Do Digital Skill Certificates Help New Workers Enter the Market? Evidence from an Online Labour Platform*

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Abstract

We study the effects of a voluntary skill certification scheme in an online freelancing labour market. We show that obtaining skill certificates increases a worker's earnings. This effect is not driven by increased worker productivity but by decreased employer uncertainty. The increase in worker earnings is mostly realised through an increase in the value of the projects obtained (up to 10%) rather than an increase in the number of projects obtained (up to 0.03 projects). In addition, we find evidence for negative selection to completing skill certificates, which suggests that the workers who complete more skill certificates are, on average, in a more disadvantaged position in the labour market. Finally, skill certificates are found to be an imperfect substitute to other types of standardised information. On the whole, the results suggest that certificates play a role in helping new workers break into the labour market, but are more valuable to workers with at least some work experience. More stringent skill certification tests could improve the benefits to new workers.

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1 Introduction

Newcomers often face difficulties breaking into labour markets. Even highly educated and skilled workers without work history often struggle to land their first jobs. An important reason for this is that it is difficult for prospective employers to be sure of such unproven workers' productivity Pallais (2014). This is especially true in online labour markets, or markets where buyers and sellers of digitally deliverable freelance work are matched remotely through online platforms. Without direct interactions such as face-to-face interviews, worker quality and motivation are especially difficult to ascertain Autor (2001); Malone and Laubacher (1998). These information frictions are further exacerbated by the global nature of online labour markets, as prospective employers are faced with evaluating freelancers from unfamiliar backgrounds. This leads to outcomes where new freelancers face difficulties breaking into the market, whereas older, already screened freelancers have an upper hand due to the fact that there is less uncertainty about their productivity. Partly due to these reasons many online freelancing platforms are extremely unequal in terms of earnings.[1]

Several online labour market platforms have introduced "skill certification schemes" to help skilled but unvetted newcomers break into the labour markets. The purpose of this paper is to empirically and theoretically evaluate whether completing skill certificates helps freelancers. We demonstrate empirically that obtaining skill certificates operates as a type of a signalling device in the spirit of Spence (1973). Skill certificates do not increase freelancers' productivity, but demonstrate their ability, and consequently lead to decreased employer uncertainty and increased freelancer earnings. In a textbook version of a signalling model, the agents' signalling cost depends only on their ability. We argue that in the context of online labour, the net benefit of signalling, and therefore, the freelancers' decision to signal, is determined by two parameters: their ability and the uncertainty that prospective employers have about their ability.

A recurring challenge in estimating returns to signalling is that the returns to signalling by education are confounded with increases in human capital. For instance, if we observe that education increases wages, it is oftentimes difficult to tell whether the higher earnings are caused by increased information or by the increase in individuals' productivity (Chevalier et al., 2004). Transaction level data provided by online freelancing platforms has

[1] For example, Wood et al. (2018) reports a 90:10 income inequality ratio of 19 among South-East Asian and Sub-Saharan African online freelancers based on survey data.}

two appealing features for studying this phenomenon. First, the data contains a rich set of freelancers' background characteristics, which can be used as control variables. Second, the fact that these projects are relatively short and follow each other relatively frequently allows us to use the longitudinal dimension of the data to account for freelancer unobserved heterogeneity.

In an ideal research setting, a researcher would fully control freelancer ability when studying the effect of signalling on earnings. In this paper, we approximate the ideal setting by comparing freelancers' earnings before and after acquiring a skill certificate. This allows us to capture all time-invariant unobservable factors into freelancer fixed effects. In addition, we limit our attention to a 14-day time period around the awarding of the certificate. This way, we can ensure that the return estimates are not contaminated by individual learning or other time-varying human capital effects.

We find that completing an additional certificate has a positive effect on both the number of projects obtained and the income earned from each project. The OLS estimates for returns to completing skill certificates are smaller in absolute value than the fixed effects estimates. Consequently, the positive return estimates are only found in models that control unobserved heterogeneity using freelancer fixed effects. This finding suggests that the freelancers who are worse off in the labour market, such as discriminated-against groups, tend to complete more skill certificates to offset their disadvantage.

The signalling model has a set of clear-cut empirical predictions which will be used to validate the theory. In particular, freelancers' incentive to signal is expected to be smaller if employers' uncertainty about their quality is lower. This prediction is supported by the observation that standardised information generated by completing projects on the platform decreases returns to signalling. This implies that signalling ability through skill certificates is to some extent a substitute for other types of standardised information on freelancer quality. In addition, the returns to signalling are found to be decreasing with the number of skill certificates completed. This suggests that the marginal effect of obtaining an additional certificate is smaller for freelancers who have previously earned certificates.

The results of this paper contribute to multiple strands of empirical literature. First, the research links to emerging literature on how various types of online labour market institutions affect employment outcomes on online platforms. The most closely related papers include Pallais (2014). She discusses a field experiment where she randomly hired inexperienced freelancers and then provided feedback on their performance. She compares her hires' subsequent income to other freelancers who applied for her posted jobs but were not hired. The randomly hired freelancers earned considerably more from their subsequent jobs compared to the control group who applied but were not hired. She argues that this effect is a result of the information that her feedback provided on the hired freelancers to other potential employers. Extending on Pallais' results, Agrawal et al. (2016) show that standardised information on platform-based work experience benefits all freelancers, but that freelancers from developing countries benefit more. show that platform-generated information on work experience has a greater effect on earnings than employer feedback ratings and skill certificates, and that freelancers from lower-income countries benefit from all these signals more. Lehdonvirta et al. (2018) show that platform-generated information on work experience has a greater effect on earnings than employer feedback ratings and skill certificates, and that freelancers from lower-income countries benefit from all these signals more. This suggests that employers initially have more difficulty evaluating the quality of freelancers from developing countries compared to developed countries. Relatedly, Stanton and Thomas (2015) show that information from intermediaries helps inexperienced freelancers: a freelancer affiliated with an intermediary agency has a higher job finding probability and wage. Horton (2017) shows that algorithmic recommendations of freelancers to employers can improve the functioning of online freelancing labour markets by reducing search frictions. Effects of skill certificates have not been systematically studied in literature on online labour platforms.

This paper also contributes to the literature on using standardised tests as a method for revealing information on worker quality in traditional labour markets (Autor and Scarborough, 2008; Hoffman et al., 2018). A recurring theme in this literature is that standardised tests can benefit minorities and other statistically discriminated against groups in the labour market. We provide a detailed analysis of standardised tests' effects on new entry. More broadly, our results link to empirical studies on job market signalling More broadly, the results link to empirical studies on job market signalling (Tyler et al., 2000; Lang and Manove, 2011; Pinkston, 2003; Arcidiacono et al., 2010), where we contribute an analysis of the role of employer uncertainty in signalling decisions.

In policy literature, private digital skill certification schemes have been proposed as a potential solution to improving labour market matches in an era of rapidly-changing skill requirements Painter and Bamfield (2015). Our paper presents one of the first empirical analyses of such a scheme.

2 Empirical setting

The dataset used in this paper was collected from one of the largest online labour markets, which did not wish to be identified. Before turning to the details, we briefly present a typical workflow of contracting within the platform. Employers looking to hire a freelancer for a particular task typically start the process by posting an opening on the site. The opening includes the skills required, expected contract duration, preferred freelancer characteristics and the contract type, which can be either a flat rate or an hourly billed contract. A major difference between flat rate and hourly priced projects is that with the latter, the platform allows employers to use monitoring technologies, namely screenshots taken automatically at semi-regular intervals from freelancers' screens, and records of the rate of keystrokes and mouse clicks. These technologies are not available for flat rate contracts, where the freelancer's work can only be evaluated once the output is delivered (for more details on the differences between the two project types, see Lin et al., 2016).

After the vacancy is posted, it is visible to registered freelancers, who can apply for the position by submitting private bids[2]. The interview and wage negotiation phases also take place on the platform. When posting a project, the employer also chooses a category for the project. Projects are classified into 12 broad categories (such as software development, graphic design, writing, etc.), which are further broken down to 89 distinct subcategories (such as mobile development, game development, and software testing, which are all subcategories of software development).

Of particular interest to us are the skill tests administered on the platform. Freelancers can take multiple-choice quizzes on various skills. In all, freelancers can take over 300 distinct skill tests from topics such as the English language, programming languages, graphic design techniques, and office software packages. Once a skill test has been completed, the freelancer gets a "badge" certifying its completion (see Figure 1). The badge also shows the freelancer's numerical grade and percentile rank among all test takers. When inviting freelancers to a project, employers can limit their search to those who have completed a particular skill certificate or have scored over a certain threshold in it. If the freelancer has tried to take a test and failed, a failed mark is not visible to potential employers. The freelancer can retake the test after a cooldown period lasting between 30 and 180 days. Freelancers can also choose to hide results of tests they have passed.

[2] The employers can also directly invite freelancers for a position, in which case the openings are excluded from our data.

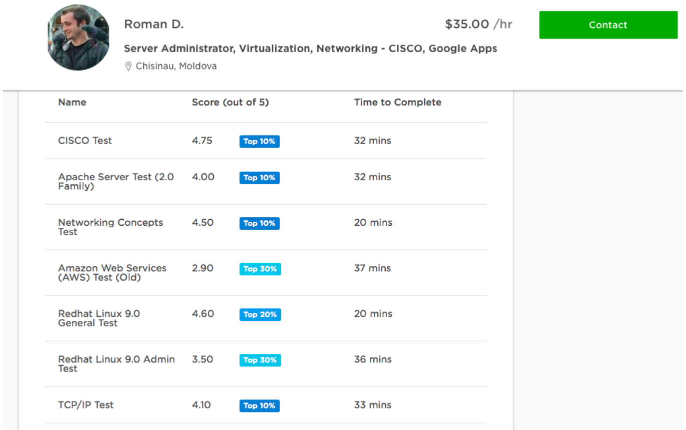


Figure 1: Screenshot of a freelancer's profile featuring skill certificates.

The tests are highly technical in nature. They are designed to test details on the particulars of the topic being tested. Therefore, the outcome of the test is not likely to depend on the general skill level of the freelancer, but rather on their specific knowledge on the topic[3]

A crucial assumption for the purposes of this paper is that a freelancer does not learn anything from just taking the test. This is a reasonable assumption, since it is not plausible that a freelancer would pick up a skill such as a programming language or a foreign language – which typically takes months or years to learn – when taking a simple multiple-choice test.

3 Motivating theoretical framework

This section introduces a signalling model, which we use to show that employer uncertainty on freelancer ability creates an incentive for freelancers to invest in a costly signal. The model is a slightly modified version of the model presented by Lang and Manove (2011). It provides testable implications on how the level of freelancer signalling varies with uncertainty about their productivity, as well as on how returns to signalling vary with uncertainty about productivity.

Freelancers differ in their ability. Only the freelancers are assumed to know their own ability. Potential employers observe freelancers' certificates accurately, but freelancer ability is observed with noise. Consequently, the freelancers have an incentive to gain

[3] A representative question from the Java programming language skill test is the following: "*Assuming the tag library is in place and the tag handler is correct, which of the following is the correct way to use a custom tag in a JSP page?*"

certificates to reduce employer uncertainty. Throughout the rest of this section we assume that there exists a separating equilibrium; freelancers' ability and employer uncertainty determines how much they signal.

Freelancer's ability is distributed along a fixed interval $[a_0, a_1]$. A freelancer's productivity p^* in a given project conditional on their ability is given by

$$p^* = a + \varepsilon, \tag{1}$$

where a is the freelancer's ability. ε is a normally distributed match specific random variable which is only realised after the match between a freelancer and employer has been formed. It has a mean of 0 and variance of σ_ε^2.

A potential employer can observe the number of skill certificates the freelancer has, s, but not their true productivity p^*. The employer observes a noisy estimate of freelancer's productivity given by

$$p = p^* + u, \tag{2}$$

where u is another normally distributed random error term. The error term u has a variance of $\sigma_u^2(s)$ which is common to all firms, continuous, and is decreasing and convex in signalling. ε and u are independent of one another, and their distributions are assumed to be common knowledge.

We denote the accuracy of employer inference as $\lambda(s) \in [0, 1]$, where

$$\lambda(s) = \frac{\sigma_\varepsilon^2}{\sigma_u^2(s) + \sigma_\varepsilon^2}.$$

For a given value of σ_ε^2, if $\lambda(s)$ is close to zero, then $\sigma_u^2(s)$ must be large, and, consequently, the employer's ability to observe freelancer productivity directly is poor. In this case the employers have to give more weight to the certificate signal. If $\lambda(s) = 1$ then $\sigma_u^2(s) = 0$ and the employer observes freelancer productivity perfectly and does not have to rely on signals.

The employers follow the rules of a competitive labour market. They pay the freelancers the wage which is determined by their expected productivity. Their equilibrium inference of the freelancers' productivity, p^*, depends on the elements they observe, p and s. Let $\hat{a} = a(s)$ denote employers' equilibrium inference on a conditional on s. Throughout this paper, we assume that there exists an unique, continuous, differentiable, strictly increasing in a equilibrium which specifies a unique best response for every ability level and λ. To solve for $E[p^* \mid p, s]$, note that, Equations (1) and (2) imply that in equilibrium, $p - \hat{a} = u + \varepsilon$. Therefore,

$$\begin{aligned} E[w \mid p, s] &= E[p^* \mid p, s] \\ &= E[p^* \mid p - \hat{a}, s] \\ &= E[a \mid p - \hat{a}, s] + E[\varepsilon \mid p - \hat{a}, s]. \end{aligned} \tag{3}$$

Since, $E[a \mid p - \hat{a}, s] = \hat{a}$, and $E[\varepsilon \mid p - \hat{a}, s] = \frac{Cov(\varepsilon, u + \varepsilon)}{Var(u - e)}(p - \hat{a}) = \lambda(p - \hat{a})$, equation (3) is equivalent to:

$$E[w \mid p, s] = \lambda p + (1 - \lambda)\hat{a}, \tag{4}$$

which is the equilibrium competitive wage offer of the employer conditional on p and s.

It is useful to note that Equation (4) implies that if there are two freelancers L, and H with the same level of a, but $\sigma^2_{u,L}(s) > \sigma^2_{u,H}(s)$, freelancer H is at an advantage because the employer can better evaluate their productivity. Therefore, freelancer L will have a larger incentive to invest in signalling.

The freelancers' problem boils down to choosing s to solve for

$$\max_s E[w] - c(a)s, \tag{5}$$

where $c(a)$ ($c(a) > 0$, for all $a \in [a_0, a_1]$) is the effort cost of getting a certificate. $c(a)$ is assumed to be decreasing and convex in a. In equilibrium, equation (5) simplifies to

$$\max_s \lambda E[p] + (1 - \lambda)\hat{a} - c(a)s. \tag{6}$$

Its first order condition reads as

$$\lambda_s a - \lambda_s \hat{a} + (1 - \lambda)\hat{a}_s = c(a) + c_a a_s, \tag{7}$$

where subscripts denote partial derivatives, (e.g. $\hat{a}_s = \frac{\partial \hat{a}}{\partial s}$). Therefore, in equilibrium, $a = \hat{a}$, 7) simplifies to

$$(1 - \lambda - c_a)\hat{a}_s = c(a), \tag{8}$$

which implicitly solves $s$for each combination of λ and a. Finally solving for a_s and inverting yields

$$s_a = \frac{1 - \lambda - c_a}{c(a)}. \tag{9}$$

Equation (9) demonstrates that the equilibrium value of $s(a)$ is strictly increasing in a. We also know that the freelancer with the lowest level of ability does not invest into signalling, or $s(a_0) = 0$. To see why this is the case, note that if $s(a_0) > 0$, the freelancer with a $a > a_0$, could deviate to smaller s without affecting employers' equilibrium inference on their ability. The only case when this is impossible is if $s(a_0) = 0$. After having confirmed that $s(a_0) = 0$, and noting that Equation (8) is continuous and differentiable, we know that $s(a)$ exists and is uniquely determined for all combinations of a and λ.

Now, assume that there are two freelancers with the same level of a but $\sigma^2_{u,L} > \sigma^2_{u,H}$ and Consequently, $\lambda_L < \lambda_H$. In words, the employers face a more uncertainty when trying to evaluate the expected productivity of freelancer L compared to freelancer H. With this assumption, the theoretical framework laid out generates the following predictions.

1. If there are two freelancers (L, H) with the same value of a but $\lambda_L < \lambda_H$, we have $s(\lambda_H) > s(\lambda_H)$ whenever $a > a_0$. That is, higher employer uncertainty on freelancer quality results in more signalling by the freelancer. To see this, note that equation (8) implies that if $\lambda_L < \lambda_H$, then $s_a(\lambda_L) > s_a(\lambda_H)$. Furthermore, we argue above that $s(a_0; \lambda_L) = s(a_0; \lambda_L)$. By the continuity of s, this is possible only if $s(\lambda_L) > s(\lambda_H)$.
2. If there are two freelancers with same a but $\lambda_L < \lambda_H$, then $\dfrac{\partial E\left[w; \lambda_H\right]}{\partial s} > \dfrac{\partial E\left[w; \lambda_L\right]}{\partial s}$, or returns to signalling are higher if the uncertainty is higher. To see why this holds, note that $\dfrac{\partial^2 E\left[w\right]}{\partial s \partial \lambda} < 0$ for all $a > a_0$.
3. Finally, signalling exhibits decreasing returns to scale, i.e. $\dfrac{\partial^2 E\left[w\right]}{\partial s^2} < 0$ for all $a > a_0$.

Predictions 1. and 2. are intuitive: for a given level of ability, the freelancers who are more statistically discriminated against, i.e. for whom productivity uncertainty is higher, get a higher marginal return from signalling, and consequently, signal more. In addition, predictions 2. and 3. suggest that signalling exhibits two types of decreasing returns: the marginal effect of signalling is lower for higher levels of signalling, and the return to signalling is also lower if employer uncertainty about freelancer productivity is lower.

Equation (9) demonstrates that the choice of the level of signalling depends on two characteristics which are unobservable to the researcher, but which affect freelancer earnings. Freelancers with higher ability signal more because the costs of signalling are lower.

On the other hand, freelancers who know that employers might have problems evaluating their productivity also signal more. As a result, failing to control for these in an OLS regression of the number of skill certificates on earnings likely leads to a biased estimate on the coefficient on s.

In the empirical analysis section, we present comparisons between OLS estimates and fixed effect estimates. Since the fixed effects arguably subsume the unobservable a and λ, the direction of the bias of the OLS estimates can be used to infer which one of the two effects dominates. If OLS estimates are biased downwards, the decision to signal is negatively correlated with earnings, and the bias due to employer uncertainty dominates the bias due to unobservable freelancer ability. If, instead, the OLS estimates are biased upwards, the unobservables in the earnings equation are positively correlated with the decision to signal, which suggests that the decision to signal is driven by differences in unobservable ability.

4 Empirical analysis

4.1 Data and descriptive statistics

The dataset used in this paper was collected with assistance from the online labour platform, which provided access to their developer API to make the data collection possible, but was not otherwise involved in any aspect of the study design or sample construction. The data was collected in three steps. In the first step we used the search functionality of the platform to sample freelancers from all job categories. The search functionality of the platform can order the search results in various ways opaque to the user in an attempt to increase the efficiency of the searches, which might lead to a nonrepresentative sample of the underlying population of freelancers. To overcome this, we randomly sampled 10% of the workers returned on each search result page. This approach also allowed us to collect a reasonably sized sample without violating the rate limits set by the API. After removing duplicates, we ended up with a sample of 46,791 freelancers. We used separate API requests to get background information on the freelancers and the details of each project they had completed, which totalled 422,199 projects. The main summary statistics of the data are presented in Table 1.

The first panel of Table 1 presents the descriptive statistics for all 422,199 projects completed by the freelancers. The empirical design is an event study where the 14-day pre-test period acts as a control group for each 14-day post-test period. Since learning a new skill such as a new programming language usually takes much longer than 14 days, limiting the investigation to a short time window allows us to make the assumption that freelancer ability remains roughly constant. The second panel thus shows the same descriptive statistics for projects falling within a 14-day window around skill certificate completion only. In cases where a freelancer has completed more than one skill test, this filtered sample contains several 14-day pre-test and 14-day post-test observation periods. We have also excluded projects where more than one freelancer was hired (4% of observations), those where the employer explicitly invited a single freelancer to the job (5% of observations), and those without dollars-earned information (0.02% of observations) from the filtered sample.

While the two samples seem fairly similar with the averages less than one standard deviation away from one another, a few differences emerge. Workers in the full sample have completed more and higher-value projects, and have consequently earned more money than the workers in the filtered sample. At the same time, freelancers in the filtered sample have completed over twice as many skill certificates as the freelancers in the full sample. The two samples have fairly similar 'ages' (measured from the start date of their first project) and feedback ratings.

Freelancers' average reputation scores tend to be very close to a full five out of five stars. This is a common observation in many online markets for both labour and goods (see e.g. Nosko and Tadelis 2015; Filippas et al. 2017). Nonetheless, as will become evident from the regression results, the ratings have some – albeit noisy – predictive power on freelancers' expected future earnings.

Since not all of the freelancers in the sample have completed projects, we present freelancer characteristics separately in Table 2. In particular, we see that the distribution of. projects is very unequal, with a median of 1 and a maximum of 630 projects. Roughly 40% of the sample have completed zero projects. This is consistent with the notion that freelancers with previous work history on the platform tend to win more projects and accumulate even more work history, which further increases their advantages in the labour market, leading to the highly skewed distribution of work history and earnings.

Table 1: Summary statistics of freelancers and projects

Full sample					
Project-freelancer characteristics					
	Mean	Std. dev.	Median	Min	Max
Number of completed tests	2.27	3.82	0	0	96
Number of completed projects	43.15	63.82	20	0	628
Dollars earned	11,521.65	22,914.17	3,501.26	0	441,602.45
Months active	23.66	19.48	19.33	0.13	138.4
Feedack rating	4.52	1.26	4.93	0	5
Project characteristics					
	Mean	Std. dev.	Median	Min	Max
Hourly project	0.42	0.49	0	0	1
Project value	482.95	2965.79	70	1	341,787.06
Hourly rate (hourly projects)	12.48	11.63	10	0.06	670
Project charge (fixed price projects)	173.46	872.56	50	1	174,298.51
Feedack rating	4.83	0.5	5	1	5
No rating given	0.07	0.26	0	0	1
Number of applicants	20.95	44.95	10	0	7,855
N	422,199				
Filtered sample					
(14-day window around skill test completion)					
Project-freelancer characteristics					
	Mean	Std. dev.	Median	Min	Max
Number of completed tests	4.54	4.7	3	0	54
Number of completed projects	22.56	45.42	6	0	560
Dollars earned	5,132.37	14,247.54	543.84	0	239,133.38
Months active	19.5	17.98	13.18	0.2	109.27
Feedack rating	4.03	1.86	4.93	0	5
Project characteristics					
	Mean	Std. dev.	Median	Min	Max
Hourly project	0.36	0.48	0	0	1
Project value	242.6	1,583.37	44.48	1	133,857.54
Hourly rate (hourly projects)	11.51	12.26	8.89	0.11	300
Project charge (fixed price projects)	101.46	285.56	30	1	8,480
Feedack rating	4.85	0.47	5	1	5
No rating given	0.17	0.38	0	0	1
Number of applicants	28.83	41.94	18	2	1,085
N	12,952				

Notes: One observation corresponds to one project-freelancer pair. The top panel presents the descriptive statistics for the full sample; the bottom panel presents the descriptive statistics for the sample limited to -14, ..., +14 days around the completion of skill tests, and to projects with more than one applicant (see main text for details). Project-freelancer characteristics are measured at the time of project start.

Table 2: Summary statistics of freelancers.

Mean	Std. dev.	Median	Min	Max	
Number of completed tests	2	2.69	3.56	0	103
Number of completed projects	1	9.99	27.9	0	630
Dollars earned	40	4,073.26	15,704.12	0	457,888.62
Months active	9.33	19.89	22.31	0.2	138.4
Feedback rating	4.8	3.15	2.32	0	5
Completed at least 1 project	1	0.6	0.49	0	1
Number of freelancers	46,791				

Notes: Descriptive statistics of the sample of workers at the time of data collection.

Table 3: Distribution of types of projects

Project category	Share (%)
Tech	34.39%
Design and creative	27.22%
Admin	9.91%
Writing	9.57%
Sales and marketing	7.43%
Translation	3.54%
Engineering	2.34%
IT and networking	2.1%
Finance	1.82%
Data science	0.83%
Legal	0.5%
Customer service	0.36%

4.2 Returns to signalling

We now turn to studying empirically how signalling efforts are rewarded in the labour market. As suggested by equation (9) in the previous section, the decision to complete certificates is driven by two types of selection on unobservable characteristics: freelancer ability and employer uncertainty about freelancer ability. In an ideal setting, we would fully contol freelancer ability and employer uncertainty when estimating the return to signalling. In the a absence of these controls, a fixed effects estimator will subsume time invariant heterogeneity and enable consistent estimation of returns to signalling. A second identifying assumption we make is that time-varying unobserved heterogeneity remains constant in the +/- 14 day time window we concentrate on. More concretely, we estimate variants of the following fixed effects regression model:

$$y_{ik} = \alpha_i + X_{ik}\beta + \gamma s_{ik} + \nu_t + \varepsilon_{ik}. \tag{10}$$

Here, y_{ik} is the log-value of a project. On the right hand side of the equation, α_i are freelancer specific fixed effects. Vector $X_i\beta$ consists of measures of observable time-varying characteristics at the start of the project: average reputation rating for previous projects, number of previously completed projects, number of (log) dollars earned on the platform, the competitiveness each individual project (measured by the number of applicants to the project), and dummy variables for project categories. In addition, to account for possible time heterogeneity, the specification includes observation year dummies, ν_t. The main parameter of interest is γ, which measures the marginal effect of earning a skill certificate on the platform, and captures the effect of signalling on earnings. Since the regression model includes fixed effects for different project categories, all comparisons are done within project categories.

We also study the employment margin, that is, how successful the freelancer is in winning projects in the first place. This is studied using the specification,

$$NumProjects_{ij} = \alpha_{ij} + X_{ij}\beta + \gamma s_{ij} + \nu_t + \varepsilon_{ij}, \tag{11}$$

where each 14-day time window is indexed with j.

Our third specification combines the two margins. Here the dependent variable is the number of dollars earned in each 14-day pre- or post-test period,

$$log(earnings_{ij} + 1) = \alpha_i + X_{ij}\beta + \gamma s_{ij} + \nu_t + \varepsilon_{ij}. \tag{12}$$

Column (1) of Table 4 presents a specification that looks at the per-project earnings margin. It shows that an additional skill certificate leads to a 4.1% increase in project value. Transformed to dollars, this corresponds to a 4% $\times$ \$243.28 $\approx$ \$9.79 return to completing a skill certificate. When looking at the number of projects won, column (3) of Table 4 shows that completing a skill certificate leads to a 0.012/0.45 $\approx$ 2.7% increase in the number of projects initiated within the 14-day window. This is a fairly small effect economically speaking, given that, on average freelancers only win 0.45 projects in the time window. Finally, when combining the income and projects won margins, column (5) of 4 shows a 6.2% increase in earnings. Transformed into dollars, this corresponds to an average earnings gain of 5.5% $\times$ 139.80\$ $\approx$ \$139.80. The three estimates line up very well. In dollar terms, both earnings and project value estimates are of the same magnitude, whereas the estimate on the projects won margin is quite small.

A few points on these specifications are worth making. First, because each observation is a count of potentially multiple projects, specifications (3)-(6) do not include project level control variables. Second, and more importantly, since our data does not include information on projects where the freelancer bids for a project but did not win, the results might be confounded by the bidding effort. In particular, if freelancers are more active in applying just after completing a skill certificate compared to just before completion, the estimate for signalling might be biased upwards. If this is the case, the estimates reported in columns (3) and (5) should be interpreted as the upper limit of the true effect of signalling on the probability of employment and earnings.

A comparison between fixed effects and OLS specifications reveals that the OLS estimates are downward biased. In other words, freelancer-specific earnings related characteristics are negatively correlated with the decision to signal. This implies that there is a negative selection effect with respect to completing skill tests. Freelancers who are in a disadvantaged position in the labour market signal more. In light of the theoretical model presented in the previous section, this suggests that the decision to signal is driven by some freelancers having a disadvantaged position in the labour market (i.e. the differences in λ), rather than by ability differences among freelancers (differences in a). We provide further evidence that the reason for positive returns to signalling is driven by increased employer information in the following sections.

Table 4: Returns to signaling.

	Dependent variable:					
	log(project value)		Num projects		log(1+dollars)	
	(1)	(2)	(3)	(4)	(5)	(6)
Feedback rating	0.071**	-0.243^{***}	0.086**	0.235***	0.142*	0.377***
	(0.027)	(0.013)	(0.030)	(0.022)	(0.066)	(0.046)
Number of completed projects	0.002*	-0.004^{***}	0.002$^{\cdot}$	0.010***	-0.004^{***}	0.007***
	(0.001)	(0.0005)	(0.001)	(0.001)	(0.001)	(0.001)
Number of certificates	0.040***	-0.010^{**}	0.012***	0.003*	0.055***	0.029***
	(0.011)	(0.004)	(0.003)	(0.001)	(0.006)	(0.003)
Baseline	\$ 244.65	\$ 244.65	0.45	0.45	\$ 139.8	\$ 139.8
Freelancer fixed effects	Yes	No	Yes	No	Yes	No
Observations	13,346	13,346	120,788	120,788	120,788	120,788
Adjusted R^2	0.401	0.181	0.359	0.187	0.335	0.153

Notes: In columns (1) and (2) unit of observation is one project. In columns (3)-(6), unit of observation is 14-day pre- or post-test period. In addition to the variables reported, all models include year-dummies, and cumulative dollars earned on the platform (log-transformed). The models in columns (1) and (2) also include project type dummies and measures fo for the competitiveness of each project measured by number of applicants. Baseline refers to the mean of the dependent variable. Standard errors are clustered on freelancer level. Significance levels in all specifications: *** 0.1%, ** 1%, and * 5%.

4.3 Signalling as a substitute for other forms of verified information

Establishing that signalling decreases employer uncertainty on freelancers' productivity is complicated by the fact that the information set of the employer, and therefore their uncertainty about freelancer productivity, is unobservable to researchers. Nonetheless, Prediction 2, outlined in the theory section, suggests that the marginal effect of signalling is lower for high levels of information. Comparing the marginal effects of completing skill certificates with different levels of platform-provided information allows us to empirically test whether Prediction 2 holds in the data.

We assume that employers have more information on more experienced workers. This assumption is plausible – more experienced workers have earned more feedback from previous employers and have established a work history, which both arguably decrease employer uncertainty. [4]

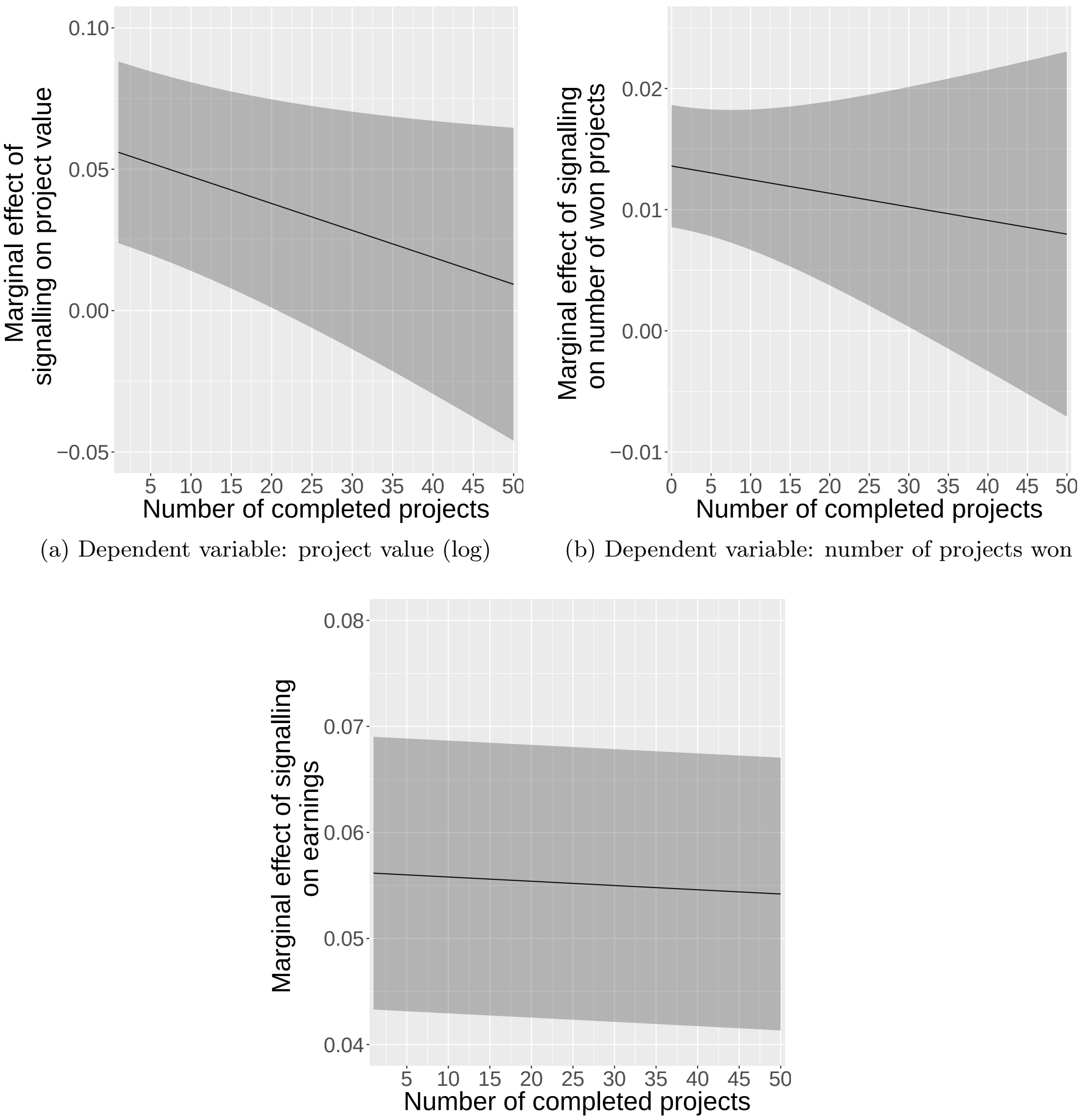
To formally test this hypothesis, we include an interaction term between the number of completed skill certificates and work experience:

$$y_{ik} = \alpha_i + X_{ik}\beta + \gamma s_k + \delta n_k + \eta s_k \times n_k + \nu_t + \varepsilon_{ik},$$

where, depending on the specification, the dependent variable is either log project value, number of projects won, or *log* of earnings. The coefficient on the interaction term between completed skill certificates and work experience, $s \times n$ captures how the marginal benefit of signalling varies with the number of completed projects. These results are presented in Table 5. In column (1), where the dependent variable is the log of project value, the point estimate of -0.031 implies an average decrease of 3.1% in the marginal return to signalling for each completed project. For the specifications presented in columns (2) and (3), where the dependent variables are the number of completed projects and earnings, respectively, the effects are smaller in absolute value terms, much noisier, and consequently statistically indistinguishable from zero.

Figure 2 illustrates the relationship between completed projects and marginal return to signalling. To summarise, the estimates reported in Table 5 suggest that return to signalling is smaller for more experienced freelancers, but this effect is only visible on the project value margin. Overall, the results lend support to the hypothesis that signalling is a substitute for experience. Nonetheless, the substitution effect is found to be fairly small, even when statistically significant. For instance, the marginal effect of completing an additional skill certificate is found to be positive even for a median freelancer in the filtered sample (with 6 completed projects). One explanation for this could be that employers face uncertainty over both freelancer ability and other freelancer characteristics, such as soft skills e.g., communication, trustworthiness, and opportunism. Skill certificates mostly decrease uncertainty over the first, while work experience and detailed feedback on completed projects will also reduce uncertainty over the latter. If this is the case, skill certificates cannot fully substitute for work experience as a signalling device.

[4] The assumption is supported by both Agrawal et al. (2016) and Pallais (2014). They demonstrate that verifiable work experience acts as a source of standardized information on freelancer quality, but does not increase their productivity.



(a) Dependent variable: project value (log)

(b) Dependent variable: number of projects won

(c) Dependent variable: log(1+earnings)

Figure 2: Marginal effect of signalling for different experience levels.

Table 5: Returns to signaling by different levels of experience

	Dependent variable:		
	log(project value)	Num projects	log(1+dollars)
	(1)	(2)	(3)
Num certificates	0.059^{***}	0.014^{***}	0.056^{***}
	(0.014)	(0.003)	(0.007)
Num certificates × Num projects / 100	-0.031^{*}	-0.011	-0.004
	(0.012)	(0.016)	(0.008)
Freelancer fixed effects	Yes	Yes	Yes
Observations	13,346	120,788	120,788
Adjusted R^2	0.402	0.359	0.335

In addition to the variables reported, all models include year-dummies, average rating for completed projects, cumulative dollars earned on the platform (log-transformed) and cumulative number of completed projects on the platform measured in the time of project start. The model in column (1) also includes project type dummies and measures fo for the competitiveness of each project measured by number of applicants. Standard errors are clustered on freelancer level. Significance levels in all specifications: *** 0.1%, ** 1%, and * 5%.

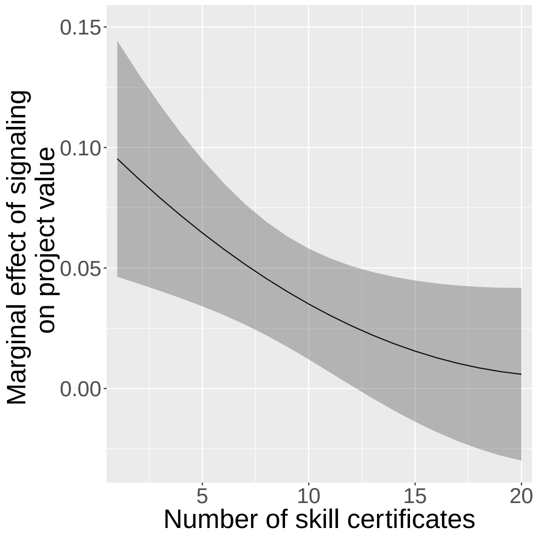
4.4 Decreasing returns to signalling

We now turn to studying how returns to signalling vary with the level of signalling. As suggested by Prediction 3, one would expect the returns to signalling be lower for higher levels of signalling. We implement the test for decreasing returns to signalling in the form of the regression model

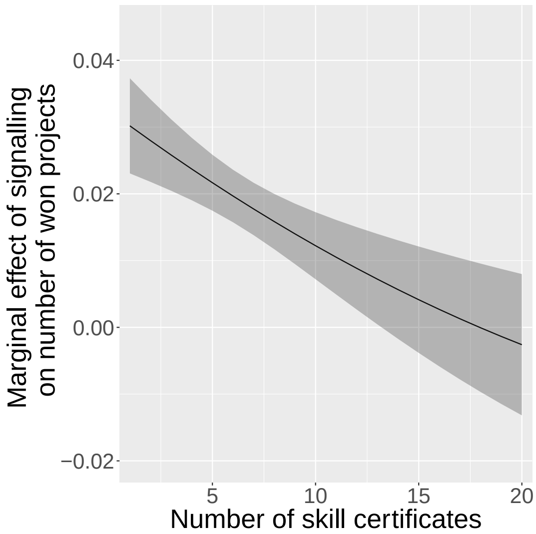
$$y_{ik} = \alpha_i + X_i\beta + \gamma_1 s + \gamma_2 s^2 + \gamma_3 s^3 + \nu_t + \varepsilon_{ik}. \tag{13}$$

Introducing the quadratic and cubic terms term of signalling into the regression allows us to test for the possible nonlinearity in return to signalling.

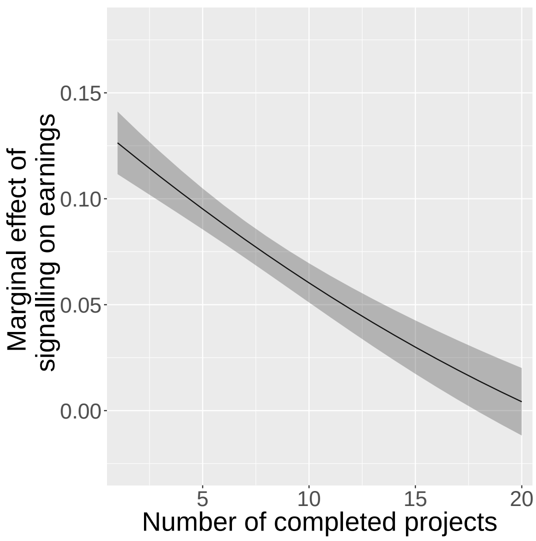
Table 6 reports the estimation results. As evidenced by the consistently negative estimates for γ_2, the returns to signalling are found to be decreasing in s. To better capture the nonlinearity of signalling, Figure 3 visualises the fitted marginal effects of signalling estimated from model 13. Decreasing returns to signalling are clearly visible. The monetary returns for signalling are fairly high (10% for project value and 14% for dollars earned) for the first few skill certificates completed. The marginal effect of the first completed skill certificates on the number of projects won is is 0.03, which corresponds to a 7% increase compared to the baseline reported in Table 4. The comparison between Tables 6 and 4 demonstrates that the average returns reported in Table 4 conceal considerable heterogeneity. The effect of the first completed skill certificate is up to twice as high compared to the average effect. Again, as in the previous section, the evidence on the decreasing returns to signalling are stronger in the earnings and project value margins.



(a) Dependent variable: project value (log)



(b) Dependent variable: number of completed projects



(c) Dependent variable: log(1+earnings)

Figure 3: Marginal effect of signalling for different levels of signalling.

Table 6: Nonlinear return to signaling

	Dependent variable:		
	log(project value)	Num projects	log(1+dollars)
	(1)	(2)	(3)
Num certificates	0.104***	0.032***	0.135***
	(0.028)	(0.004)	(0.008)
Num certificates^2 / 10	−0.044**	−0.011***	−0.042***
	(0.017)	(0.003)	(0.006)
Num certificates^3 / 100	0.007**	0.001**	0.003***
	(0.002)	(0.0003)	(0.001)
Freelancer fixed effects	Yes	Yes	Yes
Observations	13,346	120,788	120,788
Adjusted R^2	0.402	0.359	0.337

In addition to the variables reported, all models include year-dummies, average rating for completed projects, cumulative dollars earned on the platform (log-transformed) and cumulative number of completed projects on the platform measured in the time of project start. The model in column (1) also includes project type dummies and measures fo for the competitiveness of each project measured by number of applicants. Standard errors are clustered on freelancer level. Significance levels in all specifications: *** 0.1%, ** 1%, and * 5%.

4.5 Does skill certification increase productivity?

Thus far the discussion has hinged on the assumption that signalling does not increase freelancer productivity. Is this assumption justified? The online labour platform offers a particularly intuitive measure for freelancer productivity in the form of feedback ratings given by the employers to the workers. We use this measure to operationalise freelancer success in a project. Table 7 presents the results of a regression analogous to regression model (10), but with the feedback rating on the left hand side of the regression. Column (1) presents the results from regression models where the feedback rating ranging between 1 and 5 is the dependent variable. To account for the upward skewed distribution of ratings, Column (2) presents an alternative specification in which the dependent variable gets a value of 1 if the feedback rating given to a freelancer is above 4.5. In both cases, the effect of signalling on ratings is statistically indistinguishable from zero. We interpret these results as supporting the assumption that signalling does not increase freelancer productivity.

4.6 Long-term effects of completing skill certificates

By design, the results we have so far presented concentrate on the short-term effects of signalling. Nonetheless, potential longer-term effects are also interesting. For instance, signalling can lead to higher earnings, which, in turn, might result in an increased probability of being hired, since freelancers' total earnings on the platform are visible to employers. To study this, we examine how the return estimate changes when we extend the time win-

Table 7: Effect of signaling on ratings.

	Dependent variable:	
	Feedback rating	Feedback rating > 4.5
	(1)	(2)
Number of certificates	0.0002	0.001
	(0.003)	(0.003)
Freelancer fixed effects	Yes	Yes
Observations	10,095	10,095
Adjusted R^2	0.290	0.160

Notes: In addition to the variables reported, all models include freelancer fixed effects, average rating for completed projects, cumulative dollars earned on the platform (log-transformed) and competitiveness of each project (measured by the number of applicants), and dummy variables for observation years and different project types. Standard errors are clustered on freelancer level. Only projects with a non-missing rating are included in the regression models. Significance levels in all specifications: *** 0.1%, ** 1%, and * 5%.

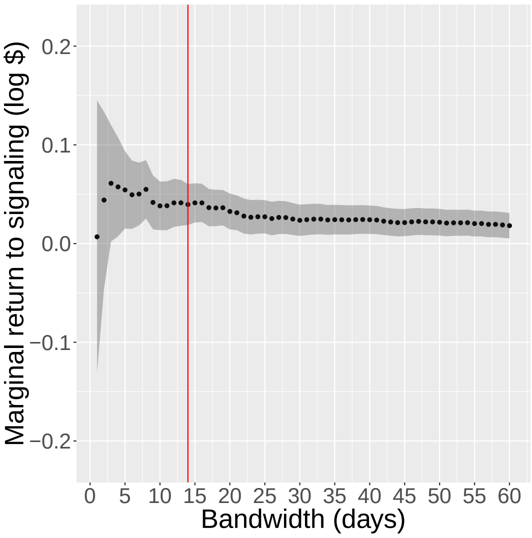
dow from +/- 14 days. Basing the estimation on time windows longer than +/- 14 days increases the possibility that time-varying unobservables such as ability are affecting the estimates. Nonetheless, the extended time windows can give an indication of the potential longer-term effects of signalling. In addition, this exercise acts as a robustness check, demonstrating that the results are not driven by a cherry-picked time window.

The effects of varying time bandwidths are plotted in Figure 4.[5] Comparing the parameter estimate at 14 days to the parameter estimates at longer time windows shows that the estimates are fairly close to one another at different time window lengths. This suggests that there are no longer-term effects that concentrating on the 14-day time window would miss. Consequently, the return estimates presented in Table 4 are also reasonable estimates for longer-term effects of completing skill certificates.

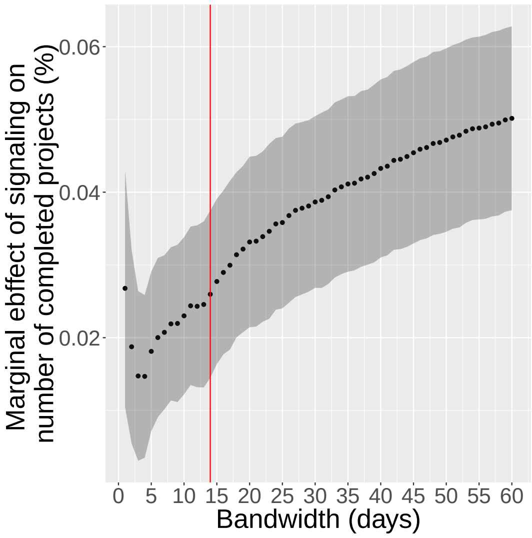
4.7 Falsification tests

An additional validity concern in our empirical strategy is that despite limiting our attention to short time windows around the time of skill certificate award, an increase in the number of completed skill certificates might be correlated with other time-varying unobservable characteristics, which might affect the estimated returns to completing skill certificates. We show that this is not the case in Table 8 by re-estimating the models in Table 4 while randomly varying the time of certificate completion. The results of this exercise are statistically indistinguishable from zero, with the exception of the model where

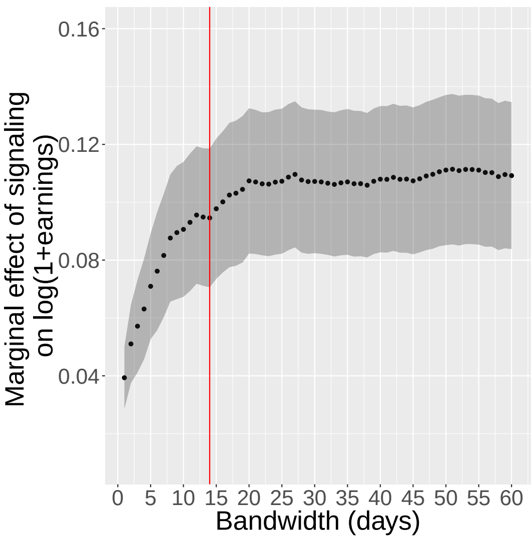
[5] In Figure 5b, where the dependent variable is the number of projects won, the treatment effect estimate increases mechanically as the time window width is increased. To account for this, in Figure 5b the parameter estimate is divided by the mean of the dependent variable.



(a) Dependent variable: project value (log)



(b) Dependent variable: number of completed projects



(c) Dependent variable: log(1+earnings)

Figure 4: Sensitivity of results to varying the time window length. Note: in all graphs, the grey band corresponds to 95% confidence interval calculated by $+/-1.96 \times s.e.$

the dependent variable is the number of completed projects, which obtains a negative but economically insignificant estimate. The results from this falsification test further increase confidence in the main estimation results.

Table 8: Falsification tests for returns to signaling.

	Dependent variable:		
	(log) project value	Num projects	log(1+dollars)
	(1)	(2)	(3)
Num certificates	0.007	-0.008^{***}	0.003
	(0.007)	(0.001)	(0.004)
Freelancer fixed effects	Yes	Yes	Yes
Observations	18,403	153,285	153,285
Adjusted R^2	0.404	0.381	0.359

Notes: This table presents falsification tests where the certification award date is randomised. In column (1) the unit of observation is one project. In columns (2)-(3), unit of observation is 14-day pre- or post-test period. In addition to the variables reported, all models include year-dummies, average rating for completed projects, cumulative dollars earned on the platform (log-transformed) and cumulative number of completed projects on the platform measured in the time of project start. The models in columns (1) and (2) also include project type dummies and measures fo for the competitiveness of each project measured by number of applicants. Baseline is the mean of the dependent variable. Standard errors are clustered on freelancer level. Significance levels in all specifications: *** 0.1%, ** 1%, and * 5%.

4.8 First certificate subsample analyses

Since some freelancers are completing several skill certificates over a longer period of time, it is possible that despite controlling for freelancer fixed effects, a part of the freelancer productivity growth taking place *between* two skill certificates would bias the estimates for monetary return to signalling. For example, this could happen if a freelancer has taken a skill test in 2014, thereafter learns a new programming language, and takes a second skill test in 2016.

To account for this, we have re-estimated (10) using a filtered sample that only looks at the return to completing the first skill test by each freelancer. These results are presented in Table 9. We find large point estimates for the effects of signalling on the project value. The point estimates for numbers of won projects and earnings are found to be indistinguishable from zero on conventional risk levels. Nonetheless, due to smaller sample sizes, the standard errors on the point estimates are considerably larger. Consequently, there are no statistically significant differences between fixed effects models reported in Table 4 and those reported in Table 9.

We interpret these results as reinforcing our main finding: the effects of signalling mostly increase project values, conditional on winning a project, whereas the effect on winning a new project is negligible.

Table 9: Returns to signaling - first certificate only.

	Dependent variable:		
	(log) project value	Num projects	(asinh) dollars
	(1)	(2)	(3)
Number of certificates	0.262*	0.027	−0.001
	(0.121)	(0.021)	(0.056)
Freelancer-month fixed effects	Yes	Yes	Yes
Observations	8,530	52,437	52,437
Adjusted R^2	0.482	0.469	0.411

Notes: In addition to the variables reported, all models include year-dummies, average rating for completed projects, cumulative dollars earned on the platform (log-transformed) and cumulative number of completed projects on the platform measured in the time of project start. The model in column (1) also includes project type dummies and measures fo for the competitiveness of each project measured by number of applicants. Standard errors are clustered on freelancer level. Significance levels in all specifications: *** 0.1%, ** 1%, and * 5%.

5 Discussion

5.1 Why do skill certificates help?

The main result of this paper is that signalling in the form of completing skill certificates increases worker earnings in an online labour market. This happens through two channels: signalling increases the number of projects won and also the project value conditional on winning a project. Nonetheless, the effect mostly operates on the project value margin; the increases in project value are economically considerably larger compared to the number of projects won. These observations reflect the general dynamics of online freelancing: new workers entering online labour markets do not have verified data on their quality. Therefore, their prospective employers do not have much data to evaluate them on. This leads to more experienced freelancers being less uncertain hires. Skill certificates do fairly little to overcome this. This implies that skill certificates are more useful for those workers who have already passed the initial hurdle of winning at least one project; they can increase the value of their subsequent projects by completing skill certificates. But for new entrants who have yet to win a single project, skill certificates are less useful, as they increase the chances of winning a project only slightly.

Another finding is that the returns to signalling vary across levels of platform-verified information; in other words, signalling is a partial substitute for other forms of verified information that increases the value of won projects. Freelancers with only a few successfully completed projects in their work history can earn a return of over 10% for completing skill certificates, while freelancers with longer work histories obtain no benefit from it. This substitution effect between signalling and other platform-verified information is only observed in the project value margin but not in the projects won margin.

Completing skill certificates is found to have decreasing returns. The first few certificates tend to bring returns of around 13%, but the returns decrease as freelancers accumulate more skill certificates. Consequently, more experienced freelancers get a higher return from working and applying for jobs than from signalling. Realising this, most freelancers tend to complete only a few skill certificates.

We quite confidently rule out the alternative explanation that unobservable increases in freelancer productivity would be driving the results. It is likely that the freelancers' skills would remain approximately constant over the short time periods we concentrate on. In addition, the effect of signalling on the feedback scores awarded after completed projects, and direct evaluations of freelancer performance, is statistically indistinguishable from zero.

Why is uncertainty costly? The theoretical model presented in this paper argues that employers prefer workers with verified skills, and therefore pay them more for the same jobs. Anecdotally, many employers want to first hire workers into small "test-piece" projects before hiring them into larger projects. The purpose of these test-piece projects is to screen workers. It might be the case that platform-administered skill certificates s allow the employers to forgo some of this or other types of screening, and this reduced employer screening cost is compensated to the freelancers in the form of higher pay.

Our research design does not allow us to make direct inferences on the general equilibrium effects of skill certificate. We cannot rule out the possibility that skill tests simply cause employers to substitute non-certified freelancers with certified freelancers. Nonetheless, this seems fairly unlikely since the effects of signalling are mostly found on the project value and earnings margins, and not on the number of won projects margin.

Recommendation algorithms described in Horton (2017) might also be more likely to recommend freelancers with completed skill certificates to employers. Nonetheless, it does not seem likely that the results would be completely driven by algorithmic recommendations for two reasons. First, the effects are fairly constant between years. When interacting year-dummies with the return estimate, the interaction terms remain insignificant across specifications. Therefore, the positive effects of signalling were already present before the algorithmic recommendation systems described by Horton were rolled out. In addition, the observation that the effects are more pronounced in the project value margin are inconsistent with the idea that an algorithmic recommendation system, which mostly affects the probability of winning a project Horton (2017), is driving the results.

It is also tempting to draw conclusions on the relative value of signalling across different project categories. Due to limitations related to statistical power, the effects are statistically indistinguishable from zero in all other project categories except the two largest ones: software development and graphic design. The effects are broadly similar in these two groups.

5.2 Where skill certification helps and where it doesn't?

Why does signalling increase earnings more than it increases the number of projects won? One likely explanation for this is that employers have uncertainty on both freelancers' hard and soft skills. Skill certificates, in principle, only certify hard skills, while soft skills and general cooperativeness need to be signalled by other means. This explanation is consistent with recent literature emphasising the beneficial effects of soft skills on the labour market (e.g. Deming (2017); Almlund et al. (2011); Heckman and Kautz (2012)).

It is also instructive to contrast these estimates to other effect sizes presented in the literature. In particular, Stanton and Thomas (2015) find that becoming affiliated with an intermediary agency leads to a roughly 10% increase in earnings. In contrast to our results, they also find that becoming affiliated with an intermediary also leads to substantially higher job-finding probabilities. Our estimates for increases in earnings for new workers roughly coincide with Stanton & Thomas's estimates, but their estimates for job finding probabilities are considerably larger. This suggests that online intermediaries and skill certificates signal different dimensions of freelancer quality. In particular, it seems likely that skill certificates provide fairly reliable information on freelancers' hard skills, whereas intermediaries can provide information on soft skills and cooperativeness in addition to hard skills.

6 Conclusions

Newcomers face considerable difficulties when entering online labour markets. Before a new worker is hired and screening information about them consequently published, there is considerable employer uncertainty about their quality, which prevents them from getting hired in the first place. Skill certificates are an online labour market institution that was designed to allow new workers to break out from this vicious cycle, by making it possible for them to demonstrate their skills to prospective employers at their own expense. However, the findings presented in this paper show that skill certificates, at least as they are implemented on the platform under study, are not very effective for this purpose. They have a statistically and practically significant positive impact on freelancer earnings conditional on winning a project, but their impact on the likelihood of winning a project is limited.

At the same time, experienced workers who have already accumulated a significant work history on the platform do not benefit from skill certificates. This is because the platform-verified work history and employer feedback scores are a substitute to skill certificates in reducing employer uncertainty. These effects leave a fairly narrow range of workers who are likely to benefit significantly from obtaining skill certificates: early-mid-career freelancers, who have won their first few projects and broken into the market, but who still lack a more extensive work history.

This result has clear implications to platform operators: to improve the informativeness of skill certificate signals, the tests should be more challenging. This would allow high-ability newcomers to separate themselves from low-ability ones, improving matches and making the market more efficient. In its current form, the skill certification scheme can substitute for other types of verified information only to a limited extent.

To the extent that evidence from an online labour market setting can be generalised to conventional labour markets, the findings from this paper suggest that private digital skill certification schemes can decrease information asymmetries. This suggests that they could indeed be helpful in improving labour market matches in situations where public qualification schemes are too slow to keep up with rapidly changing skill demands Painter and Bamfield (2015). Certification schemes could moreover help skilled members of statistically discriminated against groups such as immigrants and other minorities to thrive in labour markets. However, average returns to skill certificates remain fairly small even in a fairly low-friction online labour market environment where the effort cost of taking tests is low. This underscores the proposition that in order to facilitate separation between more and less skilled workers, the skill tests should be made "cheap" to take but difficult to do well in. This would facilitate the informativeness of skill certificates and would presumably increase labour market efficiency by reducing skill uncertainty. On the other hand, due to imperfect substitutability between skill certificates and work experience, skill certification schemes are still only a partial solution, and other institutions also continue to be needed.

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Appendix A1 Variable definitions for variables used in regression models

Table 10: Definition of variables used in regression models

Project characteristics	
Variable name	Description
Project value	Dollars paid to the freelancer after succesful completion of project
Hourly rate	Hourly rate of a freelancer hired in a project (only hourly projects)
Star rating given to worker	Rating given to the freelancer by the employer after project completion
Competitiveness of project	Number of applicants to a project
Project type	One of 87 different categories used on the platform
Freelancer characteristics	
Variable name	Description
Months active	Difference in full months between the start of the first freelancer project and date of data collection
Number of completed projects	Number of completed projects at the time of project start.
Dollars earned	Dollars earned at the time of project start (log(1+)-transformed)
Feedback rating	Average star rating of past projects. The past projects are weighed using the same algorithm that is being used on the online labour platform.