Career Technical Education And Labor Market Outcomes: Evidence From California Community Colleges

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Introduction

For the past half-century, the earnings of Americans with less than a four-year college degree have stagnated or fallen. Despite widespread increases in postsecondary participation, the fraction of Americans completing BA degrees has not risen substantially in decades, and is actually declining for minority groups. Although many efforts have focused on increasing educational attainment, it is clear that encouraging traditional college enrollments in academic pathways is not sufficient. Important demographic and labor market changes have demanded a more skilled workforce with increased postsecondary training.

National efforts to increase college attainment and to address the nation's skills gap have focused heavily on community colleges. The Obama Administration identified community colleges as key drivers in the push to increase the stock of college graduates in the U.S. and to raise the skills of the American workforce, with the President noting: "It's time to reform our community colleges so that they provide Americans of all ages a chance to learn the skills and knowledge necessary to compete for the jobs of the future."[1] The rising demands for skilled workers necessitate states' need to strengthen the community colleges to accommodate much of this expansion, including increased offerings of technical certificate programs (Bosworth, 2010; Complete College America, 2011; Public Policy Institute of California, 2010; Holzer and Nightingale, 2009). Despite this enthusiasm from policy-makers at all levels for both vocational education and community colleges more generally, very little is known about the effectiveness of vocational programs within community colleges at raising workers' earnings and employment prospects. This paper takes a major step towards filling that gap, using administrative data from the largest community college system in the nation to estimate the returns to specific vocational certificates and degrees.

Community colleges are the primary point of access to higher education for many Americans. Many turn to community colleges on the road to a BA, while others arrive at community

[1] http://www.whitehouse.gov/sites/default/files/uploads/community_college_summit_report.pdf.

colleges to learn English as a second language or to obtain a technical certificate. The multiple missions and goals of community colleges have been well documented in the academic literature (Bailey and Smith Morest, 2006; Rosenbaum, 2001; Dougherty, 1994; Grubb, 1991, 1996; Brint and Karabel, 1983). In California, two-thirds of all college students attend a community college. The role of community colleges as a vehicle in human capital production was the cornerstone of California's 1960 Master Plan for Higher Education, which stipulated that the California Community Colleges are to admit "any student capable of benefiting from instruction."[2] Over the years, the California community colleges have grown and have been both applauded for remaining affordable, open-access institutions, and also continually criticized for producing weak outcomes, in particular low degree receipt and low transfer rates to four-year institutions (Shulock and Moore, 2007, Sengupta and Jepsen, 2006). Vocational programs within the California community colleges, many of which do not have explicit or implicit transfer goals, have often been omitted from these discussions.

Growing awareness of the need for post-secondary training beyond traditional academic programs, combined with long-term declines in the real earnings of Americans without college degrees makes it essential to better understand the training potential of postsecondary career technical education (CTE) programs. Although the returns to BA attainment in the labor market have been well documented, there is little research on the payoff to sub-baccalaureate degree receipt, particularly in technical/vocational fields.[3] In this paper we investigate the returns to sub-baccalaureate certificates and degrees in vocational or CTE fields among those enrolled at California community colleges. Our approach also addresses the tremendous heterogeneity in

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[2] California Master Plan for Higher Education. Available at: http://www.ucop.edu/acadinit/mastplan/MasterPlan1960.pdf. The Master Plan articulated the distinct functions of each of the State's three public postsecondary segments. The University of California (UC) is designated as the state's primary academic research institution and is reserved for the top eighth of the State's graduating high school class. The California State University (CSU) is primarily intended to serve the top third of California's high school graduating class in undergraduate training, and graduate training through the master's degrees, focusing primarily on professional training such as teacher education. Finally, the California Community Colleges are to provide academic and instruction for students through the first two years of undergraduate education (lower division), as well as provide vocational instruction, remedial/developmental instruction, English as a Second Language courses, adult non-credit instruction, community service courses, and workforce training services.

[3] In this paper we use the term vocational and career technical education (CTE) interchangeably.

types of program offerings within the broad grouping of CTE programs, and we separately analyze fields that include a wide range of courses preparing students for careers as police or prison officials, health care providers or construction workers, among others.

Prior Research On The Returns To Postsecondary Schooling

Prior research has found that community college enrollment and degree receipt more generally are rewarded in the labor market. Belfield and Bailey (2011) review a large number of studies on earnings and other returns to community college attendance, degrees and certificates. Kane and Rouse (1999) estimate the returns to some college relative to just a high school diploma to be 8 percent, while Leigh and Gill (1997) estimate the returns at 10 percent. Bailey, Kienzl, and Marcotte (2004) find, on average, a 16 percent increase in earnings by advancing from a high school diploma to an associate degree. Utilizing 2000 Census data, Kolesnikova and Shimek (2008) also found that associate degree holders earned more than high school graduates, with important differences by race/ethnicity and gender (18 percent more for white men, 25 percent more for Black men, 27 percent more for Hispanic men, 29 percent more for white women, 30 percent more for Black women, and 29 percent more for Hispanic women). And, in a recent descriptive study of a large sample of community colleges, de Alva and Schneider (2013) compare the differences in wages between community colleges graduates with an associate degree to those who only earned a high school diploma. After factoring in the individual costs for earning the degree, they calculate an annualized median rate of return of 4 percent, with key differences identified by community college campuses.

What has been less well-established is whether these returns apply to vocational programs, including both associate degrees in vocational fields and shorter-term vocational certificates. Bailey et al. (2004a), for example, find that occupational associate degrees were associated with higher earnings gains than academic associate degrees. Looking at nationally-representative longitudinal surveys of students from the 1980s and 1990s, they find that vocational certificates had particularly large benefits for women, though the earnings benefits of this credential for men was less clear. More recently, Jepsen, Troske, and Coomes (2014) analyze certificates, diplomas and AA degrees for community college students in Kentucky and find sizeable returns. Returns to vocational programs are reported separately and suggest positive returns to vocational associate degrees and to vocational diplomas for men, but less evidence of returns to shorter term vocational awards for women. Bahr (2014) also examines returns to a large number of programs (including vocational programs) and degrees at California Community Colleges.

Vocational programs within community colleges have also been evaluated in the context of displaced workers. Jacobson, LaLonde and Sullivan (2005) use detailed administrative data from the early 1990s in Washington state to evaluate the returns to retraining older (35+) displaced workers. They find that although older displaced workers were less likely to enroll at community colleges relative to younger workers, those that did enroll for a year witnessed similar returns, specifically a 7 percent increase in long-term earnings for men and a 10 percent increase in long-term earnings for women. More descriptive work from the same era looking at California community colleges finds smaller returns to schooling for older workers when compared to younger workers (Laanan, 1998). Importantly, the demand for retraining displaced workers is particularly high during a recession, but it is also the most cost-effective time since a large part of the cost to training is foregone earnings. Importantly, in this paper we evaluate the returns to college at a time when jobs in California were scarce, and as such, workers faced lower opportunity costs for training.

Focusing more narrowly on particular fields of study, there is a dearth of research on the impact of specific vocational fields of study in community colleges (Holzer and Nightingale, 2009). This remains true despite numerous recommendations that metrics be developed so policymakers can better understand how well such vocational programs are preparing students to meet the skill demands of employers (National Governors Association, 2011; Jenkins and Boswell, 2002).

Career technical education programs at community colleges are intended to both enhance school to work transitions for students entering or returning to the labor market and to provide opportunities for retraining when individuals and local areas are confronted with changing economic opportunities and conditions. Such programs can take on a variety of forms, from very specific workforce instruction (e.g. construction or nursing), developmental education to improve basic skills, adult basic education such as computing, and English as a Second Language (Van Noy, Jacobs, Korey, Bailey and Hughes, 2008). Over the last 10 to 15 years, community colleges have become particularly important in training health and medical workers; for example, almost two thirds of registered nurses receive their nursing degrees from community colleges (Van Noy, et al., 2008). Moreover, community colleges have continued to expand their short-term certificate and degree offerings in a variety of CTE oriented fields such as police science, early childhood education, and computing. To date there is little research about the labor market payoff to such short-term certificates. In this paper we address some of this gap by investigating the labor market returns to a wide range of sub-baccalaureate degree and certificates in a range of CTE fields.

Data

The California Community College system consists of 112 campuses and is one of the largest public higher education systems in the country, enrolling over 2.6 million students annually (California Community College Chancellor's Office, 2012). The State's large public postsecondary system of sub-baccalaureate colleges offers great individual and institutional diversity. Colleges represent urban, suburban and rural regions of California, range in size from 1,000 to over 40,000 students enrolled each semester, and offer a wide range of CTE and traditional academic programs to a diverse set of students (See Figure A1 in the Appendix for a map of California's community colleges.)

We combine two sources of data for the analysis, tracking California community college students through their postsecondary schooling and into the labor market between 1992 and

2011. First, we use detailed administrative records from the California Community College Chancellor's Office (CCCCO), which includes college-level and student-level information. Specifically, we employ information on students' demographic backgrounds, course-taking behavior, and degree receipt by term.[4] We match these data to quarterly student earnings information from the state's unemployment insurance (UI) system.[5] These data are linked to student information by the CCCCO and extend from 1992 to 2012. Approximately 93% of students in our college data are matched to earnings records.[6]

The CCCCO data contain a vast amount of student-level information. Demographics, such as a student's age, race, and gender, are recorded in each academic term for which a student was enrolled in a course. We define enrollment based on the units attempted in a given term (part-time between six and 12 units, and full- time as more than 12 units). These two definitions are consistent with the number of units needed to qualify for different levels of financial aid. We do not differentiate between students taking fewer than six units and those not enrolled because the workload of a single course is not likely to depress earnings.

We categorize the content of different courses and programs according to the Taxonomy of Programs (TOP), a system unique to California's community colleges. All community colleges in the state are required to use the TOP, which grants us a uniform categorization of the topical content of degrees and courses across time and is common across all of California's community colleges. In particular, the CCCCO identifies some TOP codes as career technical (vocational), which allows us to note students who take such courses and earn CTE-identified degrees. In this analysis we focus on awards in TOP codes designated as CTE, or vocational, programs. The

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[4] Only three colleges use the quarter system, which makes synchronizing the school year to the calendar year straightforward. For the rest, which are on the semester system, we categorize the spring semester (January to June) as the first and second quarters, with summer term and fall semester as the third and fourth quarters, respectively.

[5] We have access to these data as they are provided to the CCCCO through the California Employment Development Department (part of the California Department of Finance).

[6] Students may not be observed in the earnings records for several reasons including being only self-employed over the period, a true lack of any formal earnings, or having moved out of the state with no recorded earnings in California.

narrowest TOP code is a six-digit number denoting a field. The first two digits identify one of 24 broad disciplines, such as Education, Biological Sciences, or Health. Another advantage of the TOP code classification is that we are able to align TOP codes to the Classification of Instructional Programs (CIP), which are tied to the Standard Occupational Classifications used by the U.S. Department of Labor to classify occupations. There are CTE and non-CTE fields within each discipline, though the distribution is not uniform across disciplines; for example, Engineering and Industrial Technologies (TOP code 09) has many more CTE fields than Social Sciences (TOP code 22).

We evaluate the effects of CTE award attainment by looking at four categories representing a traditional sub-baccalaureate degree (Associates Degree) and several other short-term certificates. Specifically, we categorize award holders into four categories: Associate of Arts/Sciences degrees (typically 60 credit hours); 30-60 credit certificates; 18-30 credit certificates, and 6-18 credit certificates. Students enrolled full-time typically take 15 units per semester, so these various awards range from two years of full-time coursework to less than a semester.

SAMPLE CONSTRUCTION

To evaluate the returns to vocational awards, we first construct a sample of students who earned a CTE certificate or degree between 2003 and 2007. We begin with relatively broad categories of TOP code disciplines. We limit our initial analysis to just the six largest TOP code disciplines: Business and Management; Information Technology; Engineering and Industrial Technologies; Health; Family and Consumer Sciences; and Public and Protective Services. Combined, these disciplines cover approximately 50% of all CTE degrees granted between 2001 and 2010. We conduct the analyses separately by discipline. Focusing on these large disciplines allows us to look separately at degrees within specific disciplines. Summary statistics of our full sample of CTE award recipients are shown in Table A1 in the Appendix.

We limit the sample of treated individuals to just those students who earned a CTE degree—though this may not have been their highest degree. We place no restrictions on the first term of enrollment, which means some of students may have earned their degree in just a year while others may have taken a long time. In fact, on average students take four years to complete their first CTE award (see Table A1). We observe course taking behavior and other academic data extending as far back as 1990 for the older students. We match wage data back to 1992, regardless of when students began their coursework. For most students, the wage data extend from before they enrolled for the first time in a community college course until after they graduated. We drop wage and academic data for students in the years before they turned 18 years old. Students may take classes at multiple colleges throughout their academic careers and they can also transfer credits from one community college to another. For the purposes of our sample and because of certain data limitations, we consider each student at each college as an individual case.[7]

We also construct control groups to compare to our treated group of degree and certificate recipients. The control groups consist of students who demonstrated some intention to earn a vocational degree or certificate in the given discipline but never did. As with the degree recipients, we create a separate control group for each TOP code. Students qualify for the control group if they earned at least eight units in that discipline within their first three years of enrollment at the college. This qualification is based on the CCCCO's own definition of a CTE-degree bound student, and one utilized by the community college system to track degree completion for accountability purposes. Since the treatment groups are based on students who received a degree between 2003 and 2007 and the normative time to degree is approximately two years, we limit the control groups to students who started between 2001 and 2005. A student can qualify for multiple control groups if he took more than eight courses in two different disciplines without ever earning a degree. However, the control group consists only of

[7] A student who earned a degree at college X and a degree at college Y will be included in our data twice, once for his career at each college. For a student who took courses at college X and college Y, but only earned a degree at college Y, we only observe the coursework and degree earned at college Y; the coursework at college X drops out of our sample.

students who never earned any degree, so if the student took more than eight units in one discipline and actually earned a degree in another, then that student does not qualify for the former control group. We also experiment with alternative definitions of our control group, to check for sensitivity of our estimates to this definition.

Two types of students are not represented in either the treatment or control group for any particular discipline. The first is students who did not earn a degree, but also did not take enough courses to qualify for a control group. There are also students in the treatment group who would be excluded from the control group had they not earned a degree. For example, some students may have earned their degree slowly, not completing eight units within the first three years.[8] The second excluded group of students is those who earned non-CTE degrees. We only include CTE degree earners in the treatment group, and only students who never earned any degree in the control groups. It is likely that a number of the students in a control group may have been attempting to complete a non-CTE degree, but because they never earned a degree we cannot know their intentions.

STATISTICAL FRAMEWORK FOR ESTIMATING RETURNS TO CTE PROGRAMS

To better answer the question of whether CTE programs improve the earnings potential of award recipients, we use a regression framework similar in spirit to the literature on non-experimental evaluations of worker training programs.[9] Specifically, we estimate equations of the form:

[8] Overall, approximately a quarter of degree or certificate holders would not have qualified for a control group if they had not earned a degree (Table 1).
[9] See, for example Heckman and Smith (1999).

$$(1) Ln\ (Earnings)_{it} = \alpha_i + \gamma_t + \beta Enrolled_{it} + \sum_{k=1}^{5} \beta_k\ (GotDegree\_Type\_k)_{it} + \sum_{j=18}^{65} \delta_j 1(Age = j)_{it} + \varepsilon_{it}$$

These regressions include individual fixed effects (α_i), so that the effect of the award receipt is identified from the within person changes in earnings from before to after the award is received. We also include controls—in the form of dummy variables—for calendar year (T) and age (A); in the fixed effects specification we cannot separately identify linear effects of age, but enter age as a series of dummy variables (δ_j) to capture non-linear age effects on earnings. The coefficient β captures the effect of an indicator for periods in which the individual is enrolled at the community college either full or part-time. This is to avoid conflating the part-time or otherwise reduced earnings while working toward an award with the pre-enrollment earnings as a base against which this specification implicitly compares post-award earnings. The coefficients of interest, vector β, takes a value of one in periods after the student has graduated, depending on the type of degree. We estimate one regression of the form summarized by (1) for each TOP discipline (of which there are six).

This equation can be estimated using only degree recipients with earnings observed both before and after the award receipt. In this approach, the dummy for "award_completed" initially equals zero, and then turns to one upon completion of the award. By the end of the sample period, every individual in this sample has completed the award. It is also helpful, however, to make use of a control group of individuals who never complete an award (or have not completed an award by several years after they first appear in our sample of community college enrollees). In the worker training program literature control groups are either composed on those randomized out of participation in the training program (in experimentally-based evaluations) or are those rejected or do not complete program participation.

Our control group is constructed on the basis of both data availability and the desire to best identify those individuals most similar to award recipients in particular CTE programs. We have earnings data only for individuals who have had some contact with the California Community College system, but that involvement can be as minimal as enrollment in a single class. We are also motivated by what is perhaps the most critical issue in estimating returns to education, that of whether individuals who select into higher levels of education are more productive, motivated, or have other unobservable characteristics that would lead to higher wages than those who do not choose more education. With this in mind, we construct our control group from individuals who have shown some indication of participating in each separate CTE program.

Much earlier literature on the effects of worker training programs suggests that it will be critical to look at employment and earnings relative to a control group in the time period just prior to enrollment in a vocational education program (see, for example, Heckman, Lalonde, and Smith, 1999, or Heckman and Smith, 1999). The inclusion of a control group here is critical to establish the counterfactual pattern of earnings or employment in the absence of CTE course enrollment. To illustrate the importance of the control group, consider a hypothetical finding of five percent earnings growth following CTE course enrollment. The correct interpretation of this will depend on how earnings of a similar worker would have evolved over the same labor market and time period. If similar workers in the area were experiencing declining earnings over the same period, this might be judged a very successful program. In contrast, if a control group worker would also have been expected to see five percent earnings growth over several years there is less evidence that CTE degrees are effective at enhancing preparation for the workforce.

A common concern with estimates of the effects of education on earnings is that individuals who actually choose to enroll and complete degrees may be more motivated or productive than those who take only a few courses. This can lead to a systematic overstatement of earnings effects of these programs. Recall, however, that here we are able to include individual fixed-effects, which will control for fixed levels of ability or motivation. In most estimates of the return to higher education, inclusion of fixed-effects is not feasible since students following a traditional path through K-12 and college education lack a meaningful pre-enrollment earnings history. Because many CTE students are already involved in the labor market prior to their enrollment, however, we view this fixed-effects approach as feasible in this context.[10]

Finally, even with fixed effects included, we face several potential sources of bias. First, individuals who choose to enroll (or complete) CTE training may have earnings growth rates that are higher or lower than those who do not. This will lead to correlation between award receipt and expected earnings growth rates and so may also lead to biased estimates. We can directly address this by adding individual-specific earnings growth rates to our specification, indicated by:

$$(2)\ \ln(Earnings)_{it} = \alpha_i + \gamma_t + \theta_i trend + \beta Enrolled_{it} + \textstyle\sum_{k=1}^{5} \beta_k\, GotDegree\_Type\_k)_{it} + \displaystyle\sum_{j=18}^{65} \delta_j 1(Age = j)_{it} + \varepsilon_{it}$$

Here, we allow for the possibility that our award recipients enrolled specifically because they faced declining earnings prospects and were seeking to improve their earnings possibilities. Similarly, this will also capture the possibility that more highly motivated individuals are both more likely to have fast growing wages and are more likely to enroll in and complete CTE training.

It is also possible that transitory, unobserved shocks to our treated group could affect both their likelihood of completing a degree and their subsequent earnings, leading to a probable upward bias in our estimated returns. To some extent, this cannot be remedied with the observational data available here, a caveat similar to that made by Jepsen, Troske, and Coomes (2014). We argue, however, that the ability to control in a rich way for pre-enrollment earnings and earnings trends and the very large samples available from this unique data set, allow us to

[10] Note that this means we will be identifying off of individuals that do have a pre-enrollment earnings history. If there is heterogeneity in returns to these vocational programs across more- and less-experienced workers, our estimates based on equation (1) will predominantly represent the returns to award recipients with more prior work experience, since those without such experience will not contribute much of the within person variation we need for this identification approach. For this reason, we investigate below (and in future work) heterogeneity across workers of different ages, which may have important implications for interpretation of our overall results.

provide the most convincing estimates to date of the labor market returns to specific CTE programs.

RESULTS

A. Summary statistics and visual depictions of the effects of CTE programs on earnings

We begin by showing the number of CTE and total awards issued by California Community Colleges by years covered in our sample (Figure 1). The top line shows all awards from the colleges for each year from 2001 to 2011, and the line immediately below shows the subset of CTE degrees. This demonstrates the importance of CTE programs to the overall mission of the community colleges. In a typical year, more than half of all awards issued are for a CTE degree, and more than 60,000 of these vocational awards are given annually in recent years. The figure also shows that these CTE awards are distributed across the various certificate and degree lengths described earlier.

Next, Table 1 provides summary statistics for our CTE awards (under the treated) columns for the six largest TOP codes, or CTE disciplines. Table 1 also provides these statistics for the associated control groups. Several points from Table 1 will inform our interpretation of the figures and regression results below. First, there is tremendous heterogeneity in student characteristics, distribution of award types, and pre-enrollment labor market attachment, across the six areas. Just 30 percent of those receiving awards in the area of business and management are employed just prior to their initial enrollment, but 50 percent of those in health or public and protective services are employed immediately prior to their initial enrollment. Gender differences across fields are also striking; 93 percent of those receiving awards in Engineering and Industrial Tech are male, but only 14 percent in Family and Consumer Sciences. Only one-third of award recipients in Health are male. This points out the potential importance of estimating returns to degrees separately across discipline, since observable (and unobservable) characteristics vary dramatically across disciplines and may have important implications for interpreting overall returns.

The average age at enrollment in our sample ranges from a low of 25 for business and management to 29 for information technology, differentiating this sample from more traditional, non-vocational college programs. Despite being older than traditional college students, substantial numbers of these students are not employed for four of the eight quarters immediately prior to enrollment (more than half in many cases) and so our fixed-effects estimates may apply to a particular segment of these students. Conditional on being employed, however, we observe several years of earnings (7 to 15 quarters, depending upon the field) prior to enrollment. This suggests that we will have a substantial pre-enrollment earnings history off which to identify our fixed-effects models, but that it will be important to look for heterogeneity in returns across ages, since we will be effectively identifying returns over only that portion of degree recipients with prior earnings.

Finally, Table 1 provides information on how similar our treatment and control groups are to one another. Age and gender distributions are similar across the treatment and control groups within TOP codes. This is important given the large differences in these characteristics across TOP codes and suggests the potential value of having control groups that are specific to each discipline. One potentially important difference between the treatment and control groups is that, across TOP codes, the control group is always more likely to be employed prior to enrollment. This may reflect the greater tendency of employed students to take only a few courses, rather than completing a full degree or certificate program. While our use of fixed-effects should prevent this from being a major source of bias (by effectively conditioning on pre-enrollment earnings), it is important to keep in mind.

Figure 2 shows the patterns of earnings for our award recipients in the six largest (in terms of CTE awards granted) TOP codes from the period five years prior to their award date to seven years after the award. Each panel represents a different CTE program and TOP code. Focusing first on panels a and d shows the types of heterogeneity across different fields and award lengths that we anticipated. Panel a shows the earnings of individuals who receive certificates or degrees in the area of Business and Management. In this panel, individuals receiving the shortest term certificates (indicated by the lowest dashed line) offer little evidence of improved earnings (relative to their own earnings). In years after degree receipt, earnings are generally below average earnings before enrollment in the programs. Such a pattern could reflect many things. First, our sample period includes a strong economy at the start, and the great recession near the end so that all worker groups viewed over this period may face some decline in earnings over time. This makes it essential to use a more complete regression specification and control group that can explicitly control for calendar year effects and broad earnings trends that occur regardless of educational investments. Second, for some TOP code groups there is suggestive evidence of declining earnings prior to CTE award receipt. In TOP codes representing health and engineering occupations, for example, earnings decline in the years prior to degree receipt. If the true counterfactual facing these workers was continued deterioration of their earnings, the level of earnings in the years after their award may reflect a true improvement in their employment and earnings prospects. Thus, in later specifications we can also account for not only the pre-award level of earnings, but pre-award trends in earnings as well.

The other lines in panel a show more evidence of earnings increases following degree receipt. In particular, workers receiving AA/AS degrees in the business and management area show a rather steep increase in earnings starting a few years after the award receipt. Given the delay in this earnings increase to several years after the AA/AS award receipt (labeled as “year 0” in the figures), this pattern may reflect experiences of students who went on beyond the community college to complete baccalaureate degrees at other institutions. Given the availability of BA/BS programs in the areas of business and management, this seems especially likely for these programs.

Panel d of Figure 2 shows a dramatically different picture for the earnings of those receiving awards in health related CTE programs. All of the award types show moderate to large improvements in earnings after award receipt. The extent of the increase grows monotonically with the length of the award program, with the shortest certificate recipients showing some earning gains of approximately 10 percent, but the longest certificate and AA recipients showing very large increases in earnings of .5 log points or more, or returns in excess of 50%.

The other panels of Figure 2 show a variety of patterns both across and within TOP codes. In panel B, for example, the earnings of Information Technology award recipients are very flat prior to the awards and then increase (and the profile over time steepens) by a similar proportion regardless of the length of the certificate. This is difficult to explain in a framework in which more coursework generates additional human capital and may suggest the need to further disaggregate into more narrowly defined programs. It may also simply reflect that these graphs cannot control for economy-wide and other labor market features. Finally, patterns for Engineering and Industrial Technologies (Panel c) shows little evidence of earnings increases among those who complete awards in that area.

These figures are suggestive of the ability of our longitudinal data to illustrate the labor market results of CTE programs, but also show the many difficulties in interpreting the earnings patterns over time. To provide a better structure for understanding these labor market effects, control for confounding factors and include comparison groups of similar individuals, we next describe the results from our regression framework.

B. Regression Results

We next turn to regression results, initially using the fixed-effects specification summarized in equation (1) and an initial set of control groups as defined above. Recall that our control group for each TOP code consists of students that earned at least eight units in that discipline within their first three years of enrollment at the college, following the CCCCO's definition of a CTE-degree bound student. Later, we vary this definition slightly.

In the left-hand panel of Table 2, we present our individual fixed effects regression results by certificate or degree length and discipline. We also show results for the full sample, and for the subsample of students over 30, for whom we are more confident in the fixed effects identification strategy. The first result from Table 2 is that, in most cases, there are positive and statistically significant earnings effects of these vocational certificate and degree programs. [11] This is true despite reliance on a fixed-effects approach that should eliminate any fixed individual characteristics, such as “ability” or “motivation” that would conflate estimated returns with positive unobserved characteristics of degree completers. One exception to this pattern of positive returns is Information Technology, where there is little evidence of positive returns. This set of programs represents a relatively small number of award recipients, particularly in the longer-term certificate programs, with fewer than 500 awards granted for certificates between 18 and 60 units.

This leads to a second broad finding from Table 2; there is a striking degree of heterogeneity in estimated returns across different TOP codes. A 30-60 unit certificate in Business, for example, produces an earnings effect of approximately 10% (coefficient .099), compared to an estimated return of 18% (coefficient of .166) in Public and Protective Services, and nearly 36% in Health (coefficient of .307).

A third pattern in Table 2 is heterogeneity, not always in the expected direction, by degree or certificate type. In many cases, there is a tendency for returns to increase as the length of the program increases, though there is not perfect monotonicity. For example, in Health, and when focusing on results for the older subsample, estimated returns move from essentially zero for the very short-term certificates, to approximately 14% for longer certificates of 18 to 30 units, to 35% for still longer certificates. In contrast, in Public and Protective Services, the estimated return to very short-term certificates is a surprisingly high 26%, with lower estimated returns for longer certificate programs.

Finally, Table 2 also shows that, in most cases, our results for the full sample and the sample of those age 30 and over at the time of enrollment are similar. One exception to this pattern is the result for AA/AS degrees in Business and Management. Below, we show and discuss that this pattern seems to be related to students who transfer to other institutions.

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[11] In the log earnings specification, the percentage effect on earnings is given by exp(Beta)-1, where Beta is the reported coefficient.

In our fixed-effects regression approach, any differences in earnings *levels* prior to enrollment will be absorbed by the fixed effects. If, however, there are differences in earnings growth rates between the treatment and control groups, our results may still be subject to bias. In Table 3, we present results comparing the pre-enrollment earnings *changes* between treatments and controls. Each entry in the Table is the coefficient on degree receipt (our treatment indicator) from a regression of pre-enrollment earnings changes. Thus, the coefficient in the upper left corner indicates that degree recipients had earnings changes prior to their initial enrollment that were (a statistically insignficiant) .002 higher than in the associated control group. In general, statistically significant coefficients suggest that treatment and controls have systematically different earnings growth profiles prior to enrollment and that even our fixed-effects specification may not adequately control for these differences. Negative coefficients suggest that the treatment group has slower rates of earnings growth and thus estimates based on the fixed effects specification may understate the true effect of degree receipt.

In the upper panel of Table 3 for our full sample, we get statistically significant coefficients on 7 out of the 24 separate regressions, suggesting some concern about differences between treatments and controls. Most of these statistically significant effects are negative, which is not consistent with the idea that those who successfully complete the degrees and certificates are positively selected, or have higher earnings growth rates. Rather, this suggests that those who correctly perceive declining earnings prospects may be more likely to complete vocational certificates and degrees. In the lower panel of Table 3 we limit our samples to those who are at least 30 at their time of initial enrollment. This is a group for which we are more confident that the fixed-effects and individual-specific trends estimates will be well-identified, since older students are much more likely to have some substantial pre-enrollment earnings history. Among this slightly older group, we find four cases in which there are significant differences in earnings growth, all negative. These results suggest that it may be important to estimate models based on equation (2), including individual-specific trends, but also that, if anything, our initial fixed-effects estimates are likely to understate returns to these vocational programs.

The right-hand panel Table 2 shows results when we add an individual-specific trend, as in equation (2), to the regression specification.[12] Not surprisingly, given the pattern of results in Table 3, which suggested that several of our treated groups had earnings trends below those of the controls prior to enrollment, the addition of individual-specific trends increase the returns in several cases. For example, in Information Technology, results controlling for individual-specific trends show larger positive returns to all award lengths, though only the shortest term certificates show a statistically significant return. This is consistent with the visual evidence in Figure 2, which showed a downward trend prior to enrollment for prospective IT award recipients. Similarly, estimated returns within Engineering and Industrial Technology, where Table 3 showed significantly lower pre-entrollment earnings trends prior to enrollment, are larger in Panel B in several cases.

These results also suggests that, while individual fixed-effects can capture many fixed-omitted variables, it may also be important to control for pre-existing earnings trends for prospective degree recipients. This echoes, but extends, the approach taken in Jepsen, Troske, and Coomes (2014), who include several fixed, observable worker characteristics interacted with time trends in their main specification.

To summarize the broad pattern of results from Table 2, Figures 3 and 4 plot the estimated returns by TOP code and by award type. The results discussed thus far are represented in the vertical dimension of these figures (below, we explore and discuss an alternative control group, and those results are reflected on the horizontal axes in these figures). This further emphasizes that most programs studied here produce positive earnings effects, with the bulk of the points on the figure in the range of substantial positive returns, between five and twenty percent. Recalling that these programs range from a half-year to two years worth of full-time college enrollment, we view this as a very positive indicator of the potential effectiveness of these programs at increasing earnings. The broader literature on the returns to education suggests

[12] To estimate this equation, we run separate regressions of all variables, for each individual, on an intercept and time trend, and calculate residuals from all of these regressions. These residuals are then the transformed variables, purged of individual-specific trends, and are used to estimate the regressions reported in the right-hand side of Table 2.

that a single year of education can raise earnings by seven to eight percent (see, for example, Card, 2010); roughly speaking, these returns to CTE programs suggest that these programs produce the same or larger earnings effects per year of study.

We have also estimated returns across these TOP codes and degree types separately by age, gender, and ethnicity, and include these results in Appendix Tables 2 through 6. The disaggregation by age speaks directly to the validity of our main estimation strategy using fixed effects, since this approach is identified through those workers with an established, pre-enrollment earnings history. For four of the six TOP codes, results are qualitatively similar between younger (18 to 30) and older (over 30) students. In Business and Management programs, however, we find substantially larger returns for older students, suggesting some caution in interpreting those estimated returns as applicable to the broader population. In Family and Consumer Science, the certificates requiring 18 to 60 units show much larger returns for younger students. We note that the correspondence between "older" students and those identifying the fixed effects estimate is loose, so these results are only suggestive at this point.

Summary statistics from Table 1 indicated large gender differences in patterns of disciplines in which individuals enrolled and earned degrees. Because we also document substantial heterogeneity in returns across disciplines, it is important to investigate the overall returns to vocational education by gender. In Table 4, we repeat our preferred specifications by discipline, with both individual fixed effects and individual-specific trends, separately for men and women. Some disciplines show notable differences in estimated returns by gender. In Business and Management, for example, returns for women are higher, often substantially higher, and often by a statistically significant margin. In Information Technology, certificates of 30 to 60 units show large, significant returns for women and low or no returns for men. Interestingly, relatively few women receive certificates and degrees in the Information Technology TOP code. Among all AAs awarded to women, less than 2 percent are in this TOP code. This also raises the possibility of some gender-specific selection that could complicate interpretation of these returns. Business and Management, in contrast, account for a large fraction of all vocational awards to women, comprising 28 percent of vocational AA/AS degrees to women in our sample, and nearly one-third of certificates of 18 to 30 units. For the remaining disciplines, returns are similar across genders, and are not typically statistically different between men and women.

Given this evidence of gender differences in returns, and the different distributions of men and women across TOP codes, it is difficult to draw conclusions about the payoff of vocational programs as a whole by gender. This also makes it difficult to compare our results with the handful of prior studies of returns to vocational programs, which has often combined all vocational programs. One way to summarize these estimated returns is to calculate a weighted average return where the weights take account of the relative frequency of men and women earning the discipline-specific degrees. In Table 5, we summarize the overall returns, and the returns by gender, across the different disciplines. Specifically, we take the estimated returns from the left-hand panel of Table 4 (and similar estimates from Table 2) and calculate a weighted average across TOP codes for each degree type. The weights are simply the fraction of all degrees of a specific type (length) earned in the TOP code out of all such degrees earned.[13] This will provide an estimate of the typical return for a random student receiving an AA/AS vocational degree (or a certificate of a given length), with TOP codes that grant relatively large numbers of degrees receiving greater weight. This shows larger overall returns for women than for men. For women, the returns range from .35 for the AA/AS to approximately .10 for certificates requiring just six to 18 units. For men, the comparable range is .20 to .13. For comparison, Jepsen, Troske, and Coomes (JTC 2014) report earnings returns for "vocational" associate degrees of approximately $1300 to $1500 in quarterly earnings, or increases of 26 to 30 percent given their baseline quarterly earnings of approximately $5000. Thus, our results are in a similar range, although JTC report slightly larger returns for men than for women.

[13] This is not the only sensible way to aggregate returns across disciplines. This approach produces an overall return to the "average" degree recipient. Another strategy might be to weight by the number of students attempting degrees in this field; this would produce an average return more appropriate to a typical "potential" awardee.

These weighted averages do highlight some of the importance of the differential selection into TOP codes by men and women. The overall estimated returns of .35 for women is driven by the large fraction of women receiving AAs in health areas. Nearly 44 percent of women earnings AA/AS degrees in our sample do so in a health TOP code; only 20 percent of men earning AA/AS are in health. For men, there is a very heavy concentration of degrees and certificates received in public and protective services (which also have high returns, though not as high as health). Public and Protective Services account for more than 40 percent of six to 18 unit and 30 to 60 unit certificates for men.

This highlights a potentially important difference between our results and the earlier work by JTC 2014; these authors list both "vocational" programs and then, separately, health. Because the health TOP code produces some extremely large estimated returns, we have also calculated the weighted average of vocational returns excluding the health TOP codes. These results are shown in the lower panel of Table 5. Notably, the AA/AS degrees excluding health produce lower returns of four to seven percent. Outside of health, returns are larger among the shorter term certificates (as opposed to Associates degrees), with many returns in the neighborhood of ten percent. This highlights both the strong role of the health sector in generating these substantial returns to vocational programs, and the sensitivity of the overall returns (especially for women), to this prominent role for the health disciplines.

B.1. Robustness of results to control group definition.

We have argued above that an appropriate and well-matched control group is an important part of our identification strategy. In this section, we begin to explore how varying our control group definition affects the estimated returns. Our initial control group includes individuals who have taken at least eight units within the 2-digit TOP code examined, but who have not received any degree or certificate. This likely includes a mix of (at least) 2 types of students: (1) those who have completed only very few units of study and (2) those who are very close to completion of a certificate, but lack a few critical courses. The interpretation of our estimated returns hinges on which of these types of students dominate the control group. If it is the latter, the estimates may be largely capturing a "sheepskin" effect, or the effect of persistence in meeting all requirements, since the control group may also have completed the majority of the coursework.

Figure 5 illustrates the distribution of completed units among the control groups for each of the six broad TOP codes. The common feature across all TOP codes is the concentration of control group students at very low numbers of units completed. This suggests that the control group is mainly composed of students who are not close to degree or certificate completion. To further focus our estimates on the contrast between degree completers and students relatively far from degree completion, we create an alternative set of control groups. Specifically, we add the requirement that control group members have not completed more than half the required number of units in the TOP code for the required degree. This results in relatively modest changes from our initial control group, but it is of interest to see if this affects the estimated returns. These results are summarized by the horizontal dimension of Figures 3 and 4. These figures show the similarity of our results based on the two different control groups—the "Full" control based on our original definition, and the "Half" control where we eliminate individuals who have completed more than half the required units. The fact that the estimates for most TOP codes (Figure 3) and degree types (Figure 4) are close to the 45 degree line emphasizes that there are not large effects, on average, of this variation in the control group definition.

In general, our expectation is that the estimated returns should be higher when we use this alternative control group, since we eliminate controls who may have accumulated levels of human capital that are close to those of the degree recipients. In terms of Figures 3 and 4, this would predict a clustering of estimates below the 45 degree line, which is precisely what we see. In Figure 5, it is notable that the greatest divergence in estimates by control group definition occurs for the shortest certificates, requiring just six to eighteen units. For these awards, the potential difference in units accumulated by the treatment and control students is low and so forcing a greater contrast (in the "half" control group) leads to larger estimated effects. This is also consistent with there being some return to accumulating even a few units of vocational credit in some areas.

Finally, we have also constructed a single control group across all TOP codes. This is perhaps more comparable to a typical approach in this literature, where treatment and control students may not be in the same field of study. These estimated returns, along with returns from our original control groups, are arrayed in Figures 6 and 7. Here, there is less agreement between the two approaches, suggesting that conditioning on participation in coursework within the specific discipline whose return is being measured may be important.

B2. Results for more detailed program definitions (4-digit TOP codes)

Because these results already show substantial heterogeneity by program of study and certificate length, and because those two factors may be correlated with one another, and with a host of student characteristics, we have also estimated these specifications at the more detailed, 4-digit TOP code. This means, for example, that instead of estimating the return to all 18 to 30 unit certificates in the field of "Family and Consumer Sciences", we instead allow separate coefficients for returns to programs in "Child Development/Early Care and Education", "Fashion", and "Interior Design." We do this for two reasons. First, as suggested by the example just given there remains substantial heterogeneity in content within some of these 2-digit TOP codes, and it might prove important to distinguish among different programs within the same broad heading. Second, there may also be very different student populations across specific subfields, and so narrowing the focus to more specific certificates may eventually help identify returns for potentially different populations.

These results are summarized in Figures 8 and 9, which again array our estimated returns by the definition of the control group, the TOP code, and the length of the certificate. In this case, the figure shows several estimated returns for each 2-digit TOP code and certificate length. There is, as expected, great variation in estimated returns within TOP codes. To see this, focus on the unfilled circles in Figure 6, which indicate returns to different vocational programs in the broad field of Health. The estimated returns (based on the half control group) in Health range from -.08 to .50. Most of the other TOP codes show a similarly broad range of returns. Another important result illustrated in Figures 6 and 7 is again, the overall positive returns to most of the vocational awards considered here. In this more disaggregated examination of returns to specific awards, there are some point estimates at or below zero. The vast majority of estimates, however, are in the positive range, often indicating fairly substantial labor market returns to vocational education.

B3. The potential role of transfers to four-year institutions

In much work on community college students and degrees, it is critical to consider the role of transfers to four-year institutions in generating any observed earnings increases. In more traditional academic settings, for example, earning a two-year degree may simply be a milepost on the way to earning a four-year degree, or even just accumulating additional college credits. Thus, while estimates such as ours would capture a meaningful return to the program, the mechanism by which it generates earnings increases might depend critically on successful transfer and completion of another degree. This point is made in JTC (2014) when they note the difficulty of signing the bias if some of their associate degree recipients also complete additional college at a four year institution.

In our work focusing specifically on vocational degree and certificate programs, the role of the transfer process in helping to generate returns is even less certain. On one hand, students focused on these vocational awards may be less inclined to transfer and so there may be less concern that the vocational awards are associated with higher earnings partially because they facilitate additional degrees or college attendance. This should mean that eliminating students who transfer would reduce our estimated returns. On the other hand, transfers could work in a very different way in if academic and vocational tracks are viewed as substitutes for one another. Suppose that individuals take a few vocational courses (and thus qualify as a member of our control group), if many of these students then decide instead to pursue a transfer path, the earnings of our controls may benefit disproportionately from their decisions to transfer to four-year colleges. In some sense, receiving a vocational degree could signal that a student has not opted for a four year degree. This is a slight twist on the "diversion" effect of community colleges (see Belfield and Bailey (2011) for a review and discussion) in which attendance diverts students from a four year degree. For vocational programs, there may be an additional issue of diverting students from non-vocational programs that are intended to lead to transfers. If this story is important for our vocational students, we might expect that eliminating students who successfully transfer would disproportionately eliminate high earning control-group members and so increase our estimated returns.

Table 6 repeats the basic analysis in Table 2, but drops students (in both treatment and control groups) who transfer. This results in dropping from 12 to 40 percent of our samples across different TOP code groups. Despite dropping a large number of cases for some TOP codes, results in Table 6 are very similar to those shown in Table 2, suggesting that transfers do not play a major, systematic role in generating the returns estimated here. One exception to this patterns if for the AA/AS degrees in Business and Management. Once those transferring are dropped, we see positive returns to the AA/AS degrees in this field across age groups and specifications. Business programs may be a particularly heterogeneous group, since many four-year colleges offer business degrees, but they are also listed as part of the vocational offerings. It seems likely that the Business TOP code combines more traditional academic business tracks that are aimed at transferring to four year colleges and more typically vocational programs which are not.

Discussion & Conclusion

The California Community Colleges, enrolling 2.6 million students across 112 campuses represent the largest public higher education system in the nation. The potential promise of California's community colleges to improve labor market outcomes is highlighted in recent state reform efforts to strengthen CTE offerings, and in recent federal funding initiatives directed at technical/vocational education and community colleges. Research on the CTE mission of community colleges, the diverse needs of their students, and on the relationship between CTE program offerings and the labor market has been scarce.

The approached used here suggests quite substantial, and generally statistically significant, returns to a variety of popular vocational certificates and awards offered in California community colleges. By controlling for both individual specific fixed effects and individual specific trends, we address many concerns about using observational data to estimate returns to higher education. Our results suggest average returns ranging from more than 25 percent for AA/AS degrees to approximately 10 percent for shorter term certificates. Health programs produce very large returns, and this drives both large overall estimated returns to vocational programs in our data, and fairly large apparent gender gaps in vocational returns because of the large concentration of women in this high-return field. Excluding health leads to substantially lower returns to the AA/AS degrees and certificates, although short-term certificates outside the health field continue to show substantial returns.

For the purpose of improving human capital development of less skilled workers, these results raise several important points. First, the substantial heterogeneity in returns to CTE, even within the single system we examine, emphasizes that all vocational education programs are not equal. The returns to awards with the same number of credit hours vary enormously. While some health occupations have double-digit returns for relatively short programs, other certificate programs offer returns that are mere fractions of those high returns. Even within our broad disciplines (two-digit TOP codes) there is substantial variation across specific programs. While this is not different from results across college majors in more traditional four-year college settings, it is particularly important to acknowledge in CTE settings. Second, and very much related, there is substantial heterogeneity in the observable (and likely unobserved) characteristics of students across disciplines and programs. Thus, sensible policies cannot simply funnel workers into “high-return” programs, since underlying differences in the types of students who enroll in them could be quite important. In particular, a deeper understanding of how students choose their courses of study, and how redirecting students to other fields can alter their returns, remain very underexplored areas.

Third, these points about heterogeneity in returns and student characteristics also relate to another critical point for workforce development policies. Once we understand these interactions between individuals, programs and returns, providing concise information to potential students and college administrators is a top priority. Students should, or course, be aware of the likely returns on investments they are making. Calls to provide better information on labor market returns have begun to be common in the broader realm of education policy, but in the CTE area, given the direct connection to labor market outcomes, this information is especially critical.

Finally, the extremely large returns to health occupations, and the substantially smaller average returns among non-health occupations merit careful consideration. Health occupations are currently receiving a great deal of attention as promising career pathways for those without four-year college degrees. While our results largely confirm the high potential of health occupation training, it remains unclear which types of workers will be able to benefit from such training. Many health-related programs may have substantial requirements for prerequisite courses that not all workers will meet. Much previous and current work on health occupations comes from smaller, randomized training program trials. Our results confirm high returns in a broader, non-experimental setting, but more research is needed to better understand these high returns, and to understand whether and when they will continue.

It has never been more critical to find effective paths to human capital development for individuals who are unlikely to complete standard four-year academic programs. In California and the nation, declining real wages and record high unemployment for those without college degrees, combined with cuts to many state programs serving these populations, make it essential to understand what programs can be most effective. The identification strategy we employ provides for a far more rigorous evaluation of the labor market returns than the simple before and after comparisons of CTE participants' earnings that currently exist. A large literature in economics has considered the most appropriate methods for evaluating worker-training programs, and we draw on the lessons from that literature in our analytic strategy (see Lalonde, 1986, or Card, Luve and Weber, 2010, for a recent review and meta-analysis of the job training evaluation literature). Short of a randomized assignment of workers into CTE courses or programs, our approach combining longitudinal data with a control group provides the most common approach in the recent literature.[14] Our results suggest that many of these programs, even after accounting for individual pre-enrollment earnings levels and economy-wide earnings growth, have substantial, positive earnings effects.

[14] Card, Luve, and Weber (2010) report that more than half of the qualifying evaluation studies included in their meta-analysis, published since 1990, used longitudinal data with a comparison group.

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Figure A1: Map of California's Community Colleges

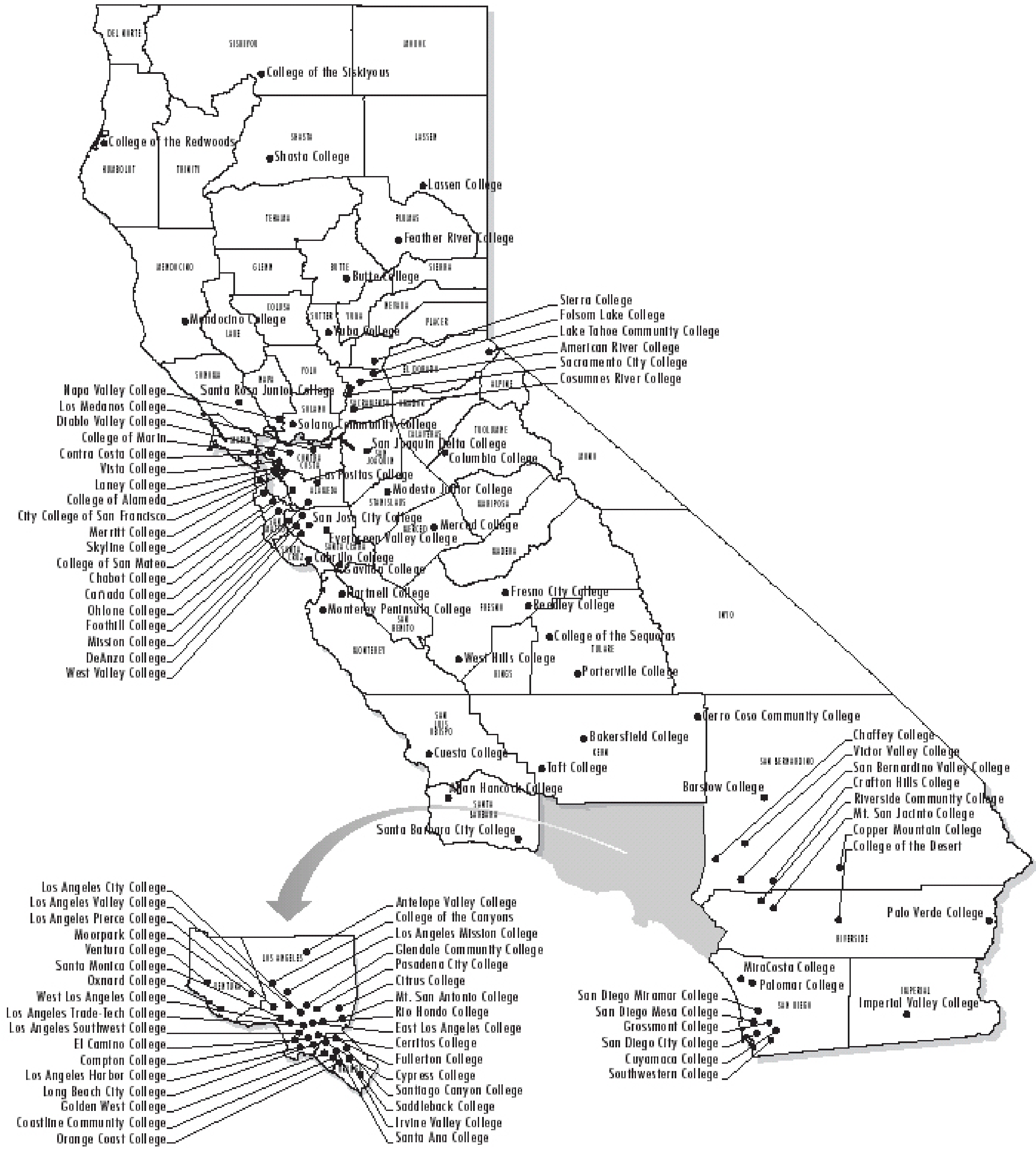

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Table 1: Summary Statistics by Discipline

	Business		**Information Tech**		**Engineering**	
	Treat	*Control*	*Treat*	*Control*	*Treat*	*Control*
AA/AS	0.67		0.38		0.20	
Cert 30-60	0.04		0.05		0.30	
Cert 18-30	0.10		0.10		0.16	
Cert 6-18	0.11		0.27		0.19	
Other	0.06		0.16		0.12	
Pre-enrollment quarters	7.79	9.57	15.20	11.04	12.21	11.02
Employed pre-enrollment	0.30	0.41	0.39	0.47	0.42	0.47
Age at enrollment	25.50	27.30	29.02	29.66	26.19	27.55
Male	0.43	0.46	0.78	0.73	0.93	0.88
White	0.36	0.38	0.45	0.38	0.37	0.35
Black	0.08	0.07	0.06	0.05	0.06	0.07
Hispanic	0.25	0.20	0.17	0.15	0.32	0.32
Asian	0.17	0.21	0.15	0.25	0.11	0.09
N	20,440	61,457	3,611	21,633	18,324	46,837

	Health		**Family/Consumer**		**Public/Protective**	
	Treat	*Control*	*Treat*	*Control*	*Treat*	*Control*
AA/AS	0.49		0.30		0.32	
Cert 30-60	0.15		0.12		0.12	
Cert 18-30	0.04		0.11		0.15	
Cert 6-18	0.16		0.38		0.26	
Other	0.14		0.04		0.12	
Pre-enrollment quarters	12.08	12.92	9.17	9.39	12.42	12.76
Employed pre-enrollment	0.48	0.54	0.35	0.40	0.50	0.53
Age at enrollment	26.32	29.22	28.23	28.80	25.17	26.46
Male	0.34	0.34	0.14	0.11	0.75	0.70
White	0.42	0.41	0.29	0.36	0.47	0.44
Black	0.07	0.09	0.11	0.09	0.07	0.07
Hispanic	0.20	0.21	0.37	0.33	0.28	0.29
Asian	0.10	0.09	0.10	0.09	0.04	0.04
N	36,407	15,736	15,461	35,831	26,842	40,637

Table 2: Estimates by Discipline and Length

Specification:	Individual Fixed Effects		Individual Fixed Effects and Trends	
Business/Management	*All*	*Older than 30*	*All*	*Older than 30*
AA/AS	0.0106	0.107***	0.0375***	0.103***
	(0.00810)	(0.0144)	(0.00898)	(0.0155)
30-60 Units	0.0984**	0.144**	0.116**	0.113*
	(0.0346)	(0.0440)	(0.0356)	(0.0462)
18-30 Units	0.148***	0.164***	0.141***	0.129***
	(0.0190)	(0.0217)	(0.0221)	(0.0251)
6-18 Units	0.0508**	0.0626*	0.157***	0.129***
	(0.0193)	(0.0246)	(0.0232)	(0.0281)
Information Technology				
AA/AS	0.00496	-0.00453	0.0657*	0.0442
	(0.0242)	(0.0348)	(0.0266)	(0.0376)
30-60 Units	0.0799	0.0236	0.0724	0.0780
	(0.0596)	(0.0699)	(0.0559)	(0.0674)
18-30 Units	0.00657	0.00150	0.0288	0.0368
	(0.0421)	(0.0480)	(0.0495)	(0.0551)
6-18 Units	0.0176	0.0258	0.0930***	0.119***
	(0.0255)	(0.0287)	(0.0277)	(0.0319)
Engineering/Industrial				
AA/AS	0.166***	0.136***	0.161***	0.185***
	(0.0138)	(0.0229)	(0.0154)	(0.0256)
30-60 Units	0.116***	0.0862***	0.0722***	0.0456**
	(0.0103)	(0.0155)	(0.0115)	(0.0170)
18-30 Units	0.0578***	0.0734***	0.0428**	0.0562**
	(0.0135)	(0.0184)	(0.0144)	(0.0196)
6-18 Units	0.0697***	0.0404*	0.125***	0.135***
	(0.0139)	(0.0195)	(0.0157)	(0.0221)
Health				
AA/AS	0.644***	0.644***	0.690***	0.672***
	(0.00778)	(0.0105)	(0.00810)	(0.0109)
30-60 Units	0.307***	0.324***	0.394***	0.392***
	(0.0116)	(0.0158)	(0.0129)	(0.0180)
18-30 Units	0.108***	0.131***	0.282***	0.298***
	(0.0226)	(0.0313)	(0.0244)	(0.0340)
6-18 Units	0.0104	0.00790	0.0964***	0.113***
	(0.0134)	(0.0201)	(0.0147)	(0.0223)
Family/Consumer Sciences				
AA/AS	0.105***	0.137***	0.0921***	0.122***
	(0.0125)	(0.0185)	(0.0144)	(0.0220)
30-60 Units	0.0829***	0.0392	0.196***	0.225***
	(0.0215)	(0.0287)	(0.0246)	(0.0314)
18-30 Units	0.112***	0.0651**	0.124***	0.0851**
	(0.0199)	(0.0252)	(0.0229)	(0.0272)
6-18 Units	0.0679***	0.0782***	0.0996***	0.112***
	(0.0123)	(0.0167)	(0.0138)	(0.0183)
Public/Protective Services				
AA/AS	0.123***	0.0787***	0.126***	0.150***
	(0.0102)	(0.0200)	(0.0111)	(0.0217)
30-60 Units	0.170***	0.164***	0.151***	0.0911***
	(0.0136)	(0.0185)	(0.0154)	(0.0212)
18-30 Units	0.199***	0.147***	0.163***	0.167***
	(0.0116)	(0.0163)	(0.0119)	(0.0156)
6-18 Units	0.232***	0.166***	0.132***	0.135***
	(0.00914)	(0.0139)	(0.00932)	(0.0142)

Coefficients on degree received (interacted with award type/length) from separate regressions for each discipline (2-digit TOP code). Standard errors clustered by individual.

Table 3: Differences in Pre-Enrollment Earnings Changes, Treatments versus Controls

Full Sample				
	AAAS	Cert 30-60	Cert18-30	Cert 6-18
Business/Management	0.00236	-0.03823	-0.01625	0.0056
	(0.006)	(0.022)	(0.009)	(0.011)
Information Tech	0.02919	-0.0395	-0.007	0.0217*
	(0.016)	(0.034)	(0.019)	(0.011)
Engineering/Industrial	-0.0374*	-0.0185*	-0.021*	-0.0135
	(0.011)	(0.008)	(0.008)	(0.008)
Health	0.00713	-0.00425	-0.01725	-0.00686
	(0.005)	(0.007)	(0.011)	(0.007)
Family/Consumer Sciences	0.012	0.01456	-0.0306*	0.00054
	(0.014)	(0.012)	(0.012)	(0.008)
Public/Protective	-0.023*	-0.0229*	0.00756	0.0076
	(0.009)	(0.010)	(0.007)	(0.005)
Students Age 30+ at Enrollment				
	AAAS	Cert 30-60	Cert18-30	Cert 6-18
Business/Management	0.01221	-0.04992	-0.0118	0.0086
	(0.008)	(0.026)	(0.010)	(0.011)
Information Tech	0.03708	-0.0635	-0.0093	-1.01E-02
	(0.020)	(0.039)	(0.020)	(0.010)
Engineering/Industrial	-0.0343*	0.00114	-0.02*	0.01231
	(0.010)	(0.009)	(0.009)	(0.008)
Health	-0.01009	-0.00554	-0.0011	-0.01397
	(0.006)	(0.008)	(0.012)	(0.009)
Family/Consumer Sciences	0.007	0.0013	0.0036	0.00094
	(0.015)	(0.013)	(0.013)	(0.009)
Public/Protective	-0.0257*	-0.0289*	0.01273	0.0003
	(0.012)	(0.012)	(0.009)	(0.006)

Entries are regression coefficients by two-digit TOP code and control group type.
Each coefficient is from a regression of pre-enrollment earnings changes on treatment, age, and year dummies
Standard errors clustered at individual level.

Table 4: Estimates by Discipline and Length, by Gender

Sample:	Full Sample		Older than 30	
Business/Management	*Men*	*Women*	*Men*	*Women*
AA/AS	-0.0283*	0.0400***	0.0727**	0.122***
	(0.0121)	(0.0109)	(0.0243)	(0.0179)
30-60 Units	-0.123	0.185***	-0.0733	0.219***
	(0.0698)	(0.0382)	(0.0995)	(0.0456)
18-30 Units	0.0327	0.203***	0.0641	0.206***
	(0.0312)	(0.0235)	(0.0364)	(0.0266)
6-18 Units	-0.0176	0.0853***	0.0241	0.0698*
	(0.0292)	(0.0251)	(0.0357)	(0.0315)
Information Technology				
AA/AS	0.00499	0.0186	-0.00572	0.0211
	(0.0264)	(0.0595)	(0.0383)	(0.0804)
30-60 Units	0.00167	0.240**	-0.0884	0.210*
	(0.0756)	(0.0878)	(0.0926)	(0.0951)
18-30 Units	0.00337	0.0359	0.0160	-0.0282
	(0.0454)	(0.108)	(0.0523)	(0.115)
6-18 Units	0.00477	0.0987	0.0145	0.0998
	(0.0285)	(0.0555)	(0.0324)	(0.0611)
Engineering/Industrial				
AA/AS	0.174***	0.0672	0.142***	0.0760
	(0.0143)	(0.0547)	(0.0240)	(0.0776)
30-60 Units	0.117***	0.134*	0.0861***	0.127
	(0.0105)	(0.0532)	(0.0159)	(0.0665)
18-30 Units	0.0587***	0.0521	0.0723***	0.104
	(0.0138)	(0.0612)	(0.0191)	(0.0708)
6-18 Units	0.0695***	0.0620	0.0406*	0.0316
	(0.0143)	(0.0583)	(0.0204)	(0.0664)
Health				
AA/AS	0.630***	0.657***	0.604***	0.663***
	(0.0147)	(0.00916)	(0.0193)	(0.0125)
30-60 Units	0.282***	0.326***	0.264***	0.364***
	(0.0187)	(0.0147)	(0.0243)	(0.0206)
18-30 Units	0.0579	0.130***	0.0570	0.157***
	(0.0520)	(0.0251)	(0.0585)	(0.0369)
6-18 Units	0.0243	-0.0137	-0.0303	0.0274
	(0.0196)	(0.0183)	(0.0363)	(0.0239)
Family/Consumer Sciences				
AA/AS	0.0632	0.111***	0.0249	0.148***
	(0.0405)	(0.0131)	(0.0688)	(0.0191)
30-60 Units	0.0676	0.101***	0.0873	0.0510
	(0.0393)	(0.0259)	(0.0583)	(0.0332)
18-30 Units	0.0683	0.130***	0.0140	0.0888**
	(0.0453)	(0.0219)	(0.0599)	(0.0276)
6-18 Units	0.128***	0.0622***	0.213***	0.0634***
	(0.0381)	(0.0130)	(0.0509)	(0.0177)
Public/Protective Services				
AA/AS	0.132***	0.105***	0.0426	0.145***
	(0.0122)	(0.0181)	(0.0253)	(0.0325)
30-60 Units	0.135***	0.248***	0.126***	0.242***
	(0.0159)	(0.0264)	(0.0231)	(0.0308)
18-30 Units	0.184***	0.213***	0.151***	0.120**
	(0.0126)	(0.0294)	(0.0178)	(0.0385)
6-18 Units	0.217***	0.235***	0.161***	0.169***
	(0.0101)	(0.0212)	(0.0157)	(0.0298)

Coefficients on degree received (interacted with award type/length) from separate regressions for each discipline (2-digit TOP code). Standard errors clustered by individual.

Table 5: Estimated Returns by Award length

All Disciplines

	All	Men	Women
AA/AS	0.286	0.198	0.351
	(0.011)	(0.017)	(0.016)
30-60 Units	0.203	0.128	0.321
	(0.018)	(0.023)	(0.029)
18-30 Units	0.135	0.114	0.164
	(0.020)	(0.026)	(0.033)
6-18 Units	0.117	0.131	0.098
	(0.015)	(0.019)	(0.023)

Excluding Health

	All	Men	Women
AA/AS	0.055	0.072	0.042
	(0.010)	(0.015)	(0.015)
30-60 Units	0.083	0.079	0.090
	(0.016)	(0.021)	(0.026)
18-30 Units	0.103	0.102	0.106
	(0.018)	(0.023)	(0.031)
6-18 Units	0.097	0.112	0.076
	(0.013)	(0.017)	(0.021)

Table 6: Estimates by Discipline and Length, Excluding Transfer Students

Specification:	Individual Fixed Effects		Individual Fixed Effects and Trends	
Business/Management	*All*	*Older than 30*	*All*	*Older than 30*
AA/AS	0.134***	0.155***	0.136***	0.137***
	(0.0128)	(0.0179)	(0.0141)	(0.0199)
30-60 Units	0.129***	0.153***	0.120**	0.117*
	(0.0371)	(0.0436)	(0.0408)	(0.0499)
18-30 Units	0.191***	0.192***	0.158***	0.144***
	(0.0204)	(0.0230)	(0.0233)	(0.0260)
6-18 Units	0.0803***	0.0644*	0.178***	0.136***
	(0.0212)	(0.0259)	(0.0256)	(0.0305)
Information Technology				
AA/AS	0.0903**	0.0397	0.119***	0.0474
	(0.0293)	(0.0408)	(0.0343)	(0.0487)
30-60 Units	0.0913	0.0294	0.0641	0.104
	(0.0599)	(0.0694)	(0.0608)	(0.0720)
18-30 Units	0.0440	0.0405	0.0841	0.107
	(0.0469)	(0.0530)	(0.0530)	(0.0587)
6-18 Units	0.0714**	0.0566	0.0957**	0.113**
	(0.0274)	(0.0304)	(0.0307)	(0.0357)
Engineering/Industrial				
AA/AS	0.214***	0.160***	0.183***	0.193***
	(0.0152)	(0.0249)	(0.0172)	(0.0277)
30-60 Units	0.129***	0.0931***	0.0760***	0.0543**
	(0.0106)	(0.0159)	(0.0118)	(0.0176)
18-30 Units	0.0766***	0.0801***	0.0490***	0.0562**
	(0.0139)	(0.0191)	(0.0148)	(0.0200)
6-18 Units	0.0760***	0.0428*	0.130***	0.139***
	(0.0144)	(0.0201)	(0.0163)	(0.0223)
Health				
AA/AS	0.666***	0.655***	0.690***	0.668***
	(0.00935)	(0.0120)	(0.00989)	(0.0125)
30-60 Units	0.336***	0.339***	0.398***	0.399***
	(0.0124)	(0.0166)	(0.0136)	(0.0186)
18-30 Units	0.134***	0.134***	0.263***	0.276***
	(0.0250)	(0.0346)	(0.0261)	(0.0361)
6-18 Units	0.0303*	0.0131	0.118***	0.118***
	(0.0147)	(0.0210)	(0.0166)	(0.0239)
Family/Consumer Sciences				
AA/AS	0.145***	0.150***	0.115***	0.125***
	(0.0156)	(0.0215)	(0.0180)	(0.0254)
30-60 Units	0.0935***	0.0462	0.197***	0.229***
	(0.0229)	(0.0300)	(0.0262)	(0.0329)
18-30 Units	0.106***	0.0642*	0.117***	0.0823**
	(0.0212)	(0.0262)	(0.0245)	(0.0284)
6-18 Units	0.0892***	0.0919***	0.109***	0.113***
	(0.0133)	(0.0170)	(0.0149)	(0.0191)
Public/Protective Services				
AA/AS	0.186***	0.120***	0.155***	0.172***
	(0.0133)	(0.0242)	(0.0150)	(0.0265)
30-60 Units	0.178***	0.171***	0.154***	0.103***
	(0.0152)	(0.0202)	(0.0177)	(0.0234)
18-30 Units	0.193***	0.151***	0.169***	0.176***
	(0.0133)	(0.0183)	(0.0140)	(0.0180)
6-18 Units	0.213***	0.169***	0.142***	0.146***
	(0.0106)	(0.0157)	(0.0111)	(0.0156)

Coefficients on degree received (interacted with award type/length) from separate regressions for each discipline (2-digit TOP code). Standard errors clustered by individual.

Figure 1. Number of Awards Granted, 2001-2010

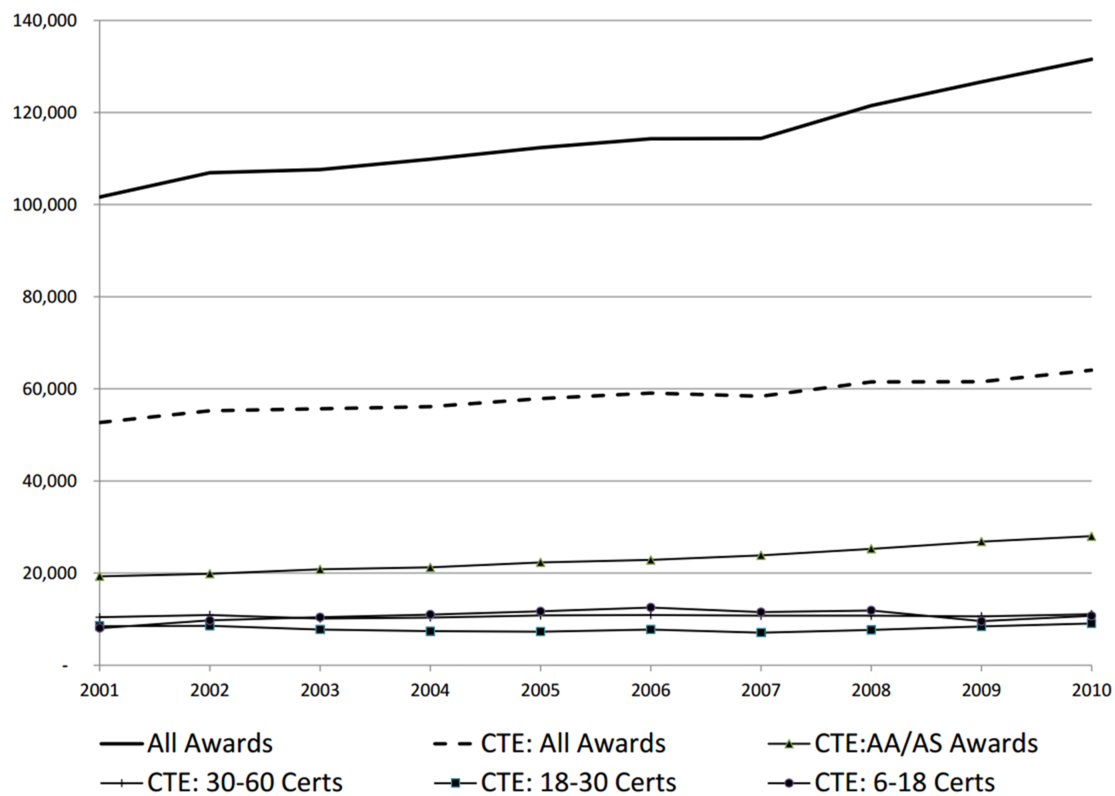
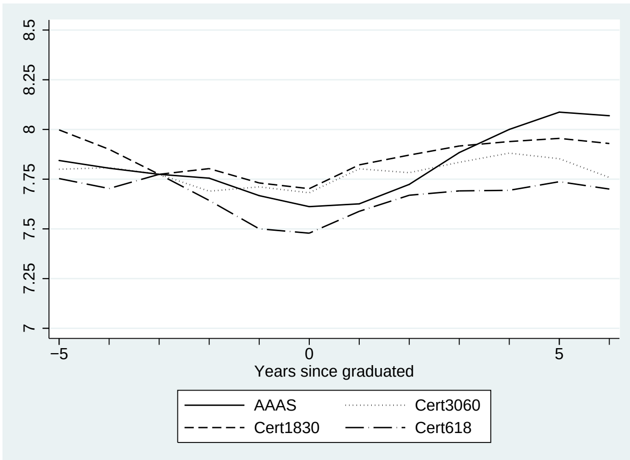
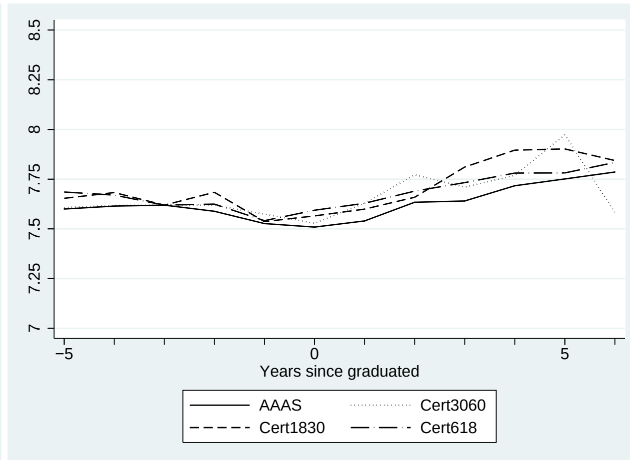


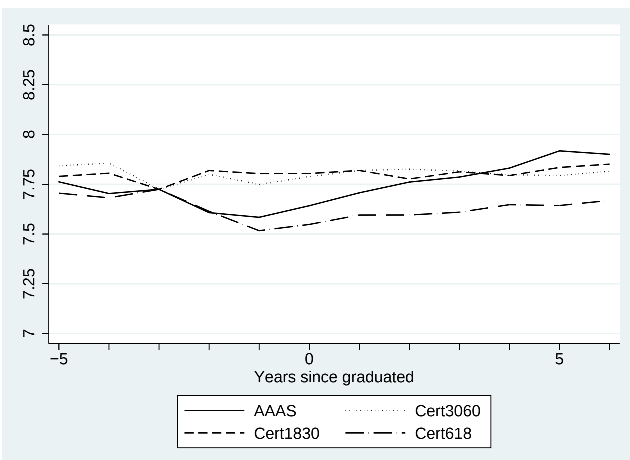
Figure 2. Earnings trajectories of degree recipients



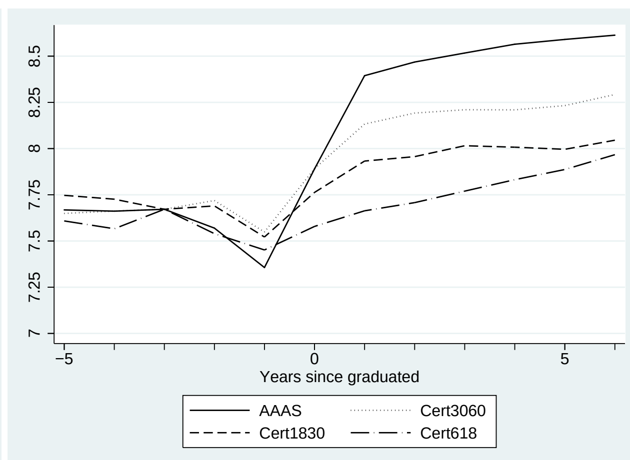
Business/Management



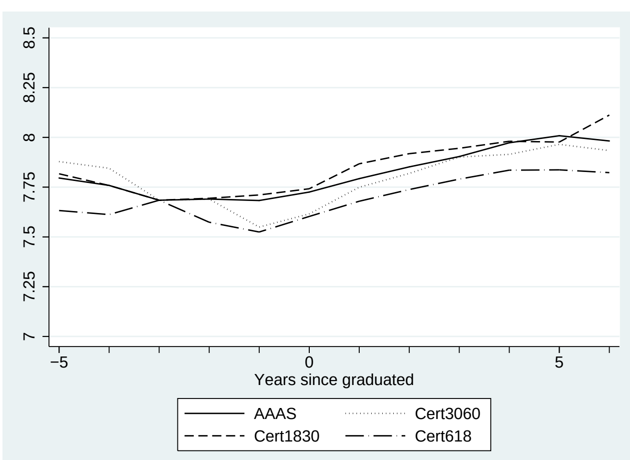
Information Technology



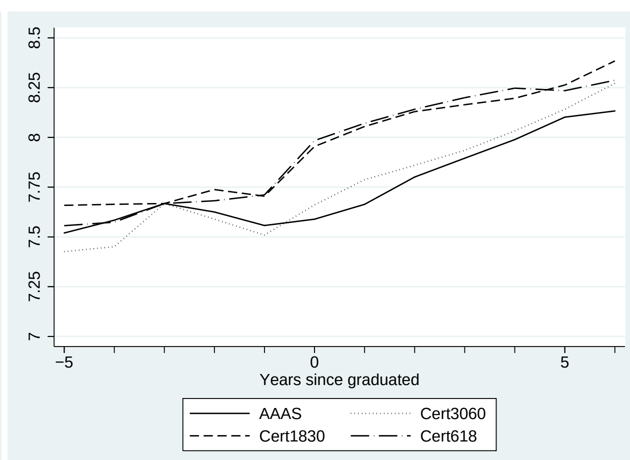
Engineering/Industrial



Health



Family/Consumer



Public/Protective

Note: Earnings expressed in log quarterly wages. Award recipients are included if they received their highest award between 2003 and 2007. These charts control for race, gender, and calendar quarter effects. They also control for whether a student was enrolled part time (6-12 units per semester) or full-time (more than 12 units).

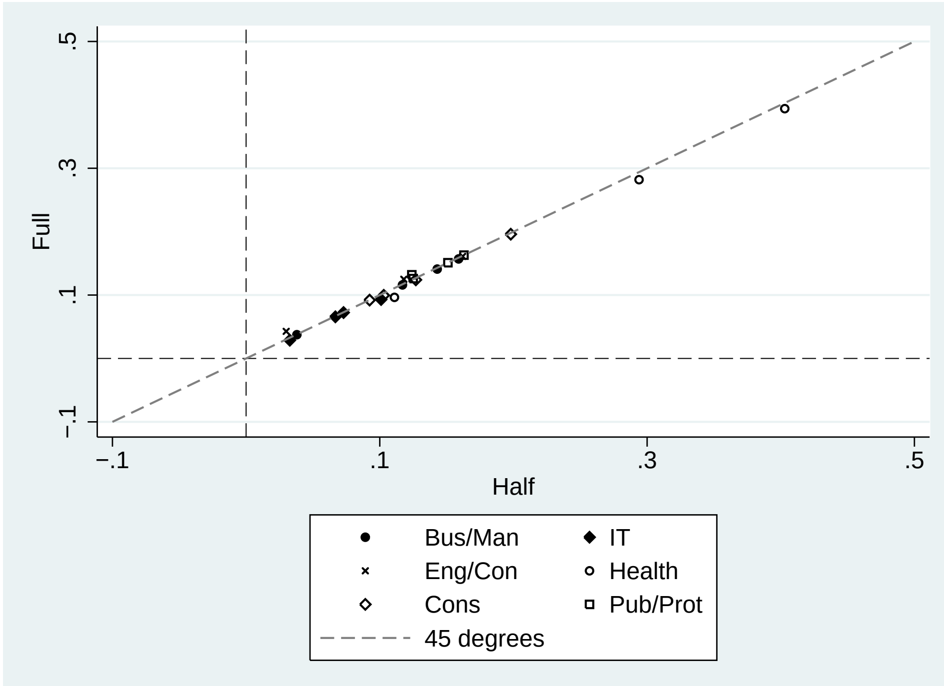


Figure 3: Full and Half Control, by Discipline (2-digits)

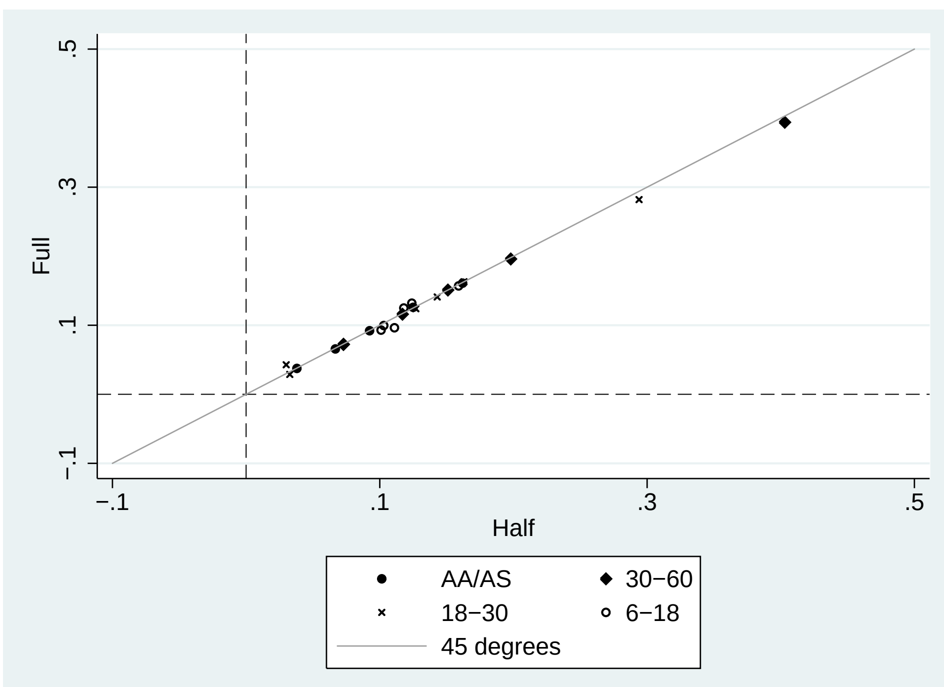
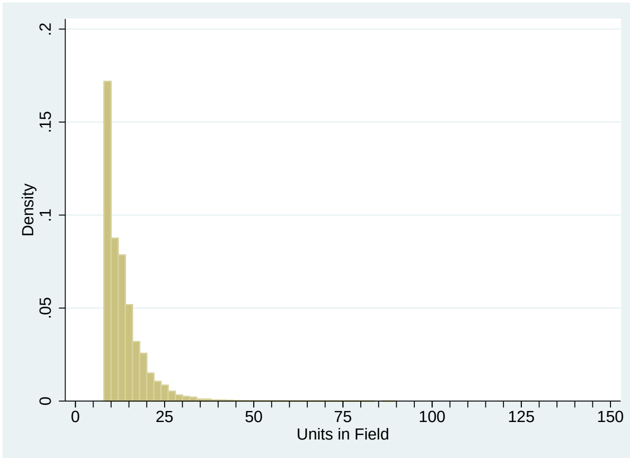
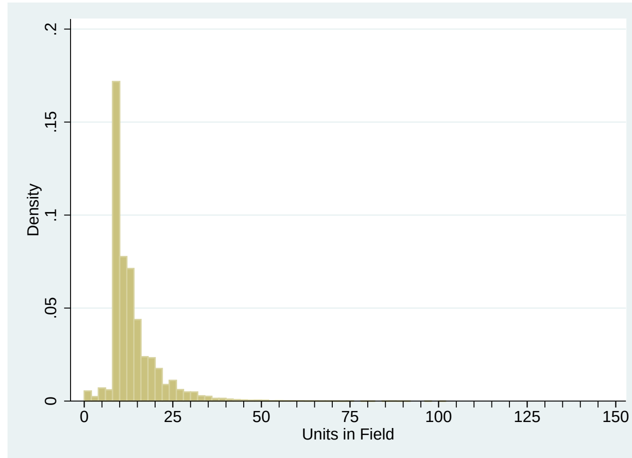


Figure 4: Full and Half Control, by Degree Type

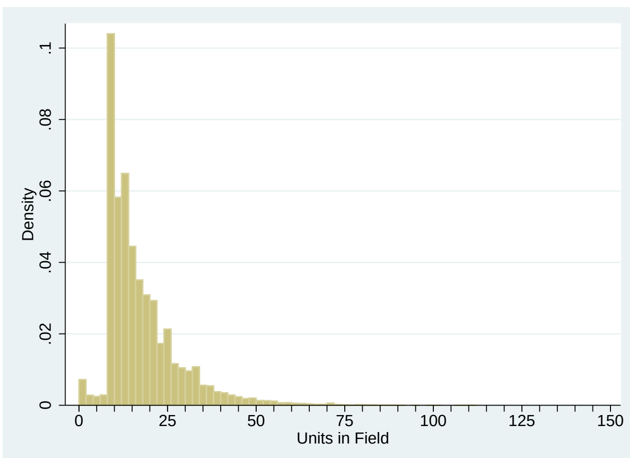
Figure 5. Units Earned by Control Groups, by Discipline



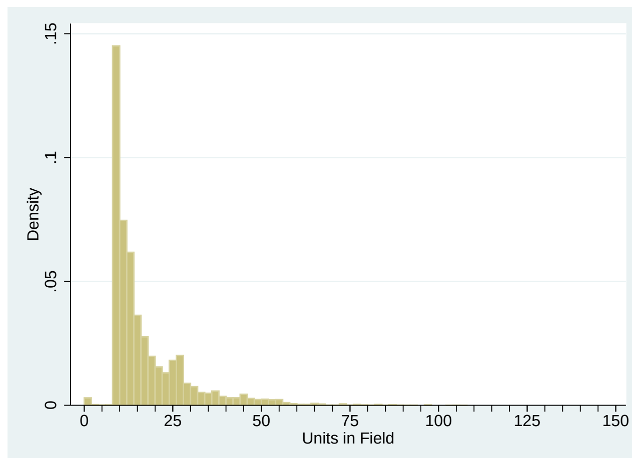
Business/Management



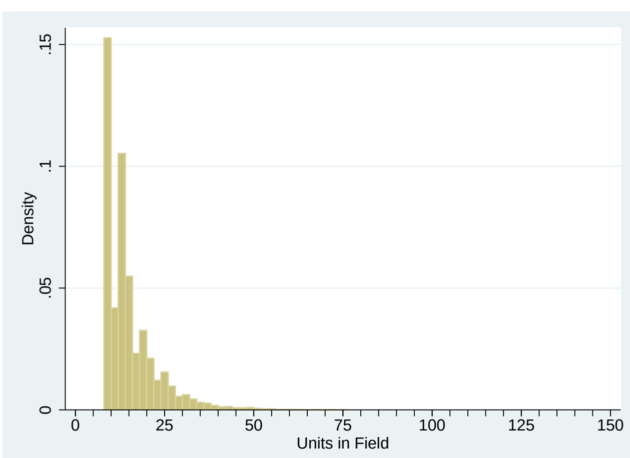
Information Technology



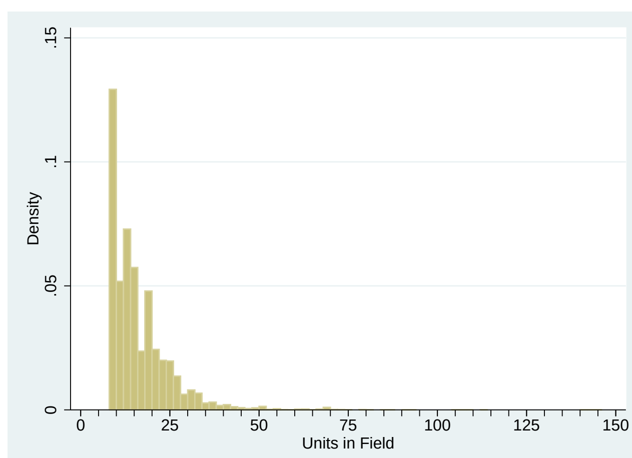
Engineering/Industrial Technology



Health



Family/Consumer Sciences



Public/Protective Services

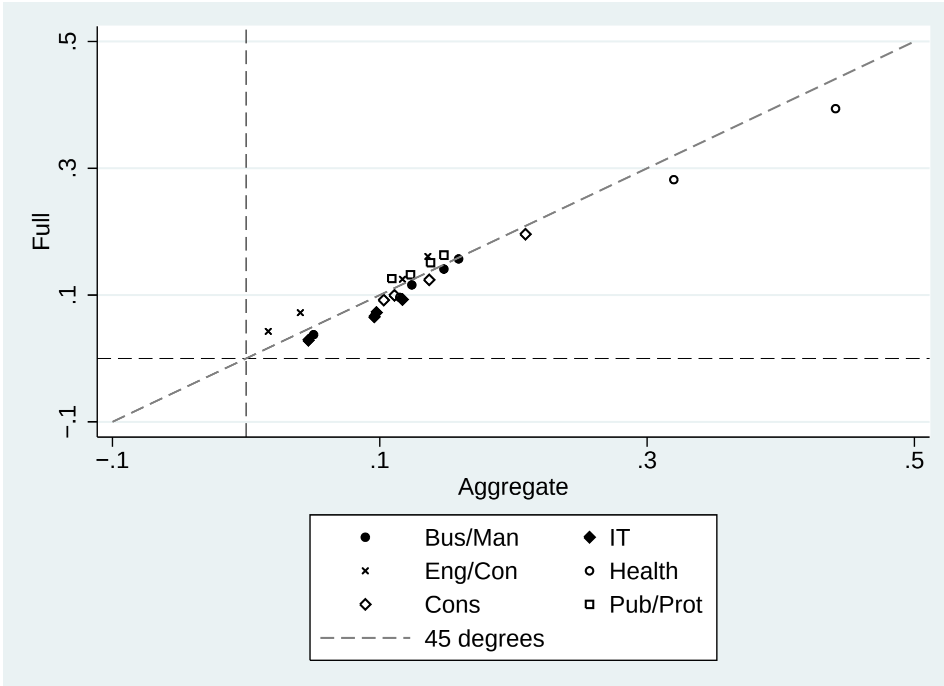


Figure 6: Full and Aggregate Control, by Discipline (2-digits)

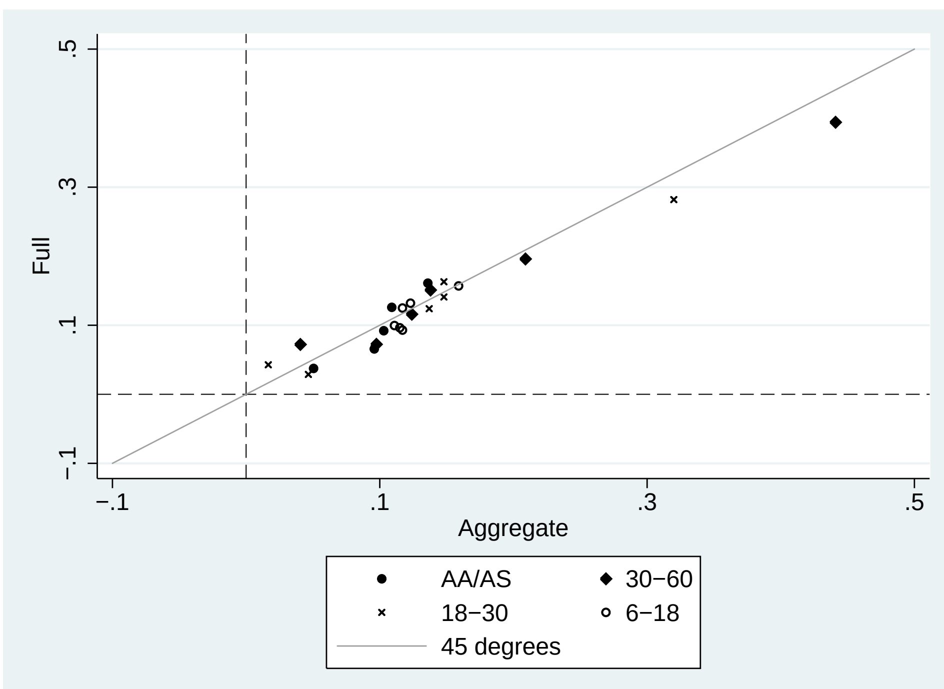


Figure 7: Full and Aggregate Control, by Degree Type

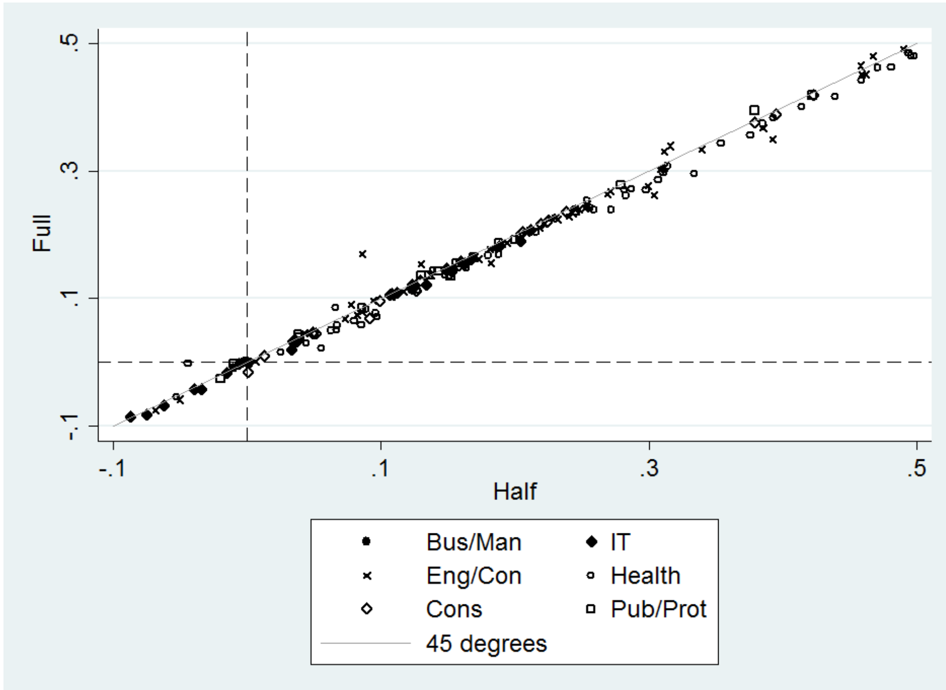


Figure 8: Full and Half Control, by Sub-Discipline (4-digits)

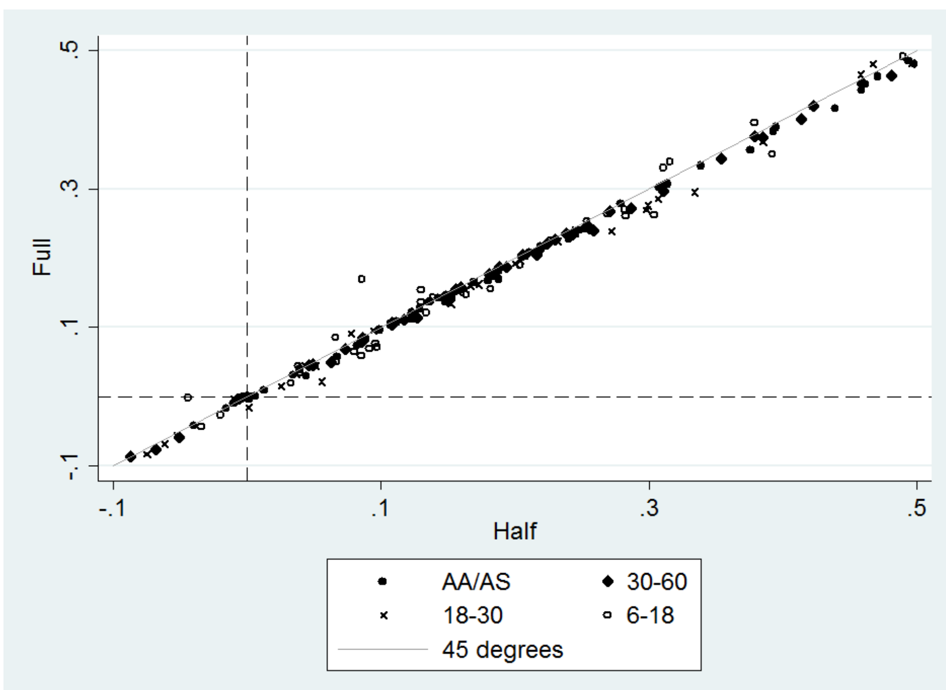


Figure 9: Full and Half Control, by Degree Type

Table A. 1: Summary Statistics for CTE award holders

		Career Technical Awards				
	All	All	AA/AS	30-60 Cert	18-30 Cert	6-18 Cert
Number of degrees	1.33	1.52	1.82	1.84	1.94	1.76
Number of CTE degrees	0.69	1.38	1.55	1.70	1.81	1.63
Years to first degree	4.46	4.40	5.02	4.40	4.39	3.73
Years to first CTE degree	4.48	4.48	5.16	4.46	4.43	3.79
Courses	39.88	37.42	45.93	39.38	39.66	38.39
Transfer Courses	26.85	22.86	30.75	22.12	24.25	22.23
Credit/Transfer Courses	33.01	30.81	38.43	33.40	32.57	30.50
Credit Courses to first degree	28.81	25.27	32.20	26.73	24.91	21.47
Credit Courses to first CTE degree	25.63	25.63	32.89	27.01	25.08	21.71
Units	81.22	77.04	96.05	84.91	80.38	74.82
Transfer units	64.09	54.70	75.65	54.02	54.39	49.82
Transfer/Credit units	68.55	61.38	77.57	66.94	59.00	50.50
Credit units to first CTE degree	62.31	62.31	79.38	67.70	59.40	51.07
Age	25.10	27.77	26.30	28.12	29.50	28.18
Female	0.59	0.52	0.59	0.52	0.51	0.51
Male	0.40	0.47	0.40	0.47	0.48	0.48
White	0.40	0.39	0.39	0.39	0.39	0.35
Black	0.07	0.07	0.07	0.08	0.07	0.08
Hispanic	0.27	0.27	0.26	0.27	0.27	0.32
Asian	0.12	0.12	0.13	0.11	0.13	0.10
Other Race	0.01	0.01	0.01	0.01	0.01	0.01
Meets Control Group Criterion	0.43	0.67	0.68	0.78	0.76	0.65
Pre-enrollment wages (median)	19015.33	20691.59	19336.87	19889.08	22019.67	18631.76
Employed pre-enrollment	0.74	0.71	0.70	0.73	0.69	0.72
N	528847	264805	136197	65828	47238	65700

Note: Sample includes degree holders whose largest degree was granted between 2003 and 2007. Recipients of multiple degrees are included in multiple columns. Wages pre-employment are defined as annual wages in the 2nd year prior to a student's first enrolled term. Employment pre-enrollment is defined as nonzero earnings in the 2nd year prior to that first enrolled term.

Table A. 2: Earnings Effects, Business and Management

	30 or older	18-30	Black	Hispanic	Asian	White	Male	Female
AA/AS	0.114	-0.0232	0.0227	0.0569	-0.00741	0.0194	-0.0251	0.0412
	(0.017)	(0.009)	(0.033)	(0.015)	(0.022)	(0.013)	(0.012)	(0.011)
Cert 30-60	0.169	0.000176	-0.156	0.144	0.322	0.0791	-0.128	0.182
	(0.043)	(0.054)	(0.173)	(0.068)	(0.080)	(0.049)	(0.070)	(0.038)
Cert 18-30	0.173	0.104	0.0925	0.0898	0.196	0.208	0.0361	0.21
	(0.024)	(0.031)	(0.054)	(0.033)	(0.038)	(0.035)	(0.031)	(0.024)
Cert 6-18	0.0581	0.0203	0.0468	0.065	0.0452	0.0791	-0.0224	0.0778
	(0.026)	(0.028)	(0.059)	(0.035)	(0.056)	(0.032)	(0.029)	(0.025)
Treatment N	7,354	16,352	1,693	5,592	5,255	7,970	10,298	13,408
Control N	18,479	41,657	3,959	11,615	13,968	21,879	28,094	32,042

Table A. 3: Earnings Effects, Information Technology

	30 or older	18-30	Black	Hispanic	Asian	White	Male	Female
AA/AS	0.0284	-0.00498	-0.101	0.0384	0.0412	0.0354	0.00617	0.00992
	(0.037)	(0.032)	(0.085)	(0.058)	(0.076)	(0.034)	(0.026)	(0.061)
Cert 30-60	0.0173	0.083	0.500	-0.108	0.462	0.0594	-0.00416	0.153
	(0.075)	(0.101)	(0.064)	(0.112)	(0.174)	(0.102)	(0.075)	(0.099)
Cert 18-30	-0.0136	0.0315	-0.0702	0.0896	-0.123	0.0155	0.0049	0.0313
	(0.054)	(0.068)	(0.133)	(0.087)	(0.105)	(0.077)	(0.045)	(0.109)
Cert 6-18	0.0646	-0.0488	-0.0992	0.0708	-0.0244	0.028	0.00438	0.096
	(0.033)	(0.039)	(0.112)	(0.048)	(0.069)	(0.038)	(0.028)	(0.056)
Treatment N	1,631	2,072	204	667	698	1,536	2,878	825
Control N	7,522	11,969	981	2,974	5,181	7,221	14,137	5,354

Table A. 4: Earnings Effects, Engineering and Industrial Technologies

	30 or older	18-30	Black	Hispanic	Asian	White	Male	Female
AA/AS	0.138	0.187	0.169	0.187	0.176	0.151	0.177	0.0589
	(0.026)	(0.016)	(0.065)	(0.025)	(0.041)	(0.022)	(0.014)	(0.055)
Cert 30-60	0.0718	0.140	0.158	0.106	0.123	0.120	0.113	0.160
	(0.019)	(0.012)	(0.052)	(0.017)	(0.033)	(0.016)	(0.010)	(0.054)
Cert 18-30	0.0674	0.0546	-0.0222	0.0475	0.0766	0.0645	0.0585	0.0656
	(0.023)	(0.017)	(0.077)	(0.024)	(0.042)	(0.020)	(0.014)	(0.062)
Cert 6-18	0.0802	0.0613	0.0867	0.0819	0.0876	0.0385	0.0674	0.0501
	(0.020)	(0.019)	(0.077)	(0.020)	(0.037)	(0.027)	(0.014)	(0.059)
Treatment N	6,774	11,919	1,009	6,188	2,076	6,865	17,412	1,281
Control N	14,047	30,520	3,101	14,624	3,850	15,293	38,972	5,595

Table A. 5: Earnings Effects, Health

	30 or older	18-30	Black	Hispanic	Asian	White	Male	Female
AA/AS	0.663	0.667	0.638	0.664	0.717	0.658	0.659	0.680
	(0.012)	(0.009)	(0.027)	(0.016)	(0.025)	(0.012)	(0.014)	(0.009)
Cert 30-60	0.334	0.303	0.278	0.360	0.259	0.323	0.299	0.329
	(0.018)	(0.014)	(0.039)	(0.022)	(0.037)	(0.019)	(0.018)	(0.014)
Cert 18-30	0.128	0.108	0.236	0.209	0.134	0.0546	0.0793	0.138
	(0.036)	(0.028)	(0.106)	(0.041)	(0.070)	(0.032)	(0.051)	(0.025)
Cert 6-18	0.0338	0.0425	0.0556	0.0123	0.0291	0.0458	0.0341	0.0179
	(0.023)	(0.016)	(0.045)	(0.025)	(0.042)	(0.021)	(0.019)	(0.018)
Treatment N	12,208	24,121	2,424	7,420	3,748	15,011	12,387	23,942
Control N	5,590	8,811	1,299	3,012	1,463	5,885	4,919	9,482

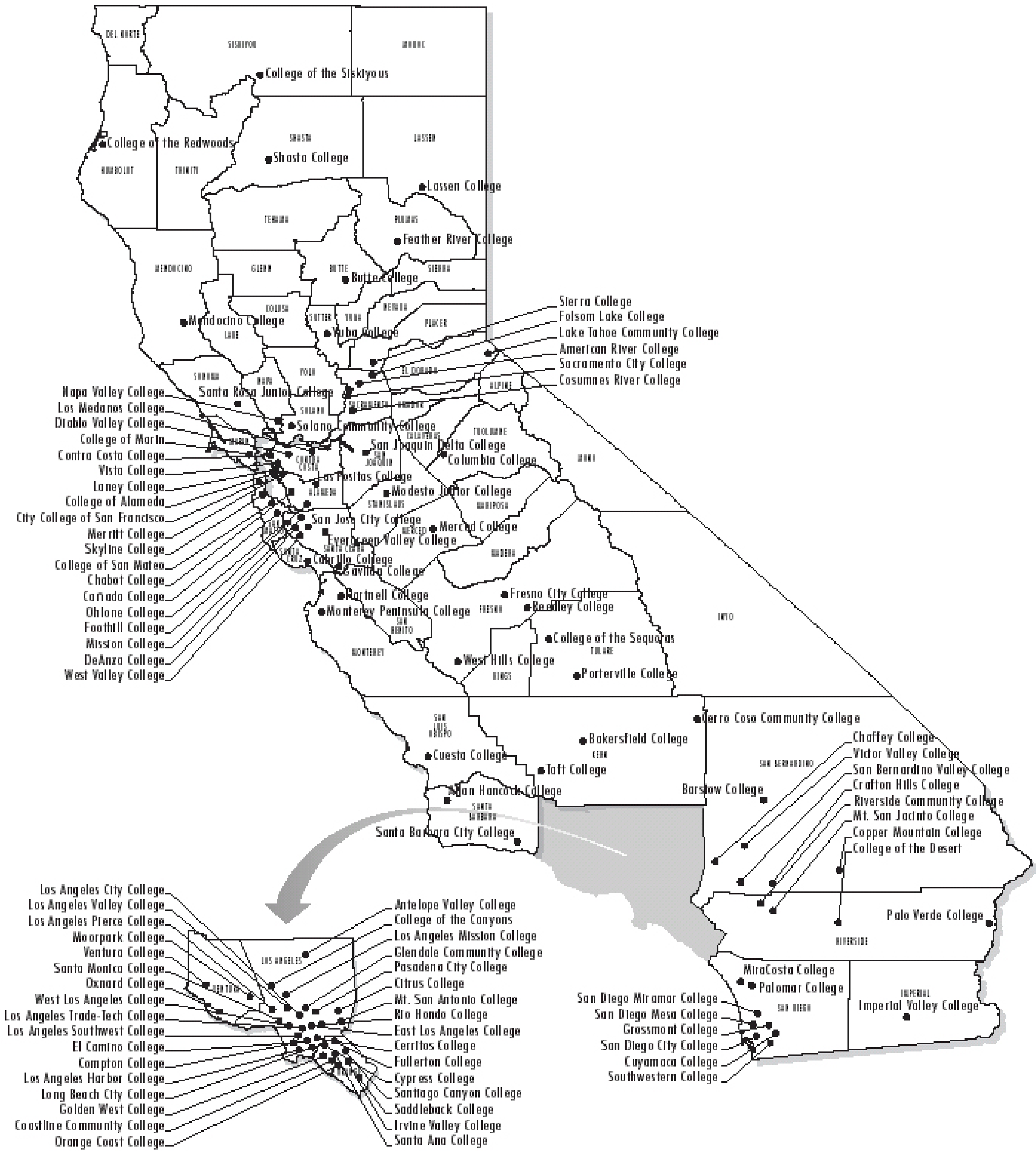
Table A. 6: Earnings Effects, Family and Consumer Sciences

	30 or older	18-30	Black	Hispanic	Asian	White	Male	Female
AA/AS	0.133	0.0942	0.119	0.11	0.147	0.11	0.0918	0.112
	(0.021)	(0.016)	(0.044)	(0.018)	(0.045)	(0.023)	(0.043)	(0.013)
Cert 30-60	0.0256	0.1	0.0896	0.0576	0.149	0.0151	0.0647	0.0859
	(0.033)	(0.029)	(0.063)	(0.038)	(0.062)	(0.045)	(0.039)	(0.027)
Cert 18-30	0.0543	0.193	0.128	0.122	0.202	0.0283	0.0666	0.136
	(0.026)	(0.029)	(0.055)	(0.029)	(0.052)	(0.042)	(0.045)	(0.022)
Cert 6-18	0.0722	0.0687	0.122	0.0646	0.0532	0.0769	0.136	0.0671
	(0.019)	(0.017)	(0.037)	(0.017)	(0.041)	(0.028)	(0.038)	(0.013)
Treatment N	7,023	9,740	1,736	6,133	2,127	4,734	2,230	14,533
Control N	12,584	20,612	2,867	11,058	3,286	11,674	3,873	29,323

Table A. 7: Earnings Effects, Public and Protective Services

	30 or older	18-30	Black	Hispanic	Asian	White	Male	Female
AA/AS	0.0892	0.119	0.0915	0.118	0.126	0.0921	0.120	0.0858
	(0.0228)	(0.0112)	(0.0436)	(0.0159)	(0.0479)	(0.0157)	(0.0120)	(0.0178)
Cert 30-60	0.175	0.152	0.217	0.163	0.129	0.159	0.132	0.237
	(0.0218)	(0.0171)	(0.0499)	(0.0246)	(0.0618)	(0.0203)	(0.0156)	(0.0263)
Cert 18-30	0.131	0.218	0.118	0.209	0.127	0.190	0.183	0.203
	(0.0214)	(0.0136)	(0.0521)	(0.0227)	(0.0747)	(0.0157)	(0.0125)	(0.0296)
Cert 6-18	0.170	0.254	0.182	0.230	0.287	0.214	0.221	0.235
	(0.0192)	(0.0102)	(0.0370)	(0.0147)	(0.0439)	(0.0147)	(0.00997)	(0.0211)
Treatment N	7,207	20,558	2,040	8,109	993	12,065	20,517	7,248
Control N	11,345	26,477	2,800	11,133	1,432	16,713	26,896	10,926

Figure A1: Map of California's Community Colleges



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