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The education and earnings returns to postsecondary technical education: Evidence from Missouri

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Introduction

Career and technical education (CTE) programs offer practical, career-oriented training. Most community colleges offer at least some CTE programming, in which students can earn credentials ranging from short-term certificates and diplomas to associate's degrees. A small number of colleges focus exclusively, or almost exclusively, on CTE. Research on the labor-market returns to postsecondary CTE training is mixed but mostly positive, with the largest returns typically accruing in technical and health fields (Bettinger and Soliz, 2016; Liu, Belfield, and Trimble, 2015; Stevens et al., 2018; Xu and Trimble, 2016). A related literature on CTE in high schools also generally finds positive impacts on students' education and labor-market outcomes (Brunner, Dougherty, and Ross, forthcoming; 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 education programs at public community colleges in Missouri. Our definition of technical education includes a subset of CTE programs that are technically oriented, which we focus on for two reasons. First, research suggests that technical programs have among the highest education and earnings returns among CTE fields (along with health programs). Second, our evaluation context—the state of Missouri—is somewhat unique in that one of Missouri's public colleges is a well-regarded, nationally-ranked technical school. This college—State Technical College of Missouri, or State Tech for short—offers programs almost exclusively in technically-oriented CTE fields. We compare the returns to technical education at State Tech to the returns to similar programs at other Missouri community colleges, which allows us to gain insight into the scope for institutional differences to impact student outcomes.

Our analysis is based on administrative microdata from Missouri covering community-college enrollees throughout the state, merged with earnings data from state unemployment records. We begin by using matching estimators to compare education and earnings outcomes between observationally similar students who differ by whether they enroll in a technical program statewide. We show that technical students are more likely to earn an associate's degree, and to earn a degree more quickly, compared to observationally similar non-technical students. Technical students also have higher annual earnings six years after initial enrollment. Next, we divide technical education students into two groups—those who enroll at State Tech and those who enroll at other community colleges in Missouri. We find that the statewide gaps in outcomes between technical and non-technical students are driven predominantly by positive outcomes among State Tech students.

Our evaluation is well-suited for a matching-based research design because we have access to rich observable information about students and our control-to-treatment ratio is high, facilitating strong matches. Still, to interpret our matching estimators causally we must assume conditional independence, which is a strong assumption. Therefore, we also estimate complementary instrumental variables (IV) models that leverage variation in distance-based access to technical education in Missouri. Our approach builds on a large literature on the returns to postsecondary education that relies on geographic variation for identification and is made more compelling in our context by the localized nature of community college enrollment.[1] Our instruments are carefully constructed 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: (a) the share of technical-education enrollment at the nearest community college, and (b) 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.

Our preferred estimates indicate that enrolling in a technical program at State Tech increases the likelihood of graduating with an associate's degree within six years by about 24 percentage points, or roughly 80 percent of the control-group mean, where the control group consists of non-technical students. This estimate may be inflated if non-technical students are more likely to transfer to 4-year colleges and forego their associate's degrees; however, we show State Tech's degree-attainment effects are not meaningfully reduced if we account for downstream bachelor's degrees among transfer students. We also estimate that enrolling in State Tech increases earnings six years later by $12,746 annually, or 49 percent of the control group mean. This effect is inclusive of any effect operating through the increase in degree attainment. Assuming full-time work, our earnings estimate implies an increase in the hourly wage from roughly $13 to $19.50 per hour for State Tech students.

[1] Examples of early studies that leverage geography-based variation to identify the returns to postsecondary education are Card (1993) and Kane and Rouse (1995). More recent examples include Doyle and Skinner (2016), Long and Kurlaender (2009), and Mountjoy (2021).

An initial reaction to these estimates is that they are implausibly large. Indeed, this was our initial reaction. However, several aspects of our analysis support their credibility. First, we obtain substantively similar results using our matching and IV models despite their relying on different variation for identification. Moreover, the IVs are well-powered, which minimizes concerns about correlated bias between the matching and IV estimators (Hahn and Hausman, 2005). Second, we conduct falsification tests in which we estimate the "effects" of enrolling in technical education on earnings in the year prior to initial enrollment, during which any causal effect of enrolling should be zero. These tests reveal little scope for bias in our preferred estimates. Finally, although we find very large effects of enrollment at State Tech, we estimate null-to-small effects for technical programs at other community colleges using the same methods. The fact that the State Tech estimates are so large, while the estimates for other technical programs are not, rules out bias from selection into technical education common to all programs as an explanation of our findings for State Tech.

Ultimately, we find that State Tech has large effects on students' graduation and earnings outcomes. After considerable interrogation of these findings, we conclude they reflect real impacts of State Tech. Considering our results holistically, they exemplify the potential for significant institutional heterogeneity in the efficacy of technical education and suggest great promise for high-quality programs to improve the outcomes of students who attend community colleges.

Previous Research

Research on the returns to community college has focused predominantly on the earnings returns to the attainment of credentials. Notable recent studies include Bettinger and Soliz (2016), Dadgar and Trimble (2015), Liu et al. (2015), Stevens et al. (2019), and Xu and Trimble (2016). Whether short- or long-term certificates and diplomas, or associate's degrees, these studies generally estimate positive impacts of credential attainment, on average. The impacts vary across fields and credential types, with more variation in earnings returns by field than by the type of credential. Programs more closely connected to the labor market and that provide clearer career pathways have the highest returns, with the majority of high-return credentials in health and technical fields.

In the same spirit as our study of technical education in Missouri, Bettinger and Soliz (2016) study the returns to credentials from technical and non-technical colleges in Ohio. There is a large technical-college presence in the Ohio community college system—it has 15 regular community colleges and 8 technical colleges. Bettinger and Soliz (2016) find that the earnings-returns are higher for technical-college credentials, on average. For associate's degrees in particular, they estimate earnings returns that are 5-7 percentage points higher for degrees from technical colleges compared to non-technical colleges.[2]

The predominant methodological approach used to estimate earnings returns in the extant literature is individual fixed effects. Models that use individual fixed effects leverage variation in earnings for individuals before and after receiving a credential to assess the credential's impact. We do not follow this approach for two reasons. First, we are interested in both the *education and earnings returns* to enrollment in technical versus non-technical programs. Our focal education outcomes are associate's 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, our sample is comprised primarily of young community college entrants and it is unclear if early, pre-education wages are a sufficient baseline by which to assess the earnings returns to education. Noting this, we do conduct falsification tests of our primary earnings-return estimates using pre-enrollment wage data, and in this way provide the components of estimates similar to the extant literature using individual fixed effects.

Our study also differs from most other studies in the literature because we estimate earnings returns to enrollment, rather than the attainment of a credential. This is an important distinction if the education returns differ across programs. For example, below we provide evidence that enrolling at State Tech leads to a very large increase in the likelihood of associate's degree attainment relative to enrolling in other technical or non-technical programs in Missouri. To the extent that degree attainment increases earnings—and noting that strong evidence in support of this is 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 through the increase in degree attainment. The earnings returns that we estimate

[2] Bettinger and Soliz (2016) also allow for gender heterogeneity in the returns to credentials from technical and traditional community colleges. For associate's degrees there is gender heterogeneity in the returns to technical college favoring women. For short- and long-term certificates, men benefit more for from earning their credentials from technical colleges.

below capture the returns conditional on degree attainment, in addition to the returns that operate through the increased likelihood of receiving a degree.

Missouri Context and Data

Missouri is an interesting context in which to study technical education due to the presence of State Tech. A 2020 Brookings Institution report ranked State Tech fourth in the nation for middle-class mobility among two-year colleges (Reber and Sinclair, 2020). 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 similarly high in recent years.

Ranking criteria differ across outlets, but criteria common to most rankings are graduation rates and job placements, both of which are high at State Tech. While this is suggestive of the quality of education programs at State Tech, it is not conclusive. Selection into State Tech may contribute to the positive outcomes of State Tech students; moreover, broadly speaking, the scope and scientific rigor of college rankings is unclear. We examine the efficacy of State Tech empirically in the larger context of the technical-education landscape in Missouri.

We use administrative records from the Missouri Department of Higher Education and Workforce Development (DHEWD) covering all public college students in Missouri. 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 students' family incomes and expected family contributions for college expenses, and from the Missouri Department of Labor and Industrial Relations (DOLIR) on earnings via unemployment insurance (UI) records. We track each cohort's graduation and labor market outcomes six years into the future. Our analysis covers 12 of the 13 public two-year colleges in Missouri. The only college not covered is Metropolitan Community College in Kansas City, which we omit due to data reporting problems during the sample period.

The technical fields we focus on are a subset of a larger group of programs typically identified as CTE. We use 2-digit Classification of Instructional Programs (CIP) codes to define programs in the following CTE fields as technical: Agriculture and Natural Resources; Computer and Information Services; Consumer Services; Engineering, Architecture, and Science

Technologies; Protective Services; and Manufacturing Construction, Repair, and Construction.[3] By our definition, non-technical CTE fields primarily include programs in Health Sciences; Education; and Public, Legal, and Social Services. Health Sciences is the largest area of CTE excluded by our analysis.

Our focus on technical fields is motivated in large part by our interest in studying State Tech. Overall, about 16 percent of community college students in Missouri enroll in technical fields as we've defined them and outside of State Tech, no Missouri college enrolls more than 20 percent of students in technical fields. However, at State Tech, these fields dominate the curriculum, accounting for 90 percent of enrollment. Table 1 shows technical-education enrollment shares for the 12 community colleges in our sample. State Tech is clearly an extreme outlier. 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 as is the case for State Tech.

Summary statistics for our administrative microdata 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, whether the student enrolled at State Tech. Column (1) shows women are overrepresented in community colleges in Missouri overall (54 to 46 percent). The racial-ethnic demographics of the sample are consistent with the demographics of Missouri—i.e., our sample is predominantly White with a non-negligible Black share, and then small shares for the other racial-ethnic groups. In terms of academic qualifications, the average ACT Math and English scores for community college students are about two points lower than the average scores statewide (at 19.1 and 19.2, respectively) and the average high school class rank is just below the median, at the 49th percentile. About one third of students are missing ACT scores, and about one-sixth are missing class ranks.[4] The average student in our sample comes from a family with an annual income of almost $60,000, which is just above the state median based on U.S. Census data, and has an expected family contribution on the FAFSA of $7,782 (in 2018 dollars). About 9 percent of students are missing family income data.

[3] That is, 2-digit CIP codes of 01, 03, 04, 11, 12, 14, 15, 19, 29, 31, 41, 43, 46, 47, 48, and 49.

[4] The data missingness is not surprising because community colleges are open-enrollment institutions and this information is not required. We discuss how we handle the missing data analytically in the methods section below.

Columns (2)-(5) show a sharp divergence in gender representation between non-technical and technical programs. Technical programs are male-dominated, especially at State Tech, which stands in stark contrast to the larger college-going population (and the population of students pursuing non-technical CTE credentials, primarily in health and education). Thus, our focus on technical education also implies a focus on men.[5] Men are an increasingly disadvantaged group in higher education. They are underrepresented relative to their population share in terms of enrollment and have lower grades and graduation rates compared to their female peers (Arcidiacono and Koedel, 2014; Conger, 2015; Conger and Dickson, 2017). Our focus on men via the emphasis on technical fields is also important in light of findings from Bettinger and Soliz (2016) and Liu et al. (2015) demonstrating that the returns to two-year credentials are higher for women, driven in large part by credentials in health fields. It is important to understand the types of credentials men pursue to support policy efforts to rectify the existing gender imbalance in postsecondary participation and success.

Table 2 also shows that technical students are more likely to be White, and again, especially at State Tech. This is driven in part by the geographic location of State Tech in Missouri, which is in a fairly rural area far from the urban centers in the state where most of the Black population resides. In terms of academic qualifications, technical students have slightly higher ACT math scores and slightly lower English scores, and lower class ranks, compared to non-technical students, and State Tech students look similar to other technical students along these dimensions. Technical and non-technical students come from families with similar incomes statewide, although State Tech students come from families with higher incomes.

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).[6] These characteristics do not vary dramatically across the columns, although consistent with their own demographics, students who enroll at State Tech come from areas with a higher share of White residents.

[5] Men are also overrepresented in applied science CTE coursework during secondary school (Plasman, Gottfried, and Hutt, 2020), which is substantively similar to technical CTE coursework at the postsecondary level.

[6] 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.

The bottom panel of Table 2 summarizes students' treatments and outcomes. As noted above, about 16 percent of students enroll in a technical education program statewide, with a quarter of these (4 percent of total enrollment) doing so at State Tech. Our primary education outcome is associate's degree attainment from a Missouri public college within 6 years and 29 percent of students in the full sample earn an associate's 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 in our analysis and reported in 2018 dollars). Just over 20 percent of students are missing earnings data. The 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 not working in a UI-covered position (e.g., federal employment). We discuss how we handle data missingness analytically below.

Empirical Strategy

Matching

We begin by estimating the effects of enrollment in technical education using matching. An obvious limitation of matching estimators is that they rely on the assumption of conditional independence for identification. Noting this limitation—which we discuss in more detail below—matching is an appealing strategy in our application because we have (a) access to rich observable information about students, and (b) a high ratio of control-to-treatment observations. The former is a key condition for effective use of selection-on-observables strategies (Black and Smith, 2004) and the latter allows us to assemble a well-matched control group for treated observations on observed dimensions (Frölich, 2004).

We construct three treatment-control contrasts. In our statewide models, an individual is treated if she initially enrolls in a technical education program at any Missouri community college. Students who enroll in non-technical programs are controls. We also estimate models where we split the statewide treatment into two subgroups, one consisting of students who enroll in a technical program at State Tech and the other of students who enroll in a technical program at any other college. We maintain a common control group consisting of students who enroll in non-technical programs throughout the state for all of our comparisons. Columns (2)-(5) in Table

2 show summary statistics for each treatment group and the common control group prior to matching.

The favorable control-to-treatment ratio in our comparisons permits the use of a rigid matching algorithm that ensures high-quality matches along observed dimensions. We start by matching exactly on the following binary variables from Table 2: (1) gender, (2) race-ethnicity category, and (3) data-missingness indicators for gender, race-ethnicity, ACT scores in math and English, high school percentile ranks, family income, and the expected family contribution.[7] 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 to ensure we do not use matches that rely entirely on data missingness for these key controls. We also exact-match on students' year cohorts (either 2011, 2012, or 2013). By exact-matching on these variables, we construct samples of treatment and control observations with identical demographics, data missingness profiles, and college-entry years.

Conditional on the exact matches, we further match treatment and control observations using propensity scores. The propensity scores are estimated from a probit regression where the dependent variable is an indicator for treatment. The main independent variables are the non-binary, pre-enrollment, student-level variables in Table 2: ACT math and English scores, high school percentile ranks, family income, and the expected family contribution. We also include the county characteristics in the propensity score specification, 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 in the model.

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 for our analysis. None of our findings are substantively sensitive to reasonable modifications to the caliper bandwidth.

[7] For the data-missingness variables, a separate binary indicator is constructed to indicate missingness for each variable in our dataset.

This procedure yields samples of treatment and control observations for each of our comparisons that match exactly on demographics and data-missingness profiles, and are well-balanced on pre-college academic qualifications, family income, and local-area characteristics.

As noted above, the primary identifying assumption of our matching estimators is that treatment is conditionally independent of outcomes. Denoting potential outcomes by $\{Y_0, Y_1\}$, treatment by $D \in \{0, 1\}$, and $\mathbf{X}$ as the vector of conditioning variables, the conditional independence assumption (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:

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

On the one hand, our rich data, including information on students' pre-college academic qualifications and family incomes, supports the plausibility of the CIA in that we can control for many of the consequential factors that lead to differences in students' decisions regarding technical education. However, on the other hand, it is easy to imagine unobserved factors that affect students' enrollment decisions. If these factors are also correlated with students' graduation and labor-market outcomes, which seems likely to the extent they exist, it will bias our estimates of the effects of technical education. This concern motivates our second empirical strategy, which relies on geography-based instruments for identification.

Instrumental Variables

Our IV models leverage students' geographic distance to technical programs to identify their effects and do not require conditional independence. We estimate our IV models in 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 match on from above). $\mathbf{Z_i}$ 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. Common variables are defined the same in equation (4), where Y_{it} is the outcome of interest and $\hat{T}_{it}$ is the fitted value from the first stage. The benefit of this approach is that the only variation used to identify the effect of treatment in equation (4) is from the instruments, $\mathbf{Z_i}$.

Our instruments are geography-based and aim to 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. The 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), in equations (3) and (4) we instrument for treatment by the share of enrollment in technical programs at that college, plus an interaction between the share and the distance to the college. Our preferred IV models use the matched samples following from the matching procedure outlined above; we also show IV results using all of the data in the appendix.

The identifying assumption of the IV models is that students are not geographically sorted in ways that align with the presence of technical education in Missouri's 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.

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 and Table 4 provides summary balancing information. The results in Table 4 indicate that our matching procedure is generally effective. There are few individually unbalanced covariates, the average p-value for the matched variables consistently hovers around 0.50, which is the expectation, and the absolute mean standardized differences are small by common conventions (Smith and Todd, 2005; Rosenbaum and Rubin, 1985). Note that we exclude the binary variables from all of the calculations in Table 4 because the exact matching procedure renders them uninformative (i.e., for each of these variables the p-value must be 1.0 and the standardized difference must be 0).

The only instance of even modest imbalance in Table 4 is for State Tech treatment, although Table 3 suggests the imbalance is potentially important. Most notably, State Tech students' family incomes and local-area incomes are higher than their matched comparisons (see columns 3 and 4 of Table 3). This is a caveat to the causal interpretation of our matching estimators, which we elaborate on below, and helps motivate our IV models.

Educational Attainment

Table 5 shows the main results for degree attainment using our matching estimators. For each treatment-control contrast, we estimate the effect of enrolling in a technical education program on attainment of an associate's degree in 2 years, 4 years, and 6 years. All of the standard errors in Table 5—and all subsequent standard errors for our matching estimators—are constructed 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 students in the control group statewide, conditional on observables. Specifically, they are 4.0 percentage points more likely to graduate within 6 years, 4.7 percentage points more likely to graduate within 4 years, and 6.4 percentage points more likely to graduate within 2 years. As shown in Table 2, the mean graduation rates in the (unmatched) control group over these timeframes are 29, 25, and 8 percent, respectively. 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 comparison are driven entirely by students who enroll at State Tech. State Tech students are 24.9 percentage points more likely to graduate within six years than their matched comparison group, and 27.9 and 35.5 percentage points more likely to graduate in 4 and 2 years, respectively. Even if there is some bias from non-comparability in our estimates for State Tech, the magnitudes of these estimates are so large that it would be difficult for the bias to explain them all. In contrast, when we use technical students outside of State Tech as the treated group in column (3), there is no evidence of a positive effect on degree attainment or time-to-degree. In fact, over a six-year horizon the treatment effect is negative and statistically significant, albeit small.

Our focus on associate's degree attainment 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 their associate's degrees. To assess the potential for differential transfer patterns by treatment status to bias our findings, in the bottom row of Table 5 we re-estimate the models, but this time code the outcome as a binary indicator for any associate's 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. If non-technical students are more likely to transfer and earn bachelor's degrees (while foregoing their associate's degrees), an expectation is that these models should yield estimates of the impacts of technical education that are less positive.

The bottom row of Table 5 shows the impacts of technical education on degree attainment are slightly smaller when we allow for bachelor's degrees via transfer. This is consistent with non-technical students being more likely to transfer and complete bachelor's degrees. However, allowing for bachelor's degrees only modestly affects the findings.[8]

Finally, we briefly return to the imbalance in family income in our comparison involving State Tech. In results suppressed for brevity, we use OLS regressions to get a sense of the potential bias caused by this imbalance. These models indicate that the $5,500 average difference in family income between State Tech students and the comparison group, conditional on the other controls (excluding the expected family contribution, which is highly correlated with family income), is associated with only a trivial difference in six-year degree attainment—0.22 percentage points. Of course, this is not conclusive evidence against bias in our matching estimators, as there could be other sources of imbalance that are unobserved, and again, this motivates our IV models. Still, at least in terms of bias stemming directly from the imbalance in family income, our supplementary models suggest only a small scope for bias in our matching estimators.[9]

[8] The limited impact of allowing for bachelor's degrees on our findings is due to the generally low rate of bachelor's degree receipt among students our sample, which is expected based on previous research. For example, Qian and Koedel (2021) find that most community college students lack the academic qualifications necessary to succeed at universities and Long and Kurlaender (2009) show that even among those with strong academic credentials, the transfer pathway is leaky and they are significantly less likely to complete university degrees than observationally-similar students who do not follow the community college pathway.

[9] To elaborate briefly on our procedure, we use the matched dataset for the State Tech comparison to run a linear probability model predicting graduation using all of the control variables except the expected family contribution. We omit the expected family contribution because it is highly correlated with family income and it is nonsensical to give an "all else equal" interpretation to changes in family income if the expected family contribution is included as a control. From this regression, we use the coefficient on family income to obtain the predicted gap in degree attainment due to the family income difference between treatment and control observations, conditional on the other control variables we use for matching. We find that a $10,000 increase in family income is associated with a 0.4 percentage point increase in degree attainment within six years, which we scale in the text to arrive at the 0.22 percentage point number associated with the $5,500 gap in family income shown in Table 2.

Earnings

Next, we turn to the earnings returns to technical education. We follow the same data and estimation procedures outlined above but replace the 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).

We begin in Table 6 by showing results for the sample of students with at least one non-missing quarterly earnings record during the relevant year. We find positive and significant earnings differentials favoring technical education students statewide, driven predominantly by especially large estimates at State Tech. The State Tech differential of $11,308 is 44 percent of the control group mean of $25,828 (Table 2). Unlike in the education-outcome models, the matching estimate for earnings is positive and significant for other technical programs outside of State Tech in column (3) of Table 6—at $2,357. This is much smaller than the estimate for State Tech, but similar to the premium Bettinger and Soliz (2016) estimate for associate's degree attainment from a technical versus non-technical college in Ohio.[10]

In addition to the standard concern about bias in our matching estimators—i.e., the potential failure of conditional independence—we must also be concerned about bias due to sample attrition in the earnings models. Recall from above that about 20 percent of students have no reported 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.[11]

We examine the sensitivity of our findings to different data-missingness scenarios in Table 7, where we re-estimate our models after including individuals with missing earnings via imputation. We consider three different imputation scenarios, where individuals with missing earnings are coded as having either: (1) earnings equal to zero, (2) earnings equal to the average

[10] This estimate corresponds to about 9 percent of the control group mean. Bettinger and Soliz (2016) find that the premium to earning an associate's degree at a technical college in Ohio is about 6-8 percent higher than at a non-technical college.

[11] Table 2 shows missingness rates in the earnings data for the relevant comparisons prior to matching. Students in technical programs are somewhat less likely to have missing earnings data.

earnings at the institution in which they enrolled, or (3) earnings equal to the average earnings at the institution but cut by 50 percent for technical education students only. The first two imputation scenarios address the problem of differential missingness rates by treatment status under different assumptions about selection into missingness—in scenario (1) we assume strong negative selection into missingness and in scenario (2) we assume no selection. However, both scenarios assume that the magnitude and direction of selection is unrelated to treatment status. The third scenario imputes an earnings wedge between treatment and control observations with missing earnings by assuming that individuals in the treatment group without earnings are very negatively selected relative to their counterparts with missing earnings in the control group. This is a strong assumption favoring the control group and offers an extreme test of whether the technical-education effects on earnings we estimate can be overturned by bias related to missing data on earnings.

The results in the first two rows of Table 7, in comparison to the results in Table 6, show our findings are not meaningfully sensitive to imposing the assumptions of our first two imputation scenarios. This means that bias stemming solely from differences in the rates of missingness across treatment conditions, holding the direction and magnitude of selection into missingness fixed across treatment conditions, is not causing significant bias in our findings. The assumption embedded in the third imputation scenario in row 3 of Table 7, which again we view as extreme, 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 Table 6. Still, the large positive estimate for State Tech remains even under this extreme scenario. We conclude from Table 7 that our substantive findings are unlikely to be driven by sample selection bias caused by missing earnings data.

We also consider the scope for bias in the earnings estimates due to the imbalance in family income between treatment and control observations in our comparison involving State Tech. Using the same procedure described in the preceding subsection, we find that the family-income imbalance alone conditionally predicts just a $180 annual earnings gap in favor of State Tech students. Thus, it is unable to account for the large earnings differences we report in Tables 6 and 7. Again acknowledging we cannot rule out bias due to unobservables, the scope for bias attributable to the observed family-income gap after matching, conditional on our other controls, seems negligible.

Finally, in Table 8 we use the earnings data to conduct placebo tests in which we estimate our baseline earnings models but use earnings over the four quarters prior to initial enrollment in college 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. A limitation of our placebo tests is that the students in our sample are relatively young (see Table 2), which one might worry could cause wage compression and make it more difficult for the placebo models to detect problematic selection. While this is a limitation, pre-college wage gaps are also plausible depending on the nature of the unobserved selection. For example, a more technically oriented high school student, or recent high school graduate, is likely to earn more working in a low-level technically oriented position than her counterpart working in a less-technical position.

Noting the interpretive caveat, Table 8 shows the results from our placebo tests. 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. Perhaps most importantly, the placebo models identify selection levels into technical education at State Tech, and technical education outside of State Tech, of roughly the same magnitude. In fact, 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 almost five times larger than for technical education programs elsewhere in Missouri.

Results: Instrumental Variables

Next, we report on our instrumental variables estimates. We continue to use the matched samples for analytic consistency, but the identifying assumptions of the IV models do not require the use of matched samples. Findings from models using unmatched data are similar and reported in the appendix.

Table 9 shows results from the first stage of the IV regressions. As foreshadowed by the descriptive statistics in Table 1, our instruments are highly effective at predicting enrollment at State Tech but ineffective at predicting enrollment in other technical education programs. For example, the first-stage partial F-statistic is 107.22 when we define treatment as enrollment in a technical program at State Tech (column 2), but just 0.12 when we define treatment as enrollment in a technical program elsewhere in the state (column 3). These results indicate that the differences across community colleges outside of State Tech in their technical-education enrollment shares are not sufficient to generate meaningful exogenous variation in our IV models. Given this, we focus the IV portion of our analysis on recovering the effects of State Tech only.

Table 10 shows second-stage results for educational outcomes, which 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 24.2 percentage point increase in the likelihood of earning an associate's degree. This estimate can be compared to the control-group attainment rate of 29 percent and is large by any reasonable standard.[12]

In Table 11, we report our findings from the IV models of earnings. The first row shows earnings estimates conditional on non-missing values, comparable to our matching estimates in column (2) of Table 6, and rows 2-4 show results using the different imputation scenarios from Table 7. Again, our earnings estimates are similar using either the matching or IV approach. Our primary non-imputed earnings estimate using IV indicates that State Tech raises annual earnings by $12,746 compared to the control group mean of $25,828, an increase of 49 percent. The estimates from the first two imputation scenarios fluctuate around this value and the estimate in the third scenario is again lower by about $3,000. Still, even in that extreme case, the implied effect of enrollment at State Tech on annual earnings is almost $10,000.

Conclusion

We estimate the education and earnings returns to enrolling in technical education programs at Missouri community colleges relative to non-technical programs. A unique contextual feature of Missouri is the presence of State Technical College, a highly-regarded and nationally-ranked technical college. 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's degree attainment within six years by 24.2 percentage points and annual earnings six years after

[12] We briefly address the odd result in Table 10 in the last row, where the coefficient of interest becomes nominally larger when we allow for bachelor's degree receipt, which is the opposite of what we would expect (and what happens in the matching model). We are not sure what is causing this result given the complex nature of identification via the IV, but we do not put much stock in it because the surprising coefficient is not statistically or economically different from the coefficient in the previous row.

initial enrollment by $12,746 (this corresponds to an hourly wage increase of roughly $6.50 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 suggest their earnings impacts are much smaller than the impact of State Tech.

The education and earnings impacts that we estimate for State Tech are very large; so large, in fact, that we were initially skeptical of their plausibility. However, no non-substantive explanation emerges to account for them. They are present in our analyses of both education and earnings outcomes. They persist whether we use matching estimators that rely on conditional independence for identification or IV estimators that leverage geographic variation in exposure to State Tech. They are maintained even under a strong assumption of severe negative selection into wage missingness among State Tech students, which puts downward pressure on the estimates. They are not overturned by our placebo regressions. Finally, within our matching framework, we estimate null-to-small effects for technical programs outside of State Tech using the same methods we use to evaluate State Tech. This rules out bias due to selection into technical education common to all programs as an explanation for our findings.

We highlight three ways that our findings contribute to the broader discourse on postsecondary technical education. First, they indicate that State Tech is an exceptionally productive community college. Future work should aim to understand what makes State Tech so effective. Methodologically it will be difficult to conclusively link particular aspects of how State Tech operates to the summative program impacts we estimate here, but perhaps alternative strategies like qualitative inquiry can be informative.

Second, above we noted that enrollment at State Tech is male-dominated. The 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, and Conger and Dickson, 2017). 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 enrollment on average. It is only when we separate out State Tech that it becomes apparent this single institution is primarily driving the statewide effects. If we did not separate out State Tech, we would have generated misleading inference about the general efficacy of technical education in Missouri. This finding raises the possibility of institutional heterogeneity elsewhere as well, but we are not aware of any other studies that test for this. While other states may not have an institution like State Tech, it is important to recognize we know little about what characteristics of community colleges generate heterogeneity in their efficacy. Our Missouri findings suggest it would be prudent to test for institution-level 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 a larger fraction of the population.

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

College	Technical Education Enrollment Share
State Technical College of Missouri	0.90
Jefferson College	0.20
Southwest Missouri State University-West Plains	0.19
Ozarks Technical Community College	0.17
Crowder College	0.16
Mineral Area College	0.15
Three Rivers Community College	0.13
State Fair Community College	0.13
St. Charles Community College	0.13
East Central College	0.13
North Central Missouri College	0.11
SLCC-Forest Park	0.08
Moberly Area Community College	0.08

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		19.47	19.96	19.21	20.17
Female	0.54		0.60	0.23	0.04	0.29
Male	0.46		0.40	0.77	0.96	0.71
Unknown Gender	<0.00		<0.00	0.00	0.00	0.00
Black	0.09		0.10	0.07	0.01	0.09
White	0.83		0.83	0.86	0.95	0.84
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		19.08	19.39	19.42	19.38
ACT Math Score Missing	0.35		0.33	0.47	0.44	0.47
ACT English Score	19.21		19.29	18.82	18.59	18.89
ACT English Score Missing	0.35		0.32	0.47	0.44	0.47
High School Class Percentile Rank	0.49		0.50	0.45	0.45	0.45
High School Class Percentile Rank Missing	0.16		0.16	0.11	0.03	0.13
Family Income	$59,841		$59,768	$60,212	$74,938	$56,131
Family Income Missing	0.09		0.09	0.09	0.07	0.09
Expected Family Contribution	$7,782		$7,719	$8,102	$11,572	$7,141
Expected Family Contribution Missing	0.09		0.09	0.09	0.06	0.09
Local Area Characteristics						
Unemployment Rate	0.09		0.09	0.08	0.08	0.09
Median Household Income	$53,538		$53,771	$52,349	$52,636	$52,269
Educational attainment ≥ of BA	0.16		0.16	0.15	0.14	0.15
Share of population that is White	0.92		0.92	0.93	0.95	0.92
Treatments, Instruments, and Outcomes						
Technical Educ Enrollment	0.16		0.00	1.00	1.00	1.00
Technical Educ Enrollment at State Tech	0.04		0.00	0.22	1.00	0.00
Distance to Nearest Comm College	18.45		18.00	20.75	29.34	18.37
Distance to State Tech	89.65		89.91	88.29	66.08	94.44
Two-year Associate's Attainment	0.08		0.07	0.14	0.43	0.06
Four-year Associate's Attainment	0.25		0.24	0.27	0.53	0.19
Six-year Associate's Attainment	0.29		0.29	0.30	0.54	0.23
Annual Earnings Six Years After Entry	$26,720		$25,828	$31,280	$39,759	$28,930
Earnings Data Missing	0.21		0.21	0.19	0.16	0.20
No. of Observations	32,874		27,496	5,378	1,167	4,211

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	19.91	19.91	19.24	19.36	20.02	19.95
Female	0.24	0.24	0.04	0.04	0.29	0.29
Male	0.76	0.76	0.96	0.96	0.71	0.71
Unknown Gender	0	0	0	0	0	0
Black	0.07	0.07	0.01	0.01	0.09	0.09
White	0.88	0.88	0.98	0.98	0.86	0.86
Hispanic & Latino	0.01	0.01	<0.00	<0.00	0.01	0.01
Asian & Pacific Islander	0.01	0.01	<0.00	<0.00	0.01	0.01
Other Race	0.03	0.03	0.01	0.01	0.03	0.03
Pre-College Academic Qualifications & Family Income						
ACT Math Score	19.38	19.33	19.40	19.39	19.37	19.31
ACT Math Score Missing	0.47	0.47	0.42	0.42	0.47	0.47
ACT English Score	18.86	18.85	18.59	18.58	18.92	18.91
ACT English Score Missing	0.47	0.47	0.42	0.42	0.47	0.47
High School Class Percentile Rank	0.45	0.45	0.46	0.46	0.45	0.45
High School Class Percentile Rank Missing	0.10	0.10	0.03	0.03	0.12	0.12
Family Income	$59,539	$58,005	$74,039*	$68,569*	$55,415	$54,126
Family Income Missing	0.08	0.08	0.05	0.05	0.08	0.08
Expected Family Contribution	$8,111	$7,919	$11,410	$10,767	$7,134	$6,907
Expected Family Contribution Missing	0.08	0.08	0.05	0.05	0.08	0.08
Local Area Characteristics						
Unemployment Rate	0.08	0.08	0.08	0.08	0.09	0.09
Median Household Income	$52,336	$52,157	$52,215*	$51,256*	$52,244	$51,891
Educational attainment ≥ of BA	0.15	0.14	0.14*	0.13*	0.15	0.15
Share of population that is White	0.93*	0.93*	0.94	0.94	0.92	0.92
No. of Observations (weighted for controls)	5,190	9,244	1,031	2,286	4,046	8,356

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.

Variable	Statewide Evaluation	State Tech Only	Technical Education Excluding State Tech
No. of unbalanced covariates, matched *t* tests (5%)	1	3	0
Mean absolute standardized difference of covariates (%)	1.38	4.53	1.38
Average *p* value	0.50	0.46	0.50
No. of students (*Treatment / Control*)	5,190 / 9,244	1,031 / 2,286	4,046 / 8,356

Notes: There are 23 covariates included in the balancing tests. The binary variables are not included in computing the average p-values or standardized differences because they are exactly matched, which ensures p-values of 1.0 and standardized differences of zero.

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

Variable	Statewide Evaluation	State Tech Only	Technical Education Excluding State Tech
Associate’s Degree Attainment in 2 years	0.064*	0.355*	-0.007
	(0.002)	(0.004)	(0.002)
Associate’s Degree Attainment in 4 years	0.047*	0.279*	-0.013*
	(0.004)	(0.007)	(0.004)
Associate’s Degree Attainment in 6 years	0.040*	0.249*	-0.016*
	(0.004)	(0.007)	(0.004)
Associate’s or Bachelor’s Degree Attainment in 6 years	0.029*	0.221*	-0.023*
	(0.004)	(0.007)	(0.004)
Number of Observations	14,434	3,317	12,402

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.

Variable	Statewide Evaluation	State Tech Only	Technical Education Excluding State Tech
Annual Earnings Six Years After Initial Enrollment, Conditional on Non-Missing Earnings	$4,551* (168)	$11,308* (298)	$2,357* (184)
Number of Observations	11,434	2,690	9,770

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. Sensitivity Tests for Earnings Effects, Estimated Using Matching.

Variable	Statewide Evaluation	State Tech Only	Technical Education Excluding State Tech
Annual Earnings Six Years After Initial Enrollment, Earnings Imputed to Zero if Missing	$4,501* (154)	$10,630* (285)	$2,642* (178)
Annual Earnings Six Years After Initial Enrollment, Earnings Imputed to Institution Mean if Missing	$4,219* (128)	$11,553* (246)	$1,964* (140)
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	$1,387* (132)	$8,685* (249)	-$693* (149)
Number of Observations	14,434	3,317	12,402

Notes: Standard errors bootstrapped using 1,000 repetitions are reported in parentheses. Missing earnings records are replaced with imputed values as described by the rows (see text for details). The imputation scenario in row 3 imputes 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 is (strong) differential negative selection into missing wages for technical students. Earnings reported in 2018 dollars.
* $p < 0.05$.

Table 8. Placebo Effect Estimates of Enrollment in Technical Education Programs on Annual Earnings Prior to Enrollment for Each Treatment, Estimated Using Matching.

Variable	Statewide Evaluation	State Tech Only	Technical Education Excluding State Tech
Annual Earnings During the Year Prior to Initial Enrollment, Conditional on Non-Missing Earnings	$303*	$343*	$451*
	(47)	(89)	(53)
Number of Observations	14,434	3,317	12,402

Notes: Standard errors bootstrapped using 1,000 repetitions are reported in parentheses. 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 9. First-Stage Results from the Instrumental Variables Models of Educational Attainment, Estimated on the Matched Sample.

Variable	Statewide Evaluation	State Tech Only	Technical Education Excluding State Tech
Enrollment Share in Technical Fields	0.547*	0.941*	0.033
	(0.054)	(0.078)	(0.077)
Enrollment Share in Technical Fields*Distance	-0.012*	-0.019*	-0.001
	(0.002)	(0.002)	(0.002)
First-stage Joint F-Statistic for the Instruments	64.59	107.22	0.12
Observations	14,434	3,317	12,402

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

Variable	IV Set 1
Associate's Degree Attainment in 2 years	0.205*
	(0.052)
Associate's Degree Attainment in 4 years	0.252*
	(0.065)
Associate's Degree Attainment in 6 years	0.242*
	(0.067)
Associate's or Bachelor's Degree Attainment in 6 years	0.258*
	(0.067)
Number of Observations	3,317

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

Variable	
Annual Earnings Six Years After Initial Enrollment, Conditional on Non-Missing Earnings	$12,746*
	(3,304)
Annual Earnings Six Years After Initial Enrollment, Earnings Imputed to Zero if Missing	$12,894*
	(3,380)
Annual Earnings Six Years After Initial Enrollment, Earnings Imputed to Institution Mean if Missing	$12,543*
	(2,722)
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	$9,572*
	(2,821)
Number of Observations	2,690/3,317

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.
* $p < 0.05$.

Appendix Tables
Replication of IV Results Using Unmatched Data

Table A1. Analog to Table 9: First-Stage Results from the Instrumental Variables Models of Educational Attainment, Estimated Using Unmatched Data.

Variable	Statewide Evaluation	State Tech Only	Technical Education Excluding State Tech
Enrollment Share in Technical Fields	0.393*	0.474*	0.039
	(0.029)	(0.015)	(0.033)
Enrollment Share in Technical Fields*Distance	-0.008*	-0.010*	-0.001
	(0.001)	(0.000)	(0.001)
First-stage Joint F-Statistic	118.20	689.73	1.08
Observations	32,874	32,874	31,626

Notes: Standard errors are in parenthesis.
* $p < 0.05$.

Table A2. Analog to Table 10 Using Unmatched data: Effects of Enrollment in Technical Education Programs at State Tech on Graduation Outcomes.

Variable	
Associate's Degree Attainment in 2 years	0.268* (0.040)
Associate's Degree Attainment in 4 years	0.302* (0.062)
Associate's Degree Attainment in 6 years	0.286* (0.065)
Associate's or Bachelor's Degree Attainment in 6 years	0.340* (0.066)
Number of Observations	32,874

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.
* $p < 0.05$.

Table A3. Analog to Table 11 Using Unmatched data: Effects of Enrollment in Technical Education Programs at State Tech on Earnings.

Variable	
Annual Earnings Six Years After Initial Enrollment, Conditional on Non-Missing Earnings	$13,982* (2,911)
Annual Earnings Six Years After Initial Enrollment, Earnings Imputed to Zero if Missing	$17,032* (2,906)
Annual Earnings Six Years After Initial Enrollment, Earnings Imputed to Institution Mean if Missing	$15,107* (2,375)
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	$12,612* (2,411)
Number of Observations	26,058/32,874

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.
* $p < 0.05$.