Institutional heterogeneity in the education and earnings returns to postsecondary technical education: Evidence from Missouri

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We estimate the education and earnings returns to enrolling in technical two-year degree programs at community colleges in Missouri. A unique feature of the Missouri context is the presence of a highly regarded, nationally ranked technical college: State Technical College of Missouri (State Tech). We find that enrolling in a technical program in Missouri increases the likelihood of associate degree attainment and post-enrollment earnings, but that the positive effects statewide are driven largely by students who attend State Tech. These findings demonstrate the potential for a high-performing community college to change students' education and labor market trajectories. At the same time, they exemplify the potential for substantial institutional heterogeneity in the returns to postsecondary education.

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Introduction

Postsecondary education both (a) promotes generalized knowledge and (b) provides students with specific skills of direct value in the labor market (Grubb and Lazerson, 2005). Elements of each are found in both traditional and career and technical education (CTE) programs, but with different emphasis. Traditional programs primarily emphasize general skills, whereas CTE programs primarily emphasize specific skills that match a particular occupation or small set of occupations. For individuals who are confident about their career paths, CTE programs offer the opportunity to make shorter and more-targeted educational investments.

Whether investments in CTE pay off in the labor market has been a topic of longstanding interest among researchers and policymakers. At the postsecondary level, research on the returns to CTE is mixed but mostly positive, with the largest returns accruing in technical and health fields (Bettinger and Soliz, 2016; Carruthers and Sanford, 2018; Jacobson, LaLonde, and Sullivan, 2005; Jepsen et al., 2023; Liu, Belfield, and Trimble, 2015; Stevens et al., 2018; Xu and Trimble, 2016). Research at the secondary level also generally finds positive labor-market impacts of CTE (Brunner, Dougherty, and Ross, 2023; Dougherty, 2018; Hemelt, Lenard, and Paeplow, 2019; Kreisman and Stange, 2020).

We contribute to the literature by estimating the education and earnings returns to enrolling in technical CTE programs at community colleges in Missouri. We focus on technical CTE programs for two reasons. First, technical CTE programs are male dominated. The recent struggles men face in postsecondary education are well documented and motivate work to improve our understanding of the returns to the types of credentials men are more likely to pursue (Arcidiacono and Koedel, 2014; Conger, 2015; Conger and Dickson, 2017; Reeves, 2022). Second, our research setting is Missouri, which is home to a highly regarded and nationally ranked technical community college. This college—State Technical College of Missouri, or State Tech for short—offers programs almost exclusively in technical CTE fields and focusing our evaluation these fields facilitates a deeper investigation of State Tech's impacts on student outcomes.

Our analysis is based on administrative microdata covering all community college students in Missouri, which we merge with earnings data from state unemployment records. We estimate the effects of enrollment in technical CTE programs on educational attainment and earnings outcomes using two different empirical approaches. First, we use matching estimators that compare outcomes between observationally similar students who differ by whether they enroll in a technical CTE program. Our evaluation context is well-suited for a matching design because we have rich observable information about students and our control-to-treatment ratio is high, which facilitates good matches (Black and Smith, 2004; Frölich, 2004). Still, our matching estimators rely on the strong assumption of conditional independence for identification. This motivates our second approach using instrumental variables (IV). Our instruments are distance-based and constructed carefully to make conditional exogeneity plausible. We control directly for the distance a student must travel to attend the nearest community college and use as instruments: (1) the share of technical-education enrollment at the nearest community college, and (2) the interaction between the distance to the nearest college and the technical-education enrollment share. Thus, our IV estimates are identified from variation in local exposure to technical education conditional on distance to the nearest community college.

We find positive impacts of enrollment in technical CTE programs in Missouri statewide, and further show these positive impacts are driven largely by students who attend State Tech. Our preferred estimates (from the IV models) indicate that enrolling in a technical program at State Tech increases the likelihood of graduating with an associate degree within six years by 21 percentage points, or roughly 75 percent of the control-group mean, where the control group consists of non-technical community college students. This estimate may be inflated if non-technical students are more likely to transfer to 4-year colleges and forego their associate degrees; however, we show it is upheld even after we account for downstream bachelor's degrees. We also estimate that enrolling at State Tech increases earnings six years later by

$11,324 annually (in 2018 dollars), or 44 percent of the control group mean. Assuming full-time work, this estimate implies an increase in the hourly wage from roughly $13.00 to $18.50 per hour.

Several aspects of our analysis lend credence to these results. First, our matching and IV estimates are similar despite their reliance on very different variation for identification. Moreover, our instruments are strong, which minimizes concerns about correlated bias between the matching and IV estimates (Hahn and Hausman, 2005). Second, in a placebo test, we estimate the “effects” of enrolling in technical education on earnings in the year prior to initial enrollment, which reveals little scope for bias. Third, although we find large effects of enrollment at State Tech, we estimate much smaller effects (and null effects for some outcomes) for technical programs at other community colleges using the same methods. This rules out bias from selection into technical education common to all programs as an explanation of our findings for State Tech.

Ultimately, our findings indicate great promise for high-quality technical education programs to improve student outcomes. They also exemplify the potential for significant institutional heterogeneity in the efficacy of postsecondary technical education.

Previous Research

There is a large literature on the returns to education at community colleges (a partial list of studies includes Bettinger and Soliz, 2016; Carruthers and Sanford, 2018; Dadgar and Trimble, 2015; Jacobson, LaLonde, and Sullivan, 2005; Jepsen et al., 2023; Jepsen, Troske, and Coomes, 2014; Liu et al., 2015; Marcotte, 2018; Marcotte et al., 2005; Mountjoy, 2022; Stevens et al., 2019; and Xu and Trimble, 2016). Most research finds positive effects of community college attendance on earnings, and even larger effects of the attainment of credentials (e.g., short- or long-term certificates, associate degrees). When studies estimate effect heterogeneity across types of credentials and fields, a common finding is that there is more heterogeneity across fields than types of credentials. Programs more closely connected to the labor market with clearer career pathways—e.g., CTE programs—tend to have the highest returns, and most high-return credentials are in health and technical fields. Carruthers and Sanford (2018) show that even the attainment of short-term, sub-associate credentials in technical fields leads to improved outcomes and increase student access to new industries.

Prior studies have relied on a variety of methodological approaches. Some studies use matching (e.g., Marcotte et al., 2005, 2018) and instrumental variables techniques (e.g., Mountjoy, 2022) that leverage cross-sectional variation for identification. Another common approach is to estimate individual fixed effects models using panel data (e.g., Carruthers and Sanford, 2018; Stevens et al., 2019; Jepsen et al., 2023). We use cross-sectional matching and IV methods for two reasons. First, we are interested in both the *education and earnings returns* to enrollment in technical education. Our focal education outcomes are associate degree attainment and time-to-degree, and there is no way to operationalize an individual-fixed-effect model to study these outcomes because they are observed just once for each individual. Second, the community college students in our sample are relatively young, especially at State Tech, raising concerns about the sufficiency of pre-education wages as a baseline for assessing the earnings returns to college enrollment (as is done in fixed effects models).[1] Noting this caveat, we conduct supplemental placebo tests for our earnings estimates using pre-enrollment wage data, and in this way provide the components of an individual fixed effects estimator.

Our study also differs from most other studies because we emphasize earnings returns to enrollment, rather than the attainment of a credential. This is an important distinction if the education returns differ across programs, which our analysis suggests is the case in Missouri. In particular, we show that enrolling at State Tech leads to a large increase in the likelihood of associate degree attainment relative to enrolling in other technical or non-technical programs. To the extent that degree attainment increases earnings—and there is strong evidence in support of this provided by the studies discussed above—conditioning our earnings estimates on individuals who attain degrees would understate the total effect of State Tech by missing the effect operating

[1] The average age at first entry of all community college students in Missouri is 19.6; at State Tech it is 19.2.

through the increase in degree attainment. The earnings returns that we estimate below capture the returns conditional on degree attainment, in addition to the returns operating through the increased likelihood of receiving a degree.[2]

Missouri Context and Data

State Tech makes Missouri an interesting context in which to study postsecondary technical education. In their report on the importance of higher education for promoting economic mobility, Reber and Sinclair (2020) ranked State Tech fourth in the nation for middle-class mobility among two-year colleges. Also in 2020, WalletHub ranked State Tech as the best two-year technical college in the country. The Aspen Institute, Washington Monthly, Bankrate.com, StateUniversity.com, Forbes, and CNN Money have all ranked State Tech highly in recent years. Ranking criteria differ across outlets, but criteria common to most rankings are graduation rates and job placements. These are easily observable metrics, and both are high at State Tech. While this is suggestive of the quality of educational programming, it is not conclusive. Selection into State Tech may contribute to the positive outcomes of students; moreover, broadly speaking, the rigor of college rankings is unclear.

We examine the efficacy of State Tech empirically in the larger context of the community college system in Missouri. We use administrative records from the Missouri Department of Higher Education and Workforce Development (DHEWD) covering all students who enroll in a public college statewide. For our analytic sample, we focus on degree-seeking students who enrolled in a public two-year college in Missouri for the first time in the fall of the 2010-11, 2011-12, and 2012-13 school years. We supplement these data with data from the U.S. Department of Education (DOE) on family income and the expected family contribution for college expenses, and from the Missouri Department of Labor and Industrial Relations (DOLIR)

[2] We are not the first to estimate the returns to enrollment, but few studies make this their focus and some studies do not estimate enrollment effects at all (a recent exception is Jepsen et al., 2023). Recent studies that include estimates of enrollment in addition to Jepsen et al. (2023) include Carruthers and Sanford (2018) and Marcotte (2018). Some studies also estimate the effects of college credits earned regardless of whether they lead to a credential (e.g., Jacobson et al., 2005; Marcotte et al., 2005), which can be viewed as a treatment between enrollment and credential attainment.

on earnings via unemployment insurance (UI) records. We track each student's graduation and labor market outcomes six years after initial enrollment. Our analysis covers 13 of the 14 public two-year colleges in Missouri. The omitted college is Metropolitan Community College in Kansas City, for which there are data reporting problems during the sample period. Figure 1 shows the locations of the 13 colleges in our sample along with information about the geographic distribution of the population in Missouri.

To identify technical CTE fields, we begin with the list of all fields under "occupational education" from the National Center for Education Statistics (NCES). From these, we select a subset of technical fields. Specifically, we use 2-digit Classification of Instructional Programs (CIP) codes to define programs in the following fields as technical: Agriculture and Agriculture Operations; Architecture; Computer and Information Science and Services; Engineering; Engineering Technologies; Science Technologies/Technicians; Construction; Mechanic and Repair Technologies; Precision Production; and Transportation and Materials Moving.[3] The CTE fields we exclude are in Business and Marketing; Communications; Consumer Services; Education; Health Sciences; Protective Services; and Public, Legal, and Social Services.

Defining technical education using these CTE fields facilitates our investigation of State Tech. This is illustrated in Table 1, which shows technical-education enrollment shares at the 13 community colleges in our sample. Overall, 11 percent of students enroll in technical fields and outside of State Tech, no Missouri college enrolls more than 12 percent of students in technical fields. However, at State Tech these fields dominate the curriculum, accounting for 94 percent of enrollment.[4]

Our focus on these technical fields is useful for our evaluation of the returns to education at State Tech, but we do not claim that the excluded CTE categories are entirely non-technical.

[3] Specifically, we define majors with the following 2-digit CIP codes as technical: 01, 04, 11, 14, 15, 41, 46, 47, 48, and 49.

[4] The uniqueness of State Tech's curriculum is despite the fact that it is not the only "technical college" in Missouri, at least by name. The other technical college is Ozarks Technical Community College (OTCC), but Table 1 shows it offers a wide range of programs and is not dominated by technical education programming. This is true even if we use a broader definition of technical fields.

The fields we focus on are best described as a subset of CTE fields that are highly technical. In addition to facilitating our analysis of State Tech, our focus on these fields is also of broader interest because they are male dominated. There is clear evidence that young men are underperforming young women in terms of enrollment and attainment of postsecondary credentials (Arcidiacono and Koedel, 2014; Conger, 2015; Conger and Dickson, 2017; Reeves, 2022). Moreover, Bettinger and Soliz (2016) and Liu et al. (2015) show the returns to two-year credentials are generally higher for women, driven in large part by credentials in health fields. Understanding the returns to the types of credentials men are more likely to pursue can inform policy efforts to rectify the growing gender imbalance in postsecondary participation and success.

Student-level summary statistics for our dataset are provided in Table 2. The first column reports on the entire sample and subsequent columns split students by technical education status, and within technical education status, whether the student enrolled at State Tech or elsewhere. Beginning with basic demographics, column (1) shows women are overrepresented in Missouri community colleges overall (54 to 46 percent). However, gender representation differs dramatically between technical and non-technical programs: the subsequent columns show 59 percent of non-technical enrollment is female and just 9 percent of technical enrollment is female.[5] The racial-ethnic shares in the sample are consistent with Missouri demographics—i.e., the sample is predominantly White with a non-negligible Black share, and small shares of students from the other racial-ethnic groups. Black students are notably underrepresented in technical education and White students are overrepresented. The overrepresentation of White students is especially large at State Tech, driven in part by its geographic location far from the urban centers in the state where most of the Black population lives.

In terms of academic qualifications, the average ACT Math and English scores for community college students are about two points lower than the average statewide among all

[5] This is not unique to Missouri and the gap is apparent even prior to college—e.g., Plasman, Gottfried, and Hutt (2020) show men are overrepresented in applied science CTE coursework during high school.

test-takers (at 19.1 and 19.2, respectively), and the average high school class rank is just below the median, at the 49th percentile. Technical students have higher ACT Math scores, and lower ACT English scores and class ranks. About one third of students are missing ACT scores and one-sixth are missing class ranks (the high rate of missing data on academic qualifications reflects the open admissions policies at community colleges).[6] In terms of family income, the average student comes from a family with an annual income of almost $60,000 (in 2018 dollars), which is just above the state median. Technical students come from wealthier families, especially at State Tech. The local area characteristics reported in the third horizontal panel of Table 2 are for students' counties of residence during high school and taken from the American Community Survey (ACS).[7] These characteristics do not vary significantly across treatment conditions.

Finally, the bottom panel of Table 2 summarizes students' treatments and outcomes. As noted above, about 11 percent of students enroll in a technical education program as we've defined it statewide, with about a third of these (4 percent of total enrollment) enrolling at State Tech. Our primary education outcome is associate degree attainment from a Missouri public college within 6 years. 29 percent of students in the full sample earn an associate degree within this timeframe. We also examine degree attainment in 2 and 4 years, for which the analogous attainment rates are 8 and 25 percent, respectively. Average annual earnings among all community-college entrants, measured 6 years after initial enrollment, is $26,720 (this is the main earnings outcome used in our analysis and reported in 2018 dollars). Just over 20 percent of students are missing earnings data. The earnings data are from UI records and missingness can be for a variety of reasons, including: (a) the individual is not employed, (b) the individual is employed but left the Missouri workforce, and (c) the individual is employed in Missouri, but

[6] We discuss how we handle these and other missing data analytically in the methods section below.
[7] These are ACS five-year estimates from 2012, with the exception of educational attainment, which is not available in the 2012 ACS and for which we use the 2014 ACS instead. We use the fraction of the local area that is White to measure local area racial-ethnic composition, noting that the primary demographic groups in Missouri are White and Black.

not working in a UI-covered position (e.g., federal employment). We discuss missingness in the UI data in detail below.

Empirical Strategy

Matching

We identify individuals who enroll in a technical education program as treated, and those who enroll in non-technical programs as controls. We then split the larger treatment group into two smaller groups: students who enroll in technical education at State Tech versus elsewhere. We use a common control group throughout that consists of students who enroll in any non-technical program in the state. This facilitates comparability across the treatment conditions. That is, because each treatment effect is estimated relative to a common control group, it allows for an indirect comparison of the returns to technical education at State Tech versus elsewhere in Missouri (which we further corroborate with a direct comparison later on).

The favorable control-to-treatment ratios in our comparisons permit use of a rigid matching algorithm. We start by matching exactly on indicators for student gender, race-ethnicity, and missing-data indicators for ACT scores in math and English and the high school percentile rank. We require all treatment and control observations to have at least one non-missing pre-college academic qualification (i.e., an ACT math score, ACT English score, or high school percentile rank) to be included in the analysis, which ensures we do not use matches that rely entirely on data missingness for these key controls. We also match exactly on students' year cohorts (either 2011, 2012, or 2013).

Conditional on the exact matches, we further match using propensity scores. The propensity scores are estimated from a probit regression where the dependent variable is an indicator for treatment and the independent variables are those listed in the first three horizontal panels of Table 2. At the student level, these variables include ACT math and English scores, high school percentile ranks, family income, and the expected family contribution. We also include local area characteristics in the propensity score model, along with the exact-matching variables. The exact-matching variables are redundant due to the exact matching, but useful because they allow us to isolate within-student-category variation in the other variables to construct the propensity scores.

We match treatment observations with up to three control observations, with replacement, within a caliper of 0.25 standard deviations of the distribution of propensity scores. Control observations outside of the caliper range of any treated observation are dropped, as are treatment observations without any controls within the caliper range. This defines the common support (none of our findings are substantively sensitive to reasonable modifications to the caliper bandwidth). This procedure yields samples of treatment and control observations for each of our comparisons that match exactly on demographics and are well-balanced on pre-college academic qualifications, family income, and local-area characteristics.[8]

Matching is an appealing strategy in our application due to the rich observable information in our administrative data (Black and Smith, 2004); still, the conditional independence assumption (CIA) required for causal identification is strong. Denoting potential outcomes by $\{Y_0, Y_1\}$, treatment by $D \in \{0, 1\}$, and $\mathbf{X}$ as the vector of conditioning variables, the CIA can be expressed generically as follows:

$$Y_0, Y_1 \perp D \mid \boldsymbol{X}. \tag{1}$$

In our application, where we exact-match on a subset of $\mathbf{X}$, which we denote by $\mathbf{X_1}$, and match using a propensity score inclusive of the other variables, it is written as:

$$Y_0, Y_1 \perp D \mid \boldsymbol{X_1}, \mathrm{P}(\mathbf{X}). \tag{2}$$

While some aspects of our evaluation make matching appealing, unobserved factors may affect students' enrollment decisions and outcomes. Such factors are difficult to rule out with certainty, and if present, will violate the CIA and cause bias. This concern motivates our instrumental variables strategy, which we describe in the next section.

[8] We also provide complementary estimates that match treatment and control observations using Mahalanobis distance metrics, as in Carruthers and Sanford (2018). These estimates are similar to the estimates we obtain from our primary matching approach (see Appendix Tables A8 and A9).

Instrumental Variables

Our IV strategy leverages students' geographic distances to technical programs for identification. We use a two-stage-least-squares framework as follows:

$$T_{it} = \alpha_0 + \mathbf{X_i}\boldsymbol{\alpha_1} + D_i\alpha_2 + \mathbf{Z_i}\boldsymbol{\alpha_3} + \lambda_t + \eta_{it} \tag{3}$$

$$Y_{it} = \beta_0 + \mathbf{X_i}\boldsymbol{\beta_1} + D_i\beta_2 + \hat{T}_{it}\beta_3 + \delta_t + \varepsilon_{it} \tag{4}$$

In the first-stage regression in equation (3), T_{it} is an indicator equal to one if student *i* in year-cohort *t* is treated. $\mathbf{X_i}$ is a vector containing the student and local-area control variables listed in Table 2 (these are the same variables we use for our matching estimators). $\mathbf{Z_i}$ is the set of excluded instruments, and D_i is a new control variable we add to make a stronger case for the conditional exogeneity of the instruments—we elaborate on both of these below. λ_t is a cohort fixed effect and η_{it} is the idiosyncratic error. In Equation (4), Y_{it} is the outcome of interest, $\hat{T}_{it}$ is the fitted value from the first stage, and common variables from equation (3) are defined the same. The variation used to identify the effect of treatment is from the instruments, $\mathbf{Z_i}$.

The instrument vector $\mathbf{Z_i}$ includes two variables: (1) the share of enrollment at the nearest community college in technical programs and (2) this share interacted with the distance between the student's high school and the nearest community college. The newly-added variable to the main model, D_i , is a scalar variable that measures the distance between the student's high school and the nearest community college. Thus, conditional on how close a student lives to the nearest community college (i.e., D_i), we instrument for treatment by the share of enrollment in technical programs at that college, plus an interaction between this share and the distance to the college. Our instruments leverage plausibly exogenous variation in access to technical education based on where students attend high school and where technical education programs are located in Missouri.

Our IV approach builds on a large literature on the returns to postsecondary education that relies on geographic variation for identification.[9] A notable recent example is Mountjoy (2022), who also studies community colleges and uses distance instruments that condition on other dimensions of distance to improve the case for exogeneity (for example, he varies two-year distance while holding four-year distance fixed). Our instruments have a similar flavor.

The identifying assumptions of our IV models are as follows. First, students are not sorted geographically in ways that align with the presence of technical education in Missouri community colleges, conditional on how close they are to a community college independent of the technical education enrollment share (and the rich vector of other control variables). As is often the case in IV applications, it is difficult to provide conclusive evidence in support of this assumption, but it is plausible. Second, we must assume that our instruments do not influence students at the margin of community college attendance. Said another way, while we allow the local-college technical education enrollment share to influence whether students pursue technical education, it cannot influence whether they enroll at all. We must make this assumption because our administrative data begin at the point of entry into a Missouri public college—we do not have access to pre-college data (i.e., we cannot use our instruments to predict technical education enrollment among *potential* college entrants, only observed entrants). Thus, it is a maintained assumption of our IV models. The third assumption is that community colleges' technical education enrollment shares are not correlated with other local-area factors that also influence student outcomes—in our case, either graduation or earnings six years after enrollment. Of the assumptions necessary to interpret our IV estimates causally, this one is the most worrisome. Even if the community college programs we study are not drivers of industry in their local areas, their geographic placements may nonetheless align with differences in local labor market opportunities and related factors. A testable prediction of this third threat to identification is as

[9] Examples of previous studies that leverage geography-based variation to identify the returns to postsecondary education include Card (1993), Doyle and Skinner (2016), Kane and Rouse (1995), Long and Kurlaender (2009), and Mountjoy (2022).

follows: if such local-area factors exist and are predominantly in the labor market, we would expect them to cause more bias in our models of student earnings than our models of educational attainment. One piece of evidence against this type of bias is that our earnings and educational-attainment estimates are generally aligned. We also conduct several other tests to examine the potential for this type of bias (among others) and find no indication that it drives our findings.

Finally, we acknowledge a measurement issue with the instruments. We measure distance based on local high school attended, rather than the home address, because the home address is not provided in the administrative data. The use of the high school attended in our distance calculations will likely lead to more measurement error in rural areas where high schools and residences are more dispersed. Below we assess the extent to which this may influence our findings indirectly by using conceptually similar but blunter versions of our distance-based instruments, which should exhibit less differential measurement error. Our findings are not substantively different using the alternative instruments.

Results: Matching

Tables 3 and 4 document the efficacy of our matching procedure. Table 3 provides variable-by-variable comparisons for each treatment-control contrast using the matched samples and Table 4 provides summary balancing information. Focusing on the summary in Table 4, there are few individually unbalanced covariates, the average p-value for the matched variables is around 0.50, as expected (with some sampling variability across columns), and the absolute mean standardized differences are small by common convention (Smith and Todd, 2005; Rosenbaum and Rubin, 1985).[10] On the whole, we interpret these results as showing that the matching procedure produces a sample of treatment and control observations that are well-balanced on observables.

[10] We exclude the exact-matching variables from the calculations in Table 4 because for each of these variables, the p-value must be 1.0 and the standardized difference must be zero by construction.

Educational attainment

Table 5 shows our main results for degree attainment using the matching estimators. For each treatment-control contrast, we estimate the effect of technical education enrollment on attainment of an associate degree in 2 years, 4 years, and 6 years. All standard errors in Table 5—and all subsequent standard errors for our matching estimators—are estimated by bootstrapping the entire estimation procedure 1,000 times.

The estimates in column (1) show that technical education students graduate more often and more quickly than matched non-technical students statewide. They are 7.9 percentage points more likely to graduate within 6 years, 8.6 percentage points more likely to graduate within 4 years, and 10.8 percentage points more likely to graduate within 2 years. The mean graduation rates in the (unmatched) control group over these timeframes are 29, 25, and 8 percent, respectively (Table 2). Thus, our matching estimates imply large impacts of technical education on degree completion and time-to-completion.

Columns (2) and (3) show that the positive estimates in the statewide comparisons are driven entirely by students who enroll at State Tech. State Tech students are 24.7 percentage points more likely to graduate within six years than the matched comparison group, and 27.1 and 35.0 percentage points more likely to graduate in 4 and 2 years, respectively. In contrast, when technical students outside of State Tech are the treated group in column (3), there is no evidence of an effect on degree attainment or time-to-degree.

Our focus on associate degrees may bias our estimates in favor of technical education if students who enroll in non-technical programs are more likely to transfer to universities and forego these degrees. To assess this possibility, in the bottom row of Table 5 we re-estimate the models after recoding the outcome to be a binary indicator for any associate or bachelor's degree. To allow ample time for transfer students to earn their bachelor's degrees, we only estimate models of degree attainment within 6 years for this scenario. We find the impacts of technical education on degree attainment are slightly smaller when we allow for bachelor's degrees via transfer, but substantively unchanged.[11]

Earnings

Next, we turn to the earnings returns to technical education. We follow the same data and estimation procedures outlined above but replace graduation outcomes with annual earnings six years after initial enrollment. We calculate annual earnings by summing the four quarterly earnings entries from the UI records after what would be the end of the sixth academic year post-enrollment (e.g., for the 2011 cohort, who entered college in fall-2010, we sum the earnings records from quarters 3 and 4 of calendar-year 2016, and 1 and 2 of calendar-year 2017). Missing values for quarterly earnings are treated as zeros and we focus initially on students with positive earnings during the relevant year (i.e., we drop individuals with missing earnings in all four quarters).

Our results are reported in Table 6. We find a positive and significant earnings differential, conditional on positive earnings, favoring technical education students statewide. The State Tech differential of $13,236 is 51 percent of the control group mean ($25,799 per Table 2). For technical programs outside of State Tech, the matching estimate for earnings is also positive and significant, at $4,153, but much smaller than at State Tech. This estimate for other institutions corresponds to an effect size of roughly 16 percent of the control group mean, which is in the range of similar estimates from Jepsen et al. (2023), who study the earnings returns to technical education using statewide data from Missouri and Kansas.[12]

Unlike in our analysis of educational attainment, we must be concerned about bias due to missing outcome data in our earnings analysis. Recall from above that missing earnings data may reflect unemployment but can also be caused by cross-state migration and some types of

[11] The limited impact of allowing for bachelor's degrees is due to the generally low rate of bachelor's degree receipt among students in our sample, which is expected based on previous research (Long and Kurleander, 2009; Qian and Koedel, 2024).

[12] Jepsen et al. (2023) estimate earnings returns to enrollment in vocational, computer related, and engineering fields at public community colleges in the range of 13-18 percent. Their counterfactual is "no enrollment" and ours is enrollment in a non-technical community college program.

employment not covered by UI (e.g., federal employment). We cannot distinguish between the different sources of missing data. Table 2 shows about 20 percent of students have no reported UI earnings during the four-quarter span we use to measure annual earnings. Missingness rates are similar, but not the same, across treatment conditions. It is also possible that individuals are differentially selected into data missingness between technical and non-technical fields.

Foote and Stange (2022) provide a general investigation of the potential for bias in estimates of the earnings returns to education due to missingness in UI data. They find the most problematic bias is for high earners and flagship university graduates, who are most likely to move across state lines and attrit from statewide UI data. Of particular relevance for our study, Foote and Stange (2022) examine 2-year CTE students directly and find evidence of only a very small negative bias in earnings estimates based on UI data—about 0.01 log points. This is consistent with 2-year CTE students having lower cross-state mobility than their peers from more selective institutions.

Bias of the magnitude suggested by Foote and Stange (2022) is ignorable in our study. Still, we examine the sensitivity of our findings to hypothetical data-missingness scenarios in Appendix Table A1. To do this, we re-estimate our models after adding individuals with missing earnings back into the sample and imputing their earnings to reflect possible differences in selection into data missingness. We consider two boundary scenarios in which we assume all individuals with missing UI records are either (1) unemployed with zero earnings (i.e., strong negative selection into missingness) or (2) employed in non-covered employment with earnings equal to the mean of observed earnings among students from the same institution (i.e., no selection into missingness). We also consider a third scenario where there is negative selection into data missingness, but only for technical students. The results under the first two scenarios are very close to our main findings, largely because attrition from the UI data is similar by treatment status. The estimated returns to technical education attenuate under the third scenario when we build in extreme, asymmetric selection into data missingness by treatment status, but even then our substantive findings are upheld.

Results: Instrumental Variables

Next, we report on our instrumental variables estimates. We continue to use the matched samples for analytic consistency (though this is not required under the identifying assumptions of the IV models). Table 7 shows results from the first stage of the IV regressions. Recall from Table 1 that there is little variation across colleges outside of State Tech in the technical education enrollment share. Correspondingly, Table 7 shows that while our instruments are highly effective at predicting enrollment in a technical program at State Tech, they are ineffective at predicting enrollment in other technical education programs. For example, the first-stage partial F-statistic is 106 when we define treatment as enrollment in a technical program at State Tech (column 2), but just 0.50 when we define treatment as enrollment in a technical program elsewhere (column 3). We conclude from these results that differences across community colleges in their technical-education enrollment shares outside of State Tech do not generate meaningful variation in technical education enrollment.

Based on the first-stage results, we only estimate IV models for our evaluation of State Tech.[13] Applying our instruments to predict enrollment at State Tech specifically may initially seem odd—i.e., the first stage leverages the fact that having a community college with more technical programs nearby (**Z**) makes a student more likely to attend a technical program *at State Tech*. However, it is important to recognize that the primary community college with a high share of technical enrollment *is* State Tech. Noting there is some cost in terms of instrument strength associated with leaving the instruments in general form and applying them to predict enrollment at State Tech specifically, at a high level their functionality and the underlying exogeneity argument is unchanged.[14]

[13] Focusing on just-identified IV models, Lee et al. (2022) show that traditionally estimated standard errors require an adjustment when the first-stage F statistic is sufficiently small. While their guidance does not apply directly to our setting (we are overidentified), it is of some comfort that our first-stage F statistic in the State Tech model is above the threshold they identify for adjustment in the just-identified case.

[14] Stated another way, compliers in our models of State Tech enrollment are students who are induced to enroll in State Tech because their nearest community college (which may or may not be State Tech) has a large technical education enrollment share. This generalized instrument works because the overwhelming majority of the variance in the instrument is attributable to State Tech. The fact that there is modest variation among the other community

We also complement our primary IV models with models that use two State-Tech specific instruments. The first is the distance to State Tech, and the second is a binary indicator for whether State Tech is the nearest community college. These instruments require stronger exogeneity assumptions because unlike our more generalized instruments, they contain more precise information about students' geographic locations within the state of Missouri. Thus, geographic correlates of student interest in technical education and subsequent outcomes could cause bias, although the direction is uncertain. That said, a benefit of these alternative instruments is that they are less likely to be affected by the rural/non-rural distance-measurement issue described above. We lead with our generalized instruments, which we prefer conceptually, and show results using the other instruments in Appendix Tables A2 and A3. The different instruments indicate State Tech has substantively similar impacts on students' education and earnings outcomes.

Educational attainment

Table 8 shows second-stage results for graduation outcomes using our preferred instruments. These results can be compared to their matching-estimator analogs in column (2) of Table 5 for State Tech. The main takeaway from this comparison is that the IV and matching estimates are substantively similar. Focusing on six-year degree attainment as the outcome, our IV model indicates that State Tech causes a 21.4 percentage point increase in the likelihood of earning an associate degree.

Earnings

In Table 9, we report IV results for earnings. Our IV estimate indicates that State Tech raises annual earnings by $11,324, which is similar to our matching estimate of $13,236 from Table 6. Compared to the control group mean of $25,799, this represents an increase of 44 percent. As with our matching estimates, we examine the sensitivity of our IV earnings estimate

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colleges in the technical education share (Table 1) does not invalidate the IV, although it does introduce some variation that is not predictive of enrollment at State Tech. The primary consequence is that this weakens the first stage, but as shown in Table 7, the first stage is still quite strong.

to potential bias from missing outcome data in the appendix (Appendix Table A4). Again, we find no scope for bias if selection into missingness is the same across treatment arms. Moreover, the degree of differential negative selection into missingness across treatment arms would need to be very large to offset our positive findings for State Tech.

Robustness & Extensions

Earnings Placebo Tests

We conduct placebo tests in which we estimate our earnings models, but use earnings over the four quarters prior to initial enrollment as the dependent variable. If our estimates are capturing the effects of technical relative to non-technical education, and not sorting bias, we should get null results in the placebo models. Recall from above that a limitation of these tests is that the students in our sample are relatively young, which could cause compression in their pre-enrollment earnings. This would make it more difficult for the placebo models to detect problematic selection. Noting this caveat, pre-college wage gaps are also possible depending on the nature of the unobserved selection. For example, a more technically oriented high school student, or recent high school graduate, may earn more working in a low-level technically oriented position than his or her counterpart working in a less-technical position.

Table 10 shows the results from placebo tests using our matching and IV models. Although the placebo models imply a small amount of positive selection into technical education, it is not enough to account for the magnitudes of our post-enrollment earnings estimates. Moreover, when we use matching, the placebo models identify selection into technical education at State Tech and other colleges of roughly the same magnitude and if anything, selection into technical programs outside of State Tech appears slightly more positive. This stands in stark contrast to our post-enrollment earnings results, where the estimates for State Tech are over three times larger than for technical education programs elsewhere in Missouri.[15]

[15] Appendix Table A7 documents data missingness for pre-enrollment earnings overall and by treatment status. As expected, pre-enrollment earnings are missing more often than earnings six years after enrollment. However, the patterns of missingness are substantively similar across treatment conditions, giving little cause for concern about the credibility of the results in Table 10.

Can Local Area Economic Conditions Explain Our Positive Findings for State Tech?

Our analysis thus far uncovers no evidence of substantial bias in our estimates due to individual student sorting into State Tech. Perhaps the biggest remaining threat is the possibility that our findings are driven by especially favorable economic conditions in the area around State Tech. To the extent that such conditions are present, it will be difficult to disentangle them from State Tech itself because of its fixed location. Our generalized, distance-based instruments are meant to minimize the influence of geographic factors, including local economic conditions, but they cannot fully mitigate them: even using the generalized instruments, State Tech's outlying status as a purveyor of technical education creates a correlation between its surrounding area and the nearby technical enrollment share.

One piece of evidence against the presence of substantial bias from this source is that we find large effects of State Tech on both educational attainment and earnings. If our findings were driven predominantly by strong local-area economic conditions around State Tech, we would expect the degree-attainment estimates to be smaller (although we would not necessarily expect null effects, as a strong local-area economy could incentivize graduation). Moreover, on the surface, State Tech's location does not appear to be uniquely advantageous. For example, it is not located in either of Missouri's primary urban centers in Kansas City or St. Louis, where the labor market should be thicker and opportunities more widespread.

To provide some direct evidence on this latter point, we re-estimate our models after restricting the comparison group for State Tech to include only students who attend community colleges in Missouri counties with income levels similar to Osage County, where State Tech is located. Specifically, Osage County has the 10th highest median household income among Missouri's 114 counties and we compare State Tech to the five other community colleges in the top-20 Missouri counties by median household income. Appendix Tables A5 and A6 show that our findings are substantively unchanged in these narrower comparisons, giving no indication that our estimates of State Tech's impacts are due to favorable local economic conditions.

Finally, a related but more idiosyncratic concern is that State Tech is the second closest community college to Missouri's only nuclear power plant (the Callaway Plant), at about a one-hour drive, which may afford unique opportunities for State Tech students given the technical nature of the curriculum. Again, a general argument against the notion that our findings are driven by bias from the presence of the Callaway Plant is that any such bias would likely manifest mostly in our wage models, but we find large positive impacts of State Tech on both wages *and* graduation. Perhaps more importantly with respect to this specific concern, very few State Tech students enroll in nuclear-related degrees: in our sample of State Tech enrollees, just 2.4 percent (N=28) enrolled in a nuclear-related degree program based on the 4-digit CIP code. Excluding these students has no substantive bearing on our findings.

What makes State Tech different?

Next we consider mechanisms that may explain the high returns to attendance at State Tech. First are two notable features of educational programming at State Tech: (1) the composition of degree programs under the umbrella of technical education as we've defined it is different at State Tech compared to elsewhere in Missouri, and (2) State Tech students are more likely than their counterparts at other colleges to enroll full-time at entry. These differentiating features have an ambiguous interpretation. They could be viewed as sources of bias in our evaluation—i.e., dimensions of non-comparability—or part of what can broadly be described as the bundle of treatments associated with attending State Tech. Our view is more along the lines of the latter. In this section, we explore how much these factors can account for the outcome differences we see between students who enroll at State Tech and elsewhere in Missouri.

We begin in Table 11 by showing the shares of technical enrollment by the 2-digit CIP code at State Tech and the other Missouri colleges. We define technical education broadly by these CIP codes, but the table shows the composition of enrollment is different at State Tech. Most notably, State Tech has no students in general engineering programs, compared to 23 percent of technical education students at other community colleges, and State Tech has many more students in mechanic and repair technology programs (41 versus 22 percent). There are several other enrollment differences between State Tech and the other colleges.

We test the extent to which the different composition of programs at State Tech drives our positive estimates within our matching framework. First, to set a baseline for this portion of our analysis, we compare State Tech to other technical programs in Missouri directly. This comparison is indirect in the preceding analysis through our use of a common control group of non-technical students. We make it directly by defining the treatment condition as enrollment at State Tech and the control condition as enrollment in technical programs at other community colleges. Column (1) of Table 12 shows that as expected based on the preceding analysis, State Tech students have higher graduation rates and post-graduation earnings than other technical students in Missouri.

In columns (2) and (3) of Table 12 we force alignment between State Tech and other technical students in our sample in terms of the distribution of 2-digit and 4-digit CIP codes, respectively. We operationalize this by exact matching on the CIP codes, in addition to using the other matching covariates as described above. Thus, the education- and earnings-returns estimates for State Tech are conditional on degree-program offerings within technical education fields. The results for educational attainment indicate that the different distributions of enrollment across technical fields at State Tech and elsewhere do not contribute to our findings in any meaningful way—i.e., when we align the distributions by matching on CIP codes, our results are substantively similar. The results for earnings indicate a larger role for the distribution of programs, especially at the 4-digit CIP level. Our earnings estimate in column (3) suggests that the different distribution of programs at State Tech at the 4-digit level can account for about a third of the total earnings effect in column (1).[16]

Next, in Table 13, we take a similar approach conceptually, but this time we exact match on the number of credit hours attempted in the first semester. Here, the educational-attainment

[16] The matched sample size shrinks as we make the matching criteria stricter, which leads to an increase in our standard errors, but the substantive implications of the results are unaffected by this.

returns shrink by about one third and the earnings returns are essentially unaffected. Like in Table 12, both the educational-attainment and earnings returns to enrolling at State Tech remain large and statistically significant.

To summarize our findings in Tables 12 and 13, the returns to enrolling at State Tech are driven in part by degree offerings, and in part by the emphasis on full-time enrollment, but neither of these explanations can account for most of the positive returns to enrolling at State Tech.

Finally, in Table 14 we use data from the Integrated Postsecondary Education Data System (IPEDS) to document observable differences in tuition, educational expenditures, resources, and financial aid between State Tech and the other community colleges. State Tech is a clear outlier along several dimensions. Most notably, it has much higher tuition and instructional expenditures. It also has a disproportionate share of students receiving federal loans, which may be related to the higher cost of attendance. In addition, State Tech is in the upper end of the range, but not a unique outlier, in terms of several other expenditure categories (student services, institutional support), as well as the percent of students receiving grants and scholarships, and Pell grants (again, the higher costs of attendance may explain the larger fraction of students receiving aid).

The information in Table 14 is descriptive and suggestive of pathways through which State Tech may impact students, but we cannot disentangle which aspects of these observable differences between State Tech and other colleges might drive its impacts, or if other unobserved factors are responsible. Noting this caveat, our findings contribute to the literature on the link between college resources and student outcomes. At the university level, there is considerable evidence of positive returns to attending a better-resourced college—see, for example, Bound, Lovenheim, and Turner (2010), Cohodes and Goodman (2014), Goodman, Hurwitz, and Smith (2017), and Webber and Ehrenberg (2010). However, Bound, Lovenheim, and Turner (2010) and Stange (2012) find little evidence of similar positive returns at community colleges. It is possible that our findings are different because of the focus on technical education, or technical education at State Tech specifically. Or, again, it may be that the observable differences in Table 14 are unrelated to the education and earnings returns we estimate for State Tech. While our study is ill-suited to make strong claims in this regard, the potential link between resources and outcomes suggests it would be valuable in future work to examine the resource returns to postsecondary technical education.

Conclusion

We estimate the education and earnings returns to enrolling in technical education programs at Missouri community colleges. A unique contextual feature of Missouri is the presence of State Technical College, which is highly regarded and nationally ranked. Using matching and instrumental-variables models, we find consistent evidence that enrolling in technical education at State Tech has large positive impacts on graduation and earnings. Our preferred IV estimates indicate State Tech increases associate degree attainment within six years by 21.4 percentage points relative to enrollment in a non-technical community college program. It increases annual earnings six years after initial enrollment by $11,324, which corresponds to an hourly wage increase of about $5.50 per hour assuming full-time work. Our analysis of the returns to technical education at other Missouri community colleges is less robust because we are unable to construct credible instruments for enrollment. However, our matching models give no indication that technical programs at other Missouri colleges raise graduation rates, and their earnings impacts are much smaller than at State Tech.

Our findings are robust. We estimate large positive returns to enrollment at State Tech whether we use matching estimators that rely on conditional independence for identification, or IV estimators that leverage geographic variation in exposure to State Tech. Our results are not overturned by our placebo regressions of pre-enrollment earnings. Within our matching framework, we estimate smaller effects (and null effects on degree attainment) for technical programs outside of State Tech, which suggests a limited role of bias due to selection into technical education common to all programs as an explanation for our findings.

We are not aware of any prior estimates of the education returns to technical education at community colleges, but there is a large prior literature on the earnings returns. Carruthers and Sanford (2018) find that short-term diplomas from technical colleges in Tennessee with flexible effort arrangements (e.g., part-time, self-paced) increase earnings by 13-19 percent. Stevens et al. (2019) estimate earnings returns to technical associate degrees from California community colleges in the range of 14-28 percent for men in fields similar to the fields we study (e.g., engineering/industrial, information technology, and agriculture and natural-resource fields). Jepsen et al. (2023) estimate that among associate-degree-seeking male students at community colleges in Missouri and Kansas, the earnings returns to enrollment in vocational, computer related, and engineering fields are in the range of 13-18 percent (which, again, is close to what we estimate for the earnings returns to technical education in Missouri outside of State Tech). None of these estimates are directly comparable to our estimates for State Tech, but on the whole, they provide context suggesting the earnings returns to State Tech are large (44 percent).[17]

Why are the education and earnings returns to enrollment at State Tech so large? First, it is worth noting that students in our control group do not have strong outcomes. While this is true of other similar studies, it is important to acknowledge the large gains for State Tech students are relative to a low baseline. State Tech is also an institution for which external indicators (e.g., college rankings) suggest the quality of educational programming is high, which perhaps makes it less surprising that attending State Tech has large returns. Finally, our earnings estimate for State Tech is inclusive of its substantial effect on degree attainment.

[17] The non-comparability is because different studies estimate different parameters and use different counterfactual conditions. With regard to the former, some studies focus on identifying the returns to degrees or certificates (e.g., Carruthers and Sanford, 2018; Stevens et al., 2019) while others focus on attendance like in our paper (e.g., Jepsen et al., 2023). With regard to the latter, the counterfactual in most studies is "no attendance" or "no degree attainment," whereas our counterfactual is attendance in a non-technical community college program. To the extent these differences matter, they likely put modest downward pressure on our estimates compared to the extant literature.

We highlight three ways that our findings contribute to the literature on postsecondary technical education. First, they indicate that State Tech is an exceptionally productive two-year college. Future work should aim to understand what makes State Tech so effective. We provide evidence suggesting that part of the explanation is the composition of degree programs and the focus on full-time enrollment at State Tech, but these factors do not account for the bulk of the returns to enrollment at State Tech. Methodologically, it will be difficult to conclusively link particular aspects of how State Tech operates to the summative program impacts we estimate, but perhaps alternative strategies like qualitative inquiry can be informative.

Second, enrollment at State Tech is male-dominated. Enrollment and performance gaps between men and women in postsecondary education are large and widening but have received little attention in research (with some exceptions such as Conger, 2015; Conger and Dickson, 2017; Reeves, 2022). State Tech's large and positive effects are all the more intriguing given their concentration among young men. It would also be of interest to know if similar programming could be effective at improving outcomes for young Black and Hispanic men—whose postsecondary outcomes are worse than their White counterparts—but we cannot speak to this question with our data given the overwhelmingly White population that attends State Tech in Missouri.

Third, our study is unique in the literature in that we estimate institution-level heterogeneity in the returns to technical education, albeit in a very targeted way. Our statewide models, inclusive of State Tech, yield positive effects of technical education on average. It is only when we separate out State Tech that it becomes apparent this single institution is the primary driver of the statewide effects (especially for degree attainment). This raises the possibility of institutional heterogeneity elsewhere as well, but we are not aware of other studies that test for this. While other states may not have an institution like State Tech, we know little about what characteristics of community colleges generate heterogeneity in their efficacy. Our findings in Missouri suggest it would be prudent to test for institutional effect heterogeneity in related studies. This can help to sharpen inference from the literature and could lead to the identification of other exceptional institutions. If other such institutions can be identified, it would make it easier for future researchers to combine evidence from multiple institutions to pinpoint aspects of their programming that generate positive outcomes for students, with the ultimate goal of extending high-quality educational opportunities to more students.

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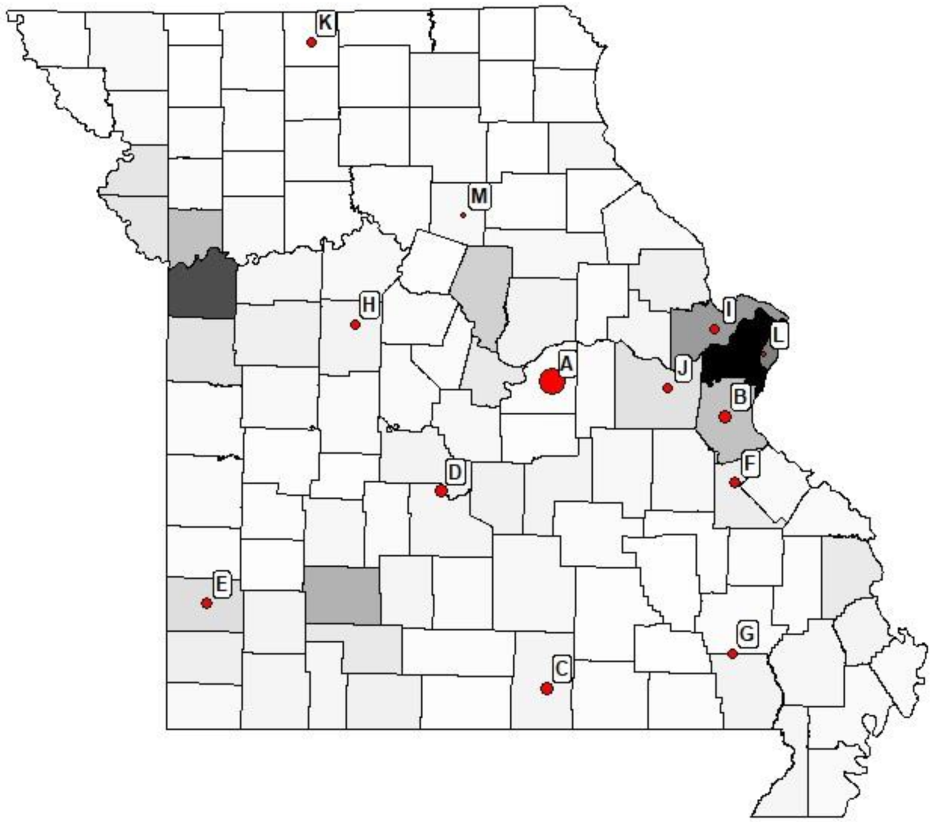
Figure 1. Locations of Missouri community colleges overlayed on a map shaded by county-level population density.



Notes: Darker-shaded counties have higher population densities. Each dot is a community college labeled following the key below. Larger dots indicate a larger share of internal enrollment in technical fields (corresponding to the numbers in Table 1). Metropolitan Community College in the Kansas City area (at the western edge of the map) is omitted from our sample due to data issues, and thus omitted from the map.

Key:

A: State Technical College	B: Jefferson College	C: Southwest Missouri State University-West Plains
D: Ozarks Technical College	E: Crowder College	F: Mineral Area College
G: Three Rivers Community College	H: State Fair Community College	I: St. Charles Community College
J: East Central College	K: North Central Missouri College	L: SLCC-Forest Park
M: Moberly Area Community College		

Table 1. Enrollment shares in technical education at Missouri community colleges.

College	Technical Education Enrollment Share
State Technical College of Missouri	0.94
Jefferson College	0.12
Southwest Missouri State University-West Plains	0.04
Ozarks Technical Community College	0.11
Crowder College	0.12
Mineral Area College	0.09
Three Rivers Community College	0.06
State Fair Community College	0.09
St. Charles Community College	0.10
East Central College	0.09
North Central Missouri College	0.07
SLCC-Forest Park	0.03
Moberly Area Community College	0.05

Notes: Colleges are ordered from largest to smallest by their internal technical education enrollment shares. Enrollment shares are averaged for the 2011, 2012, and 2013 cohorts.

Table 2. Descriptive Statistics for Community College Entrants in Missouri for the 2011, 2012, and 2013 cohorts (pooled sample).

	Sample means					
				Technical Students		
Variable	Full Sample		All Non-Technical Students	All	State Tech Only	Outside of State Tech
Demographics						
Age	19.55		19.54	19.66	19.21	19.87
Female	0.54		0.59	0.09	0.04	0.11
Male	0.46		0.41	0.91	0.96	0.89
Black	0.09		0.10	0.04	0.01	0.05
White	0.83		0.83	0.90	0.95	0.88
Hispanic & Latino	0.02		0.02	0.02	<0.00	0.02
Asian & Pacific Islander	0.01		0.01	0.01	<0.00	0.01
Other & Unknown Race	0.05		0.04	0.04	0.03	0.04
Pre-College Academic Qualifications & Family Income						
ACT Math Score	19.13		19.05	19.81	19.42	19.99
ACT Math Score Missing	0.35		0.34	0.44	0.44	0.44
ACT English Score	19.21		19.23	19.04	18.59	19.25
ACT English Score Missing	0.35		0.33	0.44	0.44	0.44
High School Class Percentile Rank	0.49		0.49	0.46	0.45	0.46
High School Class Percentile Rank Missing	0.16		0.16	0.10	0.03	0.13
Family Income	$59,841		$59,122	$65,590	$74,938	$61,200
Family Income Missing	0.09		0.09	0.09	0.07	0.09
Expected Family Contribution	$7,782		$7,595	$9,281	$11,572	$8,206
Expected Family Contribution Missing	0.09		0.09	0.08	0.06	0.09
Local Area Characteristics						
Unemployment Rate	0.09		0.09	0.08	0.08	0.08
Median Household Income	$53,538		$53,616	$52,921	$52,636	$53,055
Educational attainment ≥ of BA	0.16		0.16	0.15	0.14	0.15
Share of population that is White	0.92		0.92	0.94	0.95	0.93
Treatments, Instruments, and Outcomes						
Technical Educ Enrollment	0.11		0.00	1.00	1.00	1.00
Technical Educ Enrollment at State Tech	0.04		0.00	0.32	1.00	0.00
Distance to Nearest Comm College	18.45		18.02	21.96	29.34	18.49
Distance to State Tech	89.65		90.13	85.80	66.08	95.06
Two-year Associate Attainment	0.08		0.07	0.19	0.43	0.07
Four-year Associate Attainment	0.25		0.24	0.32	0.53	0.22
Six-year Associate Attainment	0.29		0.28	0.35	0.54	0.26
Annual Earnings Six Years After Entry	$26,720		$25,799	$34,086	$39,759	$31,421
Earnings Data Missing	0.21		0.21	0.19	0.16	0.20
No. of Observations	32,874		29,222	3,652	1,167	2,485

Notes: Family income, expected family contribution, median household income, and earnings are in 2018 dollars.

Table 3. Comparisons of matched treatment and control observations for each treatment-control contrast.

	Statewide Evaluation		State Tech Only		Technical Education Excluding State Tech	
	Treated	Control	Treated	Control	Treated	Control
Demographics						
Age	19.68	19.64	19.24	19.32	19.83	19.97
Female	0.09	0.09	0.04	0.04	0.11	0.11
Male	0.91	0.91	0.96	0.96	0.89	0.89
Black	0.04	0.04	0.01	0.01	0.05	0.05
White	0.92	0.92	0.98	0.98	0.90	0.90
Hispanic & Latino	0.01	0.01	<0.00	<0.00	0.02	0.02
Asian & Pacific Islander	0.01	0.01	<0.00	<0.00	0.01	0.01
Other Race	0.02	0.02	0.01	0.01	0.03	0.03
Pre-College Academic Qualifications & Family Income						
ACT Math Score	19.77	19.81	19.40	19.36	19.92	19.84
ACT Math Score Missing	0.44	0.44	0.43	0.43	0.45	0.45
ACT English Score	19.05	19.13	18.61	18.63	19.24	19.17
ACT English Score Missing	0.44	0.44	0.43	0.43	0.45	0.45
High School Class Percentile Rank	0.46	0.46	0.46	0.46	0.46	0.46
High School Class Percentile Rank Missing	0.09	0.09	0.03	0.03	0.12	0.12
Family Income	$64,401	$64,034	$74,190	$71,542	$60,244	$58,810
Family Income Missing	0.08	0.08	0.05	0.05	0.08	0.08
Expected Family Contribution	$9,193	$8,998	$11,473	$11,224	$8,122	$7,684
Expected Family Contribution Missing	0.08	0.08	0.05	0.05	0.09	0.09
Local Area Characteristics						
Unemployment Rate	0.08	0.08	0.08	0.08	0.08	0.08
Median Household Income	$52,872	$52,553	$52,220*	$51,290*	$52,883	$52,790
Educational attainment ≥ of BA	0.15*	0.14*	0.14	0.14	0.15	0.15
Share of population that is White	0.94	0.94	0.94	0.94	0.93	0.93
No. of Observations (weighted for controls)	3,487	6,367	1,021	2,165	2,383	5,159

Note: Control group averages are weighted averages, noting that for each treatment observation up to three controls are selected with equal weight and controls can be resampled across treatment observations. Family income, expected family contribution, median household income, and earnings are in 2018 dollars.
* $p < 0.05$.

Table 4. Summary of Results from Balancing Tests for Each Treatment.

	Statewide Evaluation	State Tech Only	Technical Education Excluding State Tech
No. of unbalanced covariates, matched *t* tests (5%)	1	1	0
Mean absolute standardized difference of covariates (%)	2.26	3.05	1.48
Average *p* value	0.36	0.50	0.79
No. of students (*Treatment / Control*)	3,487 / 6,367	1,021 / 2,165	2,385 / 5,159

Notes: There are 23 covariates included in the balancing tests. The exact-matching variables are not included in computing the average p-values or standardized differences because their p-values must be 1.0 and their standardized differences must be zero by construction.

Table 5. Effects of Enrollment in Technical Education Programs on Graduation Outcomes for Each Treatment, Estimated Using Matching.

	Statewide Evaluation	State Tech Only	Technical Education Excluding State Tech
Associate Degree Attainment in 2 years	0.108*	0.350*	0.005
	(0.003)	(0.004)	(0.003)
Associate Degree Attainment in 4 years	0.086*	0.271*	0.003
	(0.004)	(0.006)	(0.005)
Associate Degree Attainment in 6 years	0.079*	0.247*	0.005
	(0.005)	(0.007)	(0.005)
Associate or Bachelor's Degree Attainment in 6 years	0.068*	0.218*	-0.0007
	(0.005)	(0.007)	(0.006)
Number of Observations	9,854	3,186	7,542

Notes: Standard errors bootstrapped using 1,000 repetitions are reported in parentheses.
* $p < 0.05$.

Table 6. Effects of Enrollment in Technical Education Programs on Annual Earnings for Each Treatment, Estimated Using Matching.

	Statewide Evaluation	State Tech Only	Technical Education Excluding State Tech
Annual Earnings Six Years After Initial Enrollment, Conditional on Non-Missing Earnings	$7,033*	$13,236*	$4,153*
	(185)	(278)	(230)
Number of Observations	7,872	2,597	5,722

Notes: Standard errors bootstrapped using 1,000 repetitions are reported in parentheses. Individuals with missing earnings records are dropped from the sample. Earnings reported in 2018 dollars.
* p < 0.05.

Table 7. First-Stage Results from the Instrumental Variables Models of Educational Attainment, Estimated on the Matched Sample.

	Statewide Evaluation	State Tech Only	Technical Education Excluding State Tech
Enrollment Share in Technical Fields	0.591*	0.994*	-0.036
	(0.062)	(0.081)	(0.096)
Enrollment Share in Technical Fields*Distance	-0.012*	-0.020*	0.0001
	(0.002)	(0.003)	(0.003)
First-stage Joint F-Statistic for the Instruments	66.6	106.0	0.5
Observations	9,854	3,186	7,542

Notes: Standard errors are in parenthesis. These results are based on the matched samples from above; results using unmatched data are substantively similar and reported in the appendix. Earnings reported in 2018 dollars.
* p < 0.05.

Table 8. Effects of Enrollment in Technical Education Programs at State Tech on Graduation Outcomes, Estimated on the Matched Sample Using IV.

	IV Set 1
Associate Degree Attainment in 2 years	0.218*
	(0.052)
Associate Degree Attainment in 4 years	0.223*
	(0.064)
Associate Degree Attainment in 6 years	0.214*
	(0.066)
Associate or Bachelor's Degree Attainment in 6 years	0.204*
	(0.067)
Number of Observations	3,186

Notes: Standard errors are in parenthesis. The IV set includes two variables: (a) the enrollment share in technical education programs at the nearest community college and (b) the distance to the nearest community college times the enrollment share. These results are based on the matched samples from above; results using unmatched data are substantively similar and reported in the appendix.
* p < 0.05.

Table 9. Effects of Enrollment in Technical Education Programs at State Tech on Annual Earnings, Estimated on the Matched Sample Using IV.

Annual Earnings Six Years After Initial Enrollment, Conditional on Non-Missing Earnings	$11,324* (3,376)
Number of Observations	2,597

Notes: Standard errors are in parenthesis. The IV set includes two variables: (a) the enrollment share in technical education programs at the nearest community college and (b) the distance to the nearest community college times the enrollment share. We report two values for the number of observations. The first is the number of observations with non-missing earnings corresponding to the estimates in row 1 and the second is the number of observations after imputing missing values corresponding to the estimates in rows 2-4. Earnings reported in 2018 dollars. These results are based on the matched samples from above; results using unmatched data are substantively similar and reported in the appendix.
* $p < 0.05$.

Table 10. Placebo Effect Estimates of Enrollment in Technical Education Programs on Annual Earnings Prior to Enrollment for Each Treatment, Estimated Using Matching and IV.

	Statewide Evaluation	State Tech Only	Technical Education Excluding State Tech
Annual Earnings During the Year Prior to Initial Enrollment, Matching	$360* (65)	$300* (100)	$391* (80)
Annual Earnings During the Year Prior to Initial Enrollment, Instrumental Variables		$1,162 (949)	
Number of Observations	9,854	3,186	7,542

Notes: Standard errors are in parentheses (bootstrapped for the matching estimates). Missing pre-enrollment earnings are imputed to the institutional mean of the non-missing pre-enrollment wages. Earnings reported in 2018 dollars.
* $p < 0.05$.

Table 11. Degree Program Composition at State Tech and Elsewhere Among Technical Fields, by 2-Digit CIP Codes.

CIP Code	Description	Fraction of Technical Enrollment at State Tech	Fraction of Technical Enrollment Outside of State Tech
01	Agriculture, agriculture operations, and related sciences	0.02	0.09
04	Architecture and related services	0.00	0.01
11	Computer and information sciences and support services	0.09	0.19
14	Engineering	0.00	0.23
15	Engineering technologies and engineering-related fields	0.15	0.13
41	Science technologies/technicians	0.02	0.01
46	Construction trades	0.14	0.03
47	Mechanic and repair technologies/technicians	0.41	0.22
48	Precision production	0.06	0.09
49	Transportation and materials moving	0.11	0.00
All		1.00	1.00

Table 12. Effects of Enrollment in Technical Education Programs at State Tech on Graduation Outcomes, Estimated Using Technical Program Controls and Exact Matching on CIP Codes.

	Control Group Additionally Matched On:		
	Technical Education Indicator (baseline)	2-Digit CIP Code	4-Digit CIP Code
Associate Degree Attainment in 2 years	0.317*	0.405*	0.346*
	(0.008)	(0.012)	(0.012)
Associate Degree Attainment in 4 years	0.280*	0.350*	0.281*
	(0.010)	(0.014)	(0.015)
Associate Degree Attainment in 6 years	0.249*	0.320*	0.271*
	(0.011)	(0.015)	(0.016)
Associate or Bachelor's Degree Attainment in 6 years	0.236*	0.312*	0.264*
	(0.010)	(0.015)	(0.016)
Annual Earnings Six Years After Initial Enrollment, Conditional on Non-Missing Earnings	$7,884*	$7,155*	$5,241*
	(528)	(764)	(814)
Number of Observations (graduation/earnings models)	1,984/1,626	1,014/759	584/455

Notes: Column (1) makes a direct comparison of technical students at State Tech relative to technical students elsewhere in Missouri by matching on an indicator for enrolling in a technical field as we've defined it. Columns (2) and (3) match on students' exact 2-digit and 4-digit CIP codes, which aligns the distributions of degree programs at these levels between the treatment and control samples. Standard errors bootstrapped using 1,000 repetitions are reported in parentheses. Individuals with missing earnings records are dropped from the earnings sample. Earnings reported in 2018 dollars.
* $p < 0.05$.

Table 13. Effects of Enrollment in Technical Education Programs at State Tech on Graduation Outcomes, Estimated Using Exact Matching on Attempted Term Hours.

Associate Degree Attainment in 2 years	0.315*
	(0.005)
Associate Degree Attainment in 4 years	0.204*
	(0.007)
Associate Degree Attainment in 6 years	0.164*
	(0.007)
Associate or Bachelor's Degree Attainment in 6 years	0.124*
	(0.008)
Annual Earnings Six Years After Initial Enrollment, Conditional on Non-Missing Earnings	$13,215*
	(337)
Number of Observations (graduation/earnings models)	1,606/1,243

Notes: Standard errors bootstrapped using 1,000 repetitions are reported in parentheses. Individuals with missing earnings records are dropped from the earnings sample. Earnings reported in 2018 dollars.
* $p < 0.05$.

Table 14. Descriptive Statistics from IPEDS for Two-year Institutions in Missouri for the 2011, 2012, and 2013 cohorts.

	Sample Means by Two-year Institution												
IPEDS Variable	**State Technical College of Missouri**	Crowder College	East Central College	Ozarks Technical Community College	Jefferson College	Mineral Area College	Moberly Area Community College	Saint Louis Community College	Missouri State University - West Plains	State Fair Community College	Three Rivers College	North Central Missouri College	St Charles Community College
In-district Tuition	**4,500.00**	1,744.00	1,584.00	2,040.00	2,136.00	2,620.00	2,120.00	2,340.00	3,298.00	2,350.00	2,568.00	2,080.00	2,550.00
In-state Tuition	**4,500.00**	2,400.00	2,256.00	2,840.00	3,200.00	3,450.00	3,040.00	3,660.00	3,298.00	3,250.00	3,648.00	3,050.00	3,810.00
Out-of-state Tuition	**9,000.00**	3,080.00	3,392.00	3,716.00	4,256.00	4,300.00	4,530.00	5,010.00	6,498.00	5,030.00	4,332.00	4,200.00	5,690.00
Full-time Undergrad to Instructor Ratio	**9.27**	12.13	8.64	11.25	8.98	8.16	7.48	6.09	11.65	7.44	11.23	10.96	9.35
Instruction Expenses per FTE	**7,584.00**	4,111.67	3,933.67	4,079.33	4,016.67	3,953.33	2,938.33	4,887.67	2,632.00	3,159.33	2,882.33	4,745.33	5,672.00
Research Expenses per FTE	-	-	-	-	-	-	-	-	-	-	-	-	-
Public Service Expenses per FTE	**1,127.67**	426.67	21.33	-	66.67	17.67	-	-	404.00	121.33	57.33	2,200.67	-
Academic Support Expenses per FTE	**653.67**	265.33	1,093.33	910.67	370.33	878.00	845.33	971.00	938.67	998.00	399.00	375.00	409.33
Institutional Support Expenses per FTE	**1,940.00**	576.67	1,894.67	804.67	1,994.33	1,373.67	696.33	2,338.33	1,986.67	1,580.67	1,160.33	1,752.33	1,293.33
Student Services Expenses per FTE	**1,363.33**	752.33	613.67	382.67	1,033.33	861.00	737.67	1,038.00	1,222.33	589.33	1,109.67	781.00	736.67
Other Expenses per FTE	**1,120.00**	1,157.67	1,811.67	869.67	1,888.33	3,650.67	1,657.00	1,474.67	1,270.67	2,548.00	503.00	5,197.33	720.33
Percent of Students Receiving Grants/Scholarships	**78.33**	64.00	66.33	68.33	59.67	75.67	70.00	53.67	85.00	77.33	90.67	64.33	43.67
Percent of Students Receiving Pell Grants	**41.33**	47.67	47.33	55.00	47.67	55.00	54.33	47.33	55.00	56.67	60.00	46.67	27.00
Percent of Students Receiving Federal Student Loans	**60.33**	22.00	23.00	61.67	25.67	25.33	38.33	10.00	37.33	41.67	26.33	36.00	13.00

Notes: FTE is the full-time equivalent (FTE) enrollment used in the IPEDS report is the sum of the institution's FTE undergraduate enrollment and FTE graduate enrollment (as calculated from or reported on the 12-month Enrollment component). Regarding the IPEDS variables reporting percentage of students receiving different forms of financial aid, students may receive funds from multiple sources; these variables are not mutually exclusive. All reported dollar values are nominal and based on data from the 2011, 2012, and 2013 cohorts.

Appendix Tables (Online only)

Table A1. Sensitivity Tests to Earnings Data Missingness for Earnings Effects, Estimated Using Matching.

	Statewide Evaluation	State Tech Only	Technical Education Excluding State Tech
Annual Earnings Six Years After Initial Enrollment, Conditional on Non-Missing Earnings **(repeated from main text)**	$7,033* (185)	$13,236* (278)	$4,153* (230)
Annual Earnings Six Years After Initial Enrollment, Earnings Imputed to Zero if Missing	$6,570* (186)	$11,851* (277)	$4,291* (211)
Annual Earnings Six Years After Initial Enrollment, Earnings Imputed to Institution Mean if Missing	$6,568* (151)	$13,257* (228)	$3,576* (174)
Annual Earnings Six Years After Initial Enrollment, Earnings Imputed to Institution Mean if Missing, with Extra Negative Selection Built into Values for Technical Education Students	$3,805* (149)	$9,914* (239)	$1,034* (183)
Number of Observations	7,872/9,854	2,597/3,186	5,722/7,542

Notes: We report two values for the number of observations. The first is the number of observations with non-missing earnings corresponding to the estimates in row 1 from the main text, and the second is the number of observations after imputing missing values corresponding to the estimates in rows 2-4. Missing earnings records are replaced with imputed values as described by the rows. Row 2 assumes strong negative selection into missingness and row 3 assumes no selection. These are strong assumptions meant to bound the scope for potential impact of missing wage data, but both scenarios assume that the magnitude and direction of selection is unrelated to treatment status. In row 4 we impute earnings to the institutional mean for non-technical students and to 50 percent of the institutional mean for technical students, creating a wedge that would exist if there were strong differential and negative selection into missing wages for technical students. This scenario favors the control group and offers an extreme test of whether the technical-education effects can be plausibly overturned by bias due to missing data. It does meaningfully affect our findings—it reduces the average earnings estimates for the technical education treatments by roughly $3,000 compared to the estimates in the main text. Still, the large positive estimate for State Tech remains even under this extreme scenario. Earnings reported in 2018 dollars. Standard errors bootstrapped using 1,000 repetitions are reported in parentheses.
* $p < 0.05$.

Table A2. Instrumental Variables Estimates of the Education Returns to Enrolling at State Tech, Using Generalized and State-Tech Specific Instruments.

	Generalized IVs **(Repeated From Main Text)**	IV 2: Distance to State Tech	IV 3: Indicator for State Tech is Nearest College
Associate Degree Attainment in 2 years	0.218*	0.187*	0.185*
	(0.052)	(0.054)	(0.058)
Associate Degree Attainment in 4 years	0.223*	0.179*	0.173*
	(0.064)	(0.065)	(0.071)
Associate Degree Attainment in 6 years	0.214*	0.155*	0.160*
	(0.066)	(0.067)	(0.073)
Associate or Bachelor's Degree Attainment in 6 years	0.204*	0.138*	0.161*
	(0.067)	(0.068)	(0.073)
Number of Observations	3,186	3,186	3,186

Notes: Standard errors are in parenthesis. The estimates in column (1) are repeated from the main text (Table 8) for comparison purposes. Column (2) replaces the generalized instrument set with a single instrument: the distance to State Tech. Column (3) replaces the generalized instrument set with a different single instrument: an indicator variable for whether State Tech is the closest community college. Results are based on the matched samples.
* $p < 0.05$.

Table A3. Instrumental Variables Estimates of the Education Returns to Enrolling at State Tech, Using Generalized and State-Tech Specific Instruments.

	Generalized IVs **(Repeated From Main Text)**	IV 2: Distance to State Tech	IV 3: Indicator for State Tech is Nearest
Annual Earnings Six Years After Initial Enrollment, Conditional on Non-Missing Earnings	$11,324*	$12,646*	$7,486*
	(3,376)	(3,420)	(3,694)
Number of Observations	2,597	2,597	2,597

Notes: Standard errors are in parenthesis. The estimates in column (1) are repeated from the main text (Table 9) for comparison purposes. Column (2) replaces the generalized instrument set with a single instrument: the distance to State Tech. Column (3) replaces the generalized instrument set with a different single instrument: an indicator variable for whether State Tech is the closest community college. Results are based on the matched samples.
* $p < 0.05$.

Table A4. Sensitivity Tests to Earnings Data Missingness for Earnings Effects, Estimated Using IV (primary instruments).

Annual Earnings Six Years After Initial Enrollment, Conditional on Non-Missing Earnings **(repeated from main text)**	\$11,324* (3,376)
Annual Earnings Six Years After Initial Enrollment, Earnings Imputed to Zero if Missing	\$10,468* (3,265)
Annual Earnings Six Years After Initial Enrollment, Earnings Imputed to Institution Mean if Missing	\$10,876* (2,603)
Annual Earnings Six Years After Initial Enrollment, Earnings Imputed to Institution Mean if Missing, with Extra Negative Selection Built into Values for Technical Education Students	\$7,649* (2,682)
Number of Observations	2,597/3,186

Notes: We report two values for the number of observations. The first is the number of observations with non-missing earnings corresponding to the estimates in row 1 from the main text, and the second is the number of observations after imputing missing values corresponding to the estimates in rows 2-4. Missing earnings records are replaced with imputed values as described by the rows. Row 2 assumes strong negative selection into missingness and row 3 assumes no selection. These are strong assumptions meant to bound the scope for potential impact of missing wage data, but both scenarios assume that the magnitude and direction of selection is unrelated to treatment status. In row 4 we impute earnings to the institutional mean for non-technical students and to 50 percent of the institutional mean for technical students, creating a wedge that would exist if there were strong and differential negative selection into missing wages for technical students. This scenario favors the control group and offers an extreme test of whether the technical-education effects can be plausibly overturned by bias due to missing data. It does meaningfully affect our findings—it reduces the average earnings estimate for State Tech by roughly \$3,700 compared to the estimate in the main text. Still, the large positive estimate remains even under this extreme scenario. Earnings reported in 2018 dollars. Standard errors are in parenthesis.
* $p < 0.05$.

Table A5. Effects of Enrollment in Technical Education at State Tech on Graduation Outcomes, Estimated Using Matching and IV, With the Control Group Restricted to Students Who Attend a Community College in a High Wealth County.

	Matching Estimates	IV Estimates
Associate Degree Attainment in 2 years	0.356*	0.058
	(0.004)	(0.105)
Associate Degree Attainment in 4 years	0.312*	0.177
	(0.006)	(0.113)
Associate Degree Attainment in 6 years	0.296*	0.217
	(0.007)	(0.115)
Associate or Bachelor's Degree Attainment in 6 years	0.261*	0.202
	(0.007)	(0.116)
Number of Observations	2,050	2,050

Notes: State Tech is located in the county with the 10th highest income in Missouri as measured by median household income. This table replicates our analysis of State Tech from the main text but restricts the control group to students who enroll at community colleges in other high-income counties (specifically, five community colleges in counties in the top 20 by median household income: St. Charles Community College, SLCC-Forest Park, Jefferson College, East Central College, and North Central Missouri College). Standard errors are in parentheses, bootstrapped for the matching estimates.
* $p < 0.05$.

Table A6. Effects of Enrollment at State Tech on Earnings Six Years after Enrollment, Estimated Using Matching and IV, With the Control Group Restricted to Students Who Attend a Community College in a High Wealth County.

	Matching Estimates	IV Estimates
Annual Earnings Six Years After Initial Enrollment, Conditional on Non-Missing Earnings	$12,013*	$13,286*
	(292)	(6,350)
Number of Observations	1,654	1,654

Notes: State Tech is located in the county with the 10th highest income in Missouri as measured by median household income. This table replicates our analysis of State Tech from the main text but restricts the control group to students who enroll at community colleges in other high-income counties (specifically, five community colleges in counties in the top 20 by median household income: St. Charles Community College, SLCC-Forest Park, Jefferson College, East Central College, and North Central Missouri College). Standard errors in parentheses, bootstrapped for the matching estimate.
* $p < 0.05$.

Table A7. Data Missingness for pre-enrollment earnings for each treatment control contrast.

	Statewide Evaluation		State Tech Only		Technical Education Excluding State Tech	
	Treated	Control	Treated	Control	Treated	Control
Missing pre-enrollment earnings	0.281	0.251	0.256	0.270	0.293	0.254
No. of Observations (weighted for controls)	3,487	6,367	1,021	2,165	2,383	5,159

Note: Control group averages are weighted averages, noting that for each treatment observation up to three controls are selected with equal weight and controls can be resampled across treatment observations. Family income, expected family contribution, median household income, and earnings are in 2018 dollars.
* $p < 0.05$.

Table A8. Effects of Enrollment in Technical Education Programs on Graduation Outcomes for Each Treatment, Estimated Using Mahalanobis Distance-Based Matching.

	Statewide Evaluation	State Tech Only	Technical Education Excluding State Tech
Associate Degree Attainment in 2 years	0.127*	0.369*	0.013*
	(0.003)	(0.004)	(0.003)
Associate Degree Attainment in 4 years	0.107*	0.312*	0.010
	(0.004)	(0.007)	(0.005)
Associate Degree Attainment in 6 years	0.101*	0.282*	0.014*
	(0.005)	(0.008)	(0.005)
Associate or Bachelor's Degree Attainment in 6 years	0.090*	0.260*	0.009
	(0.005)	(0.008)	(0.006)
Number of Observations	9,792	3,186	7,511

Notes: These estimates can be compared to the results in Table 5 to assess how changing the matching algorithm impacts our findings. The differences are small. Standard errors bootstrapped using 250 repetitions are reported in parentheses (we use fewer bootstrap repetitions for these estimates because Mahalanobis distance-based matching is more computationally demanding than our other estimators).
* $p < 0.05$.

Table A9. Effects of Enrollment in Technical Education Programs on Annual Earnings for Each Treatment, Estimated Using Mahalanobis Distance-Based Matching.

	Statewide Evaluation	State Tech Only	Technical Education Excluding State Tech
Annual Earnings Six Years After Initial Enrollment, Conditional on Non-Missing Earnings	$6,983*	$13,350*	$3,899*
	(174)	(301)	(220)
Number of Observations	7,838	2,619	5,954

Notes: These estimates can be compared to the results in Table 6 to assess how changing the matching algorithm impacts our findings. The differences are small. Standard errors bootstrapped using 250 repetitions are reported in parentheses (we use fewer bootstrap repetitions for these estimates because Mahalanobis distance-based matching is more computationally demanding than our other estimators). Individuals with missing earnings records are dropped from the sample. Earnings reported in 2018 dollars.
* $p < 0.05$.