# Labor Market Returns to Community College: Evidence from Minnesota*

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**Abstract**

There is a growing consensus that obtaining a sub-baccalaureate credential leads to increased earnings. However, it remains unclear to what degree these returns are driven by increases in productivity or labor supply. Using detailed UI data from Minnesota, I estimate the labor market returns associated with completing sub-baccalaureate credentials from community colleges. First I show that these credentials increase quarterly earnings, consistent with prior findings. I then decompose the proportion of earnings returns attributed to productivity (wages) and hours worked. More than 60% of the earnings returns to completing an associate degree are due to an increase in hours, with substantial heterogeneity by field of study. This effect is largely driven by part-time workers being pulled into full-time work. Additionally, I find that those working few hours pre-college experience little-to-no wage gains from completing a credential, with nearly all of their earnings return stemming from working more hours post-graduation. Finally, I provide descriptive evidence that suggests community college credentials help individuals who were previously hours-constrained attain full-time work.

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# 1 Introduction

The original version of President Biden's "American Families Plan" included a proposed $109 billion in spending to make two years of community college tuition-free for most students (Hess, 2021). Policy-makers' interest in community college reflects two commonly-held beliefs—that college pays off for the students who graduate, and that those graduates in some way benefit society writ-large. In recent decades the increased availability of state-level linked education-workforce data has allowed researchers to shed light on the first of these beliefs. By estimating earnings returns to sub-baccalaureate credentials,[1] researchers have been able to document the extent to which community colleges open the door for students looking to increase their earnings. Several findings are well-established. First, associate degrees are linked with large earnings returns, with larger returns for women (around $2,400 per quarter) than for men (around $1,500 per quarter).[2] Long-term certificates are also associated with substantial returns (about $960 for men, $1,540 for women), though there is greater variation in estimated returns across analyses. Returns to short-term certificates are smaller, with some studies estimating returns that are not distinguishable from zero.[3]

These findings suggest that for many graduates, the labor market returns to community college are sufficiently large to justify the cost of investment. What remains unclear, however, is if graduates from these programs are becoming more *productive*, and thus earning a higher wage rate and potentially generating positive spillovers. This lack of clarity stems from the fact that, to date, most studies of returns to these credentials do not measure wages,[4] but rather earnings—an outcome reflecting the product of the wage rate and the quantity of labor supplied to the market. The distinction between these two mechanisms (wages vs. hours) is

[1] These credentials include associate degrees, which correspond to about 2 years of full-time coursework, long-term certificates (sometimes called diplomas) which require 1-2 years of coursework, and short-term certificates which correspond to less than a year of full-time coursework.

[2] These figures come from averaging estimates of the four studies in Figure 1 that report estimates by gender, all inflated to 2012 dollars.

[3] Some recent work in this vein includes Jepsen, Troske, and Coomes (2014), Liu, Belfield, and Trimble (2015), Bahr (2016), Bahr et al. (2015), Xu and Trimble (2016), and Minaya and Scott-Clayton (2020).

[4] Dadgar and Trimble (2015) is an exception in this regard, but the granularity of their analysis is limited due to a relatively small sample.

crucial for understanding the ways in which community college may benefit students, as an increase in *wages* is very likely beneficial to the student, while the implications of an increase in hours depends on the structure of the labor market. Additionally, the existence of wage returns has important implications for public finance considerations.

To better understand the source of the earnings gains, I estimate the earnings returns to sub-baccalaureate credentials and then decompose earnings returns into the proportion that is due to productivity gains (wages) versus increases in hours worked. If a large proportion of the earnings return stems from the labor supply mechanism, further work is needed to understand why. If credentials enable students to access previously unavailable hours choices,[5] they are likely welfare improving. Alternatively, if students were freely choosing hours prior to enrollment, an increase in hours worked post-graduation could imply a tighter budget constraint (or time-varying preferences), potentially due to newly-acquired student-debt. Additonally, an increase in hours could reflect a career-change post-graduation, which may require heavier hours up front.

The previous literature documents large heterogeneity in returns to credentials by field of study (with largest returns to health and STEM fields) and by gender (with largest returns to women) (Belfield and Bailey, 2017). Given the extensive heterogeneity in returns, there may also be substantial heterogeneity in the relative importance of the wage and hour margins across these dimensions. I therefore apply the earnings decomposition to returns by gender and field of study. To provide a deeper understanding of heterogeneity in returns, I also estimate returns for different groups of students based on their pre-college labor market attachment and wages.

The primary challenge with estimating the earnings, wages, and labor supply effects of completing a credential program is selection. Those who complete a credential are different from those who do not, in ways that likely affect their labor market outcomes. Several

[5]Such constraints have been discussed in great detail in the literature—see Dickens and Lundberg (1993) and Abowd and Card (1987).

papers employ a panel model approach, now canonical in the literature,[6] to address this. They exploit the fact that community college students often work before, during, and after attending college. Because of this work history, researchers can include person-specific fixed-effects, in addition to time-effects and other controls, in their models to purge the influence of time-invariant person-specific factors from post-college labor market outcomes.

I follow a similar approach using a large sample of students who ever enrolled in Minnesota colleges between 2003 and 2019. I find that completing an associate degrees lead to an increase in quarterly earnings of $1,057 and $1,742 for men and women, respectively, while long-term certificates are associated with increases of $1,734 and $835. Short-term certificates are associated with a $300-$500 increase. These figures are within the range of estimates in the previous literature (see Figure 1). I also estimate the hours and log hourly wage changes associated with completing credentials—an innovation made possible by a unique advantage of Minnesota UI data, the reporting of hours worked, in addition to earnings.[7] Completing a credential at any level increases hours worked post-graduation by 2-3 hours per week—nearly the equivalent of working an additional month of full-time work each year.[8] Additionally, completing any level of a credential is associated with an increase in log wages, reaching as high as 14% for women completing an associate degree.[9]

While this canonical approach eliminates much of the bias researchers are concerned about, it cannot address potential model misspecification. Two particular concerns—the set of controls included in the model and forbidden comparisons in two-way fixed effects models in the presence of staggered treatment[10]—are paramount. To address potential

[6]This specific approach was first used to study outcomes of displaced workers by Jacobson, LaLonde, and Sullivan (2005). Beyond the community college sector, the panel data approach has been employed to estimate the effect of various treatments on earnings in circumstances where pre-treatment earnings are available for analysis. Examples include joining a union (Freeman, 1984) or completing a masters degree (Arcidiacono, Cooley, and Hussey, 2008)(Altonji and Zhu, 2020).

[7]Although all states maintain UI records, only a handful of states, such as Minnesota and Washington, require employers to report hours worked for each employee.

[8]Hours effects are slightly larger for women than men.

[9]Wage returns are largest for women completing associate degrees and men completing long-term certificates. Short-term certificates are associated with the smallest wage returns.

[10]Specification problems with two-way fixed-effects models have been documented extensively in Athey and Imbens (2022), Borusyak, Jaravel, and Spiess (2021), Callaway and Sant'Anna (2021), De Chaisemartin

misspecification of controls I implement Coarsened Exact Matching as outlined in Iacus, King, and Porro (2012) which estimates treatment effects between subsets of individuals who have the same, or nearly the same values for different control variables, reducing the extent to which the results are sensitive to the parametric model assumptions. The matching approach yields results similar to, though less precise than,[11] the panel model, with slightly smaller wage effects and slightly larger hours effects.

To address specification issues with two-way fixed-effects models, I implement the imputation-based approach of Borusyak, Jaravel, and Spiess (2021),[12] which prevents forbidden comparisons by estimating the person-effects, time-effects, and coefficients on covariates using the never-treated and not-yet-treated observations, and then using these coefficients to impute counterfactual outcomes for credential completers post-graduation. Results of the imputation estimator are similar to those of the panel model in many respects, though earnings returns for men completing an associate degree are larger compared to the results of the panel model—the product of the imputation estimator properly handling earnings dynamics. I also estimate wage and hours effects of completing a credential using the imputation to properly account for dynamic effects. Using the imputation approach, I find that about 60% of the earnings returns to an associate degree are driven by an increase in hours worked, rather than higher wages. The role of hours is even larger for those earning certificates.

In addition to addressing specification issues in the two-way fixed-effects model, the Borusyak, Jaravel, and Spiess (2021) estimator provides an intuitive lens for exploring treatment effect heterogeneity. The imputation estimator generates individual treatment effects, which are then aggregated to obtain an average treatment effect over some population or time period of interest. I aggregate individual treatment effects over students in each field

and d'Haultfoeuille (2020), Goodman-Bacon (2021), and Sun and Abraham (2021).

[11] CEM prunes observations to keep only those treatment observations for which there exists a control observation with similar pre-treatment covariates.

[12] Many alternative methods have been proposed to address various issues with two-way fixed-effects models, see Callaway and Sant'Anna (2021), Gardner (2022), Liu, Wang, and Xu (2021), Sun and Abraham (2021), and Wooldridge (2021). This method was chosen because of the ease with which it can be adapted to handle multi-valued treatment and time-varying covariates, while providing an intuitive lens for the analysis of treatment effect heterogeneity.

of study to generate field-specific estimates and document large heterogeneity by field. I then decompose the earnings returns in each field into hours and wage effects. Returns to fields such as the arts and humanities are almost entirely driven by increased hours, while returns to fields such as health are primarily driven by higher wages. I then document how estimated returns evolve over time post-graduation. Wage returns for associate degrees and long-term certificates grow gradually after graduation, and more slowly for men, while hours effects appear immediately and persist over time. Additionally, I find that wage and hours returns to short-term certificates fade within a few years of graduation. Finally, I consider distributional effects of degree receipt by pre-enrollment labor market attachment, documenting which students see an increase in wages. Wage returns are highest for those with strong pre-college labor market attachment (about 20% wage return to an associate degree for women working 45 or more hours each week), and earnings returns for those with weak labor-market attachment are driven almost exclusively by the hours margin (no wage return to an associate degree for men working fewer than 15 hours per week).

For many, a large component of the earnings return to completing a community college credential stems from working more hours post-graduation—the equivalent of an additional month of full-time work every year for associate degree recipients. This effect is primarily driven by students moving into full-time work post-graduation. Earnings returns in some fields, such as public administration, are almost entirely driven by an increase in hours worked. These credentials may help students by providing access to full-time jobs that were previously unavailable to them. Alternatively, individuals may increase their labor supply at the same wage to finance their increased student debt burden. Returns in other fields, such as health and trades, are primarily driven by wage increases, implying that those programs are likely productivity improving. Additionally, wage returns are the highest among those with stronger pre-college labor-market attachment, providing suggestive evidence of complementarities between attending community college and gaining work experience, although further research is needed. Additionally, those with the weakest pre-college labor market attachment see little to no wage gains from completing a credential, suggesting that policies aimed at helping individuals connect with employers could be effective, either in tandem with, or as an alternative to the credential program.

# 2 Data

I use data from the Minnesota State Longitudinal Education Data System (MN SLEDS), which includes secondary, post-secondary, and workforce data for individuals in Minnesota. The Minnesota State College and University System (MnSCU) is home to 30 colleges and 7 universities which offer a wide range of academic programming.[13] These colleges and universities offer a mix of associate degrees and certificates of varying lengths. The SLEDS data available for this study includes information for any individual who either attended a Minnesota community college or pursued a certificate or associate degree at a four-year Minnesota college between 2003 and 2019.[14] I restrict the sample to those who attend public institutions, never pursue a baccalaureate or higher credential in Minnesota, and for whom no demographic data is missing.[15]

For this set of individuals I observe demographic data, college enrollment and completion, and work histories. The demographic data contains students' gender, race, and birth month and year. Education data include high school attended and date of high school graduation, as well as college enrollment dates, number of credit hours, institution attended, and credentials awarded. For those completing a credential, date of award, degree type (associate, long-term certificate, or short-term certificate) and field of study are observed.[16] Finally, the workforce data includes information from Minnesota's UI system, and includes quarterly

[13]The University of Minnesota system, a separate entity, is also included in the SLEDS data, but is not the primary focus of this analysis as it primarily offers baccalaureate and graduate programs.

[14]While both community colleges and four year colleges are in my sample, the vast majority of students pursuing sub-baccalaureate credentials do so at a community college.

[15]Given this restriction, estimates of returns speak directly to the outcomes of individuals who enter the labor market after completing a community college credential. As such, these estimates do not capture the option value of continuing to a higher degree program.

[16]Field of study is recorded as Classification of Instructional Programs (CIP) Codes, and is only observed for credential completers. Intended field of study is not observed for non-completers.

data on earnings, hours worked, workers' tenure at each of their employers, and employer industry for individuals employed at covered employers in the UI system. For the entirety of this analysis, earnings and hours worked are aggregated across all employers for each individual in each quarter, and employer information is retained for the employer at which the individual works the most hours. Additionally, I calculate each individual's hourly wage in a given quarter by dividing total quarterly earnings by total quarterly hours worked. Weekly hours, rather than quarterly hours, are used in this analysis for ease of interpretation, and are calculated by dividing total quarterly hours worked by 13, the number of weeks in a quarter.

I impose further restrictions to create an analysis sample. Because I'm interested in learning about the labor market returns to completing a credential, I focus on a subset of students who have some positive earnings prior to enrolling in college (but after graduating high school) in order to create a baseline against which post-college earnings can be compared. As such, I drop individuals who have fewer than three post-high-school, pre-college working quarters.[17] While this restriction cuts the size of the sample substantially, it allows for a cleaner interpretation of treatment effects. This restriction may raise concerns about interpretability of treatment effects for students that enter community college directly after completing high school. In Table 1, I show some descriptive statistics for two samples—those with fewer than three quarters of pre-college work experience, which includes those who attend college immediately after high school, and the analysis sample, which includes only those who have at least three quarters of post-high-school, pre-college work experience. These samples differ on a few margins—the sample with little pre-college work experience skews younger, and enrolls in heavier course loads. Importantly, the post-college labor market outcomes are very similar across samples.

Summary statistics for the analysis sample by degree-type and gender are presented in Table 2. A few patterns are of note. First, non-completers are the oldest at the time of

[17]Results are robust to further restricting the sample to individuals with longer pre-college work histories. See Table 7 in the Appendix 1.

enrollment, and those who eventually earn an associate degree are the youngest. Additionally, those that earn an associate degree work about as much pre-college as the other groups, but at slightly lower wages. While non-completers and long-term certificate completers see their earnings decline while enrolled, associate degree and short-term certificate completers see their earnings increase relative to pre-enrollment. Notably, all groups have similar labor market trends prior to enrollment—a small decrease in earnings, wages, and hours worked. Table 2 also illuminates substantial differences by gender. Specifically, women tend to enroll in fewer credit hours per term, but complete more credit hours overall. Differences in enrollment patterns by gender become more apparent when considering the gender distribution of students by different credentials and majors. Figure 2 shows the relative prevalence of men and women in six different field of study groupings.[18] While it is clear that some variation exists across degree-type, the most substantial gender differences in enrollment are by field of study. Men tend to enroll more heavily in Trades, STEM, and Security and Public Administration. Women tend to enroll more heavily in Health fields and Arts and Humanities.

Table 3 presents summary statistics by field of study and gender. Since field of study is not observed for non-completers, all individuals in this table hold a credential. Students in trade fields enroll more intensely than any other gender-field group. Additionally, students in the arts and humanities and STEM accumulate more credits than any other field—likely in preparation to transfer to a 4-year college.[19] The median student in each gender-field cell works at least 15 hours per week before college, with the heaviest workload for men in trade fields, of whom the median student works 26 hours per week. Most students earn between \$9 and \$11 per hour before college.

The data offer a rich understanding of community college students in Minnesota, but

[18] These groupings represent Classification of Instructional Program (CIP) codes, created by the National Center for Education Statistics, collapsed to the program-family level, which I then further aggregate. The specific aggregation scheme is detailed in Appendix 2.

[19] I exclude individuals from my sample who eventually enroll in or complete a higher credential, but many students may intend to do so.

there are a few limitations, common to the literature, which may impact the generalizability of results based on this data. Like other studies utilizing UI data, the workforce data in this study contain information only for covered employers in the UI system, meaning some groups, such as those in the clergy, independent contractors, sole proprietors, and members of the military will not appear. This is not necessarily a problem for internal validity, but it should be considered when generalizing results. Additionally, the data contain information only on individuals who attended college in Minnesota, and only include workforce data from Minnesota. As such, individuals who attended community college outside of Minnesota will not appear in the data, even if they eventually work in Minnesota, and individuals who attend community college in Minnesota but then work outside of Minnesota will appear in the education records, but not in the earnings records. Foote and Stange (2022) demonstrates that out-of-state migration can be problematic for the estimation of returns to post-secondary education, causing estimates to be biased downward when returns are estimated only on those that stay in-state. Foote and Stange (2022) documents that this bias is largest for flagship and highly selective colleges, finding considerably smaller bias of about 0.01 log points in earnings returns at Career and Technical Education (CTE) programs at 2-year colleges. This suggests that earnings returns here may be slightly understated.[20]

# 3 Empirical Approach

I investigate the effects of community college credentials on three outcomes: quarterly earnings, as well as hourly wages and hours worked. I estimate treatment effects by first estimating the canonical panel model typically used in the literature, and then add refinements to address potential concerns about sensitivity to modelling choices. I then estimate models that address some of the problems with estimating two-way fixed effects (henceforth TWFE) models in the presence of dynamic treatment effects and staggered treatment, which has the

[20]MN community colleges have open admissions policies, which require only that an individual have a high school diploma or GED to enroll.

added benefit of enabling a principled lens through which treatment effect heterogeneity can be explored.

## Canonical Model

To address the primary challenge associated with estimating returns to schooling—selection into schooling level by ability—the canonical model of returns to community college credentials exploits the fact that many community college students work in the labor market before, during, and after college.[21] This allows researchers to leverage pre-college labor market outcomes to control for time-invariant unobservables about individuals that may affect their labor market outcomes. Typically, this model takes the following form:

$$Outcome_{it} = \beta Award_{it} + \gamma Enrolled_{it} + \eta_t + \pi_i + \rho Demog_{it} + \epsilon_{it} \tag{1}$$

where $Outcome_{it}$ is the outcome of interest (either quarterly earnings, log hourly wages or weekly hours) for individual $i$ at time $t$, where $t$ is measured in quarters.[22] $Award_{it}$ is a set of three indicator variables corresponding to each type of credential (associate degree, long-term certificate, and short-term certificate). Each takes on a value of 1 for any period $t$ in which individual $i$ holds a credential of that type, and 0 otherwise. Individuals are classified by the highest credential they completed, so an individual who, for example, completed a short-term certificate and then an associate degree would appear as only holding an associate degree.[23] $\beta$, the coefficient of interest, is the change in $Outcome_{it}$ associated with receiving a credential.

$Enrolled_{it}$ is a set of four indicator variables related to an individual's college enrollment status. I include an indicator that takes a value of 1 for quarters in which a student is cur-

[21] See, for example, (Minaya and Scott-Clayton, 2020), (Dadgar and Trimble, 2015), and (Jepsen, Troske, and Coomes, 2014).

[22] Log hourly wages are constructed by performing a natural log transformation on hourly wages.

[23] Fewer than a quarter of students who complete an associate degree ever complete a certificate. By assumption, I attribute all returns to the highest credential received. As such, returns to an associate degree could be somewhat inflated relative to returns to a certificate.

rently enrolled; an indicator that takes on a value of 1 in post-enrollment quarters (regardless of whether they obtained a credential upon leaving); an indicator that takes a value of 1 in the quarter immediately prior to college enrollment; and an indicator that takes a value of 1 two quarters prior to enrollment. These variables capture changes in earnings and hours associated with the transition into and out of college that are not directly due to credential receipt. Specifically, the post-enrollment indicator captures changes in the outcome of interest that are due to exiting college, but not necessarily due to completing a credential. The current enrollment indicator captures changes in the outcomes of interest related to being actively enrolled in school while working, such as when students reduce their hours to focus on their schooling[24] The indicators for one- and two- quarters prior to enrollment, a standard in the literature, capture the fact that individuals sometimes enroll in college following a decrease in their earnings (known as the "Ashenfelter Dip") (Minaya and Scott-Clayton, 2020). It is worth noting that depending upon the treatment effect of interest, researchers may *want* to include gains relative to a lower pre-college baseline in the estimation of returns to a credential.

$\eta_t$ are indicators for each year-quarter (time effects), which control for labor market conditions over the business cycle. This is particularly helpful if certain quarters are associated with higher earnings or hours worked and also a higher (or lower) likelihood of completing a credential. For example, one might be concerned that quarters during the financial crisis and subsequent recession of 2008-2009 are associated with lower earnings *and* differential likelihood of credential completion. $\pi_i$ are individual-specific fixed-effects, which capture time-invariant person-specific factors that may influence earnings and propensity to earn a credential. $Demog_{it}$ is a vector of time-varying demographics, common to the literature, which include year of first enrollment, race, and age at entry interacted with a time trend.

I estimate this model separately for men and women, with earnings imputed as zero for

[24] I estimate an alternate specification in which I drop all quarters in which an individual is enrolled and remove $Enrolled_{it}$ from the model. The results are in appendix 3, and are qualitatively similar to the main results from the primary specification. Students are defined as currently enrolled for all quarters between their first and last recorded enrollment dates.

quarters in which no earnings are reported to the UI system.[25] All outcome variables are winsorized at the 0.05 percent level to address obvious outliers and data missreporting (such as individuals working more hours in a given quarter than is physically possible).

While this empirical approach can address a number of threats to identification—namely the bias stemming from time invariant factors that affect both labor market outcomes and credential receipt—there are still potential causes for concern. Specifically, concerns about model misspecification and dynamic selection remain. In order to address potential misspecification of controls, and to improve covariate balance between degree recipients and non-completers, I implement Coarsened Exact Matching, as outlined in Iacus, King, and Porro (2012). Additionally, to address misspecified dynamics that occur when estimating a model with two-way fixed-effects (TWFE), I implement the procedure outlined in Borusyak, Jaravel, and Spiess (2021), henceforth referred to as BJS.

## Matching Model

I estimate equation 1 on a sample of matched treated and control individuals using Coarsened Exact Matching (henceforth CEM) as outlined in Iacus, King, and Porro (2012).[26] CEM, a procedure in a larger class of balancing procedures, prunes observations (preferably control observations) that are outside the common empirical support of pre-treatment covariates between treated and control individuals. This has the benefit of limiting the extent to which estimation results are sensitive to the parametric assumptions of the model. CEM, like other matching procedures places observations into strata in which the observations have similar pre-treatment covariates, prunes strata that do not have both treated and control units, and then estimates treatment effects *within each strata*. This coarsening procedure allows for "near-matches" among observations, which is essential when matching on continuous variables. Because CEM allows for estimation of *within-strata* treatment effects, the functional form of the empirical model used to estimate the effects is less central—and misspecification

[25] This is true only for quarters between an individual's first and last appearance in the UI data.
[26] For an alternative approach using propensity scores, see Table 14 in Appendix 6.

less damaging—to estimation results. This is because the empirical model is tasked only with controlling for two factors—that which was not matched on, and that which *was* matched on, but only within-strata (within the given level of coarsening). For more details on how I implement CEM, see Appendix 5.

## Imputation Estimator

I implement an alternative to the standard panel data model estimated with two-way fixed effects. Specifically, I estimate a difference-in-differences model using the imputation procedure developed in Borusyak, Jaravel, and Spiess (2021). This procedure first regresses the outcome of interest on the non-treatment-indicator covariates (including person and time effects) *for never-treated and not-yet-treated observations only*, then uses these estimates to impute a counterfactual outcome for treated individuals in the post-treatment periods. Next, *individual level* treatment effects are calculated by taking the difference between the observed outcome and the imputed outcome in each post-treatment period. Finally, the average treatment effect on the treated individuals is calculated by taking an average of the individual treatment effects.[27] I use the BJS procedure to estimate the effect of completing a credential on earnings, hours, and log hourly wages.

This imputation procedure is particularly useful in sidestepping issues with two-way fixed effects (TWFE) models in the presence of staggered adoption of treatment and heterogeneous treatment effects. These issues stem from forbidden comparisons between late-treated individuals and early-treated individuals in the presence of dynamic treatment effects.[28] The extent of the bias due to these comparisons is not known a priori. Long panels with potential dynamic treatment effects may exacerbate the problem, but having a large pool of “control” individuals may help alleviate it. Borusyak, Jaravel, and Spiess (2021) offer an intuitive

[27] Borusyak, Jaravel, and Spiess (2021) offers multiple ways of aggregating individual treatment effects to obtain various treatment effects of potential interest.

[28] Problems with TWFE models have been highlighted in Athey and Imbens (2022), Borusyak, Jaravel, and Spiess (2021), Callaway and Sant’Anna (2021), De Chaisemartin and d’Haultfoeuille (2020), Goodman-Bacon (2021), and Sun and Abraham (2021).

procedure for addressing these concerns.

In addition to providing a solution to problems with the TWFE model, the BJS procedure, by generating individual treatment effects that may be averaged into different treatment effects of interest, provides an intuitive approach for exploring treatment effect heterogeneity across several dimensions. I utilize this method to estimate not only returns in the static model and a dynamic-effects model, but also returns by pre-college labor market attachment. To construct the dynamic estimates, I average individual treatment effects in each quarter since degree completion. To construct the estimates by labor market attachment, I split people into bins based on their pre-college hours worked, and average the treatment effects across individuals in the same bin.

# 4 Results

I present results as follows. First, I show estimated returns using the canonical model for each outcome. Next, I show results from the same model specification using the matched CEM sample. I then show results using the imputation procedure described in the previous section, documenting the extent to which gains in hours explain the earnings return, overall and by field of study. Finally, I document treatment effect heterogeneity by pre-college labor market attachment using the imputation estimator. For a visual representation of estimated returns (earnings, wages, and hours) across estimation methods, see Figures 3, 4, and 5, respectively.

## Baseline

Panel A of Table 4 shows the estimated effect of completing a credential (associate, long-term certificate, and short-term certificate) on quarterly earnings, weekly hours, and log hourly wages, by gender.[29] All three credential types are associated with higher quarterly earnings.

[29]For an outline of how coefficient estimates evolve as controls are added to the model, see Table 9 in appendix 4.

Results in Column 1 indicate that for men, associate degrees are associated with a $1,057 increase in quarterly earnings, while returns to a long-term certificate are even higher—about $1,733. Short-term certificates are estimated to increase men's quarterly earnings by $489. Women see the largest returns to an associate degree—about $1,742—while long-term certificates and short-term certificates are associated with earnings returns of $835 and $316 respectively. These findings are broadly similar to those in the literature, with a few notable differences—estimated returns to an associate degree are somewhat lower than previous estimates, while returns to long-term certificates are somewhat higher. Additionally, while finding that women see larger gains than men for associate degrees is common in the literature, my estimates suggest that men see higher returns than women to long-term certificates, a deviation from previous estimates and a finding that I revisit as alternate estimation strategies are considered.

Columns 2 and 3 show estimates of the effect of completing a credential on weekly hours worked and log hourly wages, respectively. Results indicate significant increases in hours and wages associated with each type of credential. Men and women experience similar increases in hours worked, about three hours per week on average, after completing an associate degree or long-term certificate—an effect equivalent to working one additional month of full-time (40 hours per week) work each year. Smaller but still significant effects on hours appear for the short-term certificate.[30] Results for log hourly wages are significant and positive across all credential types for both men and women, but magnitudes differ sharply by gender. Men see the largest wage increase associated with completing a long-term certificate, about 11%, while their return to an associate degree is 5%. Women achieve a nearly 14% increase in wages from completing an associate degree, while the return is closer to 8% for the long-term certificate. Both men and women receive a wage increase of about 3% upon completion of a short-term certificate. The sharp contrast in wage returns by gender and credential type

[30]Since only formal work at employers covered in the U.I. system appear in the earnings data, it should be noted that an increase in hours could reflect a shift away from informal (and thus unobserved) work and toward supplying more labor in the formal sector.

reflect an important feature of the credential programs—field of study. The vast majority of students receiving a credential in the trade fields, where long-term certificates are relatively more common, are men. In contrast, the overwhelming majority of students in health fields, where associate degrees are more common, are women. If these fields are associated high wage returns, then some of the variation in wage returns to associate degrees and long-term certificates by gender may be explained by this composition effect.

While these findings offer new insights into the returns to community college credentials, I implement two strategies to address potential model misspecification. First, I implement the matching model described in the previous section. Panel B of Table 4 provides results for earnings, hours, and log hourly wages, but using the CEM matched sample. Although the matching procedure improved the covariate balance substantially, estimated returns are very similar to those in the previous table, just less precisely estimated.[31] Earnings and wage returns for associate degrees are somewhat smaller than in the panel model. Additionally, the estimated effect of a short-term certificate on hours is higher in the CEM specification than the panel model. Most other CEM estimates are well within the confidence intervals of the panel model estimates.

Turning to the BJS imputation estimator, Panel C of Table 4 documents similar patterns in estimated returns, with most estimates of the effect of a credential on earnings, wages, and hours being slightly larger than the panel model results and generally falling within the confidence intervals of the panel model estimates. One notable exception is the earnings return to completing an associate degree, where the estimated effect for men is substantially larger than in the panel model ($1,661 as opposed to $1,057 in the panel model). This deviation highlights an advantage of the imputation estimator relative to the canonical approach - it is able to properly account for dynamic treatment effects.[32] This is particularly important in this setting, given that college credentials may offer long-run benefits in the labor market,

[31] See appendix 5 for more information on CEM implementation and covariate balance.

[32] Other proposed estimators, such as those of Callaway and Sant'Anna (2021), Gardner (2022), Liu, Wang, and Xu (2021), Sun and Abraham (2021), and Wooldridge (2021), may also be used to properly account for dynamic treatment effects.

such as increased likelihood of receiving a promotion, and students are able to be observed over a long period of time. Given these advantages, I proceed with the remainder of the analysis using the imputation estimator.

Panels A and B of Table 5 show the results of estimating equation 1 and aggregating treatment effects for individuals within the same field of study, for weekly hours worked and log hourly wages, respectively. Since field of study is not observed for non-completers, the "control group" is the same across each field of study. Several fields are associated with large increases in hours, with the largest effects in health, STEM and trade fields.[33] Due to small sample sizes, some credential-field-gender cells have been omitted. Associate degrees in health, STEM and trade fields are associated with very large wage returns for men—about 31%, 13%, and 16%, respectively. Associate degrees in health and trade fields have similarly large wage returns for women.

To understand the relative importance of the wages margin and hours margin to earnings returns, overall and by field of study, I construct an elasticity that approximately measures the proportion of the increase in earnings that is associated with an hours increase. This elasticity is defined as:

$$\varepsilon_{Credential,Field} = \frac{\hat{\beta}^{LogHours}}{\hat{\beta}^{LogQuarterlyEarnings}} \tag{2}$$

where $\hat{\beta}^{LogHours}$ is the coefficient taken from estimating equation 1 using the imputation estimator with log hours as the outcome, while $\hat{\beta}^{LogQuarterlyEarnings}$ is the coefficient taken from estimating equation 1 with log quarterly earnings as the outcome. If $\varepsilon_{Credential,Field} = 1$ this implies the entirety of the earnings increase is due to an increase in hours. Likewise, if $\varepsilon_{Credential,Field} = 0$, this implies that the earnings increase is driven entirely by an increase in the wage. If $0 < \varepsilon_{Credential,Field} < 1$, the elasticity represents the proportion of the earnings increase that would have occurred if the observed hours increase had occurred in the absence of a wage increase. In addition to this effect, if there is a wage gain, then the interaction of

[33] Public Administration is estimated to have a very large effect on hours worked at the long-term certificate level for men. The near entirety of this credential-field cell are people completing a certificate in Criminal Justice, directly tied to Minnesota licensing requirements to work in law enforcement.

the wage increase and hours increase also explains a portion of the earnings increase, with the remainder being attributable to a wage increase alone.[34] Finally, if the elasticity is below zero, this implies that either hours decreased while earnings increased, or the opposite. If the elasticity is greater than one, then earnings increased by less than the hours increase, implying that wages fell.

Elasticities are reported in Panel C of Table 5. At least 60% of the earnings return for women, and 80% of the earnings return for men, are due to an increase in hours worked for associate degree recipients. Associate degrees in health fields are primarily driven by wage increases, with about 40% of earnings returns for women, and the entirety of the earnings return for men being due to wage increases alone. Earnings returns to business fields are primarily driven by wage increases for men, but hours increases for women. Finally, some fields such as arts and humanities and public administration are either entirely or nearly entirely driven by an increase in hours worked, implying no wage increase.

Figures 3, 4, and 5 show how estimated earnings, wages, and hours effects vary depending on the estimation method. Estimates are remarkably stable across methods, and together they tell a compelling story—community college credentials are associated with positive labor market returns, although much of the return is due to students working more hours post-graduation. In addition to the these estimates, students and policymakers might like to know how the impact of these credentials evolves over time.

Dynamic effects are important for understanding how long it takes students to recoup the costs of attending, if the benefit of a credential is short-lived, or if credentials with low immediate benefit pay off over a longer horizon. This could be the case if, for example, a degree does not immediately help a student find a better job, but makes them the preferred candidate for promotion later in their careers. I present dynamic estimates for log wages and hours worked in Figures 6 and 7. Wage returns to an associate degree occur immediately for

[34]For this exercise, I assume labor supply is inelastic. If hours respond positively to wage increases, the elasticity here represents an upper-bound on the hours affect. Labor supply elasticities within the range found in the literature are not large enough to explain the hours increases found here.

women, and persist at least 8 years post-graduation, while the wage increase happen more gradually for men. Men and women both see gradual wage returns to completing a long-term credential, which eventually level-out, and perhaps taper slightly for women. Although short-term certificates are associated with slightly higher wages initially, this effect fades quickly, with wages returning to their pre-degree baseline within 3-5 years of graduation. Taken together, these findings suggest that the value of associate degrees and long-term certificates persists many years after graduation, while short-term certificates are of questionable value. The effect of completing a credential on hours worked appears within a year of graduation. This effect for associate degrees persists for men, while it begins to taper slightly for women after 3-5 years, with the pattern reversed for long-term certificates. Short-term certificates are associated with an immediate increase in hours worked, with the effect persisting for about 3-5 years, before starting to taper.

## Heterogeneity

In addition to knowing how quickly different credentials will pay off, policymakers, administrators, and students might be particularly interested in how the effect of a completing a credential interacts with a student's prior labor market attachment. This would allow policymakers to better understand the importance of connecting students to employers before or during enrollment. Table 6 documents the effect of a credential on log hourly wages. In Panel A, each column represents a subset of individuals based on the number of weekly hours they were working prior to enrolling in college. The largest wage increases are concentrated amongst those who were working full-time or more pre-college—women working 45 or more hours per week pre-college who earn an associate degree experienced a 20 log point increase in wages, compared with an 8 log point increase for those working less than 5 hours per week pre-college. A similar, more stark pattern emerges for men, with no wage gains materializing for associate degree holders working fewer than 15 hours per week pre-college. These findings suggest a potentially important link between community college students' pre-college labor market experience and their subsequent returns which warrants further exploration. Finally, Panel B documents the heterogeneity in wage returns by individuals' percentile in the pre-college wage distribution. These results suggest it is those at the very bottom of the pre-college wage distribution—the bottom 10%—for whom the wage payoff to completing a credential is largest, with gains of about 14% and 24% for completing an associate degree for men and women, respectively.

# 5 Discussion and Areas for Future Work

Each of the empirical approaches—the canonical panel model, coarsened exact matching, and the BJS imputation estimator—all do a good job of controlling for permanent differences across workers that have already manifested in labor market outcomes prior to entry. However, it remains an open question as to why some individuals leave without a credential while others graduate. If graduates and non-completers were assigned to treatment at random, then these results would reflect the average treatment effect. More plausibly, if non-completers leave school because they learn the return to a credential for them is relatively small, then my approach would be estimating the effect of the treatment on the treated. More concerning is the possibility that there is some time-varying factor that influences both degree completion and labor market outcomes. While I cannot directly rule out dynamic selection, it is worth considering a few examples of potential dynamic selection. Consider a health shock: if an individual experiences a decline in their health, or the health of a family member, this may negatively impact their ability to complete a credential, and also have a negative effect on their subsequent earnings or hours worked. If this sort of dynamic selection occurs, it would bias the estimated returns upward, but an implausibly large proportion of students would have to receive a negative health shock to be driving the main results—the graduation rates at community colleges are around 30% in Minnesota. Alternatively, consider the case of an individual receiving a high wage offer while in school that induces them to leave before completing a credential—this would bias estimated returns downward. While I cannot test for these cases directly, it is worth considering some descriptive evidence. Figure 8 shows the median hourly wage profiles over the early stages of the life-cycle for three groups—high school graduates, those with some college, but no degree (as defined in the CPS), and the SLEDS college non-completers. Both the high school graduates and some college, no degree samples are based on the Current Population Survey of individuals in MN from 2003-2019 (Flood et al., 2020). While there are level differences between the CPS and SLEDS non-completers, all three groups are on similar trajectories before and after the most common school-going ages, during which students likely have relatively lower earnings. If non-completers tended to receive negative shocks, this would likely be reflected by the SLEDS non-completers facing declining earnings relative to high-school graduates in the CPS. Alternatively, if non-completers receive high outside wage offers, we might expect to see rising earnings relative to high-school graduates. Given that such biases are unlikely to be driving the main results, I now turn to a few descriptive exercises that provide additional context beyond average treatment effects, which are useful in aiding interpretation of the findings.

Figure 9 plots individuals' hours and wages treatment effects. Hours effects and wage effects are slightly negatively correlated. More strikingly, average treatment effects mask large variation in student's outcomes. About 35% of credential completers saw an increase in both hours and wages relative to their counterfactual, while 20% of completers experienced a decrease in both hours worked and wages, and 45% saw an increase in hours or wages, but a decrease in the other. Additionally, Figure 9 shows the wide range of estimated hours effects.

When does completing a credential results in an increase in hours? First, consider Figure 10, which shows the distribution of actual and imputed-counterfactual hours worked post-graduation for credential completers. Relative to what the model predicts would have happened in the absence of credential completion, graduates are much more likely to be working full-time.[35] This suggests that the hours effect of completing a credential is largely driven by graduates being drawn into full-time work. Further, Figure 11 shows the actual and imputed percentage of credential completers working full-time post-college by their pre-college level of hours worked. Completing a credential substantially increases the likelihood of working full-time post-graduation, regardless of how many hours a student worked beforehand. This suggests that completing a credential is effective at connecting students—whether they were only marginally attached to the labor market, or already working 30 hours per week— to full-time employment.

To better understand why these effects appear, consider Figure 12, which documents the industries that students transition in- or out- of post graduation. Non-completers and graduates alike move out of food service, retail, arts and entertainment, and administrative support industries and into industries such as health care, finance, professional and scientific services, construction, mining and gas extraction, and utilities. Graduates who are in the top-quarter of the hours-effect distribution move into these industries more intensely relative to non-completers, while those in the bottom of the hours-effect distribution do so less intensely. This finding is consistent with certain industries being more closely associated with full-time employment, suggesting that those who do not experience an increase in hours may in fact be stuck—unable to transition to a new line of work post-graduation.

If those who are induced into full-time work post-graduation were previously unable to access full-time work, it is likely that the extent to which students were constrained could depend on where the student lives. Those in thicker labor markets, such as in large cities, may be relatively less constrained than those in rural areas where relatively fewer employment opportunities exist. Aggregating hours effects separately for those who went to school in rural areas and urban areas[36] provides suggestive evidence in support of this hypothesis—the estimated hours effect of a credential is about 57% higher for those in rural

[35] There is also a thicker left-tail in the actual hours distribution, relative to the imputed counterfactual.

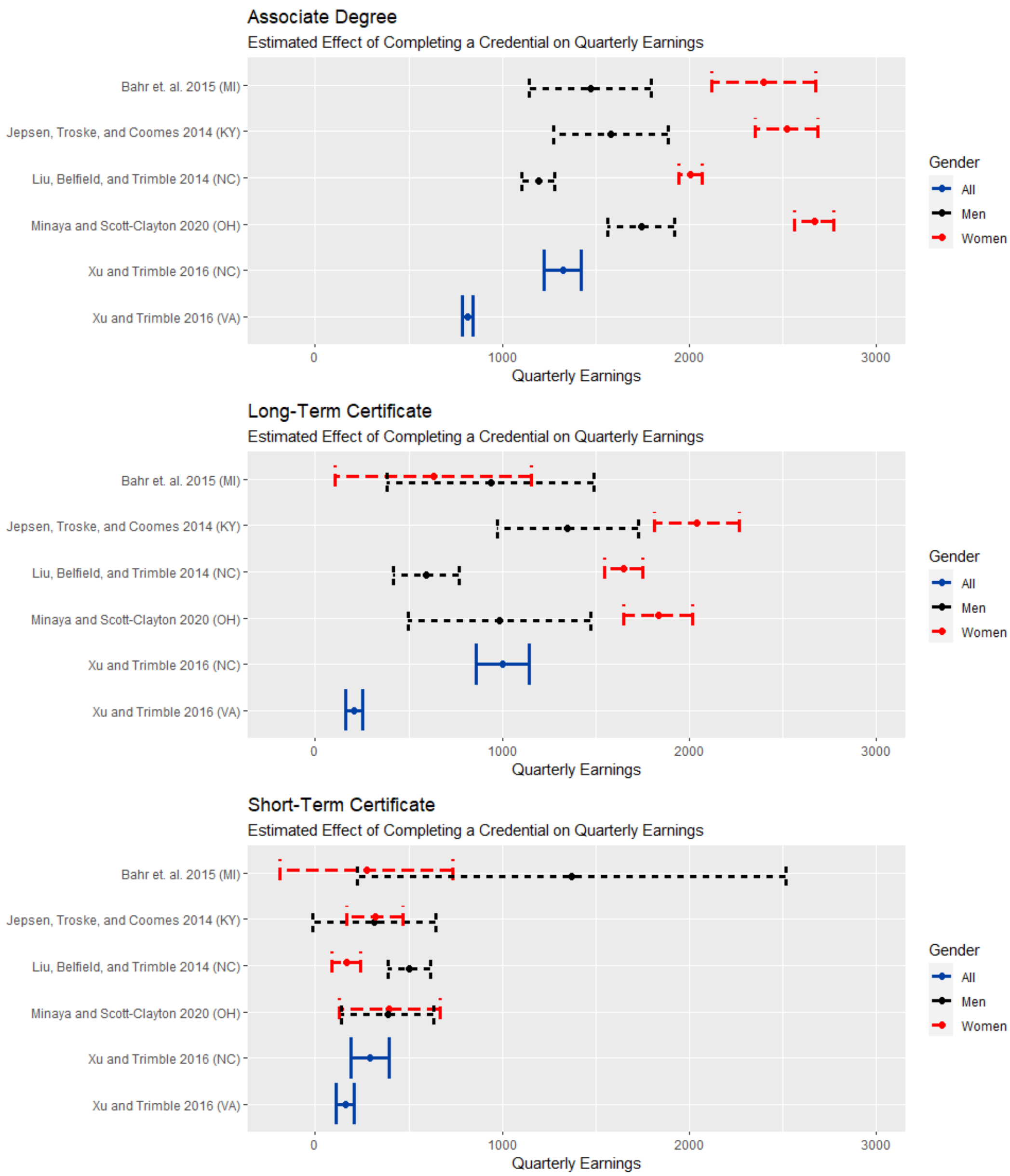
[36] I assign colleges as urban or rural by collapsing the college locale characteristics provided by the National Center for Education Statistics. I assign colleges that are in “Cities” or “Suburbs” to the urban category, while I assign colleges in “Towns” and “Rural Areas” to the rural category.

areas. This finding is consistent with those students having been more severely constrained in their access to full-time work.

Community college credentials are associated with higher earnings, but at least 60% of this effect is due to students working more hours post-graduation. The associated hours increase is equivalent to about an additional month of full-time work every year. Earnings returns for some degrees, such as those in the humanities, business, and public administration are driven entirely by hours increases, while returns for degrees in health and trade fields are more heavily driven by wage increases. Whether hours increases are welfare improving depends on competing theories of the labor market—hours constraints and shifting preferences due to student debt. Providing students access to jobs that offer higher hours could be one mechanism through which a credential benefits a student. Additionally, while associate degrees and long-term certificates appear to offer persistent wage improvements on average, short-term certificates improve wages very slightly, and only for a short window following graduation. This suggests that many short-term certificates may be of questionable labor-market value. Wage gains from completing a credential are much higher for students who have a relatively stronger labor-market attachment, an important finding for informing policy. This effect could be driven by complementarities in human capital production between work experience and college coursework, an area of inquiry worth further exploration. Additionally, men working 15 hours per week experience no wage gain from completing an associate degree. This finding highlights the need for a deeper understanding of the intersection of work and learning, and suggests that policies geared toward connecting students with employers prior to—or while enrolled in—a credential program are worth further study. At a time of renewed policy interest in community colleges, these findings suggest ways in which policy can be tailored toward programs that provide a clear, lasting value to students by increasing their wages, or potentially providing access to greater hours in some circumstances.

Figure 1

Estimates in the Literature




Note: Point-estimates and 95% confidence intervals shown for results of fixed-effects model in selected literature. All values inflated to 2012 dollars for comparability.

Table 1: Descriptive Statistics: Full and Analysis Sample

| | Men | | Women | |
|---|---|---|---|---|
| | < 3 Pre-College Working Qtrs | Analysis Sample | < 3 Pre-College Working Qtrs | Analysis Sample |
| Age at Entry | 18 | 23 | 18 | 23 |
| # Pre-College Working Quarters | 0 | 8 | 0 | 8 |
| Initial Credit Hours Attempted | 12 | 9 | 9 | 7 |
| Total Completed Credit Hours | 23 | 18 | 27 | 21 |
| Annualized Earnings | | | | |
| *Pre-College* | 0 | 14036.4 | 0 | 13029.8 |
| *Post-College* | 17231.6 | 17523.2 | 12935.6 | 13295.9 |
| Weekly Hours Worked | | | | |
| *Pre-College* | 0 | 22.50 | 0 | 22.20 |
| *Post-College* | 22.75 | 21.95 | 19.15 | 18.85 |
| Hourly Wages | | | | |
| *Pre-College* | 10.37 | 11.95 | 10.08 | 11.30 |
| *Post-College* | 15.54 | 16.35 | 13.52 | 14.44 |
| # Non-Completers | 72,133 | 38,496 | 53,817 | 34,753 |
| # Treated Individuals | 19,664 | 6,281 | 18,108 | 7,313 |

Note: Cells report median of individual-level observations. Based on sample of MN public college students between 2003-2019. Hourly wages for those with little pre-college work experience are conditioned on having positive earnings pre-college. Labor market outcomes are measured as the average value for each individual over all quarters in the relevant reporting period.

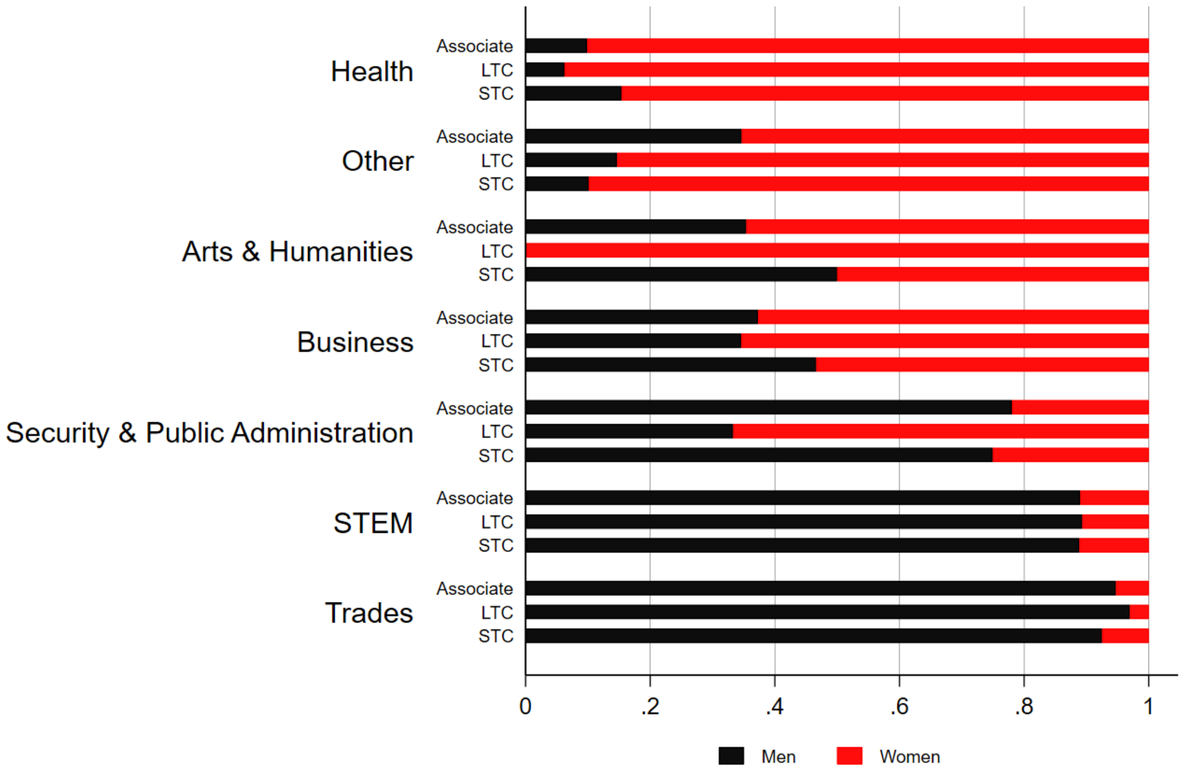
Table 2: Descriptive Statistics by Award Type and Gender

| | Non-Completer | | Short-Term Certificate | | Long-Term Certificate | | Associate Degree | |
|---|---|---|---|---|---|---|---|---|
| | Men | Women | Men | Women | Men | Women | Men | Women |
| Age at Entry | 23 | 24 | 23 | 22 | 21 | 23 | 20 | 21 |
| # Pre-College Working Quarters | 8 | 8 | 9 | 8 | 7 | 10 | 6 | 7 |
| Initial Credit Hours Attempted | 9 | 7 | 9 | 7 | 16 | 9 | 11 | 9 |
| Total Completed Credit Hours | 15 | 17 | 25 | 29 | 44 | 44 | 69 | 71 |
| Annualized Earnings | | | | | | | | |
| *Pre-College Trend* | -2.84% | -2.60% | -2.60% | -3.38% | -3.19% | -3.39% | -3.80% | -2.39% |
| *Pre-College* | 13858.9 | 13117.4 | 15590.1 | 11676.2 | 16101.4 | 13456.4 | 13636.1 | 12209.5 |
| *Post-College* | 15650.6 | 11476.6 | 23571.4 | 14731.2 | 31683.3 | 21542.9 | 30881.7 | 24528.9 |
| Weekly Hours Worked | | | | | | | | |
| *Pre-College Trend* | -1.80% | -2.06% | -0.90% | -4.35% | -2.64% | -3.26% | -2.33% | -2.12% |
| *Pre-College* | 22.08 | 22.13 | 25.52 | 21.11 | 25.50 | 23.32 | 23.63 | 22.56 |
| *Post-College* | 20.21 | 16.76 | 27.62 | 20.63 | 31.98 | 26.90 | 32.97 | 29.05 |
| Hourly Wages | | | | | | | | |
| *Pre-College Trend* | -0.29% | -0.11% | 0.49% | 0.73% | -0.33% | -0.62% | -0.21% | -0.04% |
| *Pre-College* | 11.99 | 11.42 | 12.21 | 10.68 | 12.10 | 11.13 | 11.07 | 10.61 |
| *Post-College* | 15.82 | 14.04 | 18.19 | 14.58 | 19.53 | 16.14 | 19.14 | 17.11 |
| # Individuals | 38,496 | 34,753 | 918 | 1,487 | 2,984 | 2,638 | 2,379 | 3,188 |

Note: Cells report median of individual-level measures. Based on sample of MN public college students between 2003-2019 with at least three quarters of post-high-school, pre-college earnings. Students are classified by their highest credential received. Labor market outcomes are measured as the average value for each individual over all quarters in the relevant reporting period. Pre-College trends are measured as the percentage change between the third and first quarters prior to enrollment.

Figure 2

Gender Distribution by Major and Degree Type




Note: Gender distribution in analysis sample for credential completers at MN public colleges between 2003-2019, by field of study and credential type.

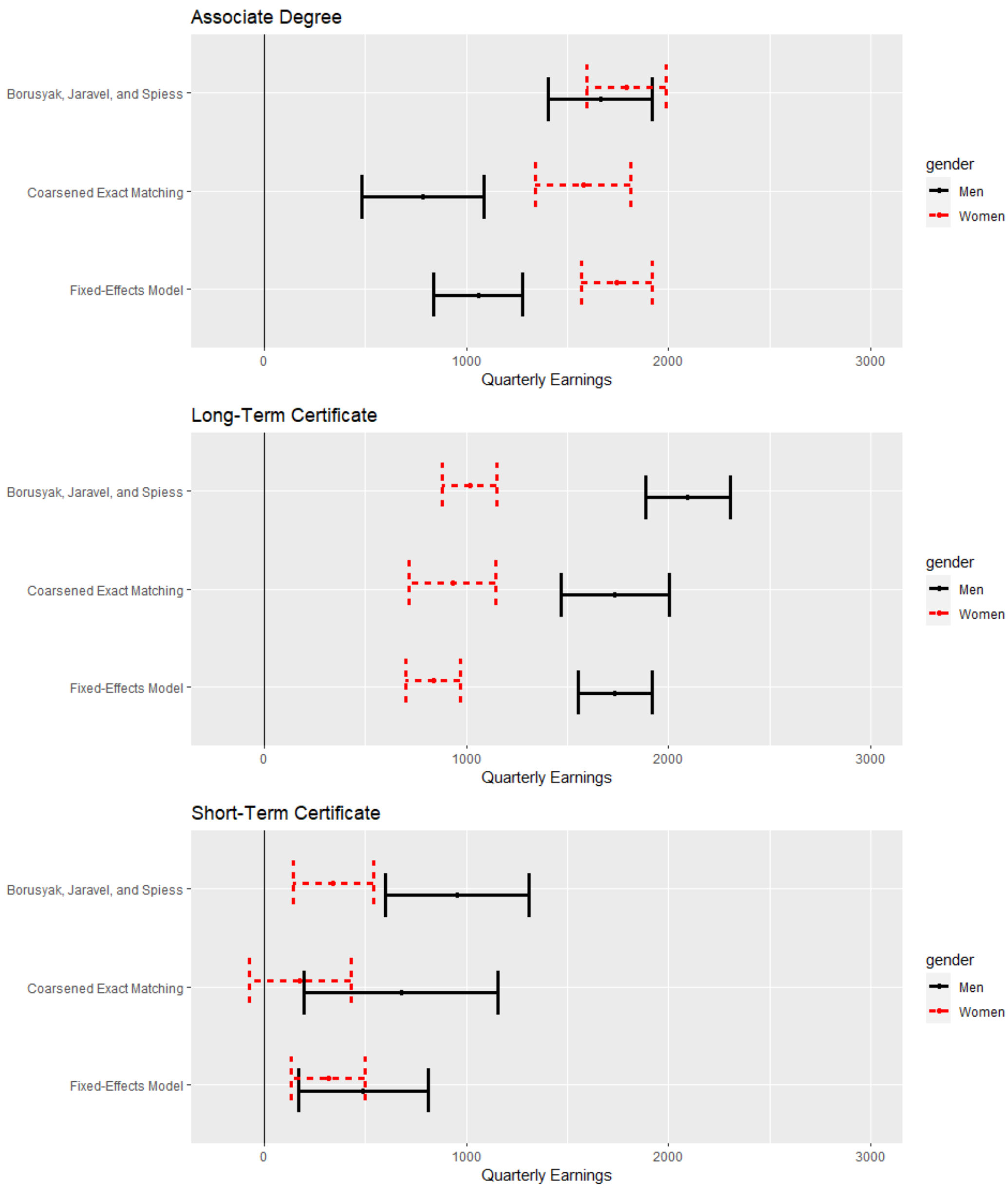
Table 3: Descriptive Statistics by Major and Gender

| | Health | | Arts & Humanities | | STEM | | Business | | Trades | | Public Admin | | Other | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Men | Women | Men | Women | Men | Women | Men | Women | Men | Women | Men | Women | Men | Women |
| Age at Entry | 20 | 20 | 19 | 19 | 19 | 19 | 19 | 19 | 19 | 20 | 20 | 20 | 19 | 19 |
| # Pre-College Working Quarters | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 4 | 5 | 4 | 4.50 | 4 | 4 |
| Initial Credit Hours Attempted | 9 | 8 | 12 | 12 | 12 | 10 | 10 | 10 | 16 | 15.50 | 12 | 9 | 10 | 10 |
| Total Completed Credit Hours | 37.68 | 45 | 63 | 62 | 63 | 68.50 | 60 | 65 | 51 | 46 | 54 | 58.50 | 64 | 60 |
| Annualized Earnings | | | | | | | | | | | | | | |
| *Pre-College* | 11508 | 10995 | 9192 | 9613 | 12285 | 10786 | 12268 | 11149 | 14644 | 10406 | 11948 | 10855 | 10515 | 9554 |
| *Post-College* | 22348 | 21357 | 22040 | 20332 | 34097 | 13295 | 27552 | 25683 | 34855 | 22031 | 35089 | 24417 | 21310 | 15669 |
| Weekly Hours Worked | | | | | | | | | | | | | | |
| *Pre-College* | 20.58 | 21.77 | 17.94 | 19.15 | 23.42 | 21.39 | 23.71 | 22.56 | 25.79 | 18.45 | 22.58 | 22.87 | 20.15 | 18.81 |
| *Post-College* | 25.05 | 26.31 | 27.94 | 24.63 | 34.82 | 25.17 | 32.95 | 32.79 | 34.99 | 28.08 | 37.55 | 33.08 | 25.72 | 23.14 |
| Hourly Wages | | | | | | | | | | | | | | |
| *Pre-College* | 10.13 | 9.849 | 9.343 | 9.255 | 10.33 | 10.20 | 10.06 | 9.537 | 10.83 | 9.876 | 10.16 | 9.466 | 9.765 | 9.449 |
| *Post-College* | 16.85 | 15.93 | 16.49 | 14.65 | 20.01 | 15.12 | 17.63 | 15.80 | 20.27 | 16.84 | 18.67 | 15.42 | 15.72 | 13.99 |
| # Treated Individuals | 161 | 1,217 | 123 | 226 | 277 | 34 | 163 | 257 | 1,285 | 54 | 217 | 64 | 247 | 553 |

Note: Cells report median of individual-level measures. Based on sample of MN public college credential completers between 2003-2019 with at least three quarters of post-high-school, pre-college earnings. Labor market outcomes are measured as the average value for each individual over all quarters in the relevant reporting period.

Figure 3

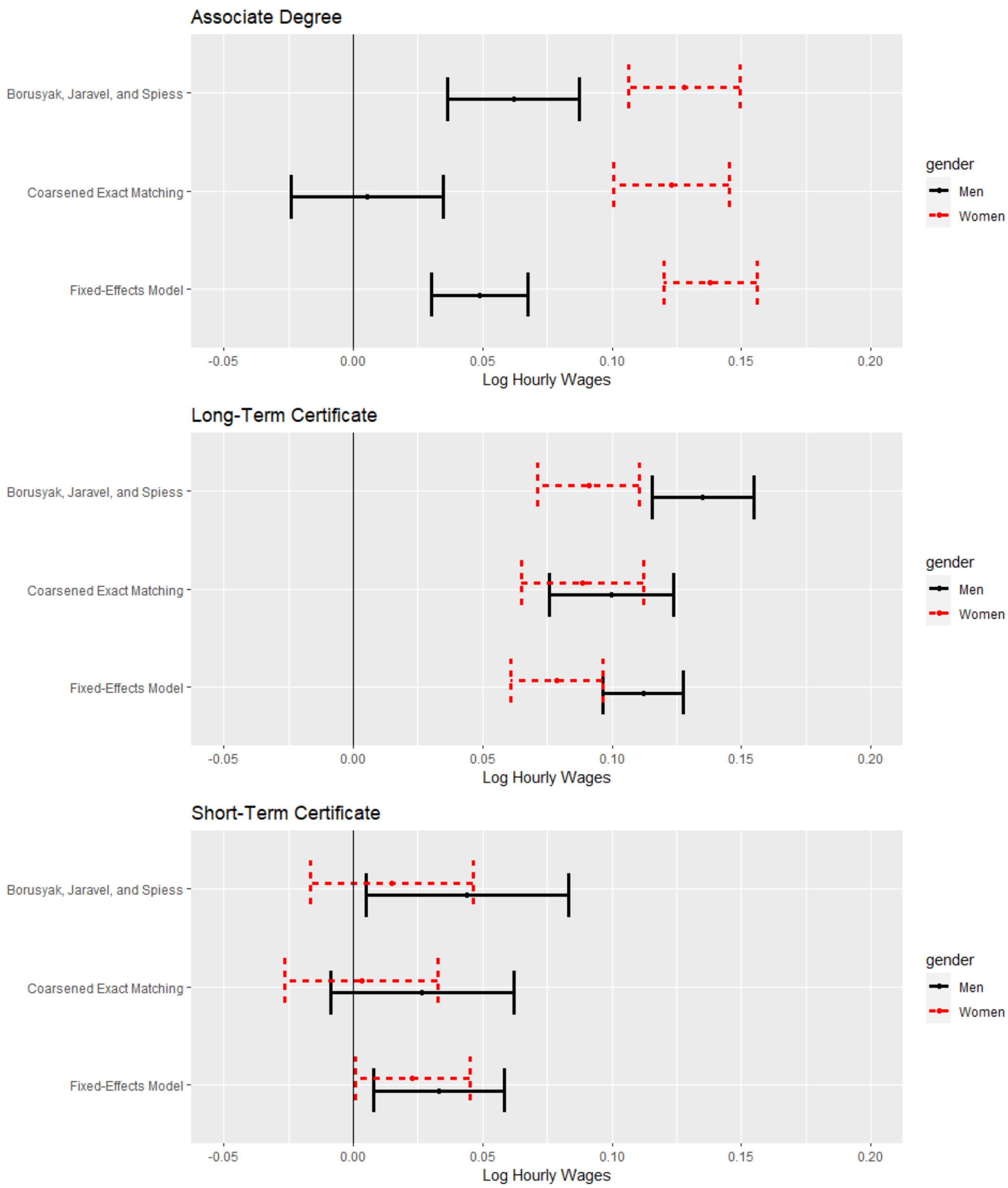
Estimates Across Specifications - Quarterly Earnings




Note: Point-estimates and 95% confidence intervals shown for results of various empirical approaches. See table 4 for additional detail.

Figure 4

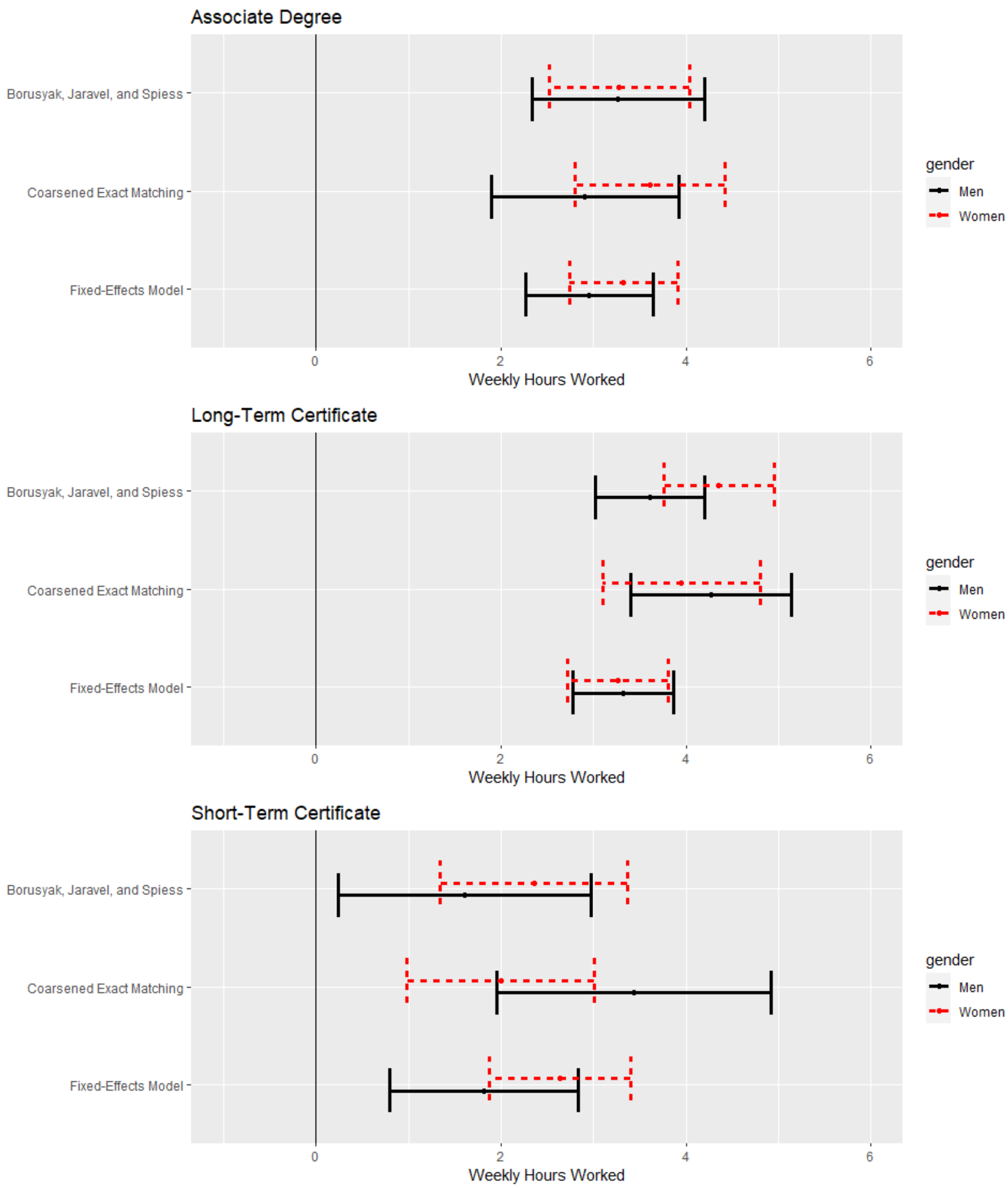
Estimates Across Specifications - Log Hourly Wages




Note: Point-estimates and 95% confidence intervals shown for results of various empirical approaches. See table 4 for additional detail.

Figure 5

Estimates Across Specifications - Weekly Hours




Note: Point-estimates and 95% confidence intervals shown for results of various empirical approaches. See table 4 for additional detail.

Table 4: Effect of Completing a Credential on Labor Market Outcomes

| | Quarterly Earnings | Weekly Hours | Log Hourly Wages |
|---|---|---|---|
| **Panel A: Panel / Canonical Model** | | | |
| *Men* | | | |
| Associate Degree | 1057.4*** | 2.955*** | 0.0488*** |
| | (112.2) | (0.350) | (0.00953) |
| Long-Term Certificate | 1733.9*** | 3.324*** | 0.112*** |
| | (93.05) | (0.278) | (0.00793) |
| Short-Term Certificate | 489.8** | 1.813*** | 0.0330* |
| | (163.9) | (0.520) | (0.0129) |
| # Non-Completers | 28,455 | 28,455 | 28,455 |
| # Treated Individuals | 5,115 | 5,115 | 5,115 |
| *Women* | | | |
| Associate Degree | 1742.4*** | 3.324*** | 0.138*** |
| | (89.01) | (0.297) | (0.00926) |
| Long-Term Certificate | 835.1*** | 3.262*** | 0.0787*** |
| | (68.21) | (0.280) | (0.00911) |
| Short-Term Certificate | 316.5*** | 2.640*** | 0.0228* |
| | (94.12) | (0.391) | (0.0113) |
| # Non-Completers | 23,838 | 23,838 | 23,838 |
| # Treated Individuals | 5,776 | 5,776 | 5,776 |
| **Panel B: CEM Matched Sample** | | | |
| *Men* | | | |
| Associate Degree | 783.9*** | 2.906*** | 0.00528 |
| | (153.6) | (0.518) | (0.0150) |
| Long-Term Certificate | 1735.3*** | 4.269*** | 0.0997*** |
| | (137.3) | (0.445) | (0.0123) |
| Short-Term Certificate | 677.0** | 3.439*** | 0.0267 |
| | (245.2) | (0.758) | (0.0180) |
| # Matched Non-Completers | 4860 | 4860 | 3979 |
| # Matched Treated Ind. | 1523 | 1523 | 1330 |
| *Women* | | | |
| Associate Degree | 1577.4*** | 3.612*** | 0.123*** |
| | (120.1) | (0.413) | (0.0114) |
| Long-Term Certificate | 930.7*** | 3.948*** | 0.0887*** |
| | (108.8) | (0.435) | (0.0120) |
| Short-Term Certificate | 177.0 | 1.995*** | 0.00323 |
| | (128.6) | (0.516) | (0.0151) |
| # Matched Non-Completers | 5647 | 5647 | 4806 |
| # Matched Treated Ind. | 1911 | 1911 | 1669 |
| **Panel C: BJS Imputation Estimator (Preferred Specification)** | | | |
| *Men* | | | |
| Associate Degree | 1661.575*** | 3.265*** | 0.062*** |
| | (129.976) | (.477) | (.013) |
| Long-Term Certificate | 2093.464*** | 3.611*** | 0.135*** |
| | (106.854) | (.302) | (.01) |
| Short-Term Certificate | 955.249*** | 1.609* | 0.044* |
| | (181.679) | (.697) | (.02) |
| # Non-Completers | 28,455 | 28,455 | 28,455 |
| # Treated Individuals | 5,115 | 5,115 | 5,115 |
| *Women* | | | |
| Associate Degree | 1791.348*** | 3.277*** | 0.128*** |
| | (99.047) | (.388) | (.011) |
| Long-Term Certificate | 1016.225*** | 4.356*** | 0.091*** |
| | (68.239) | (.303) | (.01) |
| Short-Term Certificate | 341.144*** | 2.354*** | 0.015 |
| | (100.766) | (.517) | (.016) |
| # Non-Completers | 23,838 | 23,838 | 23,838 |
| # Treated Individuals | 5,776 | 5,776 | 5,776 |

Note: Shows coefficient on treatment indicators in equation 1. Estimation sample includes MN public college students between 2003-2019 that are observed working during at least three quarters after high school completion prior to first college enrollment. Standard errors (in parentheses) are clustered by individual in panels a and b, and bootstrapped with 400 repetitions in panel c.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Effect of Completing a Credential on Labor Market Outcomes by Major

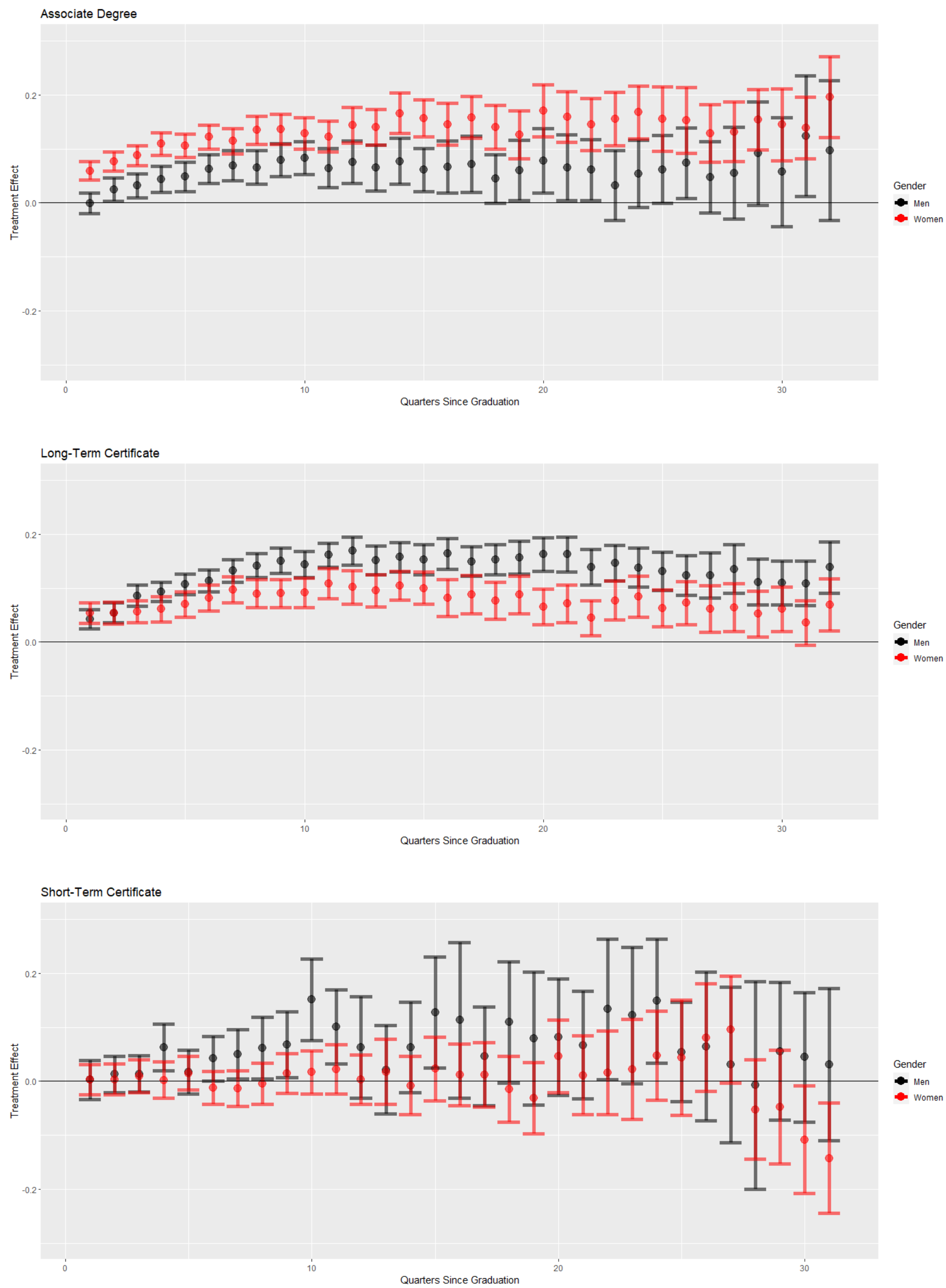
| | Health | Humanities | STEM | Business | Trades | Public Admin | Other |
|---|---|---|---|---|---|---|---|
| **Panel A: Weekly Hours** | | | | | | | |
| *Men* | | | | | | | |
| Associate Degree | 2.804 | 0.589 | 3.890*** | 3.697* | 4.363*** | 6.674*** | 1.307 |
| | (2.591) | (1.533) | (1.178) | (1.614) | (1.013) | (1.242) | (1.167) |
| Long-Term Certificate | 5.488 | | 5.220* | 7.290** | 3.837*** | 25.768*** | 3.628 |
| | (4.713) | | (2.207) | (2.516) | (.61) | (.385) | (3.72) |
| Short-Term Certificate | 1.725 | 3.794** | 1.592 | -0.691 | 1.205 | 5.572 | -7.354 |
| | (1.677) | (1.464) | (3.275) | (3.092) | (1.506) | (4.148) | (5.126) |
| # Treated Individuals | 112 | 100 | 212 | 132 | 1,060 | 185 | 180 |
| *Women* | | | | | | | |
| Associate Degree | 3.801*** | 1.617 | 8.340*** | 2.395* | 4.962* | 4.587** | 1.423 |
| | (.86) | (1.135) | (2.517) | (1.099) | (2.361) | (1.762) | (.866) |
| Long-Term Certificate | 3.806*** | 5.327 | 2.779 | 4.847 | 6.579* | 6.312 | 1.489 |
| | (.834) | (4.887 ) | (7.161) | (3.45) | (3.034) | (4.519) | (1.971) |
| Short-Term Certificate | 2.935*** | 1.537 | | 1.069 | 4.804*** | 8.680 | -1.261 |
| | (.798) | (4.595) | | (2.148) | (1.881) | (5.146) | (2.165) |
| # Treated Individuals | 928 | 180 | 22 | 207 | 39 | 54 | 398 |
| **Panel B: Log Hourly Wages** | | | | | | | |
| *Men* | | | | | | | |
| Associate Degree | 0.306** | -0.076 | 0.133*** | 0.005 | 0.160*** | 0.074* | -0.009 |
| | (.11) | (.057) | (.032) | (.032) | (.03) | (.032) | (.028) |
| Long-Term Certificate | 0.101 | | 0.087 | 0.064 | 0.190*** | 0.036** | 0.169 |
| | (.073) | | (.052) | (.083) | (.019) | (.011) | (.124) |
| Short-Term Certificate | -0.059 | -0.125*** | -0.066 | 0.110* | 0.127** | 0.175** | -0.071 |
| | (.044) | (.027) | (.097) | (.054) | (.046) | (.067) | (.081) |
| # Treated Individuals | 112 | 100 | 212 | 132 | 1,060 | 185 | 180 |
| *Women* | | | | | | | |
| Associate Degree | 0.200*** | -0.006 | 0.038 | 0.071** | 0.305* | 0.091 | 0.024 |
| | (.026) | (.037) | (.093) | (.026) | (.151) | (.052) | (.024) |
| Long-Term Certificate | 0.088* | 0.103 | -0.104 | -0.013 | 0.203*** | 0.023 | 0.117* |
| | (.042) | (.098) | (.162) | (.064) | (.057) | (.027) | (.048) |
| Short-Term Certificate | -0.022 | 0.166* | | 0.249* | 0.127 | 0.242 | 0.064 |
| | (.022) | (.072) | | (.118) | (.151) | (.132) | (.084) |
| # Treated Individuals | 928 | 180 | 22 | 207 | 39 | 54 | 398 |
| **Panel C: Elasticity** Overall | | | | | | | |
| Any Credential | .751*** | .494 | .814*** | .261 | .45*** | .676*** | .716*** |
| | (.084) | (.326) | (.089) | (.747) | (.079) | (.078) | (.190) |

Note: Panels a and b show coefficient on treatment indicators in equation 1, estimated by Borusyak, Jaravel, and Spiess (2021) and aggregated by field of study. Estimation sample includes MN public college students between 2003-2019 that are observed working during at least three quarters after high school completion prior to first college enrollment. Standard errors (in parentheses) are bootstrapped with 400 repetitions. Panel c shows estimated elasticity as described in equation 2. Major is unobserved for non-completers.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 6

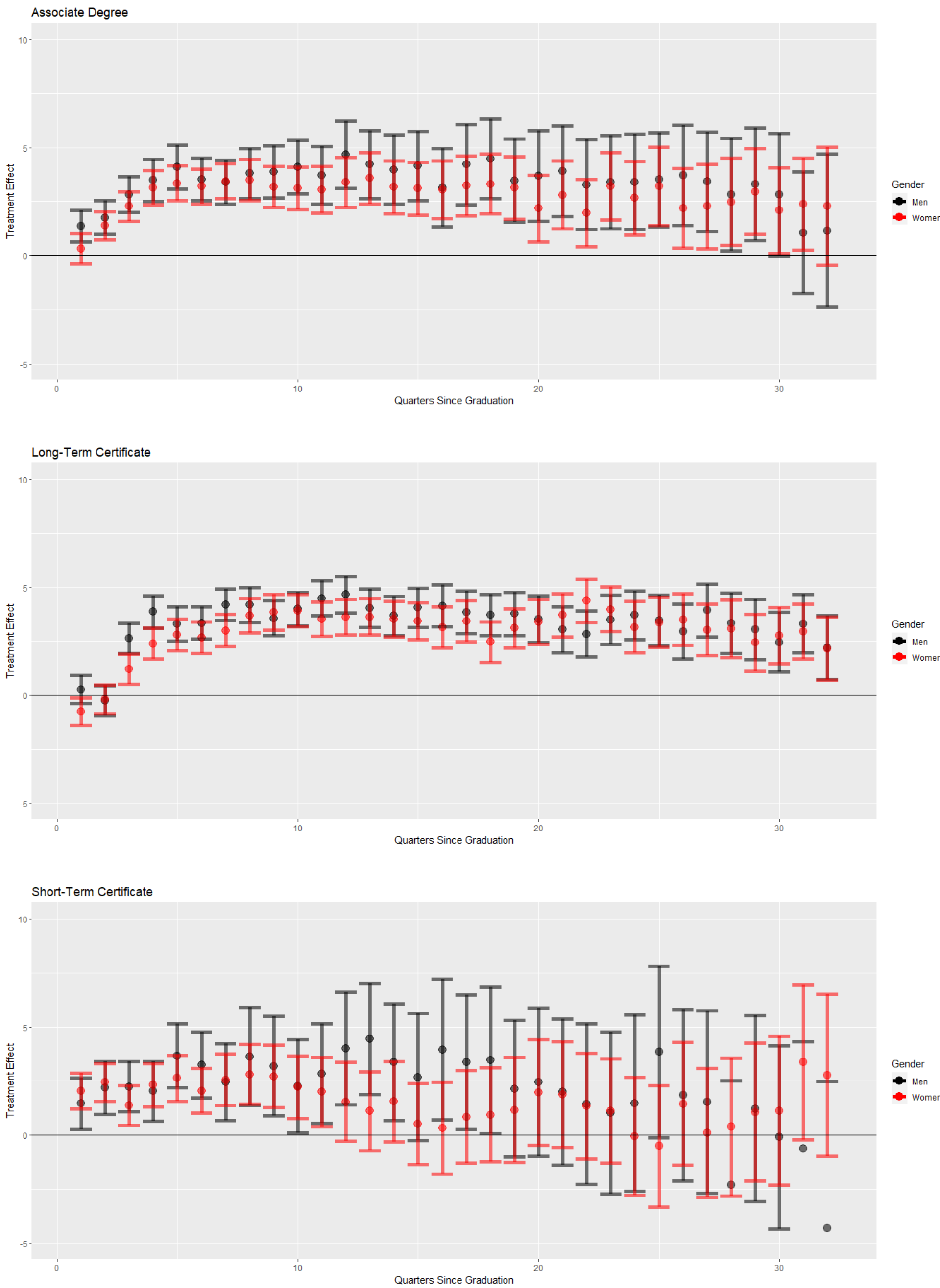
Dynamic Effect of Completing a Credential on Log Hourly Wages




Note: Coefficients estimated by imputation method of Borusyak, Jaravel, and Spiess (2021), with 95% confidence intervals. Estimate reflects average of individual treatment effects in each quarter since graduation. Estimation sample includes MN public college students between 2003-2019 that are observed working during at least three quarters after high school completion prior to first college enrollment. Standard errors and bootstrapped with 400 repetitions.

Figure 7

Dynamic Effect of Completing a Credential on Weekly Hours Worked




Note: Coefficients estimated by imputation method of Borusyak, Jaravel, and Spiess (2021), with 95% confidence intervals. Estimate reflects average of individual treatment effects in each quarter since graduation. Estimation sample includes MN public college students between 2003-2019 that are observed working during at least three quarters after high school completion prior to first college enrollment. Standard errors and bootstrapped with 400 repetitions.

Table 6: Effect of Completing a Credential on Log Hourly Wages by Pre-College Labor Market Outcomes

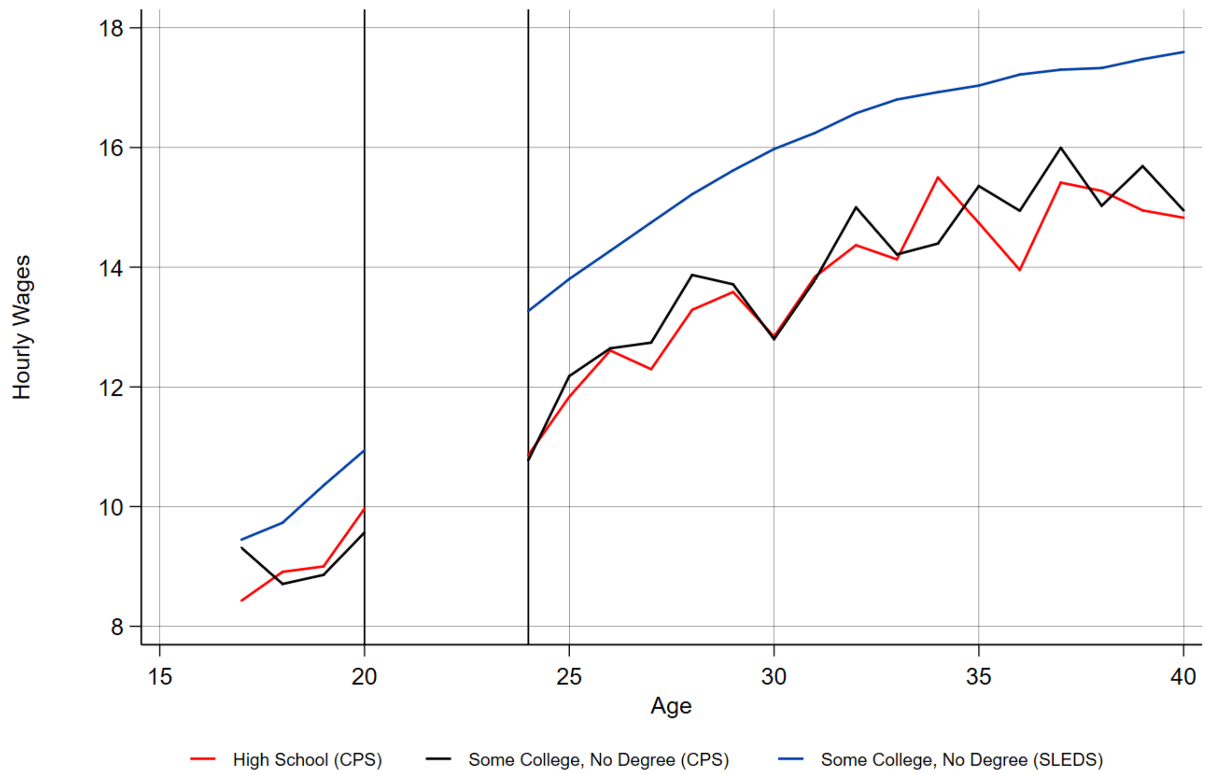
| **Panel A:** **Pre-College Hours Bin** | $\leq 5$ | 5 - 15 | 15-25 | 25-35 | 35-45 | $> 45$ |
|---|---|---|---|---|---|---|
| *Men* | | | | | | |
| Associate Degree | 0.006 | 0.027 | 0.090*** | 0.085*** | 0.061** | 0.101*** |
| | (.032) | (.031) | (.027) | (.025) | (.02) | (.03) |
| Long-Term Certificate | 0.085*** | 0.132*** | 0.159*** | 0.163*** | 0.141*** | 0.125*** |
| | (.022) | (.025) | (.029) | (.02) | (.016) | (.021) |
| Short-Term Certificate | -0.014 | -0.004 | 0.077* | 0.071* | 0.069 | 0.016 |
| | (.072) | (.051) | (.039) | (.032) | (.039) | (.03) |
| # Non-Completers | 8972 | 4056 | 4883 | 5813 | 9632 | 3807 |
| # Treated Individuals | 1195 | 592 | 835 | 1125 | 1708 | 721 |
| *Women* | | | | | | |
| Associate Degree | 0.081** | 0.112*** | 0.121*** | 0.126*** | 0.153*** | 0.200*** |
| | (.028) | (.028) | (.021) | (.021) | (.017) | (.031) |
| Long-Term Certificate | 0.011 | 0.051 | 0.113*** | 0.115*** | 0.098*** | 0.160*** |
| | (.039) | (.029) | (.024) | (.016) | (.015) | (.026) |
| Short-Term Certificate | 0.003 | -0.069 | 0.025 | 0.030 | 0.032 | 0.056 |
| | (.032) | (.045) | (.026) | (.035) | (.024) | (.045) |
| # Non-Completers | 6813 | 3986 | 5155 | 6396 | 8346 | 2817 |
| # Treated Individuals | 1298 | 844 | 1212 | 1533 | 1756 | 570 |
| **Panel B:** **Pre-College Wage Percentile** | 0-10 | 10-25 | 25-50 | 50-75 | 75-90 | 90-100 |
| *Men* | | | | | | |
| Associate Degree | 0.144*** | 0.132*** | 0.094*** | 0.036 | -0.055 | -0.149* |
| | (.026) | (.028) | (.024) | (.02) | (.032) | (.065) |
| Long-Term Certificate | 0.308*** | 0.255*** | 0.202*** | 0.104*** | 0.053* | -0.105** |
| | (.028) | (.023) | (.016) | (.015) | (.026) | (.038) |
| Short-Term Certificate | 0.237*** | 0.066* | 0.087** | 0.011 | -0.053 | -0.055 |
| | (.07) | (.033) | (.031) | (.028) | (.046) | (.035) |
| # Non-Completers | 3027 | 4490 | 7567 | 7588 | 4633 | 3108 |
| # Treated Individuals | 570 | 855 | 1341 | 1320 | 712 | 455 |
| *Women* | | | | | | |
| Associate Degree | 0.235*** | 0.151*** | 0.115*** | 0.141*** | 0.115*** | -0.146* |
| | (.025) | (.02) | (.021) | (.021) | (.027) | (.065) |
| Long-Term Certificate | 0.317*** | 0.148*** | 0.114*** | 0.083*** | 0.036 | -0.287*** |
| | (.027) | (.018) | (.015) | (.017) | (.02) | (.075) |
| Short-Term Certificate | 0.144*** | 0.099** | 0.006 | -0.066** | -0.049 | -0.230** |
| | (.035) | (.035) | (.034) | (.025) | (.029) | (.077) |
| # Non-Completers | 2739 | 4132 | 7063 | 7238 | 4471 | 3022 |
| # Treated Individuals | 799 | 1102 | 1662 | 1487 | 763 | 468 |

Note: Shows coefficient on treatment indicators in equation 1, estimated by Borusyak, Jaravel, and Spiess (2021). Treatment effects are aggregated within bins of weekly hours worked (panel a) or log hourly wages (panel b) 3 quarters prior to enrollment. Estimation sample includes MN public college students between 2003-2019 that are observed working during at least three quarters after high school completion prior to first college enrollment. Standard errors (in parentheses) are bootstrapped with 400 repetitions.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 8

Life-cycle Wage Profile

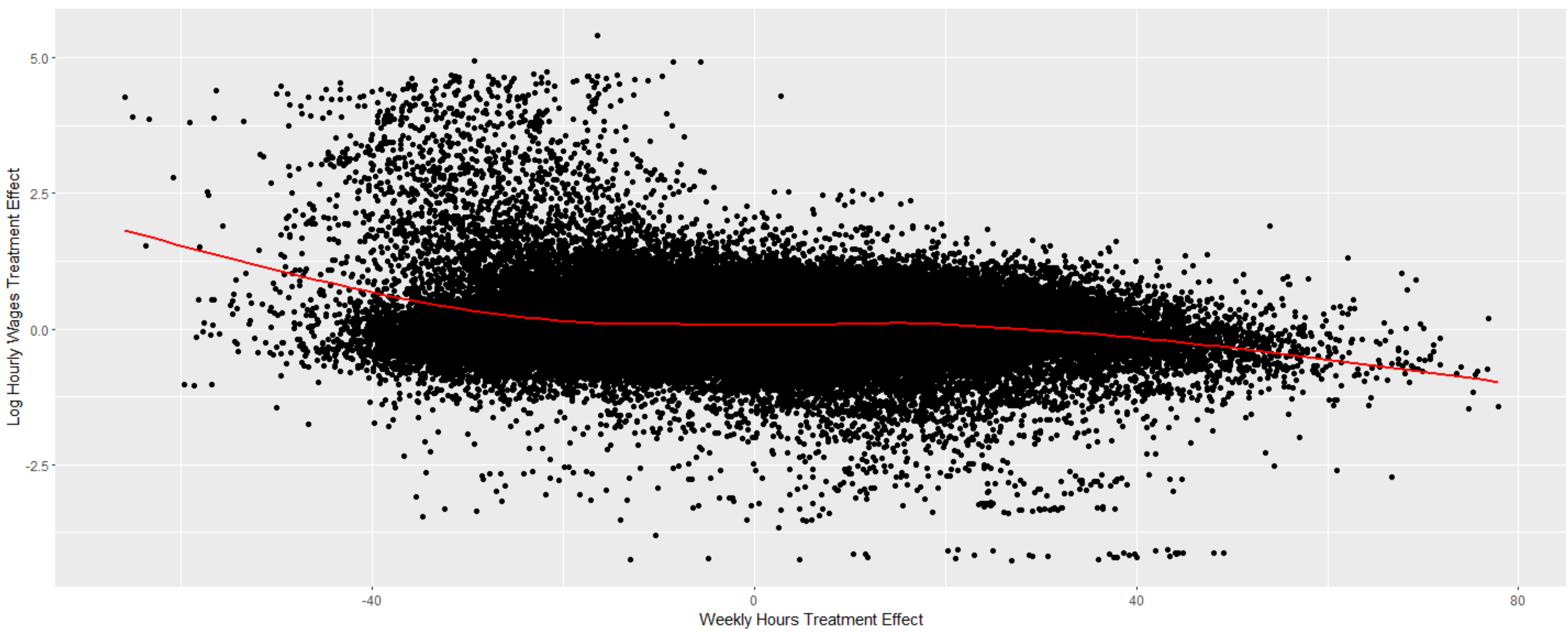
High School Graduates vs. Some College, No Degree




Note: Compares raw average for MN high school graduates and some college, no degree individuals from the CPS to those in SLEDS from 2003-2019 (Flood et al., 2020).

Figure 9

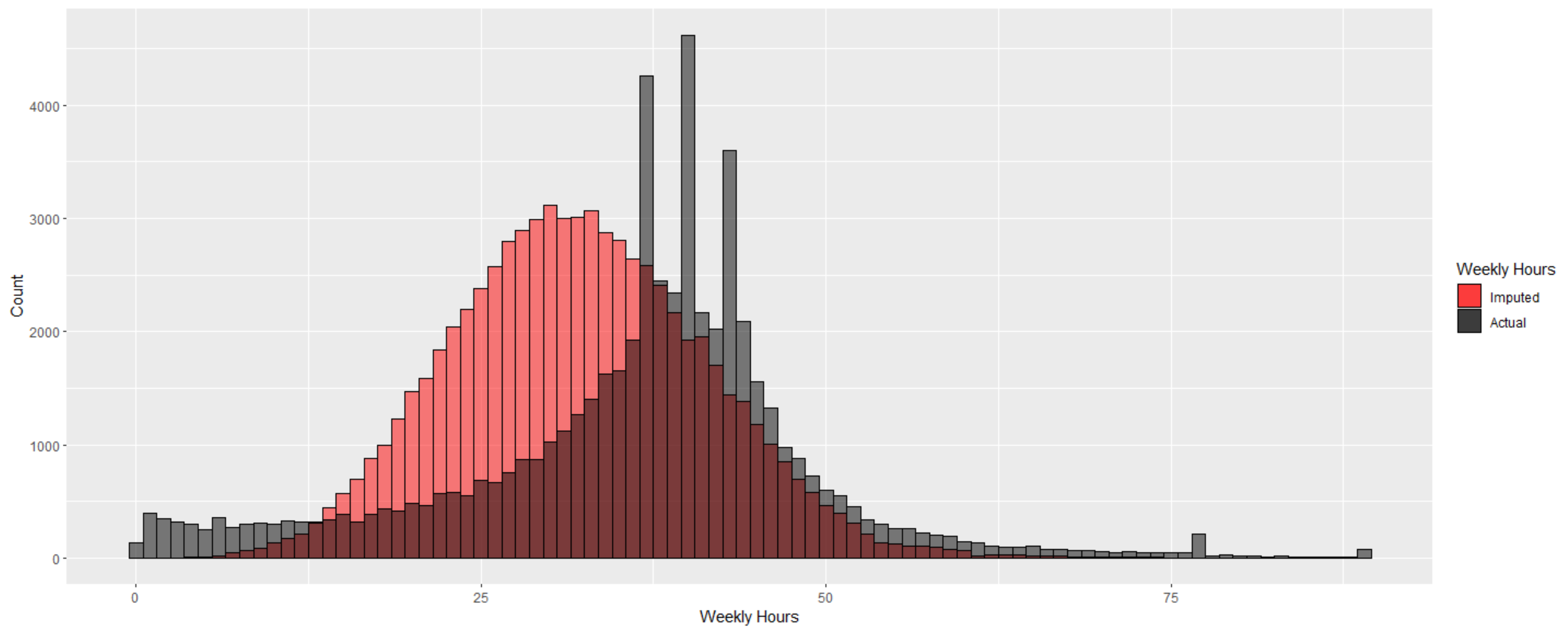
Relationship Between Estimated Treatment Effects - Hours and Wages




Note: Shows scatterplot of hours and log hourly wages treatment effects for credential completers at MN public colleges between 2003-2019, estimated using the imputation method of Borusyak, Jaravel, and Spiess (2021).

Figure 10

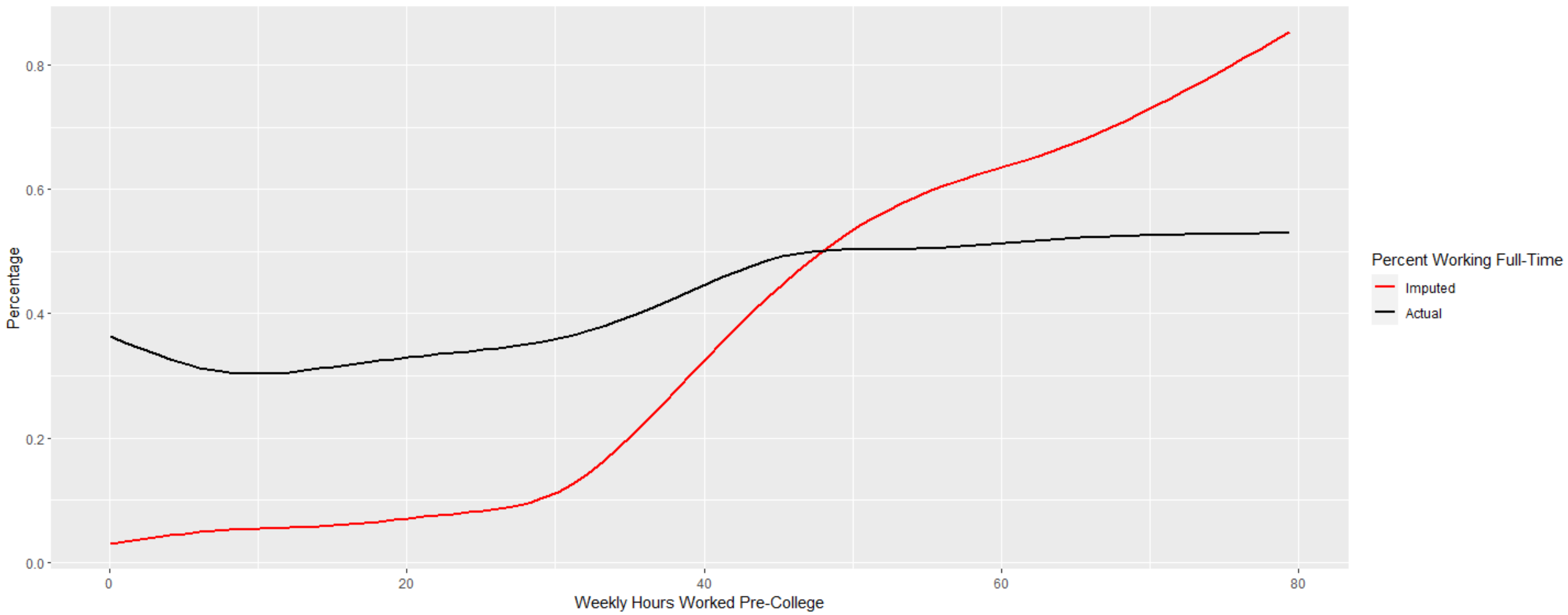
Distribution of Actual and Imputed Hours Worked Post College - Credential Completers




Note: Shows imputed and actual distribution of post-college weekly hours worked for credential completers at MN public colleges between 2003-2019.

Figure 11

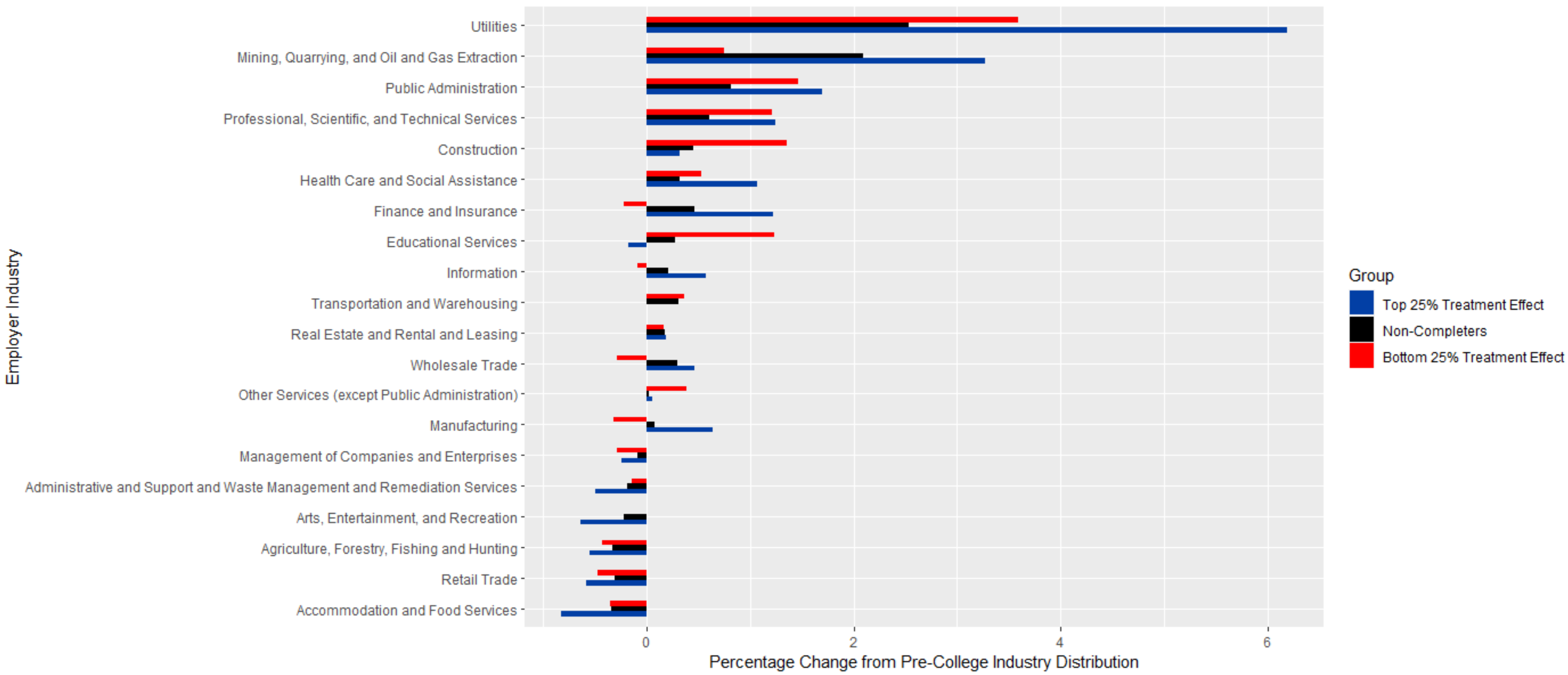
Percentage of Credential Completers Working Full-Time Post-College - Actual and Imputed




Note: Shows local polynomial of the percentage of MN public college credential completers working full-time (40 or more weekly hours) post-graduation, based on their weekly hours worked three quarters prior to enrollment.

Figure 12

Change in Employer Industry Post-College - By Estimated Treatment Effect on Hours




Note: Shows percentage change in the number of students in each group working in a given industry (defined by NAICS 6 codes) post-college, relative to 3 quarters prior to college enrollment. Students are grouped based on where their estimated treatment effect on hours worked falls in the distribution of treatment effects, with non-completers shown for comparison.

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# Appendix

## Appendix 1 - Sensitivity to Sample Selection Criteria

This section includes tables which show how the estimates for the effect of earning a credential on quarterly earnings evolve if I restrict the sample more tightly to require individuals to have a greater number of pre-college, post-HS working periods.

Table 7: Sample Restriction Comparison (Number of Pre-College Periods) - Effect of Highest Award on Quarterly Earnings

| Minimum # Pre-College Working Periods | 3 | 4 | 5 | 6 |
|---|---|---|---|---|
| *Men* | | | | |
| Associate Degree | 1057.4*** | 987.5*** | 949.7*** | 897.4*** |
| | (112.2) | (119.9) | (153.8) | (160.1) |
| Long-Term Certificate | 1733.9*** | 1718.5*** | 1524.0*** | 1492.0*** |
| | (93.05) | (97.84) | (116.3) | (119.6) |
| Short-Term Certificate | 489.8** | 519.2** | 540.6** | 595.8** |
| | (163.9) | (174.4) | (206.2) | (212.0) |
| *Women* | | | | |
| Associate Degree | 1742.4*** | 1746.6*** | 1780.2*** | 1808.8*** |
| | (89.01) | (92.89) | (111.1) | (115.4) |
| Long-Term Certificate | 835.1*** | 827.2*** | 830.0*** | 818.5*** |
| | (68.21) | (70.47) | (81.03) | (83.15) |
| Short-Term Certificate | 316.5*** | 292.5** | 228.9 | 173.3 |
| | (94.12) | (98.95) | (117.1) | (120.8) |

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

# Appendix 2 - CIP Subject Area Aggregation

| CIP Area Code | CIP Area Description | Field of Study Grouping |
|---|---|---|
| 1 | AGRICULTURAL / ANIMAL / PLANT / VETERINARY SCIENCE AND RELATED FIELDS | STEM |
| 3 | NATURAL RESOURCES AND CONSERVATION | Other |
| 4 | ARCHITECTURE AND RELATED SERVICES | STEM |
| 5 | AREA, ETHNIC, CULTURAL, GENDER, AND GROUP STUDIES | Art Humanities |
| 9 | COMMUNICATION, JOURNALISM, AND RELATED PROGRAMS | Other |
| 10 | COMMUNICATIONS TECHNOLOGIES / TECHNICIANS AND SUPPORT SERVICES | STEM |
| 11 | COMPUTER AND INFORMATION SCIENCES AND SUPPORT SERVICES | STEM |
| 12 | CULINARY, ENTERTAINMENT, AND PERSONAL SERVICES | Other |
| 13 | EDUCATION | Other |
| 14 | ENGINEERING | STEM |
| 15 | ENGINEERING / ENGINEERING - RELATED TECHNOLOGIES / TECHNICIANS | STEM |
| 16 | FOREIGN LANGUAGES, LITERATURE, AND LINGUISTICS | Art Humanities |
| 19 | FAMILY AND CONSUMER SCIENCES / HUMAN SCIENCES | Other |
| 21 | RESERVED | None |
| 22 | LEGAL PROFESSIONS AND STUDIES | Other |
| 24 | LIBERAL ARTS AND SCIENCES, GENERAL STUDIES AND HUMANITIES | Art Humanities |
| 25 | LIBRARY SCIENCE | Other |
| 26 | BIOLOGICAL AND BIOMEDICAL SCIENCES | STEM |
| 27 | MATHEMATICS AND STATISTICS | STEM |
| 28 | MILITARY SCIENCE, LEADERSHIP AND OPERATIONAL ART | Other |
| 29 | MILITARY TECHNOLOGIES AND APPLIED SCIENCES | STEM |
| 30 | MULTI / INTERDISCIPLINARY STUDIES | Other |
| 31 | PARKS, RECREATION, LEISURE, FITNESS ,AND KINESIOLOGY | Other |
| 32 | BASIC SKILLS AND DEVELOPMENTAL / REMEDIAL EDUCATION | None |
| 33 | CITIZENSHIP ACTIVITIES | Other |
| 34 | HEALTH RELATED KNOWLEDGE AND SKILLS | Health |
| 35 | INTERPERSONAL AND SOCIAL SKILLS | Other |
| 36 | LEISURE AND RECREATIONAL ACTIVITIES | Other |
| 37 | PERSONAL AWARENESS AND SELF-IMPROVEMENT | Other |
| 38 | PHILOSOPHY AND RELIGIOUS STUDIES | Art Humanities |
| 39 | THEOLOGY AND RELIGIOUS VOCATIONS | Art Humanities |
| 40 | PHYSICAL SCIENCES | STEM |
| 41 | SCIENCE TECHNOLOGIES / TECHNICIANS | STEM |
| 42 | PSYCHOLOGY | Other |
| 43 | HOMELAND SECURITY, LAW ENFORCEMENT, FIREFIGHTING AND RELATED PROTECTIVE SERVICES | Security Public Administration |
| 44 | PUBLIC ADMINISTRATION AND SOCIAL SERVICE PROFESSIONS | Security Public Administration |
| 45 | SOCIAL SCIENCES | Other |
| 46 | CONSTRUCTION TRADES | Trades |
| 47 | MECHANIC AND REPAIR TECHNOLOGIES / TECHNICIANS | Trades |
| 48 | PRECISION PRODUCTION | Trades |
| 49 | TRANSPORTATION AND MATERIALS MOVING | Trades |
| 50 | VISUAL AND PERFORMING ARTS | Art Humanities |
| 51 | HEALTH PROFESSIONS AND RELATED PROGRAMS | Health |
| 52 | BUSINESS, MANAGEMENT, MARKETING, AND RELATED SUPPORT SERVICES | Business |
| 53 | HIGH SCHOOL / SECONDARY DIPLOMAS AND CERTIFICATES | None |
| 54 | HISTORY | Art Humanities |
| 55 | RESERVED | None |
| 60 | HEALTH PROFESSIONS RESIDENCY / FELLOWSHIP PROGRAMS | Health |
| 61 | MEDICAL RESIDENCY / FELLOWSHIP PROGRAMS | Health |

## Appendix 3 - Fixed Effects Model Excluding Enrolled Periods

Table 8: Effect of Completing a Credential on Labor Market Outcomes
Enrolled Quarters Excluded

| | Quarterly Earnings | Weekly Hours | Log Hourly Wages |
|---|---|---|---|
| *Men* | | | |
| Associate Degree | 886.5*** | 2.707*** | 0.0455*** |
| | (147.2) | (0.458) | (0.0129) |
| Long-Term Certificate | 1555.3*** | 2.505*** | 0.103*** |
| | (109.8) | (0.334) | (0.00952) |
| Short-Term Certificate | 725.7*** | 2.493*** | 0.0431* |
| | (207.9) | (0.633) | (0.0169) |
| Individuals | 44777 | 44777 | 44602 |
| *Women* | | | |
| Associate Degree | 1816.6*** | 3.236*** | 0.149*** |
| | (114.2) | (0.390) | (0.0131) |
| Long-Term Certificate | 639.6*** | 2.443*** | 0.0687*** |
| | (85.37) | (0.344) | (0.0108) |
| Short-Term Certificate | 405.2** | 2.917*** | 0.0229 |
| | (137.0) | (0.537) | (0.0154) |
| Individuals | 42066 | 42066 | 41958 |

Standard errors in parentheses
Note: Standard errors in parentheses. Estimation sample includes individuals that are observed working during at least three quarters after high school completion prior to first college enrollment. Quarters in which individuals are enrolled in school are omitted.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

## Appendix 4 - Sensitivity of Estimates to Included Controls

Table 9 shows how the estimated effect of completing a credential on quarterly earnings evolves as controls are added to the model, with the results of the complete model appearing in column 5. While the estimated returns fall substantially in the presence of the person fixed effects, subsequent additions alter the results minimally. In column 6, I show estimates for a specification that, instead of including the time-varying demographics, includes an individual-specific time trend. This specification is included, as recommended by Dynarski, Jacob, and Kreisman (2018), and originally implemented by Jacobson, LaLonde, and Sullivan (2005), for comparability with other studies, because different demographic information is available in different settings, while person-trends may be implemented regardless of the demographic information available to the researcher. All other results are based upon the complete model, as reflected in column 5.

Table 9: Effect of Completing a Credential on Quarterly Earnings

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| *Men* | | | | | | |
| Associate Degree | 3317.7*** | 2443.9*** | 2320.8*** | 1337.0*** | 1057.4*** | 1205.9*** |
| | (125.7) | (129.7) | (133.0) | (111.3) | (112.2) | (111.2) |
| Long-Term Certificate | 3419.5*** | 2406.2*** | 2396.0*** | 1850.2*** | 1733.9*** | 1797.4*** |
| | (116.3) | (120.8) | (123.7) | (93.65) | (93.05) | (106.7) |
| Short-Term Certificate | 2404.2*** | 1849.7*** | 1379.3*** | 615.4*** | 489.8** | 490.5* |
| | (228.4) | (227.4) | (228.7) | (167.7) | (163.9) | (223.7) |
| Individuals | 44777 | 44777 | 44777 | 44777 | 44777 | 44777 |
| *Women* | | | | | | |
| Associate Degree | 2632.1*** | 2021.0*** | 1973.7*** | 1713.8*** | 1742.4*** | 1895.6*** |
| | (95.95) | (96.53) | (94.37) | (83.11) | (89.01) | (83.80) |
| Long-Term Certificate | 1054.6*** | 536.0*** | 396.3*** | 825.7*** | 835.1*** | 1437.2*** |
| | (77.82) | (79.42) | (77.96) | (68.81) | (68.21) | (73.79) |
| Short-Term Certificate | 432.0*** | 180.1 | 320.0** | 267.1** | 316.5*** | 508.2*** |
| | (99.37) | (100.7) | (97.55) | (87.82) | (94.12) | (103.3) |
| Individuals | 42066 | 42066 | 42066 | 42066 | 42066 | 42066 |
| Enrollment Ind. | NO | YES | YES | YES | YES | YES |
| Time F.E. and Age | NO | NO | YES | YES | YES | YES |
| Person F.E. | NO | NO | NO | YES | YES | YES |
| Time-Varying Demographics | NO | NO | NO | NO | YES | NO |
| Person-Trend | NO | NO | NO | NO | NO | YES |

Standard errors in parentheses
Note: Estimation sample includes individuals that are observed working during at least three quarters after high school completion prior to first college enrollment.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: Effect of Completing a Credential on Weekly Hours Worked

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| *Men* | | | | | | |
| Associate Degree | 8.780*** | 6.620*** | 5.576*** | 3.035*** | 2.955*** | 4.098*** |
| | (0.315) | (0.320) | (0.324) | (0.329) | (0.350) | (0.425) |
| Long-Term Certificate | 7.468*** | 5.037*** | 4.708*** | 3.344*** | 3.324*** | 6.279*** |
| | (0.268) | (0.275) | (0.275) | (0.272) | (0.278) | (0.365) |
| Short-Term Certificate | 6.993*** | 5.462*** | 4.000*** | 1.817*** | 1.813*** | 2.737*** |
| | (0.545) | (0.544) | (0.544) | (0.516) | (0.520) | (0.633) |
| Individuals | 44777 | 44777 | 44777 | 44777 | 44777 | 44777 |
| *Women* | | | | | | |
| Associate Degree | 6.508*** | 4.871*** | 4.218*** | 3.026*** | 3.324*** | 5.402*** |
| | (0.261) | (0.268) | (0.268) | (0.277) | (0.297) | (0.342) |
| Long-Term Certificate | 4.158*** | 2.755*** | 2.435*** | 3.141*** | 3.262*** | 6.532*** |
| | (0.270) | (0.276) | (0.273) | (0.280) | (0.280) | (0.342) |
| Short-Term Certificate | 3.631*** | 2.801*** | 2.325*** | 2.433*** | 2.640*** | 3.051*** |
| | (0.396) | (0.398) | (0.395) | (0.381) | (0.391) | (0.485) |
| Individuals | 42066 | 42066 | 42066 | 42066 | 42066 | 42066 |
| Enrollment Ind. | NO | YES | YES | YES | YES | YES |
| Time F.E. and Age | NO | NO | YES | YES | YES | YES |
| Person F.E. | NO | NO | NO | YES | YES | YES |
| Time-Varying Demographics | NO | NO | NO | NO | YES | NO |
| Person-Trend | NO | NO | NO | NO | NO | YES |

Standard errors in parentheses
Note: Estimation sample includes individuals that are observed working during at least three quarters after high school completion prior to first college enrollment.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11: Effect of Completing a Credential on Log Hourly Wages

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| *Men* | | | | | | |
| Associate Degree | 0.220*** | 0.143*** | 0.158*** | 0.0899*** | 0.0488*** | 0.0557*** |
| | (0.00976) | (0.00995) | (0.00984) | (0.00911) | (0.00953) | (0.0103) |
| Long-Term Certificate | 0.262*** | 0.173*** | 0.183*** | 0.127*** | 0.112*** | 0.108*** |
| | (0.00865) | (0.00896) | (0.00918) | (0.00787) | (0.00793) | (0.00945) |
| Short-Term Certificate | 0.143*** | 0.0935*** | 0.0807*** | 0.0582*** | 0.0330* | 0.0490** |
| | (0.0173) | (0.0172) | (0.0171) | (0.0130) | (0.0129) | (0.0162) |
| Individuals | 44712 | 44712 | 44712 | 44670 | 44670 | 44670 |
| *Women* | | | | | | |
| Associate Degree | 0.235*** | 0.172*** | 0.175*** | 0.151*** | 0.138*** | 0.128*** |
| | (0.00882) | (0.00895) | (0.00858) | (0.00874) | (0.00926) | (0.00954) |
| Long-Term Certificate | 0.102*** | 0.0475*** | 0.0357*** | 0.0780*** | 0.0787*** | 0.0885*** |
| | (0.00756) | (0.00779) | (0.00784) | (0.00908) | (0.00911) | (0.0107) |
| Short-Term Certificate | 0.0299** | -0.00189 | 0.0269* | 0.0373*** | 0.0228* | 0.0214 |
| | (0.0115) | (0.0116) | (0.0115) | (0.0109) | (0.0113) | (0.0151) |
| Individuals | 42020 | 42020 | 42020 | 42001 | 42001 | 42001 |
| Enrollment Ind. | NO | YES | YES | YES | YES | YES |
| Time F.E. and Age | NO | NO | YES | YES | YES | YES |
| Person F.E. | NO | NO | NO | YES | YES | YES |
| Time-Varying Demographics | NO | NO | NO | NO | YES | NO |
| Person-Trend | NO | NO | NO | NO | NO | YES |

Standard errors in parentheses
Note: Estimation sample includes individuals that are observed working during at least three quarters after high school completion prior to first college enrollment.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

## Appendix 5 - Coarsened Exact Matching Implementation

I use the coarsening and binning choices described in Figure 9, below. Specifically, I match individuals on post-secondary institution attended, number of first-term credit hours, the quarter of their first enrollment, their quarterly earnings one, three, and five quarters prior to enrollment, and average hours worked in pre-college quarters. I implement the matching procedure (and subsequently estimate the model) separately by gender and degree type. As such, I allow the pool of matched control individuals to more closely resemble individuals *within a degree type* on pre-treatment covariates. Individuals in the pool of non-completers may serve as controls in multiple matched samples.

To illustrate the ways in which the matching procedure prunes observations (from both treated and control groups) to create greater balance amongst pre-treatment covariates, consider Tables 12 and 13. Table 12 shows some descriptive statistics for men in the original pool of non-completers as well as the "treated" individuals (those who received an associate degree). Additionally, the table shows the same statistics for the remaining matched treated and control observation after implementing the CEM procedure. Table 13 shows the same for women receiving an associate degree. The matching procedure produces greater balance on most dimensions, though not all.

Figure 9

| Matching Criteria and Binning Choices | | |
|---|---|---|
| **Criteria** | **# Bins** | **Bin Ranges** |
| Institution Attended | Exact Match | |
| Age at Enrollment | 8 | $\leq 19, 20-24, 25-34, 35-44, 45-54, 55-64, 65+$ |
| First-Term Credit Hours | 5 | 0-5, 5-8, 9-11, 12-14 |
| Year of First Enrollment | 12 | One-Year Increments |
| Quarterly Earnings<br>(1 period prior to first enrollment) | 5 | Quartiles of Earnings One Quarter Prior to College Enrollment<br>(Within Gender-Field Cell) |
| Quarterly Earnings<br>(3 periods prior to first enrollment) | 5 | Quartiles of Earnings Three Quarters Prior to College Enrollment<br>(Within Gender-Field Cell) |
| Quarterly Earnings<br>(5 periods prior to first enrollment) | 5 | Quartiles of Earnings Five Quarters Prior to College Enrollment<br>(Within Gender-Field Cell) |
| Average Weekly Hours Worked<br>(over pre-enrollment working periods) | 6 | 1-10, 10.01-20, 20.01-30, 30.01-40, 40.01 + |

Note: All Matching Criteria are permitted to match on missing values, thus, the number of bins listed reflects the bin ranges above plus one additional bin for missing values.

Table 12: Descriptive Statistics for Associate Degree Holders (Men) - Donor Pool vs. Matched Sample

| | Donor Pool | Treated | Matched Control | Matched Treated |
|---|---|---|---|---|
| Age at Entry | 23 | 20 | 20 | 20 |
| # Pre-College Working Quarters | 8 | 6 | 4 | 4 |
| Initial Credit Hours Attempted | 9 | 11 | 11 | 11 |
| Total Completed Credit Hours | 15 | 69 | 16 | 69 |
| Annualized Earnings | | | | |
| *Pre-College* | 13858.9 | 13636.1 | 12725.7 | 12732.0 |
| *In-College* | 11334.1 | 15114.7 | 13020.9 | 15154.8 |
| Weekly Hours Worked | | | | |
| *Pre-College* | 22.08 | 23.63 | 23.63 | 23.42 |
| *In-College* | 17.77 | 22.04 | 21.31 | 22.66 |
| Hourly Wages | | | | |
| *Pre-College* | 11.99 | 11.07 | 10.50 | 10.57 |
| *In-College* | 12.56 | 13.28 | 11.73 | 13.11 |
| Observations | 40875 | | 6545 | |

Note: Cells report median of individual-level observations.
Based on sample of individuals with at least three quarters of post-high-school, pre-college earnings.

Table 13: Descriptive Statistics for Associate Degree Holders (Women) - Donor Pool vs. Matched Sample

| | Donor Pool | Treated | Matched Control | Matched Treated |
|---|---|---|---|---|
| Age at Entry | 24 | 21 | 20 | 20 |
| Pre-College Working Quarters | 8 | 7 | 5 | 5 |
| Initial Credit Hours Attempted | 7 | 9 | 8 | 8 |
| Total Completed Credit Hours | 17 | 71 | 18.66 | 70 |
| Annualized Earnings | | | | |
| *Pre-College* | 13117.4 | 12209.5 | 11441.9 | 11470.0 |
| *In-College* | 12229.0 | 13583.2 | 13257.0 | 13480.0 |
| Weekly Hours Worked | | | | |
| *Pre-College* | 22.13 | 22.56 | 22.58 | 22.58 |
| *In-College* | 19.50 | 21.54 | 22.84 | 21.70 |
| Hourly Wages | | | | |
| *Pre-College* | 11.42 | 10.61 | 9.992 | 10.22 |
| *In-College* | 12.32 | 12.55 | 11.49 | 12.46 |
| Observations | 37941 | | 7772 | |

Note: Cells report median of individual-level observations.
Based on sample of individuals with at least three quarters of post-high-school, pre-college earnings.

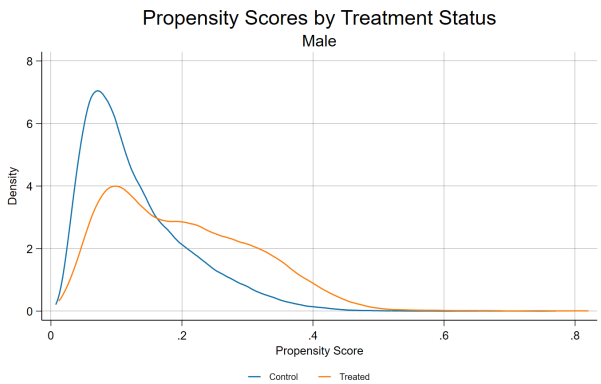
## Appendix 6 - PSM Matching Model

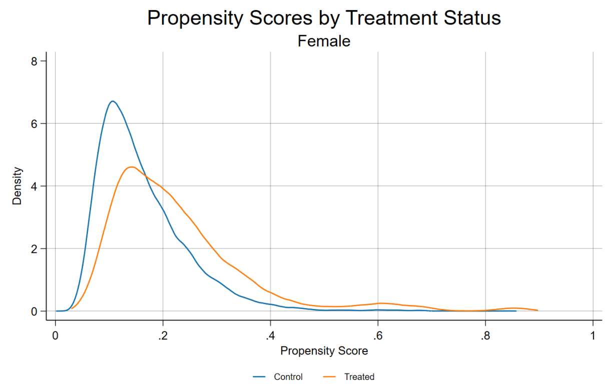
Treatment effect estimates, which have been weighted using inverse probability weights from a propensity score model are below. Propensity scores were generated using the same criteria as were used for matching in the CEM framework . The distribution of propensity scores for men and women may be found below .

Table 14: Propensity Score Inverse Probability Weighting - Effect of Highest Award on Labor Market Outcomes

| | Quarterly Wages | Weekly Hours Worked | Log Hourly Wages |
|---|---|---|---|
| *Men* | | | |
| Associate Degree | 911.5*** | 2.775*** | 0.0354*** |
| | (116.8) | (0.355) | (0.00970) |
| Long-Term Certificate | 1603.1*** | 3.278*** | 0.0949*** |
| | (95.02) | (0.284) | (0.00813) |
| Short-Term Certificate | 484.1** | 2.059*** | 0.0297* |
| | (168.1) | (0.523) | (0.0130) |
| *Women* | | | |
| Associate Degree | 1751.2*** | 3.330*** | 0.129*** |
| | (89.87) | (0.302) | (0.00932) |
| Long-Term Certificate | 855.2*** | 3.268*** | 0.0712*** |
| | (69.13) | (0.286) | (0.00925) |
| Short-Term Certificate | 374.5*** | 2.744*** | 0.0198 |
| | (92.42) | (0.393) | (0.0113) |

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$


Propensity Scores by Treatment Status
Male
Density
Propensity Score
Control
Treated


Propensity Scores by Treatment Status
Female
Density
Propensity Score
Control
Treated

## Appendix 7 - Human Capital and Signalling

Throughout this paper, non-completers are used as a control group. Since these individuals completed some college coursework, this could mean that the main estimates are understating the returns to attending college, since the comparison group might have accumulated some human capital while enrolled.[37] In order to put bounds on this potential bias, I estimate the effect of completing an associate degree using two distinct groups of non-completers: those who have accumulated fewer than 5 college credits (and thus have accumulated little-to-no human capital as a result) and those who completed enough credits to be awarded an associate degree, but haven't been awarded one (which you could assume is roughly analog to gaining an associated degree amount of human capital). Of course, there is much greater concern about dynamic selection for individuals who accumulate enough credits for a degree, but don't receive one. If these results were taken seriously as reflecting the human capital and signalling components of the earnings return, they would imply that 1/2 and 3/4 of the earnings return is being driven by returns to the *credential*, rather than attendance. This could be a result of many occupations requiring an occupational license tied to college credential completion, particularly in the health field. As such, those who complete much of the coursework for a degree, but don't hold the credential, may be legally constrained from working in occupations with higher earnings returns.

[37] I assume throughout that this problem is minimal, given that most non-completers are enrolled only very briefly.

Table 15: Human Capital or Sheepskin?

| | AA or 60+ Credits | AA or ¡ 5 Credits |
|---|---|---|
| *Men* | | |
| Quarterly Earnings | 693.8*** | 1390.5*** |
| | (159.0) | (122.9) |
| Log Hourly Wages | 0.0355** | 0.0577*** |
| | (0.0124) | (0.00997) |
| Weekly Hours | 2.121*** | 3.384*** |
| | (0.491) | (0.387) |
| *Women* | | |
| Quarterly Earnings | 1423.4*** | 1994.8*** |
| | (116.7) | (96.56) |
| Log Hourly Wages | 0.108*** | 0.144*** |
| | (0.0119) | (0.00948) |
| Weekly Hours | 3.011*** | 3.877*** |
| | (0.388) | (0.325) |

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$