Explaining the Gap in Upward Transfer Rates Between Economically Advantaged and Disadvantaged Community College Students

Audrey Light*
Department of Economics
Ohio State University
Columbus, OH USA
ORCID: 0009-0002-2201-0149

Sydney Schreiner Wertz
U.S. Department of the Treasury
Washington, DC USA
ORCID: 0000-0002-6435-4559

Audrey Light, Ph.D., is a Professor of Economics in the Department of Economics at Ohio State University. Her research focuses on the economics of education and labor economics.

Sydney Schreiner Wertz, PhD, is an Economist at the U.S. Department of the Treasury. Her research focuses on the economics of education, labor economics, and regional and urban economics.

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*Corresponding author (light.20@osu.edu)

Abstract: Using administrative data, we estimate models of community college students' upward transfer decisions and compute each covariate's contribution to the gap in transfer rates between economically advantaged and disadvantaged students and, alternatively, between white and Black students. We find that college entry age, completed credits, and enrollment duration account for over 50% of the economically advantaged-disadvantaged gap and 92% of the racial/ethnic gap; this combined effect is robust to alternative definitions of transfer. Many other factors are associated with increased transfer rates, but our findings suggest that economically disadvantaged, Black, and Hispanic students cannot catch up to their peers in transfer rates without starting college earlier and earning more credits—changes that are likely to require pre-college interventions and financial assistance.

Key words: Community colleges, transfer decisions, school choice

Introduction

A key role of community colleges in the U.S. is to serve as stepping stones to four-year institutions by offering noncompetitive admission, low tuition, flexible schedules, remedial coursework and, for many students, geographic proximity to home. As a result, students who are economically disadvantaged, constrained by job and family obligations, and/or unprepared for the academic rigors of a four-year institution often benefit from starting their post-secondary education at a community college. In response to rising costs of attending four-year colleges, even middle-class students with strong academic preparation are increasingly choosing to start their postsecondary education at a community college (Reeves & Guyot, 2019; Spencer, 2018).

Given the advantages of using community college as a stepping stone to a four-year degree, researchers and policy-makers struggle to understand why so few community college students make an upward transfer to a four-year institution.[1] Among students who signal an intent to transfer, upward transfer rates are often reported to be only 24% or even lower (Baker, 2016; Gross & Goldhaber, 2009; Jenkins & Fink 2015).[2] Moreover, economically disadvantaged and nontraditional students who are expected to benefit the most from community college are consistently found to be the least likely to transfer (Backes & Velez, 2015; Crisp & Nuñez, 2014; Dougherty & Kienzl, 2006; Lasota & Zumeta, 2016; Wang, 2012).

Of course, many students enter community college with no intention of proceeding to a four-year institution, and low transfer rates are expected among these students. However, among students for whom the cost of four-year college is outweighed by the expected wage premium associated with earning a bachelor's degree (Baum, 2014), the failure to complete an upward transfer likely reflects inefficiencies in the transfer process, an inability to finance further enrollment, or other frictions that prevent them from attaining their optimal educational level. It is important to identify barriers that prevent these students from transferring and to design policies to reduce those barriers. In particular, it is important to identify factors that might enable economically disadvantaged students to catch up to their peers in transfer rates as a means of addressing inequality in educational attainment. Currently, at least 31 U.S. states (Education Commission of the States, 2022) have comprehensive policies designed to facilitate transfers between their community colleges and four-year institutions—evidence that reflects widespread recognition that such transfers are critical to students' educational and labor market outcomes.

In light of these concerns, researchers have sought to identify factors that can be manipulated to increase the probability of upward transfer. The standard approach uses multivariate regression to identify key predictors of transfer probabilities for a sample of community college students, often after eliminating those with no apparent intent to transfer. In the current study, we extend the literature by asking: Among a wide range of factors previously identified as potentially important determinants of upward transfers, which can also explain the *gap* in upward transfer rates between economically advantaged and disadvantaged students (defined using median household income in pre-college residential zip codes) and, alternatively, between white and Black students?

To address this question, we use a sample of over half a million community college students drawn from Ohio administrative records to estimate richly specified logit models for the probability of upward transfer. We then employ Fairlie's (2005) extension to the Kitagawa-Blinder-Oaxaca decomposition method (Blinder, 1973; Kitagawa, 1955; Oaxaca, 1973) to identify the contribution of each covariate to the economically advantaged-disadvantaged or white-Black gap in upward transfer rates. Specifically, we consider hypothetical situations in which economically disadvantaged or Black students are assigned the same distribution of a factor as their comparison group, and predict the amount by which the transfer gap would change as a direct result of this change in endowments.

Our decompositions reveal that three factors explain sizeable portions of transfer gaps: community college entry age, credits earned in community college, and the number of terms enrolled in community college. If economically disadvantaged students had the same distribution of the first two factors as their advantaged counterparts, which would entail starting college earlier and earning more credits, we predict that the transfer gap between these groups would decrease by 68% using our benchmark definition of transferring that includes any transfer within six years of community college entry. If Black students had the same distribution of these factors as white students, we predict a 138% reduction in the gap, meaning transfer rates of Black students would *exceed* those of white students by 38%. However, if economically disadvantaged students and Black students increased their community college enrollment durations to match their peers' durations, we predict an *increase* in the advantaged-disadvantaged and white-Black gaps of 16% and 38%, respectively. The bottom line is that these three factors—credits earned, age at entry, and terms enrolled—combine to account for 52% of the economically advantaged-disadvantaged transfer gap and 100% of the white-Black gap using our benchmark transfer definition. When we experiment with alternative transfer definitions, ranging from requiring transfer students to move almost immediately between colleges to imposing no restrictions on enrollment patterns, the combined contribution of the three key factors varies only slightly across definitions.

For a factor to explain a significant portion of the transfer gap, it must be a strong predictor of transfer probabilities for both comparison groups *and* it must be distributed differently among students in the two groups. We find that many factors identified by other analysts as important predictors of transfers prove to have trivial effects on the gaps because they are distributed similarly for both comparison groups. While a range of factors might be manipulated to improve overall, upward transfer rates, it appears that the focus must be placed on college entry age and credit accumulation if economically disadvantaged students and Black students are to catch up to their peers.

Related Literature

Factors that account for the gap in transfer rates between two groups must be important predictors of transfer probabilities for both groups *and* be distributed differently for the two groups. As a result, our analysis relates to two strands of the literature: studies that identify key predictors of upward transfer, and studies that consider the extent to which those determinants differ systematically with race or economic status. We discuss studies of both types, although for the latter we focus on three determinants (community college entry age, completed credits, and enrollment duration) that explain most of the gaps. We then briefly describe research that applies decomposition methods to education outcomes.

Studies That Identify Determinants of Upward Transfers

We consider three categories of transfer determinants: student background, students' experiences in community college, and institutional and environmental factors. Starting with student background, there is ample evidence that the predicted probability of upward transfer increases substantially with parental socioeconomic status and/or income (Dougherty & Kienzl, 2006; Gross & Goldhaber, 2009; Lasota & Zumeta, 2016; Wang, 2012). Estimates of Black and/or Hispanic students' conditional transfer probabilities relative to white students' range from lower (Gross & Goldhaber, 2009; Wang, 2012) to higher (Backes & Velez, 2015), where the lack of robustness reflects cross-study differences in the mediating factors included in the regression specification. Measures of high school academic achievement and academic preparedness are consistently found to be strong, positive predictors of transfer probabilities (Backes & Velez, 2015; Crisp & Nuñez, 2014; Gross & Golhaber, 2009; Wang, 2012), while age at community college entry is consistently found to be strongly, negatively associated with upward transfer (Dougherty & Kienzl, 2006; Lasota & Zumeta, 2016). Measures of educational aspirations from survey data generally reveal positive associations with increased transfer probabilities (Backes & Velez, 2015; Wang, 2012).

While most studies modeling upward transfer decisions include controls for race and ethnicity, few identify separate effects of determinants for each racial/ethnic group. Crisp & Nuñez (2014) is a notable exception. They find that the estimated coefficients for many factors differ between white students and underrepresented minority students, including nondelayed college entry, the presence of dependent household members, and enrollment in a degree program. We have a similar goal of exploring differences in upward transfer rates between demographic groups, but our analytic strategy relies on cross-group differences in the factors themselves and not cross-group differences in each factor's estimated relationship to upward transfer rates, which we find to be statistically indistinguishable in most cases.

Turning to students' achievements and experiences in community college, many studies find that credits in remedial courses are negatively associated with subsequent upward transfer probabilities (Backes & Velez, 2015; Crisp & Delgado, 2014; Crisp & Nuñez, 2014), although estimated effects are sensitive to whether mediating factors are taken into account. Credit completion and full-time enrollment are typically found to be strongly, positively associated with transfer probabilities (Dougherty & Kienzl, 2006; Doyle, 2011; Lasota & Zumeta, 2016; Monaghan & Attewell, 2015), and multiple studies find that part-time employment while enrolled increases the likelihood of transferring relative to both nonemployment and full-time employment (Crisp & Nuñez, 2014; Lasota & Zumeta, 2016).

Among environmental factors, several studies assess the role of state policies designed to facilitate transfers, including California's Associate Degree for Transfer policy (Baker, 2016; Baker et al., 2023), transfer articulation policies (Boatman & Soliz, 2018; Gross & Goldhaber, 2009), and Georgia reforms intended to integrate two-year and four-year programs (Zhu, 2022). Boatman and Soliz (2018) find that completion of the Ohio Transfer Module, a set of credits guaranteed to be transferrable that we discuss below, is a strong, positive predictor of upward transfer. Baker et al. (2023) and Zhu (2022) find that exposure to the state policy under consideration leads to increased upward transfer rates, although Gross and Goldhaber (2009) find that such policies have a small effect nationwide, and only for Hispanic students. All three studies note that earlier analyses, including Baker (2016), generally point to weak relationships between state transfer policies and transfer rates, which suggests time lags in the policies' effects.

Among other environmental and institutional factors, expected travel distance is widely found to be a significant deterrent to enrollment and transfer (Alm & Winters, 2009; Backes & Velez, 2015; Jabbar et al., 2017). Other factors, including the area unemployment rate (Gross & Goldhaber, 2009), urbanicity (Jabber et al., 2017), and such college-specific characteristics as size, expenditures, and student-faculty ratios (Backes & Velez, 2015; Lasota & Zumeta, 2016) are found to have small and often imprecisely estimated associations with upward transfers.

Studies of Group Differences in College Entry Age, Duration, and Credit Completion

In addition to drawing from studies that identify determinants of upward transfers, our analysis also relates to studies that identify cross-group disparities in "endowments" of each determinant. While many determinants of upward transfers discussed in the previous subsection have been found to differ systematically with race or socioeconomic status, for brevity we focus our discussion on research that explores such disparities in the variables that combine to explain most of the economically advantaged-disadvantaged and white-Black transfer gaps: entry age, enrollment duration, and credit completion.

Empirical evidence abounds that racial minorities and especially economically disadvantaged students are far more likely than their counterparts to delay college entry (Andrews, 2018; Bozick & DeLuca, 2005; Goldrick-Rab & Han, 2011; Johnson, 2013; Wells & Lynch, 2012). These studies attribute delayed college entry to many factors, but especially to financial need and lack of academic preparedness.

Once in community college, economically disadvantaged students and racial minorities often lag their counterparts in persistence and performance (Bailey et al., 2005; Greene et al., 2008) because of the same factors that delay entry. Integration into campus life (Andrews, 2018; Dougherty, 1992), academic advising (Hatch & Garcia, 2017) and the ability to navigate the demands of college (Evans et al., 2020) have also been identified as potentially important determinants of persistence and performance. Moreover, a wealth of empirical evidence suggests that both in-school employment and part-time enrollment—while often necessary for financially constrained students—can be significant barriers to remaining enrolled and accumulating credits (Dadgar 2012; Porchea et al. 2010; Stinebrickner & Stinebrickner, 2003).

Decomposition Analyses Focused on Education Outcomes

Our study is the first to decompose the gap in transfer rates between demographic groups, so we have no existing evidence to draw from. However, decomposition methods have played a prominent role in other, education-related analyses, including those that decompose (a) the gap in bachelor's degree attainment between students who begin at a community college and those who do not (Sandy et al., 2006); (b) the gender gap in enrollment at elite four-year institutions (Bielby et al., 2014); (c) gaps between previously retained and nonretained students in the probability of completing high school (Stearns et al., 2007); (d) the gap between charter and traditional schools in teacher turnover (Stuit & Smith, 2012); and (e) the gap between high- and low-SES students in college grade point averages (Ulrick et al., 2018).

Among these studies, Sandy et al. (2006) is the only one to consider upward transfers. The authors find that differences between transfer and nontransfer students in individual characteristics (parental schooling, race, gender, test scores, etc.) account for 29-48% of the transfer-nontransfer gap in four-year degree attainment, depending on the sample used. However, the authors' focus on students who already completed an upward transfer is in direct contrast to our focus on transfer decisions, and their use of race as a determinant of college completion is distinct from our goal of explaining racial gaps in transfer outcomes.

Ohio's Higher Education System and Transfer Policies

During our observation period (summer 1998 through spring 2019), Ohio's public higher education system consisted of 23 community colleges with 29 distinct campuses, and 14 four-year institutions with 38 campuses. In 1990, Ohio implemented an articulation and transfer policy for its entire higher education system. Although the policy applies to transfers between all Ohio public institutions, we focus our discussion on features relevant to upward transfers as described in Ohio Department of Higher Education (ODHE) (2022).

Since its implementation, Ohio's articulation and transfer policy has focused on improving the ease and efficiency of the upward transfer process with a focus on minimizing credit loss. A core feature is the Ohio Transfer Module (renamed Ohio Transfer 36 in 2011), which requires each community college to specify an extensive set of courses in core fields (natural sciences, social sciences, arts, humanities, mathematics) that satisfy general education requirements at all four-year institutions. Any credits in these courses are guaranteed to transfer, and students completing an entire, prescribed set of courses or an associate degree are guaranteed admission as transfer students at Ohio's four-year institutions as long as other admissions criteria are satisfied. The policy's Transfer Assurance Guidelines extend beyond general education requirements to establish a common set of major-specific courses that, if completed at a community college, are guaranteed to transfer and fulfill requirements for the major at all four-year institutions. The policy also requires transparency and uniformity across institutions in transfer procedures and course catalogs.

Ohio's articulation and transfer policy was updated many times since 1990, with key revisions in 2005, 2007, 2011 and 2015. These revisions entailed fine-tuning existing policies and extending transferable credits to training completed outside the community college system (e.g., while serving in the military). The 2011 revision introduced the Ohio Articulation and Transfer Network, which is a consortium organized by ODHE to further promote and facilitate Ohio's transfer policies.

As noted in the introduction, at least 31 states currently have a statewide transfer policy. Baker (2016) reports that 21 states had a transfer policy in 2011, at which time Ohio was one of only eight states with a system-wide associate degree curriculum designed for students intending to transfer. Therefore, while Ohio is far from unique with respect to its efforts to facilitate upward transfers, during our observation period it belonged to a relatively small group of "transfer friendly" states. We do not believe this is a limitation of our analysis, yet a future decomposition based on nationwide data (or single-state data covering both the "before" and "after" period) would have the added advantage of identifying how much of the upward transfer gap is explained by the implementation of a statewide transfer policy.

Data

Primary Data Source

Our primary data source is Ohio's Higher Education Information System (HEI), which contains restricted-use transcript data for all students who enroll in Ohio's public community colleges and four-year colleges and universities from the 1998-99 academic year onward. We were given access to HEI data through the Ohio Longitudinal Data Archive (OLDA) for the 1998 summer term through the 2019 spring term. To construct several of our covariates we merge HEI records with other data sources, as described below.

HEI data are appropriate for our purpose, given that they contain the entire universe of postsecondary students for an extended period and provide detailed information on enrollment dates, credits attempted and completed, grades, and much more. The primary shortcomings of these data are that (a) despite providing large samples and detailed information on enrollment dates and coursework, they lack information on family background, expectations, and other factors that are often available in survey data; and (b) enrollment information is confined to Ohio's public, postsecondary institutions. Regarding the latter issue, our sample selection criteria (described below) minimize the likelihood that a student attends an unobserved college prior to appearing in our data as a community college student. We are uncertain how many upward transfers we miss in our data when students switch to an out-of-state and/or private four-year institution. Data are scarce on such transfers, but Jenkins and Fink (2015) report that private institutions account for 28% of upward transfers among respondents in the Beginning Postsecondary Students Longitudinal Study 2004/2009.

Given that our sample is limited to students in Ohio we note that, according to the 2010 decennial Census, Ohio was the 7th most populated and 22nd most urban state in the U.S. Among students enrolled in Ohio colleges in 2013, 55.2% were women, 72.6% were white, 12.1% were Black, 1.7% were Hispanic, 2.6% were Asian, and 39.6% were enrolled in community colleges. In contrast, among students enrolled nationwide in 2013, 56.2% were women, 56.6% were white, 14.3% were Black, 16.4% were Hispanic, 5.8% were Asian, and 37.9% were in community college.[3] This indicates that Ohio is typical with respect to community college enrollment rates but that its college population is considerably more white than the national average. Nonetheless, Ohio administrative data have been widely used to analyze education-related issues, including transfers (Boatman & Soliz, 2018; Long & Kurlaender, 2009; Spencer, 2019).

Sample Selection Criteria and Sample Sizes

We began with a sample of 3,865,585 students who enrolled in a public community college and/or four-year institution in Ohio from summer 1998 through spring 2019. We reduce this sample to 2,040,429 (52.8% of 3,865,585) by focusing on students for whom the first enrollment spell after high school graduation with a positive number of attempted credits falls between the 2000-01 and 2013-14 academic years. The former cutoff is imposed to focus attention on relatively recent cohorts and to eliminate an era in which select Ohio community colleges had trimester or "continuous enrollment" systems; the latter cutoff enables us to observe each student for a minimum of six years after entering college. We reduce the sample size to 1,044,963 (51.2% of 2,040,429) by dropping students for whom the initial enrollment spell is at a four-year institution, and to 879,210 (84.1% of 1,044,964) by requiring that students be recorded as freshmen during the first term of that community college enrollment spell. The latter selection rule is intended to eliminate students with prior, unobserved transfers from colleges outside our sample and those who take a significant number of college courses while enrolled in high school.

Our next selection criteria are designed to narrow the sample to students with upward transfer intentions. We lack direct information on students' intentions, which are difficult to measure in any case because students can alter their transfer plans over time. Therefore, we rely on indirect signals by confining the sample to 562,157 students (63.9% of 879,210) who attempt at least 12 nonremedial, nonvocational, community college credits, complete the Ohio Transfer Module, or both. In imposing these requirements, our goal is to drop students who complete only a handful of community college credits and/or focus primarily on vocational training, following Baker (2016), Baker et al. (2023), and Backes and Velez (2015).[4] We further reduce the sample to 545,909 students (97.1% of 562,157) whose initial community college enrollment occurs by age 50; our goal is to include nontraditional students while dropping older adults who might be pursuing non-career goals, although our findings are robust to the chosen age cutoff. As our final selection criterion, we confine our sample to 514,436 students (94.2% of 545,909) for whom pre-college residential zip codes are available, as this information is essential to our classification of students as economically disadvantaged.

We refer to the sample of 514,436 students detailed above as our *full sample*. Because economically disadvantaged students are a heterogeneous mix that includes rural white students and urban Black students, among others, we conduct one decomposition with a *large urban sample* of 248,391 students (48.3% of the full sample) whose pre-college residential zip codes map to counties that are classified as "large urban" (population of one million or more) using the U.S. Department of Agriculture's 2013 Rural-Urban Continuum Codes. When assessing the gap in transfer rates between white and Black students, we use a sample of 454,933 students (88.4% of the full sample) whose race is coded as white or Black. We do not pursue additional comparisons using the 11,898 Hispanic students and 6,308 Asian students in our sample due to length concerns, although we confirmed that estimates using combined white/Asian and

Black/Hispanic samples are virtually identical to those based on white and Black samples.

Transfer Definitions

The outcome of interest is each community college student's decision either to terminate his/her postsecondary education upon leaving community college or to transfer to a four-year university. The literature offers no consensus on how upward transfers should be defined and we find, unsurprisingly, that transfer rates are sensitive to the definition. Therefore, we consider four alternative definitions.

Our primary definition (T1) considers students to make upward transfers if they enroll at a four-year university within six years of first enrolling in community college. This definition is patterned after definitions proposed by Baker et al. (2023), Doyle (2011), Kopko and Crosta (2016) and Lasota and Zumeta (2016), and is intended to eliminate transfers that follow atypically long nonenrollment gaps, either before community college exit or between community college exit and four-year entry. Our second transfer definition (T2) modifies definition T1 by requiring that transfer students remain enrolled at a four-year university for at least two terms. Although we believe that an upward transfer followed almost immediately by a decision to drop out is no less legitimate than a transfer that "lasts," we experiment with this additional restriction because it has been proposed by other analysts (e.g., Boatman & Soliz, 2018).

Our next transfer definition (T3) is quite restrictive in that it requires students to exit community college within four years of entry *and* enroll at a four-year institution after, at most, a summer-long nonenrollment gap. Our final definition (T4) is entirely unrestrictive by including all observed transfers, regardless of enrollment and nonenrollment patterns. Our sample includes students with lengthy interruptions between two-year and four-year enrollment, and whether reenrollment after such breaks should be considered an upward transfer or a return to college after dropping out is unclear. Definition T3 excludes virtually all such cases, while definition T4 includes them; as such, these two definitions bookend any alternative definitions we might consider that impose cutoffs on enrollment and/or nonenrollment durations.

Table 1 gives the upward transfer rate for each combination of sample (full, large urban, white/Black), comparison group (economically advantaged vs. disadvantaged and white vs. Black) and transfer definition (T1-T4) used in our analysis. Transfer rates are always lower for disadvantaged or Black students than for their advantaged or white counterparts, and are considerably lower for the more restrictive transfer definitions T2 and T3 than for T1 and T4.

Covariates

We consider as many covariates as possible that have been shown to be important determinants of upward transfers, although we exclude some due to data nonavailability and, as noted below, a few that prove to be unimportant for our analysis. Sample means for the variables described here are presented in table 2.

Starting with individual background factors, we define a set of mutually exclusive indicators of whether the student is white, Black, Hispanic, Asian, or of other/unknown race. We classify students as economically advantaged or disadvantaged by determining whether the median household income in their pre-college residential zip code is less than 80% of the state-wide median, using the American Community Survey's 2007-2011 five-year estimates (Manson et al., 2023). We use "neighborhood" income to proxy actual household income because the latter measure is unavailable in our administrative data. Similar proxies have been used in the economics literature (Bostwick et al., 2022) and especially in the public health and epidemiology literatures (Hanley & Morgan, 2008; Moss et al., 2021), where the lack of income data in medical records would otherwise preclude the analysis of income-based inequality in health outcomes. As demonstrated in Hanley and Morgan (2008) and Moss et al. (2021), neighborhood-based income measures are highly correlated with actual household income. While a student-specific income measure might be preferred insofar as household income can vary around the median even in narrowly-defined geographic areas, any area-based proxy has the advantage of avoiding the considerable measurement error inherent in self-reported income data.

To control for individual background we also include a binary indicator of whether the student is female. We lack a measure of pre-college ability, which is difficult to obtain for community college students because they are not required to take standardized college admissions tests. We instead rely on two ability proxies based on academic performance during the first term of community college: the number of remedial and basic skills credits attempted, and grade point average.

We control for an extensive set of variables that account for community college academic achievement and enrollment, all defined for community college enrollment spells that occur prior to four-year entry. These controls include age at college entry using three categories (≤19, 20-25, and >25), the cumulative number of terms enrolled, whether the student transfers between community colleges or attends two colleges and/or campuses simultaneously, and whether enrollment is full-time, which we define as an average of 12 or more credits attempted per term. To capture academic achievement, we control for the total number of college credits attempted, the total number of college credits earned using five categories (≤12, 13-25, 26-46, 47-73, and ≥74), whether the student earns an associate degree, and whether the student completes the Ohio Transfer Module. We use the categorical variables described here after determining via extensive experimentation that nonlinear effects should be allowed for age at college entry and credits earned but are unnecessary for other covariates, and that these categories adequately capture nonlinearities.

In-school employment is known to be both a deterrent to upward transfers *and* a necessary means of making community college financially feasible (Riggert et al., 2006). To control for these factors, our covariates include the percent of calendar quarters during which the student reports no employment, and the average number of weeks worked per quarter between community college entry and exit. Both employment variables use quarterly data from Ohio unemployment insurance records, which, along with HEI data, are available through OLDA.

The final set of environmental covariates includes dummy variables identifying the calendar year of community college exit to capture secular variation in four-year tuition rates, economic conditions, and state-wide transfer policies in the year when each student contemplates an upward transfer. To further control for economic conditions, we include the unemployment rate in the college's county for the student's exit year, obtained from the Bureau of Labor Statistics' Local Area Unemployment Statistics.

Our college-specific factors include the outward transfer rate for the community college attended, taken from *U.S. News & World Report* for 2019. Following Jenkins and Fink (2016) and Lasota and Zumeta (2016), we use this measure to control for variation across community colleges in the information and support given to students wishing to transfer. College-specific outward transfer rates include transfers to private and out-of-state institutions, which is why the mean outward transfer rates shown in table 2 are higher than the upward transfer rates for our sample (table 1). Nonetheless, the outward transfer rate is a suitable proxy for college support for upward transfers as long as the two are sufficiently correlated, which is likely to be the case.

Our college-specific factors also include controls for whether the community college's county is in a large urban (population of 1 million or more), small urban (population 250,000 to

1 million), or rural area, based on the U.S. Department of Agriculture's 2013 Rural-Urban Continuum Codes. We experimented with an array of additional college-specific factors, including the number of students enrolled, student demographic composition, and expenditures per student. Except for the urban/rural controls described above, all institutional factors that we were able to measure are distributed similarly among our comparison groups and, therefore, explain none of the transfer gaps. We excluded such controls after confirming that all other estimates are robust to their exclusion.

Finally, given that distance traveled is often found to be an important determinant of college enrollment and transfer decisions (Backes & Velez, 2015; Jabbar & Edwards, 2020; Jabbar et al., 2017), we use three distance variables. Two indicate whether the distance from the student's pre-college residential zip code to his/her community college is over 35 miles, separately for cases where the nearest community college is over 35 miles (reflecting forced travel) or within 35 miles (reflecting voluntary travel). While these two variables indicate the student's willingness and ability to travel a substantial distance to attend college, to identify the travel cost of transferring to a four-year institution we also control for whether the distance from the pre-college residential zip code to the nearest four-year institution is over 35 miles.

Analytic Strategy

In the first step of our empirical analysis, we use a binomial logistic regression model for community college students' decisions to terminate postsecondary enrollment or transfer to a four-year institution. In estimating the logit models, we compute clustered standard errors that account for residual correlations among students attending the same community college campus. In the second step of our analysis, we use the logit estimates to compute each covariate's contribution to the gap in transfer rates between economically advantaged (A) and disadvantaged

(D) students or, alternatively between white and Black students. Our decomposition is based on Fairlie (2005), who extends the widely-used decomposition method proposed by Kitawaga (1955), Blinder (1973) and Oaxaca (1973) to nonlinear models.

Fairlie's decomposition method is best described in contrast to the Kitawaga-Blinder-Oaxaca method, so we begin with the following regression models in which a continuously-distributed outcome for student i (Y_i) is expressed as a linear function of a vector of covariates (X_i) and a vector of unobserved factors (ε_i), separately for subsamples of As and Ds:

$$\mathrm{Y_i^A = X_i^A \beta^A + \varepsilon_i^A} \tag{1a}$$

$$\mathrm{Y_i^D = X_i^D \beta^D + \varepsilon_i^D}. \tag{1b}$$

Under the standard assumption that the unobservables are mean zero for each subsample, we can use the OLS parameter estimates ($\hat{\beta}^A, \hat{\beta}^D$) to decompose the difference in group means of the outcomes as follows:

$$\begin{aligned} \bar{Y}^A - \bar{Y}^D &= \bar{X}^A\hat{\beta}^A - \bar{X}^D\hat{\beta}^D + (\bar{X}^D\hat{\beta}^A - \bar{X}^D\hat{\beta}^A) \\ &= (\bar{X}^A - \bar{X}^D)\hat{\beta}^A + \bar{X}^D\left(\hat{\beta}^A - \hat{\beta}^D\right), \end{aligned} \tag{2}$$

where the first term on the right side of (2) identifies the contribution of A-D differences in means, or endowments, to the A-D gap in outcomes and the second term identifies the contribution of A-D differences in returns. In (2), we use $\hat{\beta}^A$ and $\bar{X}^D$as weights in the first and second term, respectively, but we could just as easily use $\hat{\beta}^D$ and $\bar{X}^A$; as has been widely discussed in the literature (e.g., Fairlie, 2005; Oaxaca & Ransom, 1994), the decomposition is often sensitive to which weights are chosen.

In our application, the decomposition given by (2) becomes:

$$\bar{Y}^A - \bar{Y}^D = \left[\sum_i \frac{F\left(X_i^A\hat{\beta}^A\right)}{N^A} - \sum_i \frac{F\left(X_i^D\hat{\beta}^A\right)}{N^D}\right] + \left[\sum_i \frac{F\left(X_i^D\hat{\beta}^A\right)}{N^D} - \sum_i \frac{F\left(X_i^D\hat{\beta}^D\right)}{N^D}\right], \tag{3}$$

where F(.) represents the logistic cumulative distribution function, N^A and N^D are the number of observations in the A and D subsamples, respectively, and the summations are over the relevant *N*. This expression deviates from (2) because $\bar{Y}^A \neq \bar{X}^A\hat{\beta}^A$ and $\bar{Y}^D \neq \bar{X}^D\hat{\beta}^D$ when the underlying regression is a nonlinear, discrete choice model. Our goal is to determine how much of the A-D gap in transfer rates is due to A-D differences in endowments of each individual covariate or group of related covariates in the vector X. To do so, we focus on the first right-hand term in (3) and, in particular, on computing the change in the mean probability of transfer after Ds are assigned the As' distribution of each individual covariate (or set of related covariates). Following Fairlie (2005), the steps in these computations are as follows:

First, to contend with potential sensitivity to our choice of weights, we replace $\hat{\beta}^A$ with pooled logit estimates $\hat{\beta}^P$ obtained by estimating the logit model with a combined sample of As and Ds. Second, because $N^A \neq N^D$, we pair each D with a "like" A by drawing a random sample of As of size N^D, computing the predicted transfer probability for each A in this random sample and for each D, ranking each group by predicted probabilities, and pairing As and Ds by rank. Third, for each covariate X1 we recompute every D's predicted transfer probability using $\hat{\beta}^P$, the paired A's value of X1, and D's actual values of all other covariates. When a group of covariates are related, as in the case of calendar year dummies or our categorical measures of credits earned, we assign the paired A's values for each variable in the group.[5] Fourth, we determine the change in the average predicted transfer probability among Ds when we switch from assigning Ds their own values for all covariates to assigning them their paired A's value of X1. Fifth, we conduct steps 2-4 for 500 random samples and use the average contribution over 500 draws as X1's estimated contribution to the A-D gap. The sum of estimated contributions over all covariates gives us the summary value shown in the first right-hand term in (3).

Although we use a representative covariate (X1) to illustrate our decomposition, in practice we assign the As' distribution to the Ds for *all* covariates, including those (e.g., age at college entry) where the reassignment could potentially be achieved via policy interventions and those (e.g., race, sex) where the reassignment is purely hypothetical. In presenting our findings, we assess the relative magnitudes of each X's contribution to the transfer gaps, but note which decompositions are infeasible.

Like most decomposition analyses in the literature, ours does not employ direct solutions to self-selection and endogeneity problems. To take a concrete example, we find that starting community college at an older age decreases the likelihood of transferring, and that the A-D transfer gap is predicted to decrease substantially if Ds are assigned As' earlier (on average) entry ages. While delaying college entry might causally decrease the probability of transfer insofar as classroom learning skills depreciate and nonacademic obligations increase with age, a portion of our estimated effect might reflect the fact that students who choose to move directly from high school to community college tend to have unobserved traits that promote academic success. Instrumental variables are occasionally used to identify causal effects in decomposition analyses (Fortin *et al.* 2011), but we have too many potentially endogenous covariates and far too few suitable instruments to implement this strategy. Moreover, policies that help students move directly from high school to college will be useful regardless of the lack of causal estimates, as will policies that help students gain hard-to-measure traits that subsequently lead them to choose early college entry.

Findings

Table 3 reports pooled coefficient estimates ($\hat{\beta}^P$) referred to in the preceding section for logit models of the probability of upward transfer. Specifications 1-3 use our preferred transfer definition (T1) in combination with the full, large urban, and white/Black samples, respectively. Specifications 4-6 use the full sample in combination with alternative transfer definitions T2-T4. Specifications 1-3 (4-6) are used for the decompositions summarized in table 4 (5).

In presenting our findings, we first focus on a benchmark decomposition of the transfer gap between economically advantaged (A) and disadvantaged (D) students based on the full sample and transfer definition T1. We begin with a detailed discussion of several key factors to clarify how their contributions depend on both the magnitude of the estimated logit coefficient *and* A-D differences in the factor's distribution across students. We then summarize findings for the remaining covariates before considering how our estimates change when we switch samples, comparison groups, and/or transfer definitions.

Benchmark Decomposition

As reported at the bottom of table 4, the full sample gap in upward transfer rates between As and Ds is 0.052, and our covariates combine to explain 0.034 (65%) of this gap. Our categorical measures of the number of credits earned in community college account for 0.0235 of this gap, or 44.8%. This 44.8% is by far the largest amount accounted for by any of our covariates, and it arises because of two patterns in the data. First, Ds tend to have far few credits than As: as seen in table 2, Ds are 50% more likely than As (0.27 vs. 0.18) to earn 12 credits or fewer in community college and three percentage points less likely (0.18 vs. 0.21) to earn 74 or more credits. Second, as seen in column 1 of table 3, the predicted likelihood of transferring increases with credits earned. Therefore, when we assign the As' credit distribution to Ds, we decrease the proportion of Ds with fewer credits, which is a factor that *decreases* the probability of transferring, and increase the proportion with more credits, which *increases* the probability of transferring. In short, the reassignment of endowments increases Ds' predicted transfer probabilities across the credit distribution and decreases the A-D transfer gap by almost 45%.

Table 4 reveals that entry age explains 23.1% of the A-D transfer gap, making it the second most important contributor. As seen in table 2, Ds are 14 percentage points less likely than As to begin community college by age 19 (0.31 vs. 0.45) and nine percentage points more likely to enroll after age 25 (0.38 vs. 0.29). Table 3 shows that increased entry age is associated with lower predicted transfer probabilities. Assigning the As' age distribution to Ds (which entails lowering Ds' entry ages) leads to an increase in the Ds' predicted transfer probabilities and a 23% reduction in the A-D transfer gap.

The estimated effects of credits earned and entry age—which combine to account for 67.9% of the A-D transfer gap—are mitigated by the negative effect of the number of terms enrolled which, at -16.3% (table 4), is the third most important contributor to the gap. Table 2 reveals that Ds enroll in community college for an average of 6.52 terms, versus 6.92 terms for As. Table 3 reports a negative estimated coefficient for the effect of terms enrolled on transfer probabilities. The decomposition assigns Ds higher enrollment durations, on average, which leads to *decreased* predicted transfer probabilities and an *increase* in the A-D transfer gap. If Ds increase their enrollment durations to match those of As at the same time that they "catch up" with respect to credits and entry age, the A-D gap is predicted to decrease by only 51.6% (44.8 + 23.1 – 16.3) rather than 67.9%.

Table 4 reveals that the next-most important contributor to the A-D transfer gap is the indicator that the student's race is coded as Black. This factor explains -10.3% of the A-D transfer gap; that is, we predict a 10.3% *increase* in the A-D transfer gap if the racial composition of economically disadvantaged students were changed from 37% to 9% Black, per the means in table 2. (This is the only covariate with a nontrivial effect on the transfer gap for which this reassignment is purely hypothetical, and not something that could be facilitated by policy.) This surprising result reflects the fact that, as seen in table 3, the "Black" indicator has a large, *positive* association with the predicted probability of transferring, presumably because, conditional on our extensive array of covariates, Black students tend to possess unobserved traits that increase the likelihood of transfer.[6]

Contributions of the two employment variables reported in table 4 are best interpreted in combination. The variable identifying the percent of in-school calendar quarters with zero weeks worked has a higher mean for Ds than for As (46.7 vs. 38.9) and a negative estimated logit coefficient (-0.03). When Ds are assigned less of this transfer-deterring factor, their predicted transfer probabilities increase and the gap is predicted to decrease by 9.6%. However, the second employment variable (average weeks worked per quarter) has an offsetting effect: Ds have *less* of this transfer-deterring factor than do As, so assigning them the As' distribution results in a 5.5% *increase* in the A-D transfer gap. Together, these variables account for a 4.1% net decrease in the gap and suggest that a relatively low-intensity level of in-school employment is optimal for facilitating upward transfer, as also found by Crisp and Nuñez (2014) and Lasota and Zumeta (2016).

Turning to the remaining factors listed in table 4, completion of the Ohio Transfer Module explains an 8.8% decrease in the gap. Although relatively few students complete the module, As are twice as likely as Ds to do so (0.04 vs. 0.02). It is strongly associated with transferring, as evidenced by the estimated coefficient of 1.47 in table 3, so assigning a higher completion rate to Ds results in a nontrivial predicted decrease in the A-D gap. Improving Ds' first-term GPA, which proxies academic preparedness, is predicted to decrease the gap by 6.2%, and assigning Ds to community colleges with the same urban/rural distribution as As is predicted to decrease the gap by 5.5%; the latter effect is driven by a shift of (primarily white) Ds from rural campuses to small urban campuses with higher transfer rates. All other covariates listed in table 4 (plus an array of college-specific traits that we excluded from our model) are predicted to have a trivial effect on the A-D transfer gap, often because they are distributed uniformly among As and Ds.[7]

We use estimated logit coefficients based on a pooled sample for all decompositions. Appendix table A1 shows A-specific and D-specific estimated coefficients; the pooled estimates ($\hat{\beta}^P$) reported in column 1 of table 3 fall between these group-specific estimates in magnitude but are closer to the A-specific value given that As account for 73% of the full sample. Table A1 reveals that the A-specific and D-specific coefficient estimates are statistically indistinguishable for most covariates. More importantly, among covariates for which the D-specific estimate differs substantially from $\hat{\beta}^P$, none accounts for a large portion of the A-D transfer gap. In short, our findings prove to be robust to whether we use pooled or group-specific logit estimates.

In summary, the evidence discussed in this subsection indicates that Ds can expect to close 52% of the A-D transfer gap by starting college as early as As and accumulating as many credits as As, even if they simultaneously enroll for as many terms as As. They can close the gap by another 15% by catching up to As with respect to their first-term GPA and completion of the Ohio Transfer Module. Our findings provide no evidence that geographic proximity to college, economic conditions, year(s) attended, or college-specific factors have a key role in explaining A-D differences in transfer rates.

Decompositions Using the Large Urban and White-Black Samples

The second decomposition presented in table 4 is identical to the benchmark decomposition just discussed except that we switch to a subsample of students who reside in a large urban area. The economically disadvantaged students in our full sample are a heterogenous group, with

Black and Hispanic students disproportionately residing in large and medium urban areas and white students skewed toward rural and small urban areas. By focusing solely on students whose pre-college residences are in large urban areas, we eliminate systematic relationships between disadvantage, race/ethnicity and distance to college.

As table 4 reveals, changes in the decomposition estimates are relatively minor when we switch from the full sample to the large urban subsample. The overall A-D transfer gap increases from 0.052 to 0.072, but the percent of that gap explained by our covariates remains at about 65%. Most covariates' contributions to the gap remain largely unchanged in percentage terms and, in particular, the combined contribution of credits earned, terms enrolled, and entry age is similar for the large urban sample (57.2%) and the full sample (51.6%). However, credits earned account for a larger reduction in the gap for the large urban sample (58.2%) than for the full sample (44.8%), while terms enrolled accounts for a larger offsetting increase in the gap for the large urban sample (-23.5%) than for the full sample (-16.3%).

Among the remaining factors, the biggest differences between the full and urban samples are seen for campus urbanicity and the measure of proximity to a four-year institution. Both factors account for a small but nontrivial portion of the A-D gap when we use the full sample; when we switch to the large urban sample, both factors' contributions to the gap fall to zero. This is unsurprising, as virtually all students residing in large cities attend nearby community colleges and live within 35 miles of both community colleges and four-year institutions.

The final decomposition presented in table 4 is for the transfer gap between white and Black students. Many analysts focus on educational outcomes for racial and ethnic minorities because they are more likely than other students to face financial constraints and are historically underrepresented at higher education institutions in the U.S., so we include this alternative decomposition for comparison with the A-D decomposition. It is important to recognize that neither pairing is an error-free way to separate students with financial barriers from their counterparts: we misclassify students as A or D if their household income diverges sufficiently from the zip code-specific median value and, per our table 2 means, 19% of white students are economically disadvantaged while 39% of Black students are economically advantaged.

Table 4 shows that the white-Black transfer gap is 0.043 (vs. 0.052 for the full-sample, A-D gap), and that our covariates explain 131% of the gap (vs. 65% for the A-D gap); i.e., when Black students are assigned the same distributions of all covariates as white students, their predicted transfer rate *exceeds* that of white students by 31%. Many covariates have estimated contributions to the white-Black gap that are qualitatively similar to what is seen for the A-D gap, but larger in magnitude. For example, credits earned explain 107.2% of the white-Black gap (vs. 44.8% for A-D), terms enrolled explains -38.3% (vs. -16.3%), entry age explains 31.0% (vs. 23.1%), and first term GPA explains 19.1% (vs. 6.2%). In these and other cases, the more pronounced effects are primarily due to larger cross-group difference in the variable's distribution (table 2) rather than larger (in absolute value) estimated logit coefficients (table 3).[8]

Among factors that account for a nontrivial portion of the transfer gap, only one has a different sign in the white-Black decomposition than in the A-D decomposition: the urban/rural location of the community college accounts for a 10.7% *increase* in the white-Black gap, in contrast to a 5.5% *decrease* in the A-D gap. This discrepancy arises because a significant portion of Black students are reassigned from a large urban campus to a rural campus, where transfer rates tend to be lower. It is also worth noting that the "Black" indicator contributes to a 10.3% *increase* in the A-D gap, but being economically disadvantaged accounts for a 19.8% *decrease* in the white-Black transfer gap because the economically disadvantaged indicator is associated with lower transfer rates.[9]

In summary, our comparison of the A-D and white-Black decompositions points to two key differences. First, each factor with a large estimated effect on the A-D transfer gap has an even more pronounced effect on the white-Black transfer gap. Second, if we reassign Ds their endowments of the three key factors (age at college entry, credits earned and enrollment duration) to match the distributions of As, we predict a 52% reduction in the A-D gap and a 99.9% reduction in the white-Black gap.

Decompositions Using Alternative Transfer Definitions

We conclude our analysis by returning to the transfer gap between economically advantaged and disadvantaged students based on the full sample, and experimenting with alternative definitions of transfer. These alternative decompositions are reported in table 5 and the underlying, estimated logit coefficients are reported as specifications 4-6 in table 3. The benchmark used for comparison continues to be the first decomposition in table 4.

The first alternative definition (T2) requires students to begin four-year enrollment within six years of entering community college, as in definition T1, with the additional restriction that they remain enrolled at a four-year institution for at least two terms. As seen in table 5, this reduces the A-D transfer gap to 0.041 (vs. 0.052 with T1) but has very small effects on the decomposition estimates. Several covariates, including first term GPA, cumulative credits completed, and completion of the Ohio Transfer Module, contribute slightly less to the A-D gap with transfer definition T2 than with T1, but because the gap is smaller that contribution accounts for a larger percentage. However, even these differences are minor; e.g., credits completed contribute 0.0217 (52.4%) to the gap with T2, versus 0.0235 (44.8%) with T1.

Our remaining two transfer definitions range from restrictive T3, which allows no more than four years in community college and a summer-long nonenrollment gap, to highly inclusive T4, which includes all transfers regardless of (non)enrollment patterns. Unsurprisingly, relative to T1 both As' and Ds' transfer rates are substantially lower with definition T3 and higher with T4, as seen in table 1. These changes in transfer rates leave us with a smaller A-D transfer gap for T3 than for T1 (0.042 vs. 0.052) and a slightly larger gap of 0.055 for T4.

Although most decomposition estimates continue to be robust to the introduction of alternative transfer definitions, two of the larger changes are seen for terms enrolled and credits completed. Definition T3 limits the attainable levels of both factors among transfer students by requiring that they transfer relatively quickly, and produces estimated logit coefficients that are larger in absolute value than those obtained for T1. As a result, terms enrolled contributes more toward increasing the A-D gap for T3 than for T1 (-34.3% vs. -16.3%) and credits completed contributes more toward decreasing the gap (69.9% vs. 44.8%). Opposite patterns are found for T4, which permits considerable variation in both factors among transfer and nontransfer students. This definition produces estimated logit coefficient that are smaller in absolute value than those produced by T1, and predicts that both variables contribute less to the gap (e.g., 6.1% for terms enrolled with T4, vs. 16.3% for T1).

Given that entry age, credits completed, and terms enrolled are the three most important determinants of the gap, we end by summarizing how their estimated contributions compare across all four transfer definitions. The *combined* contribution of these three factors is fairly uniform across definitions, ranging from 52-53% with definitions T1, T2 and T4 to 59% with T3. The effect of entry age is also robust to transfer definition, with an estimated contribution of 23-24% in each case. However, the relative contributions of credits completed and terms enrolled change dramatically across definitions. We previously described transfer definitions T3 and T4 as bookending any reasonable time limits we might impose on enrollment and, indeed, these two definitions produce the largest and smallest contributions of both time-dependent covariates: the estimated contribution of credits completed ranges from 34% (T4) to almost 70% (T3), while the contribution of terms enrolled ranges from -6% (T4) to -34% (T3). Despite this sensitivity, we can conclude that if Ds had the same distribution as As for all three factors, the estimated A-D transfer gap would decrease by slightly more than 50% regardless of how transfers are defined.

Discussion and Conclusions

Our analysis is motivated by a longstanding policy question: Among students who enroll at a community college in pursuit of a four-year degree, why do so few ultimately make an upward transfer? In contrast to studies that address this question by identifying predictors of upward transfers, we identify determinants of the transfer *gap* between economically advantaged and disadvantaged students and, alternatively, between white and Black students. While these approaches are related, factors that explain the transfer gap must be predictors of transfer decisions for both groups *and* be distributed differently across the two groups.

Our key findings are easily summarized. When economically disadvantaged students are assigned the same distribution of "credits earned in community college," "age at community college entry," and "number of terms enrolled" as economically advantaged students, we predict that the advantaged-disadvantaged transfer gap falls by 52% using our preferred definition of transfer. When we repeat this experiment for a sample of white and Black students, we predict a complete (99.9%) elimination of the white-Black transfer gap. In both cases, the transfer gap is predicted to shrink because we hypothetically assign members of the economically disadvantaged group far more completed credits and younger entry ages, thus enhancing their transfer probabilities. Among the many other factors that we consider, few contribute more than

10% to the gap and most contribute only a trivial amount. Our findings based on economic disadvantage are robust to how we define transfers and whether we include nonurban students in the sample.

We are unaware of prior studies that identify determinants of the gap in transfer rates between groups of students, so we cannot directly compare our decomposition estimates to earlier findings. However, the two components of our analysis that contribute to the decomposition (logit estimates of factors that predict transfer rates and cross-group differences in endowments of each factor) are consistent with what others have found. In particular, we corroborate prior evidence that credit completion is positively associated with transfers while college entry age is negatively associated (Dougherty & Kienzl, 2006; Doyle, 2011; Lasota & Zumeta, 2016) and that economically disadvantaged and Black students tend to start college later and leave sooner than their counterparts (Bozick & DeLuca, 2005; Dadgar 2012; Goldrick-Rab & Han, 2011; Johnson, 2013; Porchea et al. 2010; Wells & Lynch, 2012). Any differences between our estimated logit estimates and other analysts' can be attributed to differences in samples, time periods, definitions of transfer, and model specifications. That said, it is noteworthy that we find no significant cross-group difference in logit estimates when we estimate our transfer model separately for white and Black students, or for economically advantaged and disadvantaged students—a finding that justifies our use of logit estimates based on pooled samples for our decompositions. This contrasts to the findings of Crisp and Nuñez (2014), who estimate transfer models separately for white students and Black/Hispanic students and point to several factors whose estimated coefficients differ across groups. However, the imprecision of their estimates (using a combined sample of only 1,360 students) makes it difficult for them to pin down statistically significant cross-group differences.

Although the logit estimates from our transfer models are largely consistent with what is reported elsewhere, our contribution to the literature stems from our use of those estimates as inputs in a decomposition analysis. By predicting how the transfer gap between economically advantaged and disadvantaged (or white and Black) students would change if the disadvantaged group were given the advantaged group's covariate distributions, we are able to quantify each factor's contribution to the gap. In contrast, when focusing solely on estimated odds ratios or marginal effects from regression models of transfer decisions, it is difficult to assess the amount by which a given factor would have to increment to bring about a substantial change in transfer rates or to affect cross-group gaps. We identify a host of factors that contribute little to the transfer gap despite being important determinants of transfer decisions. These factors include first-term GPA, completion of a transfer module, geographic proximity to college, full-time enrollment, and part-time employment. Some of these factors could potentially be manipulated by policy to increase *overall* transfer rates, but such interventions are not expected to reduce economically advantaged-disadvantaged or white-Black transfer gaps, often because the factor is distributed similarly among students in the two comparison groups.

Limitations and Proposed Extensions

Our analysis is not without limitations, most of which can be addressed by applying our analytic strategy to samples drawn from alternative data sources. By choosing to use state administrative data, we limit our sample to Ohio college students and, therefore, are unable to explore cross-state variation in transfer articulation policies, community college characteristics, and student demographics. Moreover, although our college-specific administrative data afford us a very large sample and accurate information on enrollment dates, credit accumulation and other aspects of college enrollment, they do not allow us to control directly for high school achievement and test scores, parental characteristics, students' family/household formation, educational expectations, geographic mobility, access to college counselors, and other factors that have been shown elsewhere to be related to transfer outcomes. Decomposing the transfer gap for additional demographic groups (e.g., Hispanics, Asians, first-generation students) would also be a valuable extension. Moreover, our analysis—along with most decomposition analyses and studies focused on upward transfers—does not identify causal effects. That is, we do not learn each covariate's true effect on transfer gaps independent of its correlation with unobserved factors. Additional research that identifies causal effects or simply uses alternative samples and covariates will enhance our understanding of which factors contribute to cross-group gaps in transfer rates and the channels through which they operate.

Policy Implications

Our findings suggest that transfer gaps between economically disadvantaged and advantaged students and between Black and white students can be expected to decrease substantially if education policy succeeds in closing the gaps between these groups in two key factors: age at first community college enrollment and credit completion. The transfer gap can be expected to close even more if economically disadvantaged and Black students decrease their community college enrollment durations. We focus our policy discussion on these three factors because they can be manipulated by policy *and* because they explain sizeable percentages of the transfer gap. Other factors included in our decomposition analysis, such as race and sex, cannot be manipulated by policy. Factors such as geographic proximity to college might be manipulated by policy to improve overall transfer rates, but our analysis indicates that this will not remediate *differences* in transfer rates across groups of students. Factors such as completion of the Ohio Transfer Module and in-college employment explain relatively small percentages of the transfer gap and are, therefore, less promising than the highlighted factors as potential policy levers.

If the policy goal is to decrease transfer gaps by helping economically disadvantaged and Black students start community college sooner, complete more credits, and decrease their time enrolled in community college, a number of existing programs are likely to prove effective. Accelerated Study in Associate Programs (ASAP), launched in 2007 by the City University of New York, are designed to help low-income community college students earn associate degrees relatively quickly by providing financial assistance, counseling, and other forms of support. A version of this program was adopted by three Ohio community colleges in 2014. Although we have not seen evidence of its effect on advantaged-disadvantaged or white-Black transfer gaps, the program succeeded in increasing overall transfer rates, as well as rates of both bachelor's and associate degree recipiency (Hill et al., 2025).

The guided pathways model has been used extensively by community colleges, including those in Ohio, to help students identify and maintain a clear, efficient path to a degree and/or upward transfer (Jenkins et al., 2025). Guided pathways are typically college-wide programs designed to streamline processes, help each student find the specific plan that is right for him or her, and ultimately improve equity and graduation rates among community college students. If economically disadvantaged and Black students benefit disproportionately from guided pathways, then these efforts are likely to help close the gap in credit completion while decreasing enrollment duration. Similarly, K-12/higher education alignment programs can help improve all three factors (credit completion, enrollment duration *and* age at college entry) by improving academic skills and college preparedness among pre-college students. For example, Ohio's College Credit Plus program provides students in grades 7-12 with tuition-free access to college courses to help them simultaneously build skills, increase college preparedness, and get an early start on college credit completion.

Virtually any form of financial assistance for community college enrollment is likely to help economically disadvantaged students enroll soon after high school rather than having to work and save first, and to work fewer hours (and thus complete more credits more quickly) while enrolled. In addition to federal Pell grants and other large-scale financial aid programs, programs that incentivize upward transfers are worth additional consideration. For example, Ohio's Buckeye Bridge program offers qualified students at Columbus State Community College both guaranteed admission and a "free ride" at Ohio State University upon the completion of an associate degree.

Our focus has been on policies that might decrease the transfer gap between economically disadvantaged and Black students and their peers, but we recognize that this is not the only important policy goal. Policies designed to facilitate upward transfers for *all* students should continue to be implemented even if they have a negligible effect on the cross-group gaps of interest. Moreover, we are not suggesting that students who continue to delay community college entry and/or struggle to complete credits in a timely fashion should no longer be supported. Community colleges have long been dedicated to providing access to higher education for students who are older, in need of flexibility, and/or financially constrained, and we believe they should continue to do so. These students are likely to benefit from community college enrollment and some will successfully transfer to four-year institutions, but Black and economically disadvantaged students are likely to lag their peers in upward transfer rates as long as they are disproportionately represented in these higher-risk groups.

References

Alm, J., & Winters, J.V. (2009). Distance and intrastate college student migration. *Economics of Education Review*, 28(6), 728-738.

Andrews, B.D. (2018). Delayed enrollment and student involvement. *Journal of Higher Education*, 89(3), 368-396.

Backes, B., & Velez, E.D. (2015). *Who transfers and where do they go? Community college students in Florida.* Washington, DC: National Center for Analysis of Longitudinal Data in Education Research.

Bailey, T. R., Jenkins, D., & Leinbach, D. T. (2005). *What we know about community college low-income and minority student outcomes*. New York, N.Y.: Community College Research Center, Columbia University.

Baker, R. (2016). The effects of structured transfer pathways in community colleges. *Educational Evaluation and Policy Analysis,* 38(4), 626-646.

Baker, R., Friedmann E., & Kurlaender, M. (2023). Improving the community college pathway to the baccalaureate: the effect of California's associate degree transfer." *Journal of Policy Analysis and Management,* 42(2), 488-524.

Baum, S. (2014). *Higher education earnings premium: value, variation and trends*. Washington, DC: The Urban Institute.

Bielby, R., Posselt, J.R., Jaquette, O., & Bastedo, M.N. (2014). Why are women underrepresented in elite colleges and universities? A non-linear decomposition analysis. *Research in Higher Education,* 55(8), 735-760.

Blinder, A.S. (1973). Wage discrimination. *Journal of Human Resources,* 8(4), 436-455.

Boatman, A., & Soliz, A. (2018). Statewide transfer policies and community college student success. *Education Finance and Policy,* 13(4), 449-483.

Bostwick, V.K., Fischer, S., & Lang, M. (2022). Semesters or quarters? The effect of the academic calendar on postsecondary student outcomes. *American Economic Journal: Economic Policy,* 14(1), 40-80.

Bozick, R., & DeLuca, S. (2005). Better late than never? Delayed enrollment in the high school to college transition. *Social Forces*, 84(1), 531–554.

Crisp, G., & Delgado, C. (2014). The impact of developmental education on community college persistence and vertical transfer. *Community College Revie*w, 42(2), 99-117.

Crisp, G., & Nuñez, A-M. (2014). Understanding the racial transfer gap: modeling underrepresented minority and nonminority students' pathways from two- to four-year institutions. *Review of Higher Education,* 37(3), 291-320.

Dadgar, M. (2012). *The academic consequences of employment for students enrolled in community college*. (CCRC Working Paper No. 46). New York, NY: Community College Research Center.

Dougherty, K.J. (1992). Community colleges and baccalaureate attainment. *Journal of Higher Education*, 63(2), 188-214.

Dougherty, K.J., & Kienzl, G.S. (2006). It's not enough to get through the open door: inequalities by social background in transfer from community colleges to four-year colleges. *Teachers College Record,* 108(3), 452-487.

Doyle, W.R. (2011). Effect of increased academic momentum on transfer rates: An application of the generalized propensity score. *Economics of Education Review,* 30(1), 191-200.

Education Commission of the States (2022, July 28). *50-State Comparison: Transfer and Articulation Policies.* Online database. https://www.ecs.org/50-state-comparison-transfer-and-articulation/.

Evans, W.N., Kearney, M.S., Perry, B., & Sullivan, J.X. (2020). Increasing community college completion rates among low-income students: Evidence from a randomized control trial evaluation of a case-management intervention. *Journal of Policy Analysis and Management*, 39(4), 930-965.

Fairlie, R.W. (2005). An extension of the Blinder-Oaxaca decomposition technique to logit and probit models. *Journal of Economic and Social Measurement,* 30(4), 306-316.

Fortin, N., Lemieux, T., & Fipio, S. (2011). Decomposition methods in econometrics. In O. Ashenfelter & D. Card (Eds.), *Handbook of Labor Economics*, Volume 4, Part A (pp. 1-102). Amsterdam: North Holland.

Goldrick-Rab, S., & Han, S.W. (2011). Accounting for socioeconomic differences in delaying the transition to college. *Review of Higher Education*, 34(3), 423–445.

Greene, T.G., Marti, C. & McClenney, K. (2008). The effort-outcome gap: Differences for African American and Hispanic community college students in student engagement and academic achievement. *Journal of Higher Education*, 79(5), 513-539.

Gross, B., & Goldhaber, D. (2009). *Community college transfer and articulation policies: Looking beneath the surface.* (CRPE Working Paper #2009_1). Seattle, WA: Center on Reinventing Public Education. https://eric.ed.gov/?id=ED504665

Hanley, G.E., & Morgan, S. (2008). On the validity of area-based income measures to proxy household income. *BMC Health Services Research,* 8(79). doi:10.1186/1472-6963-8-79

Hatch, D.K, & Garcia, C.E. (2017). Academic Advising and the Persistence Intentions of Community College Students in their First Week of Class. *The Review of Higher Education*, 40(3), 353-390.

Hill, C., Warner, K., & Sommo, C. (2025). *From learning to earning: Eight year findings from the Ohio ASAP demonstration*. New York: MDRC. https://www.mdrc.org/sites/default/files/ASAP_Ohio_8-Year_Findings_Brief.pdf

Jabbar, H., & Edwards, W. (2020). Choosing transfer institutions: Examining the decisions of Texas community college students transferring to four-year institutions. *Education Economics*, 28(2), 156-178.

Jabbar, H., Sánchez, J., & Epstein, E. (2017). Getting from here to there: The role of geography in community college students' transfer decisions. *The Urban Review*, 49(5), 746-776.

Jenkins, D., & Fink, J. (2015). *What we know about transfer*. New York: Community College Research Center, Columbia University. https://ccrc.tc.columbia.edu/publications/what-we-know-about-transfer.html

Jenkins, D., & Fink, J. (2016). *Tracking transfer: New measures of institutional and state effectiveness in helping community college students attain bachelor's degrees.* New York: Community College Research Center.

Jenkins, D., Lahr, H., Fink, J., Klempin, S.C., & Fay, M.P. (2025). *More essential than ever: Community college pathways to educational and career success*. Cambridge, MA: Harvard Education Press.

Kitagawa, E.M. (1955). Components of a difference between two rates. *Journal of the American Statistical Association*, 50(272), 1168–1194.

Kopko, E.M., & Crosta, P.M. (2016). Should community college students earn an associate degree before transferring to a 4-year institution? *Research in Higher Education,* 57(2), 190-222.

Lasota, R.R., & Zumeta, W. (2016). What matters in increasing community college students' upward transfer to the baccalaureate degree: Findings from the Beginning Postsecondary Study 2003-2009. *Research in Higher Education,* 57(2), 152-189.

Long, B.T., & Kurlaender, M. (2009). Do community colleges provide a viable pathway to a baccalaureate degree? *Educational Evaluation and Policy Analysis*, 31(1), 30-53.

Manson, S., Schroeder, D.V.R., Knowles, K., Kugler, T., Roberts, F., & Ruggles, S. (2023). IPUMS National Historical Geographic Information System: Version 18.0 [dataset]. Minneapolis, MN: IPUMS. http://doi.org/10.18128/D050.V18.0

Monaghan, D.B., & Attewell, P. (2015). The community college route to the bachelor's degree. *Educational Evaluation and Policy Analysis*, 37(1), 70-91.

Moss, J. L., Johnson, N.J., Yu, M., Altekruse, S.F., & Cronin, K.A. (2021). Comparisons of individual- and area-level socioeconomic status as proxies for individual-level measures: Evidence from the Mortality Disparities in American Communities study. *Population Health Metrics*, 19(article 1), 1-10. https://doi.org/10.1186/s12963-020-00244-x

Oaxaca, R. (1973). Male-female wage differentials in urban labor markets. *International Economic Review*, 14(3), 693-709.

Oaxaca, R.L., & Ransom, M.R. (1994). On discrimination and the decomposition of wage differentials. *Journal of Econometrics*, 61(1), 5-21.

Ohio Department of Higher Education (2022). *The Ohio Articulation and Transfer Policy*. Columbus, OH: Ohio Department of Higher Education. https://transfercredit.ohio.gov/ educational-partners/educational-partner-initiatives/articulation-transfer-policy-policy

Porchea, S.F., Allen, J., Robbins, S., & Phelps, R.P. (2010). Predictors of long-term enrollment and degree outcomes for community college students: integrating academic, psychosocial, socio-demographic, and situational factors. *Journal of Higher Education*, 81(6), 680-708.

Reeves, R.V., & Guyot, K. (2019). *...And justice for all: community colleges serving the middle class*. Washington, DC: Brookings Institution. https://www.brookings.edu/articles/and-justice-for-all-community-colleges-serving-the-middle-class/

Riggert, S.C., Boyle, M., Petrosko, J.M., Ash, D., & Rude-Parkins, C. (2006). Student employment and higher education: Empiricism and criticism. *Review of Educational Research*, 76(1), 63-92.

Sandy, J., Gonzalez, A., & Hilmer, M.J. (2006). Alternative paths to college completion: Effect of attending a 2-year school on the probability of completing a 4-year degree. *Economics of Education Review*, 25(5), 463-471.

Spencer, G. (2019). Can transfer guides improve the uptake of major prerequisites? Evidence from Ohio's transfer and articulation policy reform. *Research in Higher Education*, 60(4), 458-484.

Spencer, K. (2018, April 5). Middle-class families increasingly look to community colleges. *New York Times.* https://www.nytimes.com/2018/04/05/education/learning/community-colleges-middle-class-families.html

Stearns, E., Moller, S., Blau, J., & Potochnick, S. (2007). Staying back and dropping out: The relationship between grade retention and school dropout. *Sociology of Education*, 80(3), 210-240.

Stinebrickner, R., & Stinebrickner, T.R. (2003). Working during school and academic performance. *Journal of Labor Economics*, 21(2), 473-491.

Stuit, D.A., & Smith, T.M. (2012). Explaining the gap in charter and traditional public school teacher turnover rates. *Economics of Education Review*, 31(2), 268-279.

Ulrick, S.W., Mongeon, K.P., & and Giannetto, M.P. (2018). A continuous income-based grade gap decomposition on university course grades. *Applied Economics*, 50(31), 3388-3404.

Wang, X. (2012). Factors contributing to the upward transfer of baccalaureate aspirants beginning at community colleges. *Journal of Higher Education*, 83(6), 851-875.

Wells, R.S., & Lynch, C.M. (2012). Delayed college entry and the socioeconomic gap: Examining the roles of student plans, family income, parental education, and parental occupation. *Journal of Higher Education,* 83(5), 671–697.

Zhu, Z. (2022). Improving graduation rates in the two-to-four pathway to bachelor's degrees. *Education Finance and Policy*, 17(3), 432-453.

Notes

1. We use “upward transfer” to refer to transfers from community colleges to four-year colleges or universities and use the terms “community college” (also known as junior college) and “two-year college” interchangeably.
2. Upward transfer rates are sensitive to sample composition and especially the definition of transfer, so the variation around this number is considerable.
3. Ohio statistics are provided by the Ohio Department of Higher Education (https://highered.ohio.gov/data-reports/key-topic-areas/dr-enrollment/data-reports-enrollment) and the nationwide statistics are from the Digest of Education Statistics 2014 (https://nces.ed.gov/programs/digest/2014menu_tables.asp).
4. Our estimates are invariant to a wide range of alternative minimum credit requirements used to identify students with an intent to transfer. We considered dropping students attending community colleges with a largely technical/vocational mission, as proposed by Boatman and Soliz (2018), but found that upward transfer rates at those colleges are similar to those at other institutions in our sample.
5. We depart from this grouping strategy for the race/ethnicity dummies because we seek to identify separate contributions to the A-D gap of being Black, Hispanic, etc. For all groups of “like” covariates, the sum of the individual contributions is virtually identical to the group contribution computed when the variables are (correctly) treated as nonindependent.
6. Many studies report negative estimated coefficients for “Black” in transfer models (e.g., Gross & Goldhaber, 2009; Wang, 2012). When we remove from our model two sets of variables that are positively associated with transferring and negatively correlated with “Black” (grade point average in the first term, cumulative credits) and two that are negatively associated with transferring and positively correlated with “Black” (disadvantage, entry age) our estimated “Black” coefficient falls from 0.19 to -0.37.

7. Table 3 shows large estimated coefficients for many community college exit year dummies, but these dummies together account for only 1% of the A-D transfer gap because As and Ds have a similar distribution across years. The table 3 logit estimates also show a strong secular decline in transfer rates, which is driven by the fact that students who exit community college late in the observation period are only seen transferring if they do so quickly. In an (untabulated) experiment in which we replace college exit year with entry year, the secular decline is eliminated. It is worth noting that the estimated exit (or entry) year effects show no evidence of increased transfer rates following revisions to Ohio's transfer articulation policy.
8. Contrasting "percent explained" across specifications can be misleading because of differences in the magnitude of the transfer gap, which is the denominator in this computation. For example, entry age contributes roughly the same amount (0.012 vs. 0.014) to the A-D and white-Black gap, but the *percent* explained is larger in the latter case because the white-Black transfer gap is smaller.
9. Table A1 reports estimated logit coefficients for subsamples of white and Black students for comparison with the pooled estimates in table 3. This comparison yields the same qualitative findings as for the A-D comparison: relatively few estimates differ significantly across groups, and among covariates that contribute substantially to the gap, none have large differences between the white-specific, Black-specific, and pooled logit estimates.

Table 1

Upward Transfer Rates for Each Transfer Definition, Sample and Comparison Group Used for Decompositions

Transfer definition	*Sample*	*Comparison group*	*Transfer rate*
T1: Transfer within 6 years of community college entry	Full	Advantaged	.144
	Full	Disadvantaged	.092
		Gap	.052
	Lg. urban	Advantaged	.158
	Lg. urban	Disadvantaged	.086
		Gap	.072
	White/Black	White	.137
	White/Black	Black	.093
		Gap	.044
T2: Transfer within 6 years of community college entry *and* enroll for 2+ terms at 4-year college	Full	Advantaged	.104
	Full	Disadvantaged	.063
		Gap	.041
T3: Exit community college within 4 years of entry *and* transfer within 1 summer of community college exit	Full	Advantaged	.090
	Full	Disadvantaged	.048
		Gap	.042
T4: All transfers, regardless of timing	Full	Advantaged	.174
	Full	Disadvantaged	.119
		Gap	.055

Note: Relative to the full sample of 514,436 students, the large urban subsample is confined to 248,391 students who reside in large urban areas and the white/Black sample consists of 454,933 students whose race/ethnicity is coded as white or Black.

Table 2
Sample Means and Standard Deviations by Sample and Comparison Group

	Full sample		Large urban		White/Black	
Variable	*Adv.*	*Disadv.*	*Adv.*	*Disadv.*	*White*	*Black*
Individual background						
1 if sex = female	.55	.61	.55	.62	.56	.61
1 if race/ethnicity = Black	.09	.37	.13	.57	—	—
=Hispanic	.02	.03	.02	.04	—	—
=Asian	.01	.01	.02	.01	—	—
= other	.08	.08	.09	.10	—	—
1 if disadvantaged	—	—	—	—	.19	.61
Ability proxies						
Number of remedial	1.38	1.58	1.08	1.12	1.38	1.66
credits in 1st term	(2.26)	(2.42)	(2.05)	(2.15)	(2.21)	(2.56)
Grade point average in	2.37	2.09	2.32	1.92	2.43	1.74
first term	(1.35)	(1.42)	(1.37)	(1.41)	(1.34)	(1.38)
Community college enrollment and achievement						
1 if entry age ≤ 19	.45	.31	.46	.28	.45	.28
> 25	.29	.38	.27	.39	.29	.40
Number of terms enrolled	6.95	6.52	6.92	6.27	7.04	6.17
	(4.64)	(4.66)	(4.68)	(4.78)	(4.63)	(4.72)
1 if any 2- to 2-yr transfer	.11	.12	.11	.12	.11	.13
1 if enrolled full-time	.18	.18	.18	.20	.17	.19
Cum. credits attempted	56.45	53.68	56.26	51.76	57.11	50.48
	(34.80)	(35.27)	(35.62)	(36.58)	(34.61)	(35.44)
1 if cum. credits earned ≤12	.18	.27	.19	.32	.17	.35
=13-25	.20	.20	.21	.21	.20	.22
=47-73	.21	.17	.20	.14	.21	.13
≥ 74	.21	.18	.21	.16	.21	.14
1 if earn associate degree	.23	.17	.21	.13	.24	.11
1 if complete transfer module	.04	.02	.05	.03	.03	.02
Employment in community college						
Pct. quarters with no work	38.90	46.69	37.89	45.37	39.68	44.69
	(38.53)	(39.40)	(38.44)	(39.35)	(38.68)	(38.90)
Avg. weeks worked/quarter	6.86	5.77	6.99	5.91	6.79	5.88
	(4.85)	(4.85)	(4.84)	(4.84)	(4.87)	(4.79)
Environmental and college-specific factors						
County unemployment rate	6.80	6.98	6.34	6.34	6.94	6.54
	(2.03)	(2.12)	(1.66)	(1.67)	(2.12)	(1.78)
College transfer rate	18.05	18.48	20.66	21.72	17.58	20.26
	(6.50)	(6.43)	(3.67)	(3.73)	(6.53)	(6.00)
1 if campus in lg. urban area	.48	.48	.88	.94	.42	.70
in small urban area	.40	.34	.06	.02	.42	.27

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Table 2 (continued)

Variable	*Full sample* Adv.	*Full sample* Disadv.	*Large urban* Adv.	*Large urban* Disadv.	*White/Black* White	*White/Black* Black
Environmental and college-specific factors						
1 if chosen & closest CCs are both >35 miles from home	.01	.01	.01	.00	.01	.01
1 if chosen CC >35 mi. from home & closest ≤35 miles	.08	.07	.06	.04	.08	.05
1 if closest 4-yr college is >35 miles from home	.03	.01	.01	.00	.03	.05
Sample size	374,658	139,778	183,166	65,225	369,218	85,715

Note: CC, Adv and Disadv are abbreviations for community college, advantaged, and disadvantaged. Standard deviations are in parentheses. Regressions also include 18 dummy variables to identify the year of community college exit as 2000-2018 with 2010 as the omitted year.

Table 3

Estimated Pooled Logit Coefficients Used for Decompositions

	Specification					
Variable	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Individual background						
1 if sex = female	-.02	-.06	-.02	-.04	-.07	.07*
1 if race/ethnicity = Black	.19***	.15***	.18***	.14***	.09	.18***
= Hispanic	-.09	-.19**	—	-.07	-.07	-.12*
= Asian	.51***	.44***	—	.50***	.60***	.44***
= other	.13	.08	—	.08	.02	.18
1 if disadvantaged	-.24***	-.33***	-.24***	-.23***	-.27***	-.19***
Ability proxies						
No. remedial credits in 1st term	-.03***	-.04***	-.04***	-.04***	-.04***	-.05***
Grade point average in 1st term	.14***	.14***	.15***	.14***	.19***	.09***
Community college enrollment and achievement						
1 if entry age ≤ 19	.46***	.44***	.45***	.44***	.61***	.40***
> 25	-.52***	-.48***	-.53***	-.49***	-.47***	-.52***
Number of terms enrolled	-.25***	-.29***	-.25***	-.24***	-.40***	-.10***
1 if any 2-year to 2-year transfer	-.37***	-.27***	-.37***	-.40***	-.49***	-.13***
1 if enrolled full-time	.14***	.18***	.18***	.11**	.06	.32***
Cumulative credits attempted	.01***	.01***	.01***	.00***	.00	.01***
1 if cum. credits earned ≤ 12	-1.63***	-1.79***	-1.64***	-1.84***	-2.64***	-1.28***
=13-25	-.86***	-.94***	-.87***	-.92***	-1.27***	-.63***
= 47-73	.85***	.95***	.85***	.86***	1.23***	.53***
≥ 74	1.39***	1.52***	1.40***	1.39***	1.88***	.91***
1 if earn associate degree	-.37***	-.29***	-.39***	-.32***	-.72***	-.12
1 if complete transfer module	1.47***	1.19***	1.48***	1.35***	1.56***	1.25***
Employment in community college						
Percent of quarters with no work	-.03***	-.01***	-.01***	-.01***	-.01***	-.01***
Avg. weeks worked per quarter	-.01***	-.03***	-.03***	-.03***	-.03***	-.03***
Environmental and college-specific factors						
1 if year of CC exit =2000	.76**	.86***	.75**	.30	.17	.83***
2001	.63***	.82***	.62***	.51**	.32	.74***
2002	.50***	.69***	.49***	.38**	.29	.62***
2003	.32**	.50***	.31**	.22	.20	.38***
2004	.10	.20***	.10	-.01	.03	.14
2005	.01	.11*	.01	-.08	-.12	.03
2006	-.01	.08	-.00	-.09	-.16	-.01
2007	-.02	.07	-.02	-.07	-.20	-.00
2008	-.00	.07	-.01	-.02	-.14	.01
2010	-.10**	-.15***	-.11***	-.07**	-.06	-.10***
2011	-.24***	-.18***	-.24***	-.23***	-.25***	-.23***
2012	-.30***	-.29***	-.28***	-.37***	-.29***	-.32***
2013	-.44***	-.39***	-.41***	-.46***	-.40***	-.44***

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Table 3 (continued)

Variable	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
	Specification					
2014	-.56***	-.48***	-.54***	-.58***	-.59***	-.56***
2015	-.71***	-.61***	-.68***	-.71***	-.80***	-.68***
2016	-.95***	-.87***	-.93***	-.88***	-1.02***	-.90***
2017	-1.33***	-1.27***	-1.32***	-1.28***	-1.69***	-1.20***
2018	-2.21***	-2.09***	-2.17***	-2.31***	—	-1.82***
County unemployment rate	-.01	.03*	-.00	-.01	-.03	-.00
College transfer rate	.01	-.00	.01	.01**	.01*	.01
1 if campus in large urban area	.38***	.35***	.39***	.38***	.45***	.37***
1 if campus in small urban area	.35**	.38*	.36**	.34**	.46***	.32**
1 if chosen and closest CCs are both > 35 miles from home	.36*	.34	.32	.24	.19	.31*
1 if chosen CC is > 35 miles from home but closest is ≤ 35 miles	.01	-.10	.02	-.03	-.08	-.04
1 if closest 4-yr college is >35 miles from home	-.86***	-.74**	-.85***	-.70***	-.73***	-.83***
Psuedo-R^2	.164	.187	.164	.163	.228	.128
Transfer definition	T1	T1	T1	T2	T3	T4
Sample	Full	Lg. urban	White/ Black	Full	Full	Full

*Significant at the 10% level. **Significant at the 5% level. ***Significant at the 1% level.

Table 4

Decompositions of Advantaged-Disadvantaged and White-Black Gaps in Upward Transfer Rates using Primary Transfer Definition T1

	Adv.-Disadv. (full sample)		*Adv.-Disadv. (large urban)*		*White-Black*	
Variable	*Contrib.*	*%*	*Contrib.*	*%*	*Contrib.*	*%*
Individual background						
1 if sex = female	.001**	.21	.005***	.65	.001**	.24
1 if race/ethnicity =Black	-.054***	-10.33	-.069***	-9.63	—	—
=Hispanic	.001***	.19	.005***	.71	—	—
=Asian	.002***	.47	.002***	.24	—	—
=other	-.001***	-.22	-.001***	-.20	—	—
1 if disadvantaged	—	—	—	—	.088***	19.79
Ability proxies						
Remedial credits in 1st term	.007***	1.40	.003***	.45	.009***	2.08
GPA in 1st term	.032***	6.15	.047***	6.51	.084***	19.06
Community college enrollment and achievement						
Entry age[a]	.121***	23.07	.161***	22.51	.137***	30.99
Number of terms enrolled	-.086***	-16.34	-.168***	-23.48	-.170***	-38.34
1 if any 2-yr to 2-yr transfer	.000	.03	.000	.07	.003***	.67
1 if enrolled full-time	.001*	.26	-.002	-.21	.000	.08
Cum. credits attempted	.016***	3.09	.046***	6.49	.029***	6.69
Cumulative credits earned[a]	.235***	44.79	.416***	58.21	.474***	107.15
1 if earn associate degree	-.020***	-3.74	-.025***	-3.55	-.052***	-11.77
1 if complete transfer mod.	.046***	8.75	.047***	6.64	.043***	9.78
Employment in community college						
Pct. quarters with no work	.050***	9.61	.058***	8.11	.030***	6.80
Avg. weeks worked/quarter	-.029***	-5.46	-.032***	-4.52	-.025***	-5.63
Environmental and college-specific factors						
College exit year[a]	.006***	1.08	-.016***	-.218	.015***	3.44
County unemployment rate	.001	.20	-.000	-.03	-.000	-.05
College transfer rate	-.004***	-.81	.001	.20	-.030***	-6.82
Campus urban/rural status[a]	.029***	5.51	-.004**	-.60	-.047***	-10.67
Distance from home[b]	-.001	-.11	-.001	-.16	-.001	-.19
Closest 4-yr college >35 mi.	-.014***	-2.67	-.002	-.29	-.010***	-2.29
Total contribution	.034	65.13	.047	65.92	.058	131.00
Total gap	.052		.072		.044	

*Significant at the 10% level. **Significant at the 5% level. ***Significant at the 1% level.
[a]Decompositions are computed for a group of nonindependent covariates used in the transfer logit; see table 3 for the variables in each group.
Note: Decompositions are based on pooled logit estimates for specifications 1-3 in table 3. "Contribution" divided by 10 is the variable's (or grouped variables') estimated contribution to the total gap given in the bottom row; "%" is that amount as a percentage of the total gap.

Table 5

Decompositions of Advantaged-Disadvantaged Gaps in Upward Transfer Rates Using Alternative Transfer Definitions

	T2		*T3*		*T4*	
Variable	*Contrib*	*%*	*Contrib.*	*%*	*Contrib.*	*%*
Individual background						
1 if sex = female	.002***	.41	.002***	.57	-.005***	-.86
1 if race/ethnicity = Black	-.030***	-7.32	-.017***	-4.04	-.060***	-10.94
= Hispanic	.001**	.17	.001*	.15	.002***	.29
= Asian	.002***	.44	.002***	.46	.002***	.45
= other	-.001***	-.15	-.000	-.05	-.002***	-.35
Ability proxies						
Remedial credits in 1st term	.006***	1.47	.005***	1.33	.013***	2.39
GPA in 1st term	.026***	6.26	.026***	6.35	.027***	4.86
Community college enrollment and achievement						
Entry age[a]	.094***	22.71	.095***	23.02	.133***	24.32
Number of terms enrolled	-.091***	-22.02	-.142***	-34.34	-.033***	-6.06
1 if any 2-yr to 2-yr transfer	-.001	-.12	-.000	-.08	.001	.10
1 if enrolled full-time	.002	.38	.001	.22	.003***	.58
Cum. credits attempted	.013*	3.19	.009	2.17	.019***	3.50
Cumulative credits earned[a]	.217***	52.37	.290***	69.91	.187***	34.19
1 if earn associate degree	-.017***	-4.20	-.029***	-7.06	-.009***	-1.64
1 if complete transfer mod.	.039***	9.50	.037***	9.05	.045***	8.26
Employment in community college						
Pct. quarters with no work	.039***	9.38	.030***	7.25	.060***	10.92
Avg. weeks worked/quarter	-.022***	-5.40	-.020***	-4.87	-.034***	-6.17
Environmental and college-specific factors						
College exit year[a]	-.004**	-.90	-.003*	-.70	.002	.45
County unemployment rate	.002	.44	.005***	1.13	.001	.18
College transfer rate	-.005***	-1.19	-.004***	-.97	-.004***	-.73
Campus urban/rural status[a]	.023***	5.67	.026***	6.32	.031***	5.66
Distance from home[a]	-.001*	-.16	-.001**	-.20	-.001***	-.22
Closest 4-yr college >35 mi.	-.009***	-2.21	-.009***	-2.15	-.015***	-2.79
Total contribution	.028	68.71	.030	73.44	.036	66.43
Total gap	.041		.042		.055	

*Significant at the 10% level. **Significant at the 5% level. ***Significant at the 1% level.

[a]Decompositions are computed for a group of nonindependent covariates used in the transfer logit; see table 3 for the variables in each group.

Note: Decompositions are based on pooled logit estimates for specifications 4-6 in table 3. Alternative transfer definitions T2, T3, and T4 are defined in table 1. "Contribution" divided by 10 is the variable's (or grouped variables') estimated contribution to the total gap given in the bottom row; "%" is that amount as a percentage of the total gap.

Table A1

Estimated Logit Coefficients for Advantaged, Disadvantaged, White, and Black Subsamples, Using Primary Transfer Definition

Variable	*Adv.*	*Disadv.*	*White*	*Black*
Constant	-.68†	-1.31	-.78†	-.71†
Individual background				
1 if sex = female	-.03†	.02†	-.02†	-.04†
1 if race/ethnicity = Black	.21	.30	—	—
= Hispanic	-.04†	-.10†	—	—
= Asian	.51	.56	—	—
= other	.11†	.30	—	—
1 if disadvantaged	—	—	-.20	-.28
Ability proxies				
No. remedial credits in 1st term	-.04	-.03	**-.04**	**-.02**†
Grade point average in 1st term	.14	.12	.14	.15
Community college enrollment and achievement				
1 if entry age ≤ 19	**.47**	**.38**	.45	.53
> 25	-.54	-.47	-.55	-.54
Number of terms enrolled	**-.25**	**-.22**	-.25	-.24
1 if any 2-year to 2-year transfer	**-.41**	**-.24**	-.39	-.22
1 if enrolled full-time	**.18**	**-.01**†	.20	.07†
Cumulative credits attempted	.01	.00†	.00	.01
1 if cum. credits earned ≤ 12	-1.62	-1.58	-1.66	-1.48
=13-25	-.87	-.82	-.88	-.84
= 47-73	.85	.87	.84	1.03
≥ 74	1.39	1.40	1.38	1.72
1 if earn associate degree	**-.45**	**-.07**†	-.44	.21†
1 if complete transfer module	1.48	1.50	**1.51**	**1.03**
Employment in community college				
Percent of quarters with no work	**-.01**	**-.01**	-.03	-.03
Avg. weeks worked per quarter	-.03	-.02	-.03	-.03
Environmental and college-specific factors				
1 if year of CC exit =2000	**.57**†	**1.24**	**.62**	**1.20**
2001	.54	.80	.56	.78
2002	.44	.60	.45	.63
2003	.29	.35†	.28†	.44
2004	.05†	.18†	.08†	.19†
2005	-.05†	.09†	-.00†	.11†
2006	-.05†	.03†	-.01†	.01†
2007	-.07†	.06†	-.02†	-.05†
2008	-.05†	.10†	-.03†	.08†
2010	-.07†	-.21	**-.09**	**-.24**
2011	-.22	-.35	-.23	-.32

Continued on next page.

Table A1 (continued)

Variable	*Adv.*	*Disadv.*	*White*	*Black*
2012	-.31	-.36	-.25	-.44
2013	-.44	-.53	-.39	-.56
2014	-.58	-.60	-.51	-.74
2015	-.76	-.71	-.67	-.79
2016	-1.00	-.92	-.91	-1.12
2017	-1.34	-1.48	**-1.27**	**-1.69**
2018	-2.21	-2.41	**-2.08**	**-2.76**
County unemployment rate	**-.02**†	**.03**†	-.00†	.02†
College transfer rate	**.01**†	**-.00**†	.01†	.01†
1 if campus in large urban area	.42	.27†	**.41**	**.13**†
1 if campus in small urban area	.41	.28†	.34	.36
1 if chosen and closest CCs are both > 35 miles from home	**.22**†	**.72**	.25†	.49
1 if chosen CC is > 35 miles from home but closest is ≤ 35 miles	.01†	.12†	.00†	.10†
1 if closest 4-yr college is >35 miles from home	-.82	-.97	-.82	-1.06

†Estimated coefficient is *not* statistically significant at a 5% level.

Note: The primary transfer definition (T1) includes transfers within six years of community college entry. Estimates for advantaged and disadvantaged students can be compared to the pooled estimates in column (1) of table 3. Estimates for white and Black students can be compared to the pooled race/ethnicity estimates in column (3) of table 3. Boldface indicates that the difference between estimates (advantaged vs. disadvantaged or white vs. Black) differs from zero at a 5% significance level.