Online Appendix:

Do Microcredentials Help New Workers Enter the Market? Evidence from an Online Labor Platform

Otto Kässi, Vili Lehdonvirta

2022-02-14

Appendix 1. Variable Definitions for the Variables Used in the Regression Models

Table A1
Definitions of the variables used in the regression models

Project characteristics	
Variable name	A description of the variable
Project value	Dollars paid to the freelancer after successful completion of project
Hourly rate	The hourly rate of a freelancer hired in a project (only for hourly projects)
Star rating given to worker	The rating given to the worker by the employer after project completion
Competitiveness of project	The number of applicants to a project
Project type	One of 87 different categories used on the platform, grouped into six broad categories: Design, Finance, Sales and Marketing, Technology, Virtual Assistant, Writing and Translation, Other.
Freelancer tier	The desired freelancer tier set by the employer for each project. It ranges from 1 (looking for cheap freelancers) to 3 (willing to hire an expert at a higher cost).
Expected hours	The expected hours needed for the project, set by the employer. This ranges from under 10 hours to full time.
Worker characteristics	
Variable name	A description of the variable
Months active	The difference in full months between the start of the first freelancer project and the date of data collection
Number of completed projects	The number of completed projects at the time of project start.
Dollars earned	Dollars earned at the time of project start
Feedback rating	The average star rating of past projects. The past projects are weighed using the same algorithm that is being used on the online labor platform.

Appendix 2. Balance Tests for Project Characteristics

A central assumption in the event study model is that the earnings paths of the workers would have developed smoothly in the absence of microcredential completion. This assumption rules out possible unobservable shocks that are correlated with selection into treatment or that vary systematically between pre- and post-periods. While this assumption is not directly testable, we demonstrate that there are no systematic between projects won just before microcredential completion and just after it. This suggests that workers get paid more for doing roughly similar work, and that, on average, workers apply to similar projects after microcredential completion as they did before

First, we study whether workers are more likely to win fixed-sum projects after completing a test compared with before. Under hourly contracts, employers are obligated to pay workers for their time regardless of the quality of the work. In contrast, under fixed-sum contracts, workers are not monitored, but employers can withhold payment if they are not satisfied with the output. If completing microcredentials is associated with workers applying for more ambitious projects, then we would expect to see microcredential completing workers subsequently winning more fixed-sum projects, which are riskier but often pay more.

Second, we examine whether there is any difference in the competitiveness of the projects won before a test and after it. Competitiveness is understood as the number of workers bidding for the project. If completing microcredentials is associated with greater worker effort, then workers might apply for more lucrative—and therefore, more competitive—projects after earning a microcredential.

Third, we study the projects' preferred worker tier, as expressed by the employer. When creating a project, the employer can choose what tier of worker they are looking for, choosing from three options ranging from "I am willing to hire an inexperienced freelancer cheaply" to "I am willing to pay more for an experienced freelancer." This information is presented to workers considering bidding for projects. If workers' effort increases after completing a microcredential, we would expect them to subsequently win more projects targeted at higher tiers.

Finally, we study the expected contract length, as expressed by the employer. This ranges from under 10 hours to an open-ended full-time contract. If completing microcredentials is associated with more worker effort, workers might subsequently apply for and win longer-term contracts.

The regression results are reported in Table A2. We find no effects on any of the aforementioned project characteristics that result from microcredential completion. Our results give support to the interpretation that increased earnings after microcredential completion are driven by employers' preference for workers with validated skills rather than by workers applying for or winning different kinds of projects after microcredential completion compared with before.

Table A2
A Comparison of the types of won projects pre-test vs. post-test

	Dependent variable:			
	Hourly project	Log (number of applicants)	Lowest freelancer tier	On-call contract
	(1)	(2)	(3)	(4)
Number of microcredentials	0.003	-0.006	-0.011	-0.006
	(0.007)	(0.025)	(0.024)	(0.008)
Fixed effects	Event	Event	Event	Event
Observations	32,975	23,380	9,004	24,805
Adjusted R^2	0.324	0.355	0.211	0.142

Notes: The unit of observation is a project. In addition to the variables reported, all models include year dummies and cumulative (arsinh-transformed) dollars earned on the platform. Standard errors are clustered on the worker level. Only observations with a non-missing value for the dependent variable are included in the regression models. The significance levels in all specifications are: *** = 0.1%, ** = 1%, * = 5%, and + = 10%.

Appendix 3. CEM Matching Balance

This appendix reports the covariate balance between treated and control groups after CEM matching.

Table A3

Match balance

	Treated	Control
Panel A: Matching balance for estimation data used in Specification (13)		
	Treated	Control
	Mean (standard error)	Mean (standard error)
Average rating	3.242	2.665
	(2.313)	(3.997)
No rating	0.326	0.448
	(0.469)	(0.62)
Number of completed projects	4.358	2.943
	(8.9)	(8.686)
Cumulative dollars earned (arsinh)	4.070	3.405
	(3.114)	(5.068)
Number of certificates	3.023	2.848
	(2.13)	(3.508)
Dependent variable: project value (log)	3.521	3.852
	(1.526)	(3.497)
Panel B: Matched sample for estimation data used in Specification (14)		
	Treated	Control
	Mean (standard error)	Mean (standard error)
Average rating	0.085	0.101
	(0.599)	(1.162)
No rating	0.938	0.974
	(0.241)	(1.906)
Number of completed projects	0.302	0.321
	(4.032)	(7.225)
Cumulative dollars earned (arsinh)	0.185	0.210
	(1.231)	(2.344)
Number of microcredentials	2.913	2.912
	(2.536)	(6.664)
Dependent variable: Number of completed projects	0.015	0.015
	(0.137)	(0.606)

Dependent variable: Number of completed projects > 0	0.014	0.014
	(0.115)	(0.471)
Dependent variable: Earnings	1.397	1.432
	(31.591)	(95.414)

Notes: This table reports the covariate and dependent variable means of treatment and control groups in the pre-treatment period after matching. In panel A, a unit of observation is a project. In panel B, the unit of observation is a 14-day block (4 14-day blocks for each worker). None of the differences between treatment and control groups are statistically significant.

Appendix 4. Donut Estimates

A particular concern for the validity of the event study estimate is that a short-term dip in earnings just before microcredential completion could bias the estimate for return to microcredentials upwards. Moreover, a similar upward bias could emerge if workers strategically apply for more or better-paid jobs immediately after the credential completion.

A specific method for assessing the possible bias due to transitory changes in effort, recommended in the work of Hausman and Rapson (2018), is a donut specification wherein one drops the observations between [–7, ...,7] days of microcredential completion. Comparing the donut estimates with the main specification can help detect possible short-term effects that might be driving our results. These estimates are reported in Table A4. We present the *p*-values for the test for differences between the donut and main estimates. The two are statistically indistinguishable from one another at conventional significance levels. Consequently, we fail to reject the null hypothesis that short-term changes in worker effort would bias our estimates.[1]

It is also worth noting that even the donut fixed effect estimates reported in Table A4 are larger in absolute value than the OLS estimates reported in Table 3, which supports our initial claim that the OLS estimates are biased downwards because of a time-invariant selection effect.

[1] To transform the level estimates into marginal effects when the averages of the dependent variable vary, we have divided the regression coefficient estimate by the mean of the dependent variable.

Table A4
Returns to signaling: donut estimates

	Dependent variable:							
	Project value (log)		Number of projects		Number of projects > 0		Earnings	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Marginal effect of completing a micro-credential	0.1***	0.11***	0.06***	0.04***	0.01**	0.01**	0.09***	0.12***
	(0.02)	(0.04)	(0.006)	(0.006)	(0.004)	(0.005)	(0.02)	(0.03)
P-value for difference	0.74		0.13		0.62		0.52	
Fixed effects	Event	Event	Event	Event	Event	Event	Event	Event
Time window	[-14,...,14]	Donut	[-14,...,14]	Donut	[-14,...,14]	Donut	[-14,...,14]	Donut
Observations	32,975	16,434	178,478	178,478	178,478	178,478	178,478	178,478
Adjusted R^2	0.463	0.457	0.363	0.239	0.273	0.198	0.056	0.009

Notes: In Columns 1–2, the unit of observation is one project. In columns 3–8, the unit of observation is a 14 day or 7 day pre- or post-test period. “Donut” refers to a model estimated using data from days [-14,.., -7], [7,..., 14] around completion of a microcredential. In Columns 1, 2, 7, and 8, the marginal effect corresponds to the point estimate from a linear regression model; in Columns 3–8, the marginal effect corresponds to the point estimate from a linear regression model divided by the mean of the dependent variable. The standard errors in columns 3–8 are calculated using the delta method. The *p*-value for difference is the *p*-value of a *Z*-test for the difference between the regression coefficients, estimated from the standard sample and the donut sample. In addition to the variables reported, all the models include year dummies, and cumulative (arsinh-transformed) dollars earned on the platform. Standard errors are clustered on the worker level. The significance levels in all specifications are: *** = 0.1%, ** = 1%, * = 5%, and + = 10%.

Appendix 5. Falsification Tests

An additional validity concern in our empirical strategy is that our regression models might be capturing some secular positive time trends that are correlated with microcredential completion. We provide evidence against this in Table A5, where we have re-estimated Specifications (11)-(12) while adding 365 days to the microcredential completion date. The results of this exercise are either statistically indistinguishable from zero or negative but economically insignificant.

Table A5
Falsification Tests for Returns to Signaling

	Dependent variable:			
	(log) project value	Number of projects	Number of projects > 0	Earnings
	(1)	(2)	(3)	(4)
Number of microcredentials	0.043	-0.005***	-0.003***	-4.194*
	(0.027)	(0.001)	(0.001)	(1.759)
Fixed effects	Event	Event	Event	Event
Observations	19,608	178,478	178,478	178,478
Adjusted R^2	0.449	0.451	0.369	0.016

Notes: This table presents falsification tests where the microcredential award date is moved 365 days into the future. In Column 1, the unit of observation is one project. In Columns 2–4, the unit of observation is a 14 day pre- or post-test period. In addition to the variables reported, all the models include year dummies, an average rating for completed projects, cumulative (arsinh-transformed) dollars earned on the platform, and the cumulative number of completed projects on the platform, measured at the time of project start. Standard errors are clustered on the worker level. The significance levels in all specifications are: *** = 0.1%, ** = 1%, * = 5%, and + = 10%.

References

Hausman, C., and D. S. Rapson (2018). “Regression discontinuity in time: Considerations for empirical applications.” *Annual Review of Resource Economics* 10():533–552.