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The Fixed-Effects Model in Returns to Schooling and Its Application to Community Colleges: A Methodological Note

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Abstract

The purpose of this note is to develop insight into the performance of the individual fixed-effects model when used to estimate wage returns to postsecondary schooling. We focus our attention on the returns to attending and completing community college. While other methods (instrumental variables, regression discontinuity) have been used to estimate the returns to four-year colleges, the individual fixed-effects estimator has primarily been employed in the analysis of community colleges. Using data from Michigan, we test the common-trends assumption that underlies the individual fixed-effects estimation strategy. We find that the common-trends assumption is violated in our sample. We suggest an estimation strategy that allows for individual-specific pre-trends in earnings. Including these trends substantially alters the estimated returns.

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1. Introduction

The purpose of this note is to develop insight into the performance of the individual fixed-effects model when used to estimate wage returns to post-secondary schooling. We focus our attention on the returns to attending and completing community college. While other methods (instrumental variables, regression discontinuity) have been used to estimate the returns to four-year colleges, the individual fixed-effects estimator has primarily been employed in the analysis of community colleges. Community college students, more so than university students, are frequently adults with an earnings history, making feasible the use of an individual fixed-effects estimator.

We begin with a brief discussion on the literature, particularly of the origins and evolution of the analysis of returns to community colleges. We then discuss the fixed-effects model, specifying its underlying econometric assumptions. We then turn to administrative data from Michigan to test these assumptions. We conclude with a discussion of the appropriateness of the method and suggestions for future research.

2. Background

Belfield and Bailey (2011) summarize the literature on returns to community college credits, certificates, and degrees. They find returns to associate degrees of zero to 20 percent, averaging 13 percent for men and 22 percent for women. Returns to certificates (which are short-term credentials that take less time than the two-year associate degree) range from 7 percent to 22 percent for men and from 3 percent to 41 percent for women, depending on the type of certificate.

These results are largely based on the Mincer earnings model, in which log wages are modeled as a function of education and experience. This model (Ben-Porath, 1967; Mincer, 1974) posits forward-looking individuals who maximize the discounted, net-present value of human-capital investments. While early work suggested wage differentials between more and less educated workers reflect the cost of acquiring human capital, much of the subsequent literature has concerned itself with issues of selection bias in estimating these gains (see Polachek & Bargain, 2007, and Card, 2005, for comprehensive reviews).

In particular, Willis and Rosen (1979) suggest that college and high school graduates may have sufficiently different skills that the earnings of high school graduates are a poor proxy for the opportunity cost of college. This line of thinking has resulted in a long literature seeking to identify the causal effect of additional schooling on wages. To forward this agenda, researchers attempt to either (1) identify exogenous variation in the cost of schooling, or (2) difference out unobserved, fixed, individual-level factors that may bias estimated returns to education. The community-college literature has focused almost exclusively on the latter approach.

Much of the current literature references Jacobson, LaLonde, and Sullivan (2005b) [JLS hereafter], who estimate returns to credits for displaced workers in Washington state. JLS rely on a careful parameterization of individual time-trends and time-varying controls in an individual, fixed-effects model. Their analysis, replicated to one degree or another by subsequent authors, is restricted to workers with three years of tenure prior to layoff. They focus on returns to credits, rather than degrees, because displaced workers rarely earn degrees. Their study follows workers for four years after initial enrollment in a community college. Using individual fixed-effects, the authors estimate a six percent rate of return for one year of schooling. Results are positive for technical fields and zero or negative for other fields.

Along the same lines, Jacobson and Mokher (2009) estimate returns to credits for traditional-aged students (who enter college directly from high school), in Florida community colleges. Their identification strategy relies on controls for high school performance and other individual-level covariates. Like Jacobson, LaLonde, and Sullivan (2005a), they find that certificates and degrees in technical courses produce the highest returns.

In a more recent study, Jepsen, Troske, and Coomes (2014) estimate returns to degrees, certificates, and diplomas from community colleges in Kentucky. The authors restrict their sample to respondents who do not continue to a four-year college and who are over age 20 at enrollment. To estimate returns, the authors include individual fixed effects in their earnings regressions, finding returns to associate degrees of approximately $2,000 per quarter. Several other papers similarly build on the work of JLS, Jacobson and Mokher (2009), and Jepsen, Mueser, and Troske (2012) to study the same phenomena in different venues. In particular, Stevens, Kurlaender, and Grosz (2015) estimate returns in California, while Bahr et al. (2015) estimate returns in Michigan.

3. The Fixed Effects Model in Returns to Schooling

We begin by describing the model in JLS, which is the richest and most exhaustive in terms of accounting for pre-trends and individual characteristics. As we discuss later, subsequent studies typically include a subset of the controls and trends specified in JLS.

Let earnings for individual *i* at time *t* be represented as follows:

$$y_{it} = \alpha_0 + X_{it}'\beta + \delta Degree_{it} + \pi_i + \theta_t + \epsilon_{it}$$

where *X* is a vector of time-varying individual characteristics (e.g., age) and *Degree* is equal to one in periods in which *i* has a degree and is zero otherwise. The identification concern is that unobserved, individual characteristics (e.g., ability, effort, professional networks) are correlated both with completed schooling and earnings. This produces bias in our estimates to the return to schooling.

With panel data, time-invariant individual characteristics, π_i, can be differenced out by replacing both right- and left-hand side measures with deviations from their individual-level means. If all of the unobservable characteristics inducing bias in our estimates are indeed fixed, this specification will then identify the effect of earning a degree on earnings. If, instead, there are unobserved, time-varying, individual-level factors associated with schooling and earnings, the estimate will still be biased.

To tackle this problem, JLS estimate a model similar to the following:

$$y_{it} = \alpha_i + \omega_i t + \gamma_t + x_{it}\beta + \delta_{it}(s_i, z_i) + \tau_{it}(c_i, f_i, l_i, z_i) + \epsilon_{it}$$

where quarterly earnings (y_{it}) depend on an unobserved individual fixed effect (α_i) and individual time trends ($\omega_i t$). Quarter fixed effects (γ_t) and time-varying worker characteristics (x_{it}) are also included. Dummies indicate the timing of job displacement $\delta_{it}(s_i, z_i)$ which depends on time of displacement (s_i) and individual characteristics (z_i). The coefficients of interest are $\tau_{it}(c_i, f_i, l_i, z_i)$ which estimate the effect of schooling on earnings, and are allowed to vary with worker characteristics (z_i), credits earned (c_i), and first and last quarters of enrollment (f_i, l_i).

Disregarding the effects of job displacement $\delta_{it}(s_i, z_i)$, which are unique to JLS as they limit their sample to workers who experience job loss, the model not only differences out time-invariant, individual-level factors, but also allows for individual time trends, $\omega_i t$. They therefore estimate deviations from individual trends, rather than individual means. They also account for time-varying heterogeneity in schooling that is a function of individual characteristics.

This model, as the authors note, is computationally intensive. In the full model the authors have between 160 and 300 time-varying individual characteristics plus an additional 97,000 worker fixed effects and time trends (for their roughly 97,000 observations), estimated with 3.2 million person-by-quarter observations.

To ease computational intensity, the authors use a Frisch-Waugh two-step, regression-by parts-procedure in which they take the model parameters $y_{it} = \alpha_i + \omega_{it} + w_{it}\lambda + \varepsilon_{it}$, where w_{it} are all terms that are not individual-specific, and estimate $\tilde{y}_{it} = \widetilde{w}_{it}\lambda + \varepsilon_{it}$ where $\tilde{y}$ and $\widetilde{w}$ are deviations from individual-specific means and linear time trends. We note this to demonstrate that, while cumbersome, the inclusion of individual time-trends and computation of corresponding standard errors via the two-step procedure is quite feasible.[1]

Despite the feasibility of this procedure, the papers discussed above that follow JLS do not replicate it. Rather, they include individual fixed effects in the model, along with interactions between age and time-invariant, individual level controls, omitting the person-level time-trends. The omission of person-specific trends leaves fixed-effects estimates of the return to schooling vulnerable to violations of the parallel-trends assumption. Those who complete more credits and credentials may be on different earnings trends than those who do not. This will produce bias in

[1] The exact procedure can be found in Jacobson et al. (2005b), p. 284.

estimates of the return to education. The sign of this bias is ambiguous, since those who get more schooling may have been either on a higher or lower earnings trajectory than their peers.

Individual fixed effects, which account for fixed but not changing differences between workers, do not eliminate this source of bias. The interaction of time trends with observable characteristics will solve the problem only if any differences in the earnings trends of those who complete more and less schooling are completely attributable to differences in their observable characteristics. In the following we replicate the models found in Jepsen et al. (2014) and Dadgar and Trimble (2015) and then add two elements: we test the parallel trends assumption across "treatment" groups, and we add an individual time trend to their preferred specification. These additions will allow us to determine the degree to which existing work may be mis-specified.

4. Data and Sample

We obtained student records from five Michigan community colleges. These five schools represent approximately 40 percent of all students in Michigan's public and not-for-profit two-year institutions. Table 1 shows basic summary statistics comparing our schools to community colleges in Michigan and the US.

Table 1: Institution Summary Statistics

	Our 5 MI institutions	All other MI institutions	All US institutions
Demographics			
Female	57%	61%	60%
Non-White	22%	26%	36%
Full-time	38%	39%	46%
Traditional	8%	11%	14%
Tuition			
Tuition (in district)	$1,902	$2,025	$2,535
Tuition (in state)	$2,995	$3,102	$2,939
Students			
Number of schools	5	25	1,057
Average enrollment	13,150	6,271	5,537
Total enrollment	65,750	156,769	5,559,469

Note. Statistics from IPEDS, 2006. Sample is public and not-for-profit two-year degree granting institutions.

The records cover a ten-year window, from fall 2001 to spring 2011. These data include student demographics, applications for and receipt of financial aid, scores from remediation placement tests, transcripts from each term attended, and a record of each award (certificate, degree, or diploma) received, including field of study.[2]

Labor market outcomes are from the state of Michigan's unemployment insurance records. We obtained quarterly earnings for the second quarter of 1998 through the second quarter of 2011. These capture earnings only in the state of Michigan and, like all unemployment records, do not include income from self-employment. These records also do not include hours worked.

In order to capture any postsecondary enrollment prior and subsequent to enrollment in our five institutions, we match these student records to the National Student Clearinghouse database (NSC). NSC records provide information on enrollment but not credit accumulation; credits earned prior to entering our five institutions are therefore unobserved. Thus, we limit our sample to students whose first enrollment (as measured in NSC) was in one of our five schools.[3]

To allow for the observation of earnings before and after college enrollment, we further restrict our sample to students who first entered college between age 21 and 45, in fall 2002 through fall 2007.[4] Finally, in our earnings analyses, we limit the sample to workers who are between ages 17 and 65 in each quarter. Table 2 shows summary statistics by ultimate degree.

[2] Because Michigan has no central body overseeing postsecondary institutions, data across institutions are not consistently collected or coded. Accordingly, we recoded many measures to create uniformity, with some loss of detail.
[3] Our NSC records date back to 1995, so it is possible that some students enrolled prior to 1995 and then did not enroll again until they entered our schools.
[4] We drop the few students who are missing date of birth or gender.

Table 2: Summary Statistics

	No degree	Short certificate	Certificate	Associate degree	Bachelor's degree	Total
Age at first credit	30.02	30.87	31.49	30.48	28.17	29.99
	(6.91)	(7.00)	(6.92)	(6.84)	(6.40)	(6.89)
White	0.61	0.53	0.69	0.72	0.65	0.63
	(0.49)	(0.50)	(0.46)	(0.45)	(0.48)	(0.48)
Non-White	0.31	0.44	0.27	0.24	0.28	0.30
	(0.46)	(0.50)	(0.44)	(0.42)	(0.45)	(0.46)
Race missing	0.09	0.03	0.05	0.06	0.07	0.09
	(0.29)	(0.18)	(0.23)	(0.24)	(0.26)	(0.28)
Ever Pell	0.31	0.47	0.34	0.41	0.15	0.31
	(0.46)	(0.50)	(0.47)	(0.49)	(0.35)	(0.46)
Ever loan	0.05	0.27	0.13	0.07	0.06	0.06
	(0.22)	(0.45)	(0.34)	(0.26)	(0.23)	(0.24)
Non-remedial credits	4.91	5.08	6.91	6.87	6.31	5.24
first term	(3.49)	(3.35)	(4.72)	(4.04)	(3.82)	(3.67)
Remedial credits	1.44	1.02	1.21	1.22	0.73	1.36
first term	(2.57)	(2.15)	(2.38)	(2.37)	(1.85)	(2.51)
Prior employment	0.68	0.76	0.76	0.70	0.68	0.69
	(0.47)	(0.43)	(0.43)	(0.46)	(0.47)	(0.46)
Prior earnings	4,629	3,730	5,107	4,142	4,610	4,582
	(6,590)	(4,463)	(5,861)	(51,34)	(6,430)	(6,416)
Prior earnings trend	525	265	131	185	918	507
	(4,132)	(3,231)	(3,657)	(3,744)	(4,245)	(4,086)
English score	0.03	-0.05	0.12	0.46	0.48	0.09
	(1.02)	(0.99)	(0.97)	(1.00)	(0.99)	(1.03)
Math score	-0.34	-0.32	-0.31	0.02	0.47	-0.26
	(0.85)	(0.90)	(0.83)	(0.96)	(1.10)	(0.90)
Missing English	0.57	0.37	0.59	0.54	0.75	0.58
	(0.50)	(0.48)	(0.49)	(0.50)	(0.43)	(0.49)
Missing math	0.55	0.43	0.62	0.47	0.69	0.55
	(0.50)	(0.50)	(0.49)	(0.50)	(0.46)	(0.50)
N	33,971	578	1,070	3,999	2,922	42,540
Percent of total	80%	1%	3%	9%	7%	100%

5. Model Comparison

We begin by comparing estimates between pooled and fixed effects models. The pooled model we estimate is as follows:

$$y_{it} = \beta_0 + \sum_{j=1}^{4} \beta_j Award_{i,t-1} + \beta_5 Enrolled_{it} + \beta_6 (Age, Age^2)_{i,t} + \beta_7 f(race, gender)$$

$$+ \beta_8 (FinAid, TestScore, Credits1st) + \beta_9 y_{i,0} + \pi_s + \phi_a + \theta_c + \tau_t \, \epsilon_{it}$$

where *y* is earnings in quarter *t*, *Award* is a set of indicators equal to 1 if students have a degree (short certificate, certificate, associate degree, or bachelor's degree) in period *t-1*, *f*(race, gender) are interactions and main effects, and $(FinAid, TestScore, Credits1st)$ controls for receipt of financial aid, remediation test scores, and number of credits taken in the first term. The terms $\pi_s + \phi_a + \theta_c + \tau_t$ are fixed effects for school (*s*), age at enrollment (*a*), college entry cohort (*c*), and secular quarter (*t*). Lastly, $y_{i,0}$ is a control for a one-quarter earnings lag.

We compare these results with an analogous specification that differences out time-invariant individual characteristics using an individual fixed effect (ϕ_i). We also include interactions between age and several of our key covariates:

$$y_{it} = \beta_0 + \sum_{j=1}^{4} \beta_j Award_{i,t-1} + \beta_5 Enrolled_{it} + \beta_6 (Age, Age^2)_{i,t} +$$

$$\Gamma(age, age^2) * (Race, Gender, FinAid, TestScore, EnrollAge, Credits1st, y_{i0}) + \tau_t + \phi_i +$$

$$\epsilon_{it}$$

Results from these two specifications are shown in Tables 3 (pooled) and 4 (fixed effects). Column 1 includes indicators for degrees or credentials awarded but no other controls. Controlling for individual and schooling characteristics in columns 2 and 3 of Table 3 has only minimal effects on the estimated earnings gains. In fact, none of the estimates in column 3 is statistically distinguishable from its counterpart in column 1. When we control for lagged earnings, by contrast, we see large decreases in estimates for all awards.

Table 3: Earnings Gains by Award Type, Pooled Cross-Sections

	(1)	(2)	(3)	(4)
Short certificate	-69.5	337.3**	241.7	92.53**
	(165.20)	(168.50)	(167.50)	(36.94)
Certificate	1850.4***	1571.5***	1804.0***	466.8***
	(195.50)	(189.60)	(188.60)	(47.08)
Associate degree	1129.3***	883.4***	1224.0***	393.9***
	(97.68)	(100.40)	(99.18)	(26.36)
Bachelor's degree	2205.7***	2236.1***	2028.2***	614.7***
	(168.20)	(163.00)	(162.60)	(44.12)
Quarter		X	X	X
School, Enroll age, Cohort		X	X	X
Age, Age2		X	X	X
Enrolled		X	X	X
Race*Gender		X	X	X
Aid			X	X
Scores			X	X
Credits in first term			X	X
Lagged earnings				X
N	2,199,903	2,199,903	2,199,903	2,157,363
Observations	42,540	42,540	42,540	42,540
R2	0.003	0.103	0.117	0.670

*p < 0.05. **p < 0.01. ***p < 0.001.

In Table 4, we estimate specifications that include individual fixed-effects, as well as the degree indicators (column 1). We then add the interactions of observable characteristics with quadratic time trends (implemented by including the interaction of age with the listed observables and the interaction of the square of age with the listed observables). The inclusion of these time trends has little statistically significant impact on the estimates in column 1.

Finally, in column 5 of Table 4 we include individual time trends as follows:

$$y_{it} = \beta_0 + \sum_{j=1}^{4} \beta_j Award_{i,t-1} + \beta_5 Enrolled_{it} + \tau_t + \phi_i + \omega_i t + \epsilon_{it}$$

where $\omega_i t$ is a linear time trend interacted with an individual fixed effect (thus all time-invariant individual effects drop out due to ϕ_i, and all age and age interactions drop out due to $\omega_i t$ as age and the time trend are perfectly collinear). Results in column 5 indicate substantively large differences from columns 1–4. In fact, comparing to column 5, our most saturated individual fixed effects model, estimates of the return to short certificates increase by nearly 25 percent, while estimates of returns to certificates decrease by roughly the same amount. Similarly, estimates of returns to associate degrees increase by 17 percent while returns to bachelor's degrees decline by 27 percent. These dramatic differences suggest that simply including individual fixed effects and linear interactions between time and fixed observable covariates still leaves unobserved heterogeneity correlated with both degree receipt and subsequent earnings. In other words, the parallel trends assumption is violated. To demonstrate this, we next turn our attention to testing the assumptions underlying the empirical specifications in Table 4.

Table 4: Earnings Gains by Award Type, Fixed Effects Specification

	(1)	(2)	(3)	(4)	(5)
Short certificate	384.1***	410.9***	334.4**	518.5***	640.1***
	(143.50)	(143.40)	(145.30)	(144.60)	(147.73)
Certificate	755.5***	719.7***	680.6***	835.7***	624.4***
	(136.60)	(134.80)	(136.30)	(136.70)	(129.82)
Associate degree	1443.9***	1408.5***	1386.5***	1524.4***	1794.1***
	(82.69)	(81.89)	(82.31)	(82.10)	(77.94)
Bachelor's degree	2042.1***	2015.1***	2054.0***	1870.3***	1366.6***
	(138.60)	(138.10)	(138.30)	(138.90)	(128.26)
Individual time trend					X
Age, Age2*(Scores, credits first term)				X	
Age, Age2*(Prior earnings)			X	X	
Age, Age2*(Race, sex, age at enrollment)		X	X	X	
Quarter	X	X	X	X	X
Age, Age2	X	X	X	X	
Enrolled	X	X	X	X	X
Person fixed effects	X	X	X	X	X
N	2,199,903	2,199,903	2,199,903	2,199,903	2,199,903
Observations	42,540	42,540	42,540	42,540	42,540
R2	0.570	0.571	0.576	0.578	0.678

*p < 0.05. **p < 0.01. ***p < 0.001

6. Test of Common Trends Assumption

To test the common trends assumption implicitly relied upon in much of the literature, we compare earnings trajectories for students earning no degree, a short-term certificate, a certificate, an associate degree, or a bachelor's degree prior to enrollment. For our fixed effects specification to be valid, we require that these trajectories are parallel for all groups, although the levels can be different. To test this, we estimate the following:

$$
\begin{aligned}
y_{it} = \beta_0 + \sum_{j=1}^{4} \beta_j EventualAward_i + \beta_5 q_{it} + \sum_{j=6}^{9} \beta_j EventualAward_i * q_{it} \\
+ \beta_{10}(Age, Age^2)_{i,t} \\
+ \sum_{j=11}^{12} \beta_j (Age, Age^2) * (Demog_i, Aid_i, Scores_i, Cred1stTerm_i) + \phi_c + \eta_t \\
+ \varepsilon_{it}
\end{aligned}
$$

where y_{it} is real quarterly earnings and $EventualAward_i$ is the highest degree students will eventually earn. We limit the analysis to quarters *prior* to enrollment as we are only concerned with pre-existing trends. The term q_{it} is a linear time term indicating the number of quarters until initial college enrollment. The remaining variables are the same as in previous specifications. We are interested in coefficients β_6-β_9, which show differential trends for students that eventually earn each type of degree. We also test specifications where we include the square of q_{it}, allowing for non-linear trends in earnings, though F-tests suggest that the quadratic terms are unnecessary thus we omit them here for parsimony.

Table 5 show results from these exercises. Even with the richest set of controls (column 5), many of which are interacted with time, it appears that the parallel trends assumption is not met. The F-tests and p-values at the bottom of the table formally test whether those who will earn awards are on differential earnings trends from those who will not. The null of parallel trends is strongly rejected, indicating that the common trends assumption is not met.

To demonstrate this graphically, we re-estimate the full specification (column 5 in the table) omitting the award dummies and their interactions with time until enrollment. We then plot residuals from this regression against time until enrollment (Figure 1). The figure depicts clearly that earnings trends differ substantially by ultimate attainment. Those who will eventually receive an associate degree show flat earnings until a sharp dip right before enrollment. For those who will eventually earn a bachelor's degree, earnings rise for most of the quarters preceding enrollment. For those eventually earning a certificate, earnings are generally flat or declining until enrollment.

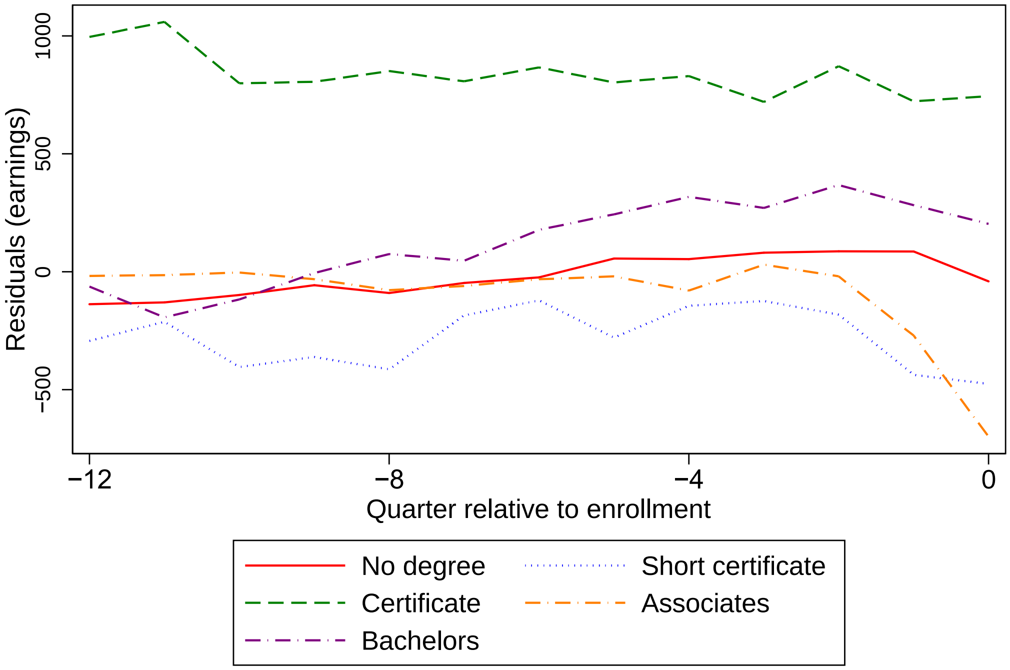
Table 5: Pre-Enrollment Earnings Trends, by Highest Degree Eventually Completed

	(1)	(2)	(3)	(4)	(5)
Short certificate	-1024.3***	-1237.7***	-406.1*	-365.8	-362.6
	(193.0)	(196.1)	(197.6)	(195.8)	(196.3)
Certificate	386.6*	1.150	369.4*	655.6***	663.9***
	(190.5)	(189.5)	(184.9)	(181.8)	(182.1)
Associate degree	-707.7***	-911.6***	-788.9***	-393.8***	-356.4***
	(89.30)	(90.57)	(89.49)	(87.85)	(88.40)
Bachelor's degree	85.95	328.6*	306.2*	154.6	285.5*
	(130.7)	(127.8)	(125.0)	(123.1)	(124.3)
Time (quarters to entry)	60.04***	27.88***	24.67***	52.96*	22.46***
	(2.640)	(4.856)	(4.762)	(22.29)	(4.791)
Short certificate*Time	-40.05*	-37.73*	-26.78	-19.66	-18.32
	(15.91)	(15.93)	(15.93)	(15.95)	(15.93)
Certificate*Time	-45.64***	-41.87**	-41.24**	-33.02*	-34.95**
	(13.56)	(13.44)	(13.50)	(13.52)	(13.49)
Associate*Time	-57.09***	-58.45***	-53.36***	-45.72***	-45.90***
	(7.303)	(7.333)	(7.363)	(7.371)	(7.378)
Bachelor's*Time	44.97***	31.59**	33.05***	22.93*	23.94*
	(9.734)	(9.908)	(9.907)	(9.915)	(9.931)
Quarter effects		X	X	X	X
Age & Age Squared		X	X	X	X
School effects			X	X	X
Age*Race*Gender			X	X	X
Age*Controls				X	X
Age*Test scores					X
N	552,924	552,924	552,924	552,924	552,924
R-Squared	0.002	0.056	0.108	0.133	0.135
P-value (Degrees*Time)	<0.001	<0.001	<0.001	<0.001	<0.001
F-stat (Degrees*Time)	26.16	23.12	19.98	13.22	13.75

Note. Clustered standard errors in parentheses

*p < 0.05. **p < 0.01. ***p < 0.001.

Figure 1: Earnings Residuals Relative to Enrollment, by Eventual Degree



Results in Figure 1 confirm our findings in column 5 of Table 4 which included individual time trends. Table 1 graphically depicts increasing earnings for bachelor's degree recipients prior to enrollment and declining earnings for eventual short-certificate and associate degree recipients. Accordingly, including individual time trends in Table 4 revises returns to short-certificate and associate degree earners upward and returns to bachelor's degree recipients downward. The pattern for certificate holders is not as clear, though comparing columns 1–3 with column 5 in Table 4 yields a pattern more similar to what we see in Figure 1. Taken together, results from Tables 4 and 5 and from Figure 1 suggest that the individual fixed-effects model does not satisfy the necessary assumptions for causal identification of the return to community college degrees.

7. Discussion and Suggestions

Given the results in Table 5 and Figure 1, it appears that the common trends assumption that underlies the individual fixed-effects assumption does not hold among students attending community colleges in Michigan. We suspect that the same is true in other settings.

We suggest that researchers interested in estimating returns to community college using panel data take the following steps. First, conduct formal tests of the identifying assumption that trends across “treatment” groups are satisfied. While we demonstrated this testing pre-enrollment trends, the same approach can be used to test common trends before college exit.

Second, we suggest that as a robustness check researchers replicate the JLS model, including individual-specific time trends and time-varying interactions. Advances in computational power coupled with regression by parts make this robustness test computationally feasible. Moreover, to further ease computational burden, researchers can conduct this robustness test on a random sub-sample of the data.

As discussed in the literature review, summaries of extant research show wide variation in estimated returns to community college awards. Our suggested estimation strategy may help to tighten this range of estimates across contexts and populations.

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