

The Labor Market Returns to Earning Industry Credentials

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Motivation

- Widening wage gap between high school graduates and those with a college degree (Autor 2014)
- Nominal costs of four-year degrees have risen dramatically
- Sub-baccalaureate options have emerged as an alternative by providing additional skills to students without high tuition costs
- **We ask:** What are the labor market returns to an industry credential?

What is an industry credential?

- What they are
 - Formal recognition of training (or demonstration of skill) by an industry association, professional association, or standards organization
 - Training provided by a community college or on-the-job
 - Attainment achieved via a test or demonstration
 - Often tiered/tied to other credentials from same org
- What they are not
 - Licenses from state government agencies
 - Certificates from community colleges
 - A degree

Data

- Partnership between the U.S. Census Bureau, the National Student Clearinghouse (NSC), and the National Association of Manufacturers (NAM)
- Data acquired by NSC from industry credential providers
 - Current: Manufacturing, welding, safety professionals, pharmacy technicians
 - Future: IT, trucking, human resources
- Credential data matched to their NSC post-secondary information
 - Enrollment and completion from late 1960s to present
- NSC-credential data transferred to the Census Bureau then linked to
 - Demographic data (ACS, Decennial Census)
 - IRS earnings and employer data (Form W2, Form 1040, Business Register)
- Comparison group drawn from ACS sample

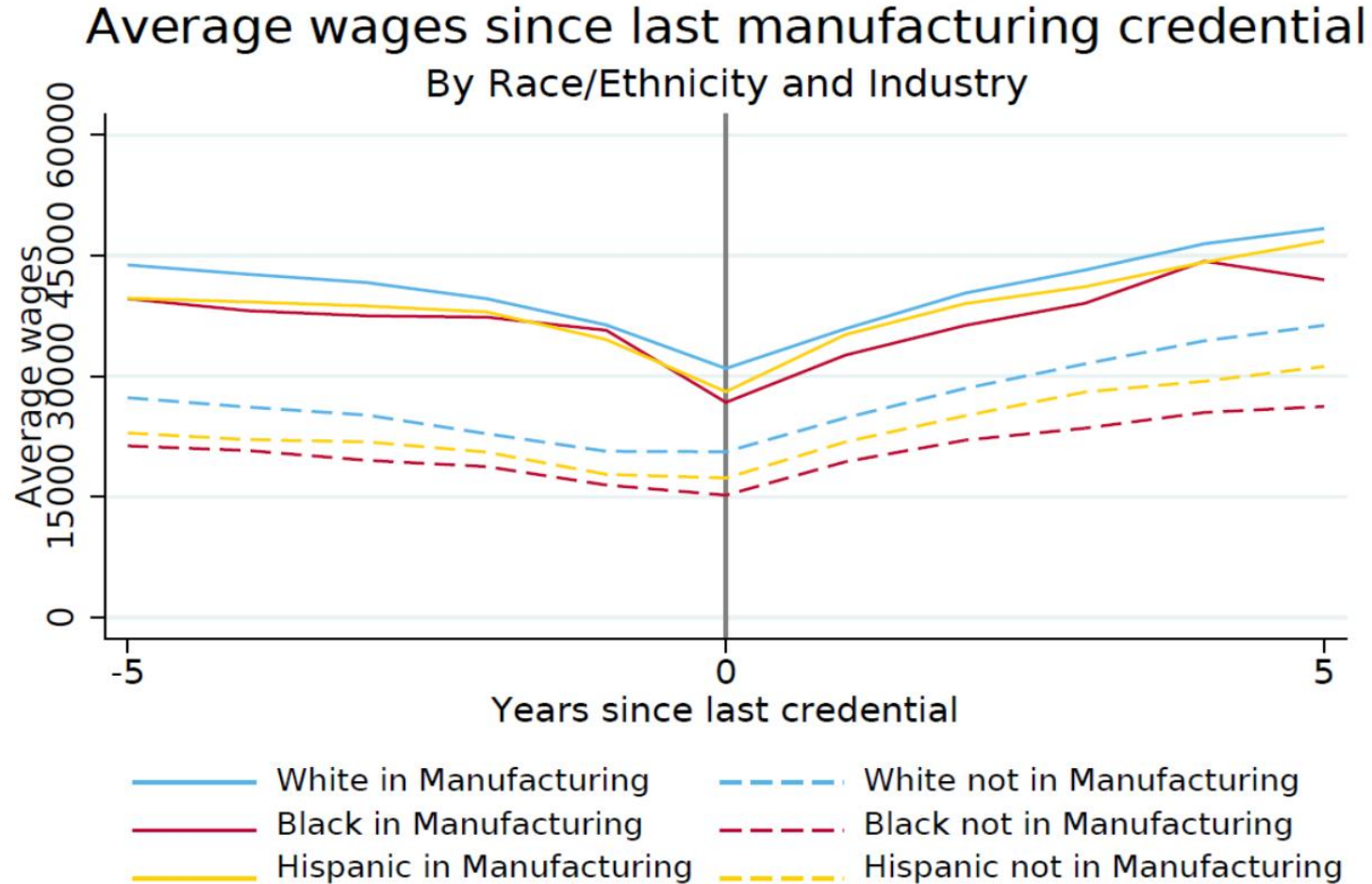
Methods: Summary Figures

- Earnings and employment trajectories before and after credential attainment by demographics/industry/level within credentialed group
- “Before and after credential” defined relative to year of *last* credential
 - Getting as close as we can to labor market entry post-credential
 - Multiple credentials may only be separated by a few months

Outcomes:

- Average W2 earnings
- Employment (has W2 earnings, employed in a particular industry)

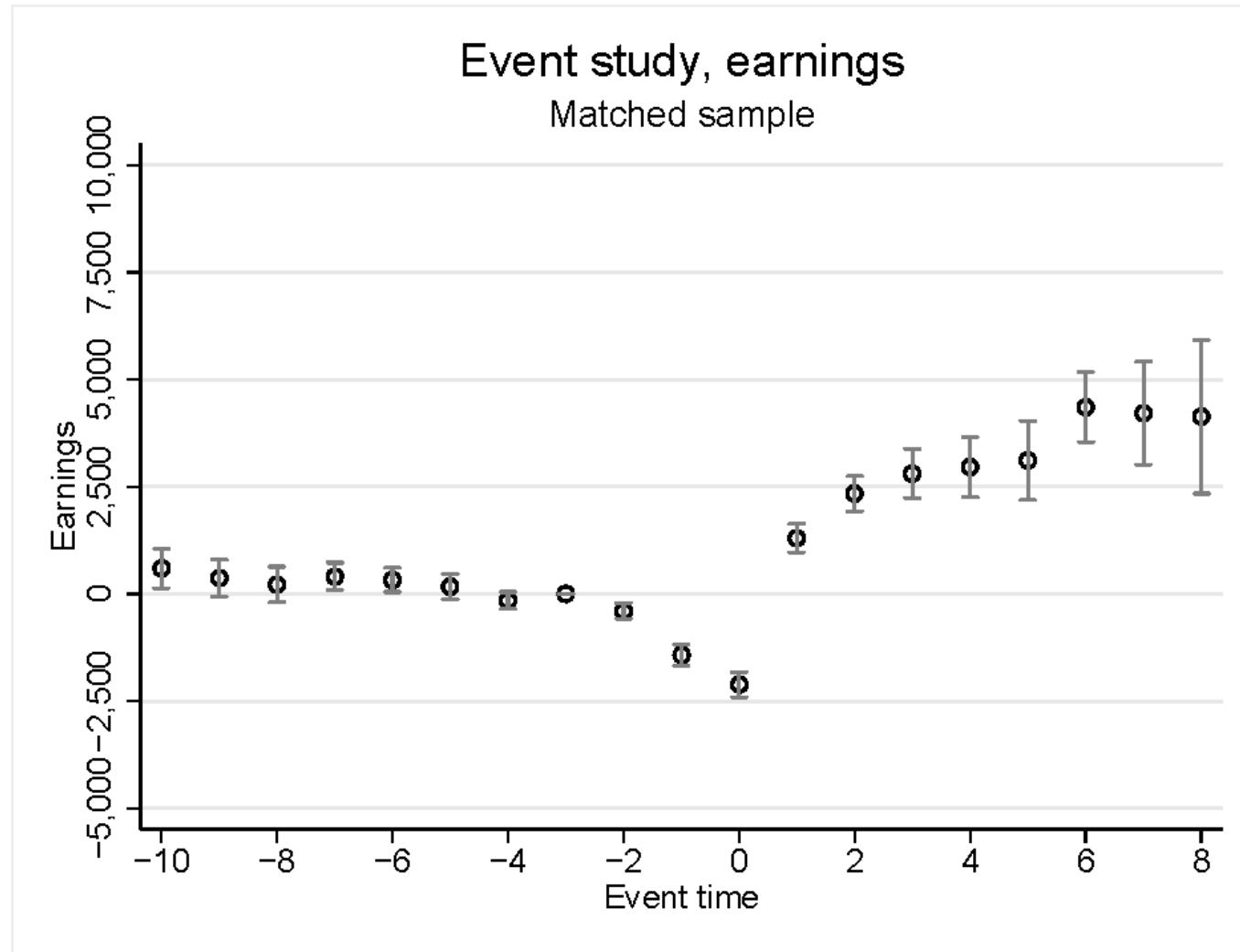
Wage Trajectories: Manufacturing



Methods: Measuring Causal Effects

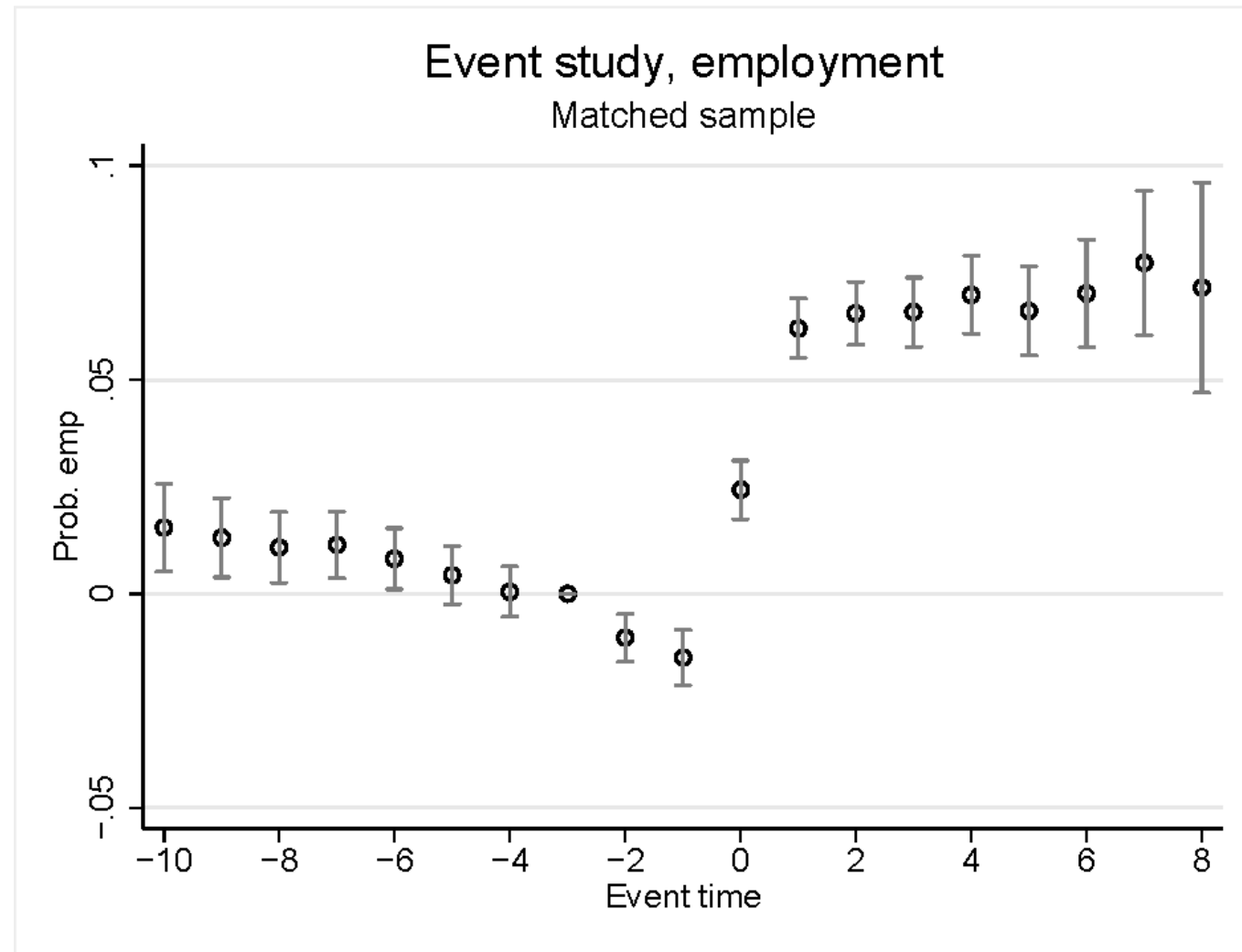
- Research paper uses coarsened exact matching (CEM) to construct an ACS comparison group
 - Takes the idea of an exact match but bins characteristics
 - Characteristics include age, race/ethnicity, gender, educational attainment, industry, family structure (married/children), average wages pre-credential, in labor force pre-credential, pre-credential firm characteristics (# employees, payroll)
- Bins chosen to maximize match quality while retaining project observations
- Define placebo treatment for comparison group as ACS survey year
- Estimate event study and diff-in-diff regressions on matched sample

Event Study: Earnings



Source: NAM-NSC, Census 2010, and 2005-2018 ACS, Form 1040, and Form W-2 data.
DRB approval number: CBDRB-FY23-CES014-032.

Event Study: Employment



Source: NAM-NSC, Census 2010, and 2005-2018 ACS, Form 1040, and Form W-2 data.
DRB approval number: CBDRB-FY23-CES014-032.

Current work: Routinizing a Comparison Group

- CEM, diff-in-diff good for academic research but less scalable and requires significant tinkering
- Goal: Want simple, standardized process that is easily interpretable for both potential credential earners and credential providers
- Sample of ACS respondents in the occupation not enough
 - Credential earners skewed by age, other characteristics
 - Ambiguous whether ACS respondents have other credentials
 - Difficult to assign an industry or occupation

Discussion and lessons learned

- Fruitful project generating estimates of academic, industry, and public interest
- Results in manufacturing sector suggest workers with industry credentials have better employment and wage outcomes than comparable workers without credentials
- Still working to establish a generalizable process for suitable comparison groups for each credential type
- Ability to paint clear picture depends on cooperation of credential providers

Thank you!

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Appendix slides

Match rates

Match rates of project data to unique identifier, demographic data, and federal tax information	
PIK rate on manufacturing credential records	0.5628
Fraction unique manufacturing learner IDs assigned PIK	0.5433
Percent of PIKed manufacturing cred students linked to ACS/Decennial	0.8203
Percent of PIKed manufacturing cred students ever linked to W2	0.8281
Percent of PIKed manufacturing cred students ever linked to 1040	0.8767

Source: NAM-NSC, decennial 2010, and 2005-2018 ACS, Form 1040, and Form W-2 data. Approved for release under CBDRB-FY2021-CES010-029.

Balance

	Unmatched			Matched		
	Cred	No cred	P-value	Cred	No cred	P-value
Birth year	1980	1971	0	1980	1980	0.01
Pre-wage	21820	25150	0	22480	23990	0
Firm emp	12900	11380	0	13230	13230	0.97
Firm pay	979,300	863,900	0	1,004,000	1,004,000	0.97
In LF	0.8199	0.7232	0	0.8408	0.8407	0.97
Male	0.8131	0.4977	0	0.8223	0.8218	0.86
White NH	0.5648	0.7136	0	0.6245	0.6241	0.92
Black NH	0.164	0.1071	0	0.1604	0.1608	0.89
Hispanic	0.1158	0.1183	0.17	0.1048	0.1049	0.97
Other race	0.1554	0.06095	0	0.1104	0.1103	0.97
Associates	0.1312	0.1601	0	0.1036	0.1033	0.91
N	30,000	1,210,000		25,000	328,000	

Regression specifications

Event study:

$$y_{it} = \sum_{t=-10}^8 \beta_t (hascred_i \times \tau_t) + \gamma X_{it} + \alpha_i + year_t + \epsilon_{it}$$

Differences-in-differences:

$$y_{it} = \alpha + \beta (hascred_i \times post_t) + \gamma X_{it} + \tau_t + year_t + \epsilon_{it}$$

where t = years since treatment

$hascred$ = indicator for whether the worker ever earned a credential

$post$ = indicator for whether the year is after the treatment year.

Diff-in-diff: Earnings

	Associates or less		Credentialed 2016-17	
	Unmatched	CEM matched	Unmatched	CEM matched
Has cred X post	5522	1981	5431	878.5
	82.86	87.86	158.7	149.3
Person-years	18600000	5299000	4736000	1551000
Persons	1240000	350000	300000	100000
R-squared	0.3867	0.4519	0.5324	0.5469

Controls: male, age, age squared, Black, Hispanic, otherrace, household structure (4 categories), associates degree, industry (5 categories), region (4 categories), average wage pre-treatment, in labor force pre-treatment, firm payroll, firm employment, treatment year, calendar year.

Diff-in-diff: Employment

	Associates or less		Credentialed 2016-17	
	Unmatched	CEM matched	Unmatched	CEM matched
Has cred X post	0.1382	0.0714	0.1315	0.0568
	0.0012	0.0016	0.0021	0.0028
Person-years	18600000	5299000	4736000	1551000
Persons	1240000	350000	300000	100000
R-squared	0.3914	0.3198	0.3962	0.3662

Controls: male, age, age squared, Black, Hispanic, otherrace, household structure (4 categories), associates degree, industry (5 categories), region (4 categories), average wage pre-treatment, in labor force pre-treatment, firm payroll, firm employment, treatment year, calendar year.