_c[G \cdot (Black_s|Hispanic_s) + H \cdot R_s].$$

(C.11)

Colleges rank applicants according to A_{cs}^{***} and admit the top applicants. In the first year of our model run, college's expected yield (the proportion of admitted students that a college expects to enroll) is given by:

$$Yield_c = 0.2 + 0.6(College\ quality\ percentile),$$

(C.12)

with the lowest-quality college expecting slightly over 20 percent of admitted students to enroll and the highest quality college expecting 80 percent of admitted students to enroll. In subsequent years, colleges admit $m/Yield_c$ students in order to try to fill m seats (where $m = 150$ in our model). After the first year of a model run, colleges are able to use up to 3 years of enrollment history to determine their expected yield, with $Yield_c$ representing a running average of the most recent enrollment yield for each college.

*Enrollment***.** Students enroll in the college with the highest estimated utility of attendance (U_{cs}^{*}) to which they were admitted.

*Iteration***.** Colleges' quality values (Q_c) are updated based on the incoming class of enrolled students before the next year's cohort of students begins the application process:

$$Q_c' = 0.9(Q_c) + 0.1(\bar{A}_c),$$

(C.13)

where $\bar{A}_c$ is the average value of A_s among the newest cohort of students enrolled in college c.

Simulation Duration

We run the model for 30 years. In our simulations, this is a sufficient length of time for key dynamics within the model to reach relatively stable states under most conditions, including all of those that we explore here.

Supplementary Table 1. Agent-Based Simulation Model (ABM) Parameters

Parameter	Value	Source
Number of students	10,000	n/a
percent White	60 percent	NCES Common Core of Data, 2012
percent Black	15 percent	NCES Common Core of Data, 2012
percent Hispanic	20 percent	NCES Common Core of Data, 2012
percent Asian	5 percent	NCES Common Core of Data, 2012
Number of colleges	40	n/a
College capacity	85 students/college	n/a
<u>Student academic achievement</u> White Black Hispanic Asian	 *achievement ~N(1052, 186)* *achievement ~N(869, 169)* *achievement ~N(895, 185)* *achievement ~N(1038, 202)*	ELS
<u>Student resources</u> White Black Hispanic Asian	 *resources~N*(.198, .657) *resources~N*(-.224, .666) *resources~N*(-.447, .691) *resources~N*(.012, .833)	ELS
<u>Resources-achievement correlations</u> White Black Hispanic Asian	 *r*=0.395 *r*=0.305 *r*=0.373 *r*=0.441	ELS
Quality reliability (how well students see college quality)	0.7 + *a**(*resources*); *a*=0.1	Reardon et al., 2016
Own achievement reliability (how well students see their own achievement)	0.7 + *a**(*resources*); *a*=0.1	Reardon et al., 2016
Achievement reliability (how well colleges see student achievement)	0.8	Reardon et al., 2016
Apparent achievement (perceived achievement, increased or decreased through achievement enhancement)	*perceived achievement* + *b**(*resources*)*(race-specific achievement standard deviation); *b*=0.1	Becker, 1990; Buchmann, Condron, & Roscigno, 2010; Powers & Rock, 1999; Reardon et al., 2016
Number of applications	4 + INT[*c**(*resources*)]; *c*=0.5	ELS
Utility of college attendance	*perceived quality* – (*a*+ *b*resource percentile* + *c* resource percentile*^{2} + *d* resource percentile*^{3}); *a*=750, *b*=900, *c*=-600, *d*=50	Calibration (see below)
Colleges using affirmative action	Top 20% of colleges	Reardon et al., 2018
Affirmative action effect	Race-based: 260; SES-based: -36	Reardon et al., 2018
College subsidy effect	.1	Calibration (see below)

Note. Quality and achievement reliability bound by minimum values of 0.5 and maximum values of 0.9. ELS = Educational Longitudinal Study.

Parameterization, Calibration, and Testing

Parameterization

Restriction to selective colleges

Colleges represented in the model are defined as those that are at least moderately selective according to 2012 IPEDS selectivity codes, which are based on the 2010 Carnegie classification system. Moderately and highly selective four-year institutions are those whose first-year students' test scores place them in the top three-fifths of baccalaureate institutions. This excludes less-than-four-year colleges and colleges that are classified as "inclusive." We define overall enrollment in selective colleges using the distribution of students across colleges by selectivity in the High School Longitudinal Study of 2009 (HSLS09), a nationally representative longitudinal survey of students who were in the ninth grade in 2009. According to our calculations using NCES PowerStats, 34% of all ninth-grade students in 2009 had ever enrolled in a selective four-year college by February 2016, so seats at selective colleges are set at 34% of the total student population.

Differentiating between selective colleges

We divide the selective colleges in the model into tiers used in policy experiments using estimates from HSLS09 and the Beginning Postsecondary Students Longitudinal Study (BPS). The latter is a nationally representative longitudinal survey of postsecondary students beginning their education in 2011-12; we use BPS only to classify schools as "in-state" or "out-of-state," which matters for subsidies that may only be used at public colleges in a student's home state. According to our estimates using HSLS09, 72% of students who attend moderately or very selective colleges are enrolled at public institutions. We apply an estimate from BPS of the percentage of students at selective public colleges who pay in-jurisdiction tuition (84%) to the estimate from HSLS09 in order to estimate that 60% of students at selective colleges are enrolled at in-state public institutions. To incorporate these sectors into the model, we assume that the 40% of students who enroll in selective private or out-of-state public institutions (which are generally costlier than in-state public institutions) do so in order to attend colleges that are perceived as higher-quality. We thus assign the top 40% of colleges in the model to be private or out-of-state institutions, which are ineligible for certain subsidies.

Because roughly half of college students attend the selective colleges represented in our model, the proportion of colleges that are "elite" (and use affirmative action admissions practices in our model) should be about double that of what is used in Reardon et al. (2018), which represents all colleges (and define the top 10% as elite). This also corresponds to the results of a similar strategy to the one used to differentiate in-state public institutions: 19% attend highly selective private or out-of-state colleges (where highly selective colleges are identified using the top IPEDS selectivity code). We thus designate the top 20% of colleges as elite.

Many real-world subsidies have been limited to community colleges, and sometimes induce some students to enroll in less selective schools than they otherwise would have (see, for instance, Gurantz's (2019) evaluation of Oregon Promise). While community colleges are not included in the model, we illustrate the enrollment effects of limiting subsidy availability to less selective schools by experimenting with a subsidy structure that is available only at the bottom 20% of selective colleges in the model. Among students who enroll in four-year colleges with admissions rates below 90% (which approximately corresponds to our definition of selectivity),[4] 23% attend public institutions with admissions rates between 75 and 90% (Digest of Education Statistics, Table 305.40). The least selective 20% of schools in the model may be interpreted as those with admissions rates within this range.

Calibration

Utility function

Previous versions of this model represented all U.S. colleges, including non-selective institutions such as community and for-profit colleges. In those versions, enrollment patterns across student resource categories approximating those seen in the real world were obtained through relationships between student resources and caliber, application enhancement, information quality, and number of applications submitted. However, when we parameterized our model as described above in order to represent only selective colleges, simulated enrollment patterns no longer matched those seen in the real world: lower-resource students enrolled in selective colleges at moderately higher rates than expected. To respond to this, we made some adjustments to our utility function. Specifically, we added in a resource-based "cost" term. This was an attractive approach for three reasons. The first is that it allows lower-resourced students in the model to engage in the application process differently than their higher-resourced counterparts in ways that can result in lower enrollment (i.e. the set of colleges they consider and how they evaluate them). The second is that it makes intuitive sense: for those with fewer resources, there are greater obstacles to attending college (e.g. direct and indirect costs relative to available assets, access to and terms of student loans, perceived opportunity costs) that can affect decision-making. And finally, it matches nicely with college subsidies, the focus of this research (i.e. college subsidies operate directly on this cost term).

Because there is no available data or research that can inform the specification of this function, we engaged in model calibration. We explored a large range of possible specifications, running the model multiple times with each and comparing model output to real-world data on overall patterns of enrollment by resource category as well

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4. 51% of all first-time college students in 2017-18 attended four-year schools with admissions rates below 90%, according to our calculations using the Digest of Education Statistics tables 305.10 and 305.40. According to our estimates from HSLS09, 47% of college students who were in the ninth grade in 2009 are enrolled in selective four-year colleges using our definition of selectivity stated above. The percentage of students enrolled in selective colleges is thus similar across these two definitions of selectivity.

as enrollment in our analogues for "in-state public" and "out-of-state or private" selective colleges, as defined above. We select a specification for which model output is very similar to expected patterns of enrollment (Supplemental Table 2).

Supplementary Table 2: Calibrating enrollment in selective colleges

	Model output			Real-world data		
Group	Overall Enrollment	In-state public	Private or out-of-state	Overall Enrollment	In-state public	Private or out-of-state
All	34%	19%	15%	34%	20%	13%
Bottom 80	26%	16%	10%	25%	15%	9%
Quintile 1	10%	6%	4%	12%	7%	5%
Quintile 2	20%	11%	9%	19%	14%	6%
Quintile 3	30%	18%	12%	26%	17%	9%
Quintile 4	44%	27%	17%	41%	25%	16%
Quintile 5	66%	35%	31%	66%	37%	29%

Note: Resource quintiles in real-world data are defined according to a composite measure of socioeconomic status designed by the National Center for Education Statistics that takes into account parent or guardian education, occupation, and income.

Subsidy effects

As with the specification of a cost term in our utility function, there are no data or literature that we can use to directly parameterize how subsidies affect utility evaluation. Therefore, we again engage in model calibration. We rely primarily on a high-quality evaluation of a relatively large-scale subsidy program for our real-world benchmark. Results from this evaluation are broadly consistent with other literature on college subsidy effects (discussed in more detail below).

Angrist, Autor, Hudson, and Pallais (2016) implemented a randomized evaluation of the Susan Thompson Buffett Foundation (STBF) scholarship, which covers up to five years of tuition and fees for graduates of Nebraska high schools who attend in-state public institutions. Between 2012 and 2015, STBF randomly offered awards to a sample of applicants who met the eligibility requirements, which take into account both merit and need. Award recipients were 3.3 percentage points more likely to enroll in a college with an admissions rate of at most 75%, and 7.4 percentage points more likely to enroll in a college with an admissions rate of at most 90%. If we assume that the 3.6-percentage-point reduction in the proportion attending out-of-state or private colleges observed resulted almost exclusively in a corresponding increase in attendance in subsidized selective colleges, then we obtain an estimated 11-percentage-point increase in enrollment at selective, in-state schools.

We first parameterized our model to best approximate the subsidy program. Eligible schools include in-state public institutions, which we define in our model as the bottom 60% of schools.

Students eligible for the STBF subsidies had minimum high school GPAs of approximately 2.7 and maximum expected family contributions (EFCs) of under $15,000. Using the High School Longitudinal Study of 2009, which has observations of non-honors-weighted GPAs drawn from students' transcripts, we selected a threshold for eligibility in our model: those above the 62nd percentile of caliber are eligible for the subsidy. The Urban Institute estimates that the median expected family contribution for students whose parents earn $90,000-$95,000 is slightly under $15,000; this corresponds to approximately the 70th to 75th percentiles of pre-tax income among parents whose children were born in 1991, measured when the children were 15 to 19 years old, according to data from Chetty et al. (2017). Therefore, we conservatively set our model threshold such that the bottom 80% of students on the resource distribution are eligible for the subsidy. Given that the program was both state-level and randomized, we randomly select a small set (10%) of recipients from those eligible in our simulations.[5]

We explore a range of subsidy effect magnitudes, selecting one that produces effects similar to those obtained from the real-world program evaluation: across the last five years of repeated runs, we see a 2.3-percentage-point increase in enrollment, with a 9.8-percentage-point increase in those attending the bottom 60% of colleges.[6]

Testing

After selecting an effect magnitude parameter value, we engaged in "out-of-sample" testing. We identified three large-scale subsidy programs that have been quantitatively evaluated and translated college and eligibility requirements into corresponding model parameters:

1. Tennessee HOPE (Bruce and Carruthers, 2014). We characterize this as providing subsidies for 10% of students in the model above the 60th percentile in observable achievement at in-state public colleges (the bottom 60% of selective colleges in our model). This achievement threshold is based on the actual achievement threshold of scoring 21 on the ACT, which we convert into a percentile of observable achievement using the distribution of ACT composite scores in the state of Tennessee for the graduating class of 2007, one of the middle cohorts included in the analysis. The 60th percentile of ACT scores in Tennessee is within one point (in terms of the ACT scale score) of the national 60th percentile for this cohort. We also check that the 60th percentile for this cohort is close to that of more recent cohorts in Tennessee since the state began requiring that all high school graduates take either the ACT or SAT (but most take the ACT), allowing us to conclude that the distribution of ACT test takers in Tennessee is a reasonable proxy for the distribution of high school graduates in Tennessee.

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5. Although our model represents all U.S. high school seniors and this program affected much less than one tenth of those students in the real world, we select this value because in practice it is small enough that spillover effects from recipients to non-recipients in our model are minimal, and doing so allows us to obtain a large enough treated sample for our analyses without the computational cost of selecting a small value and conducting more runs.

6. We deem this to be sufficiently similar given differences between the program context and that represented in our model.

2. Florida Student Access Grant (Castleman and Long, 2016). We characterize this as providing subsidies for 10% of students in the model below the 35th percentile in student resources at in-state public colleges (the bottom 60% of selective colleges in our model). Castleman and Long estimate that the actual resource threshold, which is a maximum expected family contribution of $1,590 in 2000, corresponds to a family income of approximately $30,000 in 2000 dollars. We use data from Chetty et al. (2017) on the national distribution of parent household incomes for children born in 1982 (closest to the cohort of high school seniors evaluated in Castleman and Long, 2016) to translate the income threshold (which is approximately $40,000 in 2015 dollars, inflated using the CPI-U-RS) into the 35th percentile of parent income, which we use as a proxy for family resources.

3. Massachusetts Adams Scholarship (Cohodes and Goodman, 2014). We characterize this as providing subsidies for 10% of students in the model above the 75th percentile in observable achievement at in-state public colleges (the bottom 60% of selective colleges in our model). The Adams scholarship is awarded to the top 25% of performers within each school district on a state-specific standardized exam. We approximate this to be the top 25% of all students by observable achievement in the model. In reality, since the score required to qualify for the threshold varies by school district, some students in lower-scoring districts will qualify with scores below the 75th percentile of overall achievement, while some students in higher-scoring districts will not qualify with scores above the 75th percentile.

After running simulations representing each of these three subsidy programs, we then compare model output to real-world estimates (Supplementary Table 3). Because each of the three programs was evaluated using a regression discontinuity around the relevant eligibility threshold, we restrict simulated effects to eligible students corresponding to those whose outcomes contributed to the evaluation effect estimates:

1. Tennessee HOPE (Bruce and Carruthers, 2014). The evaluation analysis is limited to those within 3 points on either side of the ACT eligibility threshold. Using the Tennessee-specific ACT score distribution discussed above, we estimate that Tennessee students between the 60th and 80th percentiles (that is, students in the regression discontinuity sample who qualify for the award) contributed to estimated effects.

2. Florida Student Access Grant (Castleman and Long, 2016). The FSAG regression discontinuity sample includes students whose expected family contributions are within $1,000 of the actual eligibility cutoff of $1590 in 2000 dollars, which we inflate to 2015 dollars using the CPI-U-RS. The Urban Institute provides an approximate crosswalk between expected family contribution and family income in 2015-16. We estimate, then, that the regression discontinuity sample includes students with family incomes of around $35,000 to $45,000, or (using data from Chetty et al., as above) the 30th to 45th percentiles of family resources. Students in this group between the 30th and 35th percentiles qualify for an award.

3. Massachusetts Adams Scholarship (Cohodes and Goodman, 2014). Students in this evaluation are included in the regression discontinuity sample if they score within 12 points of the eligibility threshold in their district. The histogram of scores displayed in the paper suggests that approximately one-third of students fall within this window. We estimate that 15% of students above the threshold and 15% of students below the threshold should be included in our window. Since the minimum achievement percentile in the model is set at the 75th percentile, this means that students from the 75th to 90th percentiles of observable achievement contribute to estimated effects.

Supplementary Table 3: Out of sample testing

	Simulated Effects		Real-world Effect Estimates	
Intervention	**Change in enrollment in any selective college (pp)**	**Change in enrollment in subsidized four-year college (pp)**	**Change in enrollment in any selective college (pp)**	**Change in enrollment in subsidized four-year college (pp)**
Tennessee HOPE	3.54	9.52	3.6	3.6
FSAG (Florida Student Access Grant)	1.68	4.59	3.2	3.2
Massachusetts Adams Scholarship	3.05	16.86	0.9	6.9

Overall, the model appears to produce similar effects on enrollment in any selective college and slightly to moderately higher effects on enrollment in subsidized, selective colleges. Evaluations of the Tennessee HOPE and FSAG programs found that change in enrollment in subsidized colleges came solely from increases in students attending selective colleges who otherwise would not (i.e. not from students who would otherwise have attended non-subsidized selective colleges), with no statistically significant changes in the likelihood of attending a private or out-of-state schools. This is seemingly at odds with evaluations of the STBF and Adams programs, which do find evidence that students substitute toward subsidized schools, though differences between these studies can likely be explained at least in part by differences in the students included in the evaluation samples. Students in the FSAG and Tennessee HOPE evaluations have lower achievement levels and/or lower incomes on average than students in the STBF and Adams evaluations and so are probably less likely to attend out-of-state or private schools in the first place. Bruce and Carruthers (2014) note in their evaluation of Tennessee HOPE that substitution between subsidized and nonsubsidized schools among the sample of students who score near the eligibility threshold is unlikely to be representative of students who score further from the threshold; higher-achieving students, such as those qualifying for the Adams scholarship, likely have more room for substitution. Effects may also vary due to differences in context (that is, the higher education system of Nebraska differs from that of Florida) and program implementation.

While the model produces somewhat larger substitution effects for students around each program's eligibility threshold, these differences in effects strike us as sensible given differences between these programs and the STBF (which we use to calibrate the effect magnitude value). Specifically, the STBF award is designed to cover a larger fraction of the total cost of attendance than is covered by the three other programs. At the time of the evaluations (and not taking into account possible crowding out of other aid sources), the fraction of tuition and mandatory fees at in-state four-year institutions that was covered by each award was approximately 57% for FSAG, 75% for Tennessee HOPE, and 20% for Massachusetts Adams. By contrast, the STBF scholarship covered the full cost of tuition and fees at in-state public institutions, and could be used to pay for other costs of attendance (such as room and board) if tuition and fees were paid by other sources of aid. Thus, we would expect simulated programs with an impact on perceived utility of attendance that is similar to STBF to induce a greater share of eligible students to eschew non-subsidized schools in favor of subsidized ones. Therefore, we believe that our out-of-sample testing provides support for appropriateness of the program effect magnitude value that we use in our primary analyses. In addition to this, we also subject this value to sensitivity analyses described below.

Sensitivity analyses

In order to address uncertainty about some of the elements that we include in our model, we conduct sensitivity analyses. Our largest source of uncertainty—that is, where model operation was least grounded in available data and literature—was around the ways in which student resources are related to information, application enhancement, and number of applications submitted. From both existing literature on college application behavior and work with prior versions of this model we were confident that there are salient pathways through which student resources affect the college enrollment process. However, we have less confidence in the specific parameter values that we use to determine the strength of these relationships.

Therefore, we repeat the full set of sweeps described in our report under two alternative specifications: one in which the parameter values that determine these relationships are set to zero, and one in which they are doubled. Results from these model runs can be found here:

"College subsidy effects data SES low," "College subsidy effects data SES high"

As expected, we find that enrollment patterns and specific subsidy effects under these alternative model specifications differ from one another and from our primary set of runs. Baseline enrollment for lower-resourced students is higher (and enrollment for higher-resourced students lower) when resource pathway parameters are zero, and the reverse is true when they are doubled. Subsidy effects are also higher in the absence of resource pathways, and lower when they are stronger. However, the relationships between subsidy conditions and subsidy effects that we describe in our report are qualitatively similar under each alternative specification. Based on this, we believe that our findings are robust to this source of uncertainty in our model (i.e. are not driven by the decisions that we made about specific parameter values).

Similarly, although existing literature (discussed below) suggests that college subsidy programs induce changes in potential recipients' college enrollment behavior, we are less certain about the selection of an effect magnitude parameter value for use within the context of our model. Therefore, we run our full sweep of policy experiments with a value that is doubled.

"College subsidy effects data magnitude"

As expected, specific policy impacts are greater in these sweeps. For example, our reference policy that is analogous to the STBF scholarship produces a 3.5 percentage point increase in attendance at any selective college and a 13 percentage point increase in attendance at subsidized colleges. However, the general trends that we obtain from our main analyses remain intact. Thus, we believe that our findings were not driven by the selection of our effect magnitude parameter value.

Additional literature on college subsidy effects

A large literature has investigated the enrollment and post-enrollment effects of college cost reductions. Most similar to our work, Avery, Howell, Pender, and Sacerdote (2019) simulate the effects of four policy approaches—including free community college, a 10% reduction in tuition and fees at public colleges, increased spending at public colleges, and reallocation of "undermatched" students to higher-quality colleges—on bachelor's degree completion rates. Their analysis differs from ours in that they use a microsimulation model to evaluate the total cost-benefit of four different policy levers, whereas we use an agent-based model to consider the distributional enrollment effects of variations in one policy lever, eliminating tuition and fees at four-year colleges. Avery et al. find that a 10% reduction in tuition and fees at four-year public colleges in a state results in a slight increase in enrollment at four-year public colleges, driven in part by a shift in enrollment from the private to public sector, and performs better in terms of a cost-benefit analysis than free community college policies but not as well as increasing spending at public colleges.

Avery et al. draw estimated elasticities for tuition changes on four-year enrollment from five papers, which we also consider here, and gauge that $1000 in aid (in 2019 dollars) tends to raise enrollment in four-year colleges by 2-3 percentage points. A review by Deming and Dynarski (2009) suggests that many studies find that aid interventions raise overall college enrollment rates by around 3-4 percentage points per $1,000 of grant aid (not adjusted for inflation) among eligible students. This range suggest that our own expected enrollment increase of 3-4 percentage points for a full-tuition subsidy are fairly modest, though effects vary by program design and geographic context. Additionally, we focus entirely on selective four-year institutions.

One strand of literature focuses on need-based grants for low-income students. Dynarski (2003) studies the elimination of the Social Security student benefit program and finds that an additional $1,000 in aid raised the college attendance rate by about 4 percentage points among children of deceased parents, who are disproportionately low-income. Early studies of the federal Pell Grant by Hansen (1983) and Kane (1995) find no impact on enrollment for low-income students; a later study by Seftor and Turner (2002) finds that changes in Pell eligibility criteria impacted the enrollment decisions of older students. Most recently, Denning, Marx, and Turner (2019) find that additional Pell aid for low-income students in Texas increases degree completion and later earnings. Hoxby and Bulman (2016) find that tax credits for educational expenses that generally benefit middle- and high-income households have no effect on college-going, though this is likely explained at least in part by the structure of the tax credits, which are received long after college payments are due.

Much of the evidence on student responses to financial aid comes from state-based merit programs, which generally offer tuition waivers at in-state public colleges for students who meet some minimum GPA or test score threshold. Dynarski (2000) finds that the Georgia HOPE scholarship increased enrollment in Georgia colleges by over 7 percentage points, with larger effects for middle- and upper-income students, likely due to the high income cap on eligibility (which was eventually eliminated altogether), crowding out of other aid sources for low-income students, and merit requirements. Another analysis of Georgia HOPE by Cornwell et al. (2006)

finds that increased enrollment in Georgia colleges was driven in large part by a reduction in students attending out-of-state colleges. Abraham and Clark (2006) find that the D.C. Tuition Assistance Grant, which is not merit-based and covers the difference between out-of-state and in-state tuition rates for D.C. residents who attend out-of-state public colleges, raised college enrollment among D.C. 17-year-olds by 3-4 percentage points per $1,000 reduction in tuition. They do not find evidence that the grant led students to substitute toward less selective institutions.

A number of recent studies use regression discontinuity (RD) designs to evaluate outcomes among students who narrowly meet eligibility cutoffs for state aid compared to similar students who do not qualify. We use three such studies in our out-of-sample analysis above: Bruce and Carruthers (2014) find that Tennessee HOPE (merit-based) led students to substitute from two- to four-year institutions but not from out-of-state or private institutions to in-state institutions, Castleman and Long (2016) find that the Florida Student Access Grant (means-tested) increased enrollment in four-year colleges without inducing students to substitute toward in-state public schools, and Cohodes and Goodman (2014) find that the Massachusetts Adams scholarship (merit-based) slightly raised enrollment in four-year schools with substantial switching from out-of-state or private schools to in-state schools. Scott-Clayton's (2011) RD analysis of West Virginia PROMISE is primarily focused on the impact of aid on post-enrollment outcomes. All but one of these studies identifies positive effects for college completion; Cohodes and Goodman actually find that completion declined for Adams-eligible students due to declines in college quality. More recently, also using an RD design, Bettinger et al. (2019) find that an early version of California's Cal Grant, which selects on family income and high school GPA, had no effect on immediate college enrollment or institutional sector but did increase persistence and completion among recipients.

Local Promise programs generally offer a combination of place-based scholarships and educational and community supports. Evaluations of Promise programs in Kalamazoo, New Haven, and Pittsburgh have generally found significant positive effects on four-year enrollment (Swanson, Watson, Ritter, and Nichols 2017). Harris et al. (2018) analyze a Promise program that offered a fixed amount equal to tuition and fees at local community colleges (but available at almost any in-state institution) to students at 18 randomly selected high schools in Milwaukee. Initial findings suggest that the program had no effect on immediate postsecondary enrollment, though Harris et al. (2018) theorize that merit requirements, the small scale of the program, and delayed disbursement of awards may have limited its effects.

Predicting the effects of a subsidy program is complicated by the possibility that the program's success will be partially determined by program administration and communication to students. Dynarski et al. (2018) use a randomized controlled trial to test an outreach campaign to promise low-income students that they would receive four years of free tuition and fees at the University of Michigan if they were admitted. While the intervention primarily informed students about aid for which they were already eligible, the share of eligible students enrolling in any highly selective college increased by fully 15 percentage points compared to those who did not receive outreach materials. Our simulations operate under the assumption that awareness and administration of subsidy programs are similar to what is observed in the real-world interventions from which we take our estimates.

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