Smoothing the transition to college? The effect of Tech-Prep programs on educational attainment

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Abstract

By promoting articulation agreements between high schools and community colleges, Tech-Prep programs aim to smooth the transition to college for the middle majority of US high school students. This paper employs a family fixed effects approach to assess the effectiveness of Tech-Prep programs in increasing educational attainment. Using data from six rounds of the 1997 NLSY and controlling for both selection and within-family spillovers, I find that Tech-Prep programs help participants complete high school and encourage enrollment in two-year colleges. On the other hand, these gains come at the expense of four-year college enrollment, suggesting that Tech-Prep programs may divert students from four-year to two-year colleges in the years immediately following high school. While Tech-Prep programs appear to increase overall educational attainment, they may be falling short of their goal of promoting college enrollment among the middle majority.

JEL classification: I2; H4

Keywords: Tech-Prep; Educational attainment; College enrollment; School-to-work; Educational economics; Human capital

1. Introduction

Programs and courses aimed at smoothing the transition from high school to college have become increasingly popular in the US in recent years. For overachievers there are advanced placement classes, summer enrichment programs at MIT, and National Merit Scholarships as early as the ninth grade. But for the often-neglected middle majority of students, programs and courses which encourage enrollment and prepare students for college are few and far between. Programs that enhance the availability of college counseling or provide community college credit for high school courses may go far in encouraging students in the middle of the academic distribution to pursue postsecondary education. On the other hand, it is entirely possible that programs promoting college-going are not effective at increasing educational attainment, especially for the middle majority. These students may not take advantage of college counselors in their high school or cash in on credits that transfer to college programs. Credit constraints and the high
cost of a college education may be insurmountable, and some students may do better without any college education at all.

This paper takes a closer look at one type of program that aims to smooth the transition from high school to college for the middle majority of US high school students. So-called “Tech-Prep” programs promote articulation agreements between high schools and community colleges to award transferable credits for high school classes. They also typically fund guidance counselors and classes with a technology focus. In the words of the US Department of Education, the goal of Tech-Prep is “to develop systematic links between secondary and postsecondary institutions to better prepare students for high-tech careers” (US Department of Education, 2003). Advocates of Tech-Prep programs claim that these programs can inspire students to continue their education and training at the postsecondary level and at the very least, keep low-performing students interested in learning long enough to graduate from high school and secure a high-paying job. But are Tech-Prep programs living up to their promise? Do students who participate in Tech-Prep programs invest more in human capital in the long run? With approximately 750,000 high school participants and over $100 million in federal funds each year since 1991, it is well worth exploring whether Tech-Prep programs work. This paper assesses the effectiveness of these programs in increasing the educational attainment of their participants and attempts to identify some of the elements of Tech-Prep that are most effective.

I examine these issues using a family fixed effects approach designed to address the selection problems inherent in any non-randomized program evaluation. Using data from the 1997 National Longitudinal Survey of Youth (NLSY97), I compare the educational attainment of Tech-Prep participants with the outcomes of their non-participating siblings, accounting for the possibility of within-family spillovers.

I find that Tech-Prep generally increases educational attainment, but may be falling short of its goal of encouraging college enrollment for the middle majority. On the up side, participants are significantly more likely to graduate from high school and enroll in two-year colleges than their non-participating siblings. They also show higher grades completed and higher degrees received. On the other hand, I find no overall impact of the program on attending any type of college, since Tech-Prep participation actually reduces the probability that a student will attend a four-year college in the years immediately following high school.

2. Related literature

Existing studies of Tech-Prep and similar school-to-work programs find mixed results when assessing the impact of these programs on the educational attainment of teens. Cullen, Jacob, and Levitt (2000) find that career academies, which may or may not include Tech-Prep, do improve students’ chances of graduating from high school. In contrast, Kemple (2004) finds that career academies improve earnings for young male participants, but have no impact on educational attainment. However, while career academies share Tech-Prep’s goal of integrating academic and technical curricula, they focus specifically on partnerships with local employers (Kemple, 2004). Tech-Prep programs, on the other hand, emphasize partnerships with postsecondary institutions, so these programs should have a much larger impact on educational attainment.

Neumark and Joyce (2001) and Neumark and Rothstein (2004) look more closely at individual school-to-work programs using the NLSY97. Early research by Neumark and Joyce (2001) examines student goals and perceptions while still in high school. Using school fixed effects they find that school-to-work programs generally (including Tech-Prep) do not improve a student’s assessment of his likelihood of obtaining a four-year college degree. On the other hand, participants did perceive themselves as more likely to graduate from high school and more likely to work full-time in the future.

More recent research by Neumark and Rothstein (2004) has followed up on these predictions and perceptions. Most striking are the authors’ findings that Tech-Prep participants are less likely than non-participants to have attended college in the years immediately following high school, suggesting that Tech-Prep may actually have adverse effects on educational attainment. These findings are all the more intriguing when compared to other school-to-work programs. Among the six school-to-work programs considered by the authors, Tech-Prep is the only program with the specific goal of smoothing the transition to college. Remarkably, it is also the only program, which shows significant negative effects on postsecondary enrollments.
While the school fixed effects and extensive proxy variables used by Neumark and Joyce (2000) and Neumark and Rothstein (2004) can control for all unobservable characteristics of a student’s school and the type of Tech-Prep program offered, they may not fully account for the individual- and family-level unobserved heterogeneity that may cause one student in the school to participate in the program while another might not. This study goes one step further in employing family fixed effects, described in detail in the following sections. By implementing this approach, adding another two years of data, and focusing on the unique characteristics of Tech-Prep programs, I seek to disentangle the results of previous studies and understand the mechanisms through which Tech-Prep impacts students.

The studies highlighted above all examine the causal effects of Tech-Prep and other school-to-work programs on students’ educational attainment. However, there are several descriptive studies and surveys that are also very helpful in understanding Tech-Prep programs and their students. The most informative descriptive research on student outcomes was sponsored by the Ohio Department of Education, Ohio Board of Regents, & MGT of America (2003a, 2003b). The first survey collected the impressions of 2272 Ohio Tech-Prep participants while they were still enrolled in the program. Thirty-five percent of participants reported that their experience with Tech-Prep influenced them to attend or plan to attend college, while 38 percent of respondents claimed to be making better grades, and 34 percent claimed to be more interested in schoolwork. On the other hand, 16 percent reported that they experienced no academic improvements as a result of their Tech-Prep experience (2003a).\(^1\) A year later, Tech-Prep program administrators provided follow-up data on 1535 of these students’ postsecondary enrollment decisions. Fifty-two percent of these former participants were pursuing a technical degree while just eight percent of students were pursuing a baccalaureate degree (2003b). Though these survey results reveal some intriguing patterns, they do not control for the many factors that may have influenced students’ participation and postsecondary education decisions, so they cannot be construed to represent the causal effects of Tech-Prep.

Other evaluations of Tech-Prep programs typically focus on implementation of the program in particular localities. However, two studies—one by Hershey, Silverberg, Owens, and Hulsey (1998) at Mathematica Policy Research and the other by Bragg et al. (1997) and Bragg and Reger (2002) at the National Research Center for Career and Technical Education—provide useful background information on the nationwide implementation of Tech-Prep and offer a convenient point of departure for this study.

3. Background

The concept of Tech-Prep was developed by Dale Parnell, a former high school principal, superintendent, and community college president (Bragg & Reger, 2002). Responding to concerns that US students would fall behind in an increasingly competitive information economy, Parnell’s 1985 book, *The Neglected Majority*, sketched a detailed plan for Tech-Prep education, and most notably, drew attention to Tech-Prep’s target population:

The tech-prep/associate degree program advocates taking a step beyond the current and usually cosmetic high-school/college partnership arrangements into *substantive* program coordination. The program seeks a middle ground that blends the liberal arts with the practical arts without diluting the time-honored baccalaureate-degree/college-prep track...The program targets are (1) the middle quartiles of the typical high-school student body in terms of academic talent and interest, and (2) the mid-range of occupations requiring some beyond-high-school education and training but not necessarily a baccalaureate degree. (Parnell, 1985, p. 140)

Parnell’s vision was institutionalized at the federal level in 1990, when Congress passed the Tech-Prep Education Act as part of the Carl D. Perkins Vocational and Applied Technology Education Act of 1990. Despite fears of cuts, the Tech-Prep Education Act has remained in place with few changes over the years.

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\(^1\)The question asked, “What changes, if any, have you experienced as a result of enrolling in Tech-Prep?” Several responses were provided and students could check all that applied. For this reason, percentages sum to more than 100.
The act required seven particular elements for local programs to be eligible for funding:

1. **Articulation agreements** between secondary and postsecondary institutions, to establish a framework for creating “seamless” programs spanning secondary and postsecondary stages.

2. A **2+2 design**, in which a common core of technically oriented classes is defined for the last two years of high school and serves as the basis for two years of more advanced courses at the postsecondary level.

3. A **Tech-Prep curriculum** appropriate to the needs of each secondary and postsecondary institution.

4. **Joint staff development** for secondary and postsecondary faculty.

5. **Training for school counselors**, to promote effective student recruiting, retention, and placement.

6. **Measures to ensure access** for special populations such as students with disabilities.

7. **Preparatory services** such as recruiting, counseling, and assessment, to help students understand the Tech-Prep option and make decisions concerning program and course selection and later career goals. (Hershey et al., 1998, p. 7–8)

The legislation leaves states and local consortia the authority to decide how to balance, fund, and implement these seven requirements. Typically, states provide oversight and additional funding for the program while consortia promote professional development, coordinate the process of articulation between secondary and postsecondary programs, develop curriculum, and provide materials and equipment to local schools (Hershey et al., 1998).

But what is a consortium exactly? As required in the federal legislation, a consortium is a partnership between secondary and postsecondary educational institutions that must consist of at least one school of each level. But consortia can, and most often do, include many more schools. As Hershey et al. point out, the average consortium in 1998 included 8 local school districts (encompassing more than 11 secondary schools), working with an average of 3.1 postsecondary institutions. These postsecondary educational institutions can include community colleges (representing two-thirds of the postsecondary institutions), technical colleges, four-year colleges and universities, proprietary schools, and registered apprenticeship programs (Hershey et al., 1998, p. 23).

The most striking feature of these consortia is their pervasiveness. As of 1998, there were 1029 Tech-Prep consortia in the US encompassing 69 percent of all school districts. And these 69 percent of school districts served 88 percent of all US high school students (Hershey et al., 1998, p. 22). There may be even more consortia today.

Not surprisingly, the flexibility of the federal legislation and the resulting large amount of discretion afforded to states and local consortia combine to create a variety of different Tech-Prep implementation models in schools. About 10 percent of schools create a structured, career-focused program of study that students consciously choose. Another 50 percent of schools design programs that supplement existing vocational or technical programs. The remaining 40 percent of schools simply introduce particular elements of Tech-Prep without targeting any particular group of students (Hershey et al., 1998, p. xvi–xvii).

Interestingly, not much is known about the students who consciously choose to participate in Tech-Prep or the related vocational or technical programs. But Bragg and Reger (2002, p. 7) point out that Tech-Prep leaders remain committed to Parnell’s concept of serving the neglected middle majority, though difficulties in identifying and serving this population have resulted in many consortia emphasizing an all-inclusive target audience.

Despite heterogeneity in implementation and student involvement, Tech-Prep programs tend to emphasize similar components. Almost every consortium in the country offers some type of career development activity to Tech-Prep students. In fact, 99 percent of consortia report offering individual career counseling to at least some member schools and 85 percent of schools make special Tech-Prep counseling materials available to member schools (Hershey et al., 1998, p. 42).

Applied coursework is another commonly emphasized element of Tech-Prep. The programs typically enhance curricula by adding hands-on activities, drawing on materials from relevant occupations, using work styles that emulate employment settings, and applying theoretical and academic skills to real-world problems. Ninety-six percent of all consortia implemented a new or revised applied curriculum to some extent between 1991 and 1995, with 89 percent of schools offering applied math courses (Hershey et al., 1998, p. 48).
Articulation agreements are also widely adopted in all three Tech-Prep implementation models. The Tech-Prep Education Act describes the goal of these agreements as providing students with a “non-duplicative sequence of progressive achievement” from high school through a degree or certification from a postsecondary educational institution (US Department of Education, 2003). In 1995, 96 percent of consortia had articulation agreements in place between member colleges and high schools (Hershey et al., 1998, p. 61). These agreements may take several forms, but the most popular is “course-to-course” articulation, in which students can earn college credit for high school courses (Hershey et al., 1998, p. 62).

While Tech-Prep programs may take on a variety of forms, there are some commonalities across programs. Three components characterize the majority of programs—career development, applied coursework, and course-to-course articulation agreements. These appear to be widespread even in schools with the shallowest levels of implementation, shedding light on the mechanisms through which Tech-Prep may influence participants.

4. Estimation

The 2+2 design of Tech-Prep programs means that most students are first faced with the choice of participating in Tech-Prep during their junior year—around the age of 16. At this juncture in their academic careers, if they have not dropped out of school already, students may choose whether or not to participate in Tech-Prep. During their senior year—roughly at age 17—students face another choice. They may drop out of school before completion (possibly obtaining a GED at a later point) or graduate from high school. If they graduate, they then have the option to enter the labor force, attend a two-year community college, or attend a four-year college. Faced with all of these choices, each student will choose the path that maximizes his or her expected lifetime indirect utility, as depicted in the game tree in Fig. 1.

In the diagram, TP represents Tech-Prep participation, LF represents labor force participation, CC represents community college enrollment, and Univ represents four-year college (or university) enrollment. V is the student’s idiosyncratic payoff to each choice—in this case, the expected indirect lifetime utility of each pathway. It is determined by the student’s forecasting of her costs and benefits for each of the choices along the pathway.

If Tech-Prep is effective in achieving the goals set out in the legislation, it will decrease a student’s cost of attending a community college. Participants should have greater access to information on curriculum and enrollment, and they should receive transfer credits from Tech-Prep courses—effectively lowering the time and monetary cost of an associate’s degree thereby increasing the relative expected utility of this option, V13. For at least some students, we would expect the likelihood of attending a community college to increase with Tech-Prep participation. Moreover, since community college class credits often transfer to four-year colleges, it may be the case that an associate’s degree reduces the cost of obtaining a bachelor’s degree, so we might also expect Tech-Prep participants to go on to four-year colleges more often than their non-participating siblings, at least a few years down the road.

While encouraging community college enrollment is the most obvious way that Tech-Prep participation might impact students, it may also be the case that Tech-Prep enhances students’ engagement in high school. The technically oriented courses may keep students interested in school longer, lowering the student’s expected utility, V11, from dropping out at age 17 relative to other options. If this is the case, we would expect to see that Tech-Prep participants have higher high school graduation rates and fewer GEDs than non-participants.

It is also possible that for some students, Tech-Prep’s emphasis on high-tech fields will make labor force participation more appealing. Tech-Prep participants may find that their technical coursework reduces the need for job training and gives them the potential to earn higher wages. These students will experience a higher V12 relative to other options. This type of reaction might explain the adverse impact of Tech-Prep on the outcome of attending college, as reported by Neumark and Rothstein (2004). I revisit this result in the following sections. If Tech-Prep discourages postsecondary enrollment, then the program may be failing in its primary goal of smoothing the transition to college, but may still be beneficial in helping students make
successful transitions to the workforce and garnering higher wages.

A final possibility is that Tech-Prep may actually increase the cost of attending a four-year college for some students. For example, participants may substitute college-preparatory classes for applied Tech-Prep classes and find themselves less prepared or at a disadvantage in the application process for four-year colleges, lowering the relative value of V14.

This conceptual framework suggests that Tech-Prep participation may affect a variety of outcome measures. The impact of each educational attainment outcome variable is explored independently according to the following reduced-form specification:

\[(\text{Educational Attainment})_i = \alpha + (\text{Tech-Prep})_i \beta + X_i \gamma + Z_i \delta + u_i + \varepsilon_i,\]

where the subscripts on the variables indicate variation at the individual (i) and family (f) levels.

Tech-Prep is a dichotomous variable equal to one if the student participated in a Tech-Prep program between 1997 and 2002.\(^4\) \(X_i\) is a vector of observable individual characteristics. \(Z_i\) is a vector of observable characteristics common to families. \(u_i\) and \(\varepsilon_i\) are individual- and family-level error terms, respectively, described in more detail below.

Following the hypotheses developed above, educational attainment is measured in several ways. To address whether Tech-Prep impacts a student’s engagement and interest in high school, the first educational attainment outcome I examine is whether or not the student completed 12th grade. Second, I consider a dichotomous variable that equals one if a student obtained a high school diploma and zero if he obtained a GED. The distinction between the two types of degrees is important since it not only reveals that the student dropped out of high school before completing 12th grade, but it is also highly correlated with future educational attainment. Cameron and Heckman (1993) show that GED recipients are not only less likely to go on to two-year and four-year colleges than their counterparts with traditional high school diplomas, but more importantly, even when GED recipients do go to college, these students are much less likely to complete their postsecondary education.

To address more explicitly whether Tech-Prep effectively smooths the transition to college, I regress Tech-Prep participation on the outcome of ever attending any type of college. I then go one step further to see if Tech-Prep participants are more or less likely to attend two- and four-year colleges than non-participants.

Finally, I consider the overall measures of the highest grade completed and highest degree received. Unlike the other outcome measures, these variables do not allow me to separate out the distinct mechanisms through which Tech-Prep affects students’ educational decisions. Rather, they provide an indication of the overall impact of the program on the student’s educational attainment.

4.1. Selection

To capture the true impact of Tech-Prep on these educational outcomes, we would ideally like students to be randomly assigned to participate in the program. However, such an experiment has not been carried out to date. Instead, as the preceding discussion suggests, students choose whether or not to participate.\(^5\) Students for whom any one of the payoffs under Tech-Prep participation (the \(V_1\) payoffs) is greater than all of the payoffs under non-participation (the \(V_2\) payoffs) will choose to participate in Tech-Prep. These students may differ from their peers in systematic ways. First, there may be observable characteristics that vary between participants and non-participants, such as gender and family resources. These are represented in \(X_i\) and \(Z_i\), respectively, and can be controlled for with measurable variables. Second, there may be unobservable characteristics that contribute to a student’s decision of whether or not to participate in Tech-Prep. If these unobservables are correlated

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\(^4\) Note that the analysis considers Tech-Prep participation in isolation, ignoring student participation in other school-to-work programs. Neumark and Rothstein’s research (2004) indicates that this simplification does not pose a problem in assessing the impact of Tech-Prep participation. In their analysis of participation in multiple programs, two-way interactions with all other school-to-work programs were not significant and the main effects of Tech-Prep participation were not altered with their inclusion.

\(^5\) It is also possible that students choose to attend a high school because it offers Tech-Prep. But since 88 percent of all high school students are in districts with consortia, I carry out my analysis assuming that all students have the choice to participate. My results are therefore conditional on the program being offered. Moreover, since siblings typically attend the same high schools, family fixed effects will control for the possible endogeneity of student school choice.
with educational attainment (and therefore captured in the error terms \(u_i\) and \(e_{it}\) in Eq. (1)) cross-sectional OLS estimates of the impact of Tech-Prep will be inconsistent.

To address the bias from unobservables that are common within families \((e_{it})\), I add family fixed effects (denoted \(d_f\)) to the model above, as shown in Eq. (2):

\[
\text{(Educational Attainment)}_i = \alpha + (\text{Tech-Prep})_i \beta + X_i \gamma + d_f + u_i. \tag{2}
\]

This method allows me to look at within-family differences in Tech-Prep participation, comparing the educational attainment of siblings who participated in Tech-Prep with siblings who did not participate.

Because biological siblings living in the same household share genetic traits, a common culture, similar values and expectations, and exposure to similar influences from friends, neighbors, and other aspects of their community, within-family estimation can control for all of these common unobservable influences that make Tech-Prep participants systematically different than their peers. For example, students from families that place a high value on a four-year college education will face higher payoffs to a university education \((V_{14} \text{ and } V_{24})\) than others. This valuation may also make these students less likely to participate in Tech-Prep, causing cross-section estimates to be biased toward zero. By holding constant these shared traits and experiences, and thereby eliminating the portion of the error common to families \((e_{it})\), within-family estimates reduce the selection bias of cross-section estimates. In short, bias is reduced because siblings are more alike than other randomly selected pairs of individuals.

If the family component is the only part of the error correlated with Tech-Prep participation then the family fixed effects strategy will completely eliminate the bias from omitted variables. However, this is not likely to be the case if siblings differ in unobservable characteristics that contribute to Tech-Prep participation and educational attainment. In fact, as Griliches (1979), Bound and Solon (1999), Neumark (1999) point out, if within-family differences in omitted variables are an important determinant of within-family differences in Tech-Prep participation, then family fixed effects estimates may actually suffer from more selection bias than cross-section estimates.

In the case of Tech-Prep there are two individual-level unobservables in \(u_i\) that may be particularly problematic in estimating the causal effects of Tech-Prep. First, innate ability is likely to impact both Tech-Prep participation and educational attainment. A student’s ability undoubtedly impacts his expected utility from the various educational options. For example, very high ability students will likely find lower psychological costs and higher intellectual rewards to a four-year college education than other students, making the expected utility payoff higher for these pathways \((V_{14} \text{ and } V_{24})\). While the impact of ability on educational attainment has been well-documented (see Card (1999) for a review of the literature on this topic), the question remains as to how exactly ability impacts Tech-Prep participation. Estimates of the impact of Tech-Prep will be biased downward (toward zero) if Tech-Prep participants have lower ability than their siblings, and biased upward (away from zero) if these students have higher ability.

A second unobservable omitted variable relevant to Tech-Prep participation and educational attainment is a student’s aptitude for technical subjects, such as those taught in Tech-Prep courses. Referring back to Fig. 1, a student’s preference for technical fields may increase the relative payoffs of certain educational pathways and make Tech-Prep more appealing. For example, a student who enjoys fixing cars might maximize his expected lifetime utility by joining the labor force as an auto mechanic immediately after graduation. He may also find the Tech-Prep curriculum more interesting than traditional coursework. If mechanically inclined students have lower overall educational attainment and are more likely to participate in Tech-Prep than their siblings because of the type of courses offered, estimates of the impact of Tech-Prep will be biased downward.

To reduce the bias generated by these two unobservable variables, I add observable proxy

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6Because siblings live in the same household and typically attend the same school, limiting the analysis to within-family differences also controls for all unobservable characteristics of the school and the Tech-Prep consortium that may also bias cross-section estimates. However, Neumark and Rothstein (2004) find no evidence of this bias using school fixed effects and an extensive set of individual control variables.

7In the discussion that follows, I use the terms “biased toward zero” and “biased downward” interchangeably. While the former is more accurate in the presence of negative effects, I adopt the convention of assuming positive effects when discussing bias generally. Similarly, I use “biased away from zero” and “biased upward” interchangeably.
variables to the model. I add each student’s 8th grade GPA as a proxy for ability, since prior academic achievement is highly correlated with ability. Also, because it is measured before the student participates in Tech-Prep, 8th grade GPA is clearly not affected by program participation and is therefore exogenous.

To address the problem of unobservable aptitude for technical coursework, I add to the model the student’s Mechanical Comprehension score on the Armed Services Vocational Aptitude Battery test (ASVAB-MC). This particular score serves as a good proxy for technical aptitude since the questions on this portion of the exam test one’s intuition based on simple diagrams. To the extent that this score measures innate aptitude for solving mechanical problems and does not rely on skills taught in school, I can use the ASVAB-MC score to distinguish more mechanically inclined youths from their siblings.

I contend that after conditioning on individual-level observable characteristics, common family effects, and proxies for individual ability and technical aptitude, the situation becomes akin to the random assignment of one sibling to Tech-Prep. If there remain no other individual-level unobservables correlated with Tech-Prep participation, then this estimation strategy will reduce the selection bias of cross-section estimates.

4.2. Spillovers

However, one additional source of bias may complicate causal inferences of the effects of Tech-Prep using family fixed effects. Spillover effects from the participating student to their non-participating siblings may cause within-family estimates to be biased toward zero (for an excellent discussion of within-family spillovers see Currie and Thomas (1995)). These externalities are particularly relevant for the aspects of Tech-Prep that enhance a student’s social capital, since these are the types of benefits that can be shared by others. For example, if the oldest child in the family participates in Tech-Prep, he may benefit from improved college counseling. He might then pass along information on local colleges to his younger sister and she may be more likely to go to college, regardless of whether she participated in Tech-Prep herself. To the extent that this externality exists, it will cause family fixed effects estimates to underestimate the impact of Tech-Prep on educational attainment since sibling differences in educational attainment will be less pronounced—particularly in families in which the oldest sibling participates. I test for the presence of these spillovers below by comparing the impact of Tech-Prep on families in which just the oldest or just the youngest child participated. If these externalities are substantial, then estimates for families in which only the youngest sibling participates will most accurately reflect the impact of Tech-Prep.

5. Data

The 1997 National Longitudinal Survey of Youth (NLSY97) is ideally suited to study Tech-Prep
programs and educational attainment. The data set follows a cohort of approximately 9000 youths born between 1980 and 1984. In 2002 (the latest round released) the cohort ranged in age from 16 to 23, with over 7750 respondents over age 18. I restrict my sample to these older respondents in order to more accurately measure decisions about labor force participation and postsecondary education after high school. I also drop any respondents whom I could not observe at age 16 since this is the age at which they were most likely to have had the choice to take Tech-Prep. Table 1 presents descriptive statistics of this sample of 7211 students.

One question in the NLSY97 is particularly salient to the task at hand. It asks all students currently enrolled in school:

Have you participated in...Tech Prep, which is a planned program of study with a defined career focus linking secondary and postsecondary education?

The bottom rows of Table 1 reveal the answer to this question: 1125 students in the restricted sample participated in Tech-Prep programs between 1997 and 2002. Students participated in the program for an average of 1.3 years, and were generally between the ages of 16 and 17 at the time of their participation.

The question above can provide an accurate basis on which to build a study of the role of Tech-Prep in smoothing the transition to postsecondary education for two primary reasons. First, the question will identify only those students who participate in the 60 percent of Tech-Prep programs that target specific groups of students, since students who answer this question affirmatively believe that they are participating in some type of “planned program of study.” In contrast, students in programs with lower levels of implementation (e.g. programs that simply use Tech-Prep funds to pay for extra computers) are not likely to identify themselves as Tech-Prep participants under this definition since the school does not treat them as part of an identifiable group.

Second, even if this question captures students involved in programs with low levels of implementation, the wording emphasizes “linking secondary and postsecondary education” and therefore focuses on those programs that emphasize aspects of the program that smooth the transition to college, such as articulation agreements and career counselors, as opposed to those that simply add computers or provide teacher training. With this question, then, the NLSY97 identifies students in what might be considered “typical” Tech-Prep programs—those programs with a targeted group of participants that emphasize the main goals of Tech-Prep—providing a solid foundation for an evaluation of the average impact of Tech-Prep.

Table 1
Descriptive statistics of NLSY97 respondents age 18 and over in 2002

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<th>Variable</th>
<th>Obs.</th>
<th>Mean</th>
<th>Std. dev.</th>
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<td>0.09</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Household % poverty line</td>
<td></td>
<td>6877</td>
<td>293</td>
<td>302</td>
<td>3227</td>
</tr>
<tr>
<td>Urban area</td>
<td>6811</td>
<td>0.75</td>
<td>0.44</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>8th grade GPA</td>
<td>7069</td>
<td>5.81</td>
<td>1.64</td>
<td>1</td>
<td>8</td>
</tr>
<tr>
<td>ASVAB-MC score</td>
<td>5694</td>
<td>−0.60</td>
<td>0.81</td>
<td>−2.77</td>
<td>2.75</td>
</tr>
<tr>
<td>Tech-Prep</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ever 1997–2002</td>
<td>1125</td>
<td>0.16</td>
<td>0.36</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Tech-Prep 1997</td>
<td>307</td>
<td>0.04</td>
<td>0.20</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Tech-Prep 1998</td>
<td>402</td>
<td>0.06</td>
<td>0.23</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Tech-Prep 1999</td>
<td>337</td>
<td>0.05</td>
<td>0.21</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Tech-Prep 2000</td>
<td>212</td>
<td>0.03</td>
<td>0.17</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Tech-Prep 2001</td>
<td>130</td>
<td>0.02</td>
<td>0.13</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Tech-Prep 2002</td>
<td>65</td>
<td>0.01</td>
<td>0.09</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Age of TP participation</td>
<td>1125</td>
<td>16.45</td>
<td>1.33</td>
<td>13</td>
<td>21</td>
</tr>
<tr>
<td>No. Years participated</td>
<td>1125</td>
<td>1.29</td>
<td>0.59</td>
<td>1</td>
<td>4</td>
</tr>
</tbody>
</table>

Source: Author’s tabulations of the National Longitudinal Survey of Youth 1997, Rounds 1–6 (unweighted).

6. Summary statistics

The upper portion of Table 2a presents some basic summary statistics on the characteristics of students who participated in Tech-Prep between 1997 and 2002 (as identified by the question above) and those who did not participate. A few interesting patterns emerge. First, there are marked demographic patterns in participation. Males and blacks are significantly more likely to participate while the opposite is true of white and Hispanic students. Second, Tech-Prep participants are significantly less likely to live in urban areas and have slightly lower income on average. Third, students’ scores on the ASVAB-MC are not significantly different between
the groups, hinting that students do not self-select on the basis of technical aptitude. Finally, perhaps the most interesting finding is that mean 8th grade GPA does not vary significantly between participants and non-participants.

There are two possible explanations for this apparent similarity in 8th grade GPA. First, it could be that Tech-Prep effectively targets Parnell’s middle majority of students. If Tech-Prep attracts students from the middle two quartiles of the ability distribution, and the distribution is symmetric, then the means for the two groups should be the same. Second, it is possible that Tech-Prep attracts students at both the high and low ends of the ability distribution. This might occur if, for example, Tech-Prep simultaneously attracts high-ability students in schools with low rates of college enrollment and low-ability students in schools with high rates of college enrollment.

In an effort to explore these explanations further, Fig. 2 plots the distribution of 8th grade GPA for Tech-Prep participants and non-participants. If the second scenario is at play we would expect the distribution for Tech-Prep participants to look bimodal or at least noticeably different than the distribution of the full sample—it does not. However, a $\chi^2$ goodness-of-fit test rejects the null hypothesis that the two distributions are the same. Moreover, the differences between the distributions lie in the tails. $T$-tests comparing the proportion of Tech-Prep participants in the tails to the proportion of non-participants reveal that participants are significantly less likely to report “mostly As” and more likely to report “mostly Ds” or “mostly below Ds” than their non-participating counterparts. So although Tech-Prep participants have roughly the same mean 8th grade achievement levels as non-participants, a closer analysis reveals some differences—with a small number of participants more likely to be lower-achievers. Still, there does appear to be some mild targeting of the middle majority, as students in the “B” grade range are slightly over-represented among Tech-Prep participants.

The lower portion of Table 2a describes (without controlling for selection) how the two groups compare on the outcome measures I use. Interestingly, these groups appear to differ significantly on all outcome measures except for attending any college. Moreover, Tech-Prep students appear to do better on all of these measures, with the exception of attending a four-year college. I explore these patterns further in the following sections.

Table 2b takes another cut at the sample, comparing Tech-Prep participants with their non-participating siblings. This comparison is particularly important since the within-family estimation identifies the effects of Tech-Prep using sibling differences. Of the 1125 Tech Prep participants, 266 have at least one sibling who did not participate in the program between 1997 and 2002. Household poverty status and whether the student lives in an urban area vary slightly (though not significantly) between siblings since these variables are measured separately for each sibling at age 16—the age at which the student was most likely to participate in Tech-Prep. No demographic characteristics in the upper portion of the table are significantly different between the two groups, and when compared to the larger sample, the sibling sample shows fewer differences in the outcome measures.

Table 2c reports the mean absolute differences between participant and non-participant siblings. In 48 percent of the sibling pairs, participants and non-participants differ in 8th grade GPA. Furthermore, Tech-Prep students are more likely to report “mostly A’s” and “mostly B’s” than their non-participating counterparts. So although Tech-Prep participants have roughly the same mean 8th grade achievement levels as non-participants, a closer analysis reveals some differences—with a small number of participants more likely to be lower-achievers. Still, there does appear to be some mild targeting of the middle majority, as students in the “B” grade range are slightly over-represented among Tech-Prep participants.

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Table 2c reports the mean absolute differences between participant and non-participant siblings. In 48 percent of the sibling pairs, participants and

---

$^{10}$The $\chi^2$-statistic with 7 degrees of freedom is 22.02 yielding a $p$-value of 0.003. I also tested the similarity of the distribution of ASVAB-MC scores (in quartiles) between participants and non-participants. The chi-square statistic with 3 degrees of freedom for the ASVAB-MC scores was 0.364 yielding a $p$-value of 0.947.
non-participants are of the opposite sex and siblings are on average 1.67 years apart in age. Interestingly, the difference in ASVAB-MC scores and 8th Grade GPA between participants and non-participants is slightly larger among siblings than within the full sample, even though it is still not significant. Nonetheless, the larger difference is counterintuitive since we would expect siblings to be more similar to each other than to other individuals. A more detailed comparison of the distribution of GPA,

\[
\begin{array}{lcccc}
\text{Gender difference} & 0.48 & 0.48 & 0 & 1 \\
\text{Age difference} & 1.67 & 0.86 & 0 & 3 \\
\text{Household % poverty line} & 48.09 & 141.38 & 0 & 1349 \\
\text{Urban area difference} & 0.08 & 0.26 & 0 & 1 \\
\text{Eighth grade GPA difference} & 1.48 & 1.33 & 0 & 6 \\
\text{ASVAB-MC score difference} & 0.72 & 0.51 & 0 & 2.25 \\
\end{array}
\]

\[
\begin{array}{lcccc}
\text{Completed 12th grade} & 0.25 & 0.43 & 0 & 1 \\
\text{Received diploma vs. GED} & 0.25 & 0.43 & 0 & 1 \\
\text{Attended two-year college} & 0.34 & 0.47 & 0 & 1 \\
\text{Attended four-year college} & 0.21 & 0.41 & 0 & 1 \\
\text{Attended any college} & 0.32 & 0.46 & 0 & 1 \\
\text{Highest grade completed} & 1.32 & 1.22 & 0 & 6 \\
\text{Highest degree received} & 0.54 & 1 & 0 & 3 \\
\end{array}
\]

Table 2b: Characteristics of Tech-Prep participants and non-participant siblings

Table 2c: Mean absolute differences between Tech-Prep participants and non-participant siblings

Source: Author’s tabulations of the National Longitudinal Survey of Youth 1997, Rounds 1–6 (unweighted).
however, reveals that siblings are indeed closer to each other than non-siblings. In contrast to the results for the full sample, a \( \chi^2 \)-test reveals that there is no significant difference in the GPA distribution of Tech-Prep participants and their siblings.\(^{11}\) Despite the slight difference in the means, 8th grade GPA does indeed appear to be closer in the sibling sample suggesting that there may be little if any selection on ability within sibling pairs.\(^{12}\)

### 7. Results

#### 7.1. Selection

Table 3 compares cross-section estimates of the effects of Tech-Prep to within-family estimates based on the sibling sample. The estimates are close in magnitude but the within-family estimates are generally larger in magnitude, suggesting that cross-section estimates may be biased toward zero by

---

\(^{11}\)The \( \chi^2 \)-statistic with 7 degrees of freedom is 6.477 yielding a \( p \)-value of 0.485. I also tested the similarity of the distribution of ASVAB-MC scores (in quartiles) between participants and non-participants in the sibling sample. The \( \chi^2 \)-statistic with 3 degrees of freedom for the ASVAB-MC scores was 1.27 yielding a \( p \)-value of 0.736.

\(^{12}\)A final point worth noting is that the respondents with siblings (and therefore those included in the family fixed effects estimation below) are significantly less likely to be white, more likely to be black, and have lower household incomes than those respondents without siblings in the data, rendering the sibling sample unrepresentative of the overall population of NLSY97 respondents.
family-level unobservables.\(^\text{13}\) This negative selection indicates that the families with children who participate in Tech-Prep are those that would otherwise obtain lower than average education levels. For example, participants’ families may not expect their children to go on to college. While negative selection at the family level is the most plausible explanation for these results, there are two additional explanations worth considering—the presence of measurement error and remaining individual-level unobservables.

Much of the literature on measurement error in sibling models focuses on exacerbated attenuation from classical measurement error (see for example, Griliches, 1979; Ashenfelter and Krueger, 1994), but Freeman (1984) shows that random measurement error in a binary independent variable (a.k.a. misclassification error) may actually reduce attenuation in fixed effects estimates under some circumstances. This type of random misclassification might explain the higher—and therefore more accurate—within-family estimates if there is a particularly high probability of purely random misclassification of Tech-Prep participants (Freeman, 1984, p. 11).

In the case of Tech-Prep, however, it is more likely that misclassification is non-random. In the presence of correlated measurement error, fixed effects estimates will again reduce the bias from measurement error, but for a different reason. As noted by Ashenfelter and Krueger (1994), any common tendency for siblings to misreport participation will be eliminated with the addition of family fixed effects. Since a student’s misreporting of Tech-Prep participation is most likely due to the nature of the program she participates in (as described in previous sections) and since siblings generally participate in the same programs, it is likely that most (if not all) misclassification error is common to siblings. Within-family estimation will therefore reduce non-random measurement error, potentially increasing the estimates and again rendering family fixed effects estimates more accurate than cross-section estimates.

Finally, returning to the observations made by Griliches (1979), Bound and Solon (1999) and Neumark (1999), the higher within-family estimates could also occur in the presence of positive selection bias, if there are any remaining unobserved differences between siblings that have a significant impact on Tech-Prep participation. This situation could cause fixed effects estimates to be biased upward more than cross-section estimates.

To test for this type of selection on individual-level unobservables (to the extent possible), Table 4 presents the results of within-family regressions that incrementally add the proxy variables for ability and technical aptitude to a constant sample. Specification I includes only baseline observable characteristics—sex, household poverty level at age

<table>
<thead>
<tr>
<th>Specification</th>
<th>Completed 12th grade</th>
<th>High school diploma vs. GED</th>
<th>Attended two-year college</th>
<th>Attended four-year college</th>
<th>Attended any college</th>
<th>Highest grade completed</th>
<th>Highest degree received</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>0.098***</td>
<td>0.013</td>
<td>0.080</td>
<td>-0.074*</td>
<td>0.016</td>
<td>0.348***</td>
<td>0.233***</td>
</tr>
<tr>
<td>(0.034)</td>
<td>(0.017)</td>
<td>(0.048)</td>
<td>(0.048)</td>
<td>(0.041)</td>
<td>(0.042)</td>
<td>(0.110)</td>
<td>(0.071)</td>
</tr>
<tr>
<td>208</td>
<td>165</td>
<td>181</td>
<td>181</td>
<td>166</td>
<td>194</td>
<td>208</td>
<td>200</td>
</tr>
<tr>
<td>II</td>
<td>0.091***</td>
<td>0.013</td>
<td>0.079</td>
<td>-0.081**</td>
<td>0.010</td>
<td>0.323***</td>
<td>0.215***</td>
</tr>
<tr>
<td>(0.033)</td>
<td>(0.017)</td>
<td>(0.049)</td>
<td>(0.049)</td>
<td>(0.040)</td>
<td>(0.041)</td>
<td>(0.106)</td>
<td>(0.071)</td>
</tr>
<tr>
<td>208</td>
<td>165</td>
<td>181</td>
<td>181</td>
<td>166</td>
<td>194</td>
<td>208</td>
<td>200</td>
</tr>
<tr>
<td>III</td>
<td>0.092***</td>
<td>0.012</td>
<td>0.079</td>
<td>-0.081**</td>
<td>0.019</td>
<td>0.324***</td>
<td>0.215***</td>
</tr>
<tr>
<td>(0.033)</td>
<td>(0.017)</td>
<td>(0.049)</td>
<td>(0.049)</td>
<td>(0.040)</td>
<td>(0.042)</td>
<td>(0.105)</td>
<td>(0.071)</td>
</tr>
<tr>
<td>208</td>
<td>165</td>
<td>181</td>
<td>181</td>
<td>166</td>
<td>194</td>
<td>208</td>
<td>200</td>
</tr>
</tbody>
</table>

Notes: All specifications include the following variables: male, household poverty, urban area, oldest child, dummy variables for age and family, and a constant. Specification II adds 8th grade GPA. Specification III adds 8th grade GPA and ASVAB-MC score. Standard errors in parentheses. Number of groups (referring to the number of families with variation in participation among siblings) is listed below the standard error.

*Denotes significance at the 10% level, **denotes significance at 5% level, ***denotes significance at 1% level.


\(^{13}\)Cross-section estimates for the full NLSY sample were similar in magnitude to the cross-section estimates of the sibling sample. However, the effects of Tech-Prep participation on all outcomes except attending a four-year college were significant at the five percent level or less in the larger sample.
16, whether the respondent lived in an urban area at age 16, whether a child is the oldest in the family, and dummies for the age of the child. Specification II adds the student’s 8th grade GPA and specification III adds the ASVAB-MC score.

The coefficients on Tech-Prep participation remain relatively stable in sign, significance, and magnitude with the addition of the proxy variables. Because the addition of 8th grade GPA and ASVAB-MC scores should reduce the bias from unobservables, and the coefficients on Tech-Prep participation show very little change in the specifications with and without them, we can hope that biases from any remaining individual-level unobservables are also negligible.\textsuperscript{14} Although we can never be certain that this is the case, the weight of the evidence suggests that family fixed effects will indeed reveal more accurate estimates of the impact of Tech-Prep on educational attainment than cross-section estimates.

### 7.2. Spillovers

As noted above, however, family fixed effects estimates of the impact of Tech-Prep may still be biased toward zero relative to the true impact of the program if there are substantial within-family spillovers. To test for the presence and strength of these effects, Table 5 reports the coefficient on Tech-Prep participation for the subsamples of families in which the youngest child participated (in the left-hand column) and the oldest child participated (in the center column). As the table shows, externalities do in fact appear to be present, as the impact of Tech-Prep is attenuated on all but one educational outcome in those families in which the eldest sibling participated. These results highlight two important points. First, Tech-Prep appears to be successful in increasing a student’s social capital—not only for himself, but for other family members as well. Second, because of these apparent externalities, estimates of the effects of Tech-Prep based only on families in which the youngest child participated are likely to be more reliable than estimates based on all families. On the other hand, the small number of families in what I will call this “youngest sibling sample” reduces the robustness of the estimates, particularly with the addition of ASVAB-MC scores. I therefore present results for both the full sibling sample and the youngest sibling sample in the analysis that follows. Together, these results reveal upper and lower bounds on our estimates of the effects of Tech-Prep on educational attainment.

<table>
<thead>
<tr>
<th>Table 5</th>
<th>Within-family estimates of the effect of Tech-Prep participation for families in which the youngest and oldest children participated</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Youngest sibling</td>
</tr>
<tr>
<td>Completed 12th grade</td>
<td>0.157* (0.095) 0.075 (0.128) 0.089*** (0.029)</td>
</tr>
<tr>
<td>High school diploma vs. GED</td>
<td>0.003 (0.037) 0.047 (0.108) 0.020 (0.020)</td>
</tr>
<tr>
<td>Attended two-year college</td>
<td>0.171 (0.121) 0.148 (0.203) 0.080* (0.043)</td>
</tr>
<tr>
<td>Attended four-year college</td>
<td>−0.160* (0.089) −0.078 (0.189) −0.083** (0.036)</td>
</tr>
<tr>
<td>Attended any college</td>
<td>0.095 (0.115) 0.024 (0.170) 0.021 (0.099)</td>
</tr>
<tr>
<td>Highest grade completed</td>
<td>0.707** (0.293) 0.285 (0.473) 0.269*** (0.096)</td>
</tr>
<tr>
<td>Highest degree received</td>
<td>0.292 (0.192) 0.209 (0.264) 0.210*** (0.063)</td>
</tr>
</tbody>
</table>

**Notes:** All regressions include the following variables: male, household poverty, urban area, oldest child, 8th grade GPA, dummy variables for age and family, and a constant. To maintain reasonable sample sizes, ASVAB-MC scores are left out. Results of regressions including the scores were similar. Standard errors in parentheses. Number of groups (referring to the number of families with variation in participation among siblings) is listed below the standard error.

*Denotes significance at the 10% level, **denotes significance at 5% level, ***denotes significance at 1% level.

**Source:** National Longitudinal Survey of Youth 1997, Rounds 1–6 (unweighted).

\textsuperscript{14}Moreover, even if remaining omitted variables cause a slight decrease in the coefficients on Tech-Prep participation, it is unlikely that the coefficient would fall below the cross-section estimate—making positive selection bias is unlikely.
7.3. Educational attainment

Table 6 reports the impact of Tech-Prep participation on educational attainment using a linear probability model with family fixed effects. The first two rows of the table report the effects of the program on high-school related outcomes. In the first row, Tech-Prep appears to increase the probability of high school graduation by between nine and 16 percentage points. This result is significant at the one percent level for the full sibling sample for both specifications (with and without ASVAB-MC scores), though it is only significant at the 10 percent level in one specification in the youngest sibling sample.

The outcome of obtaining a high school diploma versus a GED is not distinguishable from zero in both samples and specifications, perhaps due to the relatively small number of students who obtained a GED—just five percent of students in the full sibling sample—resulting in very little variation in this outcome. Still, given the strong results on high school completion it appears that Tech-Prep is generally effective at increasing student engagement in high school.

Tech-Prep’s impact on college outcomes is more intriguing. As the third row of Table 6 shows, Tech-Prep increases the probability that a student will attend a two-year college by between eight and 22 percentage points. Though the effects are only significant at the 10 percent level in the full sample, when taken together, the results of both samples are promising, suggesting that Tech-Prep articulation agreements may be effective in lowering the cost of a community college education.
On the other hand, the gains in two-year college enrollment may come at the expense of four-year college enrollment. As the next row shows, Tech-Prep participants are much less likely to attend four-year colleges than their non-participant siblings. Interestingly, the negative effect of Tech-Prep on this outcome seems to almost exactly offset the positive effect on two-year college enrollment. The full sample shows a decline in the probability of attending a four-year college of eight percentage points—exactly opposite the increase in two-year college attendance for this sample. The youngest sibling sample shows an even steeper decline of about 16 percentage points for the first specification—again almost exactly opposite the 17 percentage point increase in the probability of attending a two-year college.

The outcome of attending any college confirms this offsetting effect. No effects are distinguishable from zero in any specification or sample, with the full sample showing a slightly negative impact and the youngest sibling sample showing a slightly positive impact. While Tech-Prep does not appear to be effective in smoothing the transition to college, at least it does not appear to discourage enrollment, as Neumark and Rothstein (2004) find. In their study, using just four rounds of the NLSY97, it may have been the case that the negative impact on four-year college going outweighed the positive impact of Tech-Prep on two-year college enrollment in the years immediately following high school. Drawing on two additional years of data, the results reported here may indicate that over time, the enrollment effects on two- and four-year college just barely balance out, with some participants returning to college after taking time off.

The bottom two rows of Table 6 report the results of two aggregate measures of academic achievement. Tech-Prep participants appear to have completed significantly more grades than their siblings in both samples. Estimates based on the full sample also reveal that participants received higher degrees than their non-participating siblings, with positive, but not significant effects for the youngest sibling sample. Though these results do not distinguish between gains in high school or college outcomes, they are promising in that they reveal that Tech-Prep programs generally encourage students to invest in human capital.15

8. Conclusion

After controlling for selection into the program and adjusting for substantial within-family spillovers, this study finds that on average, Tech-Prep participants are more likely to complete high school and attend two-year colleges than their non-participating siblings-leading to higher aggregate educational attainment for program participants.

While these results are promising, they must be viewed with caution, as the probability of attending a four-year college declines with Tech-Prep participation. The decline appears to offset the positive impact of the program on two-year college enrollment, causing the net effect of Tech-Prep on any type of college enrollment to be close to zero, and suggesting that Tech-Prep is falling short of its goal of smoothing the transition to college for the middle majority.

Further, these findings on college outcomes suggest that at least some students are diverted from four-year to two-year colleges when they participate in Tech-Prep. And while this apparent diversion effect may have negative implications for some middle majority students at the high end of the ability distribution, it may be beneficial for other students who will do better in the long run by attending a community college before transferring to a four-year institution. Moreover, the results on college enrollment are more promising than previous studies suggest, as it does not appear that the program actively discourages enrollment in post-secondary education.

Patterns in the effects of Tech-Prep provide a few clues to understanding which aspects of the program are the most beneficial for students. The positive results for high school completion suggest that the program’s hands-on teaching and applied coursework increases student interest and engagement in high school. Another effective component of Tech-Prep is its ability to increase a student’s social capital, perhaps through enhanced college counseling. The information and networks gained by older siblings who participate in Tech-Prep seem

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15I also tested whether the impact of Tech-Prep was different for students in Parnell’s middle majority using the full sibling sample. Coefficients on the interaction of a dummy variable for the middle majority (middle two quartiles of 8th grade GPA) and Tech-Prep participation were significant for only one outcome—attending a two-year college. For middle majority students, the increase in the probability of attending a two-year college was lower, but still positive.
to be passed on to their younger siblings, diminishing the difference in educational attainment between siblings and benefiting the whole family. Moreover, since participants are more likely to attend two-year colleges than non-participants, it appears that articulation agreements between community colleges and high schools are effective at encouraging student enrollment in this postsecondary option. In fact, articulation agreements may be too effective, as students who would otherwise attend a four-year college may find community colleges more appealing. Despite the good intentions of founder Dale Parnell, Tech-Prep may indeed be “diluting the time-honored baccalaureate-degree/college-prep track” (Parnell, 1985, p. 140). The negative impact of Tech-Prep on four-year college enrollment raises concerns that Tech-Prep coursework leaves students without the requirements or skills needed to enter a four-year college immediately after high school.

More research is needed on Tech-Prep and similar programs that aim to smooth the transition to college. This analysis helps us understand the impact of these types of programs on students’ educational attainment in the two to six years immediately following their participation in Tech-Prep. It is possible that further gains (or costs) to participation will be realized down the road if, for example, participants who began their postsecondary education in two-year colleges are more likely to transfer to four-year colleges and complete baccalaureate degrees than non-participants, or if participants enjoy higher wages than their counterparts. More time and research is needed before we can adequately assess the longer-term impacts of Tech-Prep and know definitively which educational innovations work for the middle majority—and more importantly—why.

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