The value of non-traditional credentials in the labor market*

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Abstract

This study investigates the labor market value of credentials obtained from Massive Open Online Courses (MOOCs) and shared on business networking platforms. We conducted a randomized experiment involving more than 800,000 learners from developing countries and without college degrees who completed technology or business-related courses on the Coursera platform between September 2022 and March 2023. We targeted learners who had recently completed their courses, encouraging them to share their credentials and simplifying the sharing process. One year after the intervention, we collected data on certificate views and LinkedIn profiles of a subset of approximately 40,000 experimental subjects. We find that the intervention leads to a 17 percentage point increase in credential sharing. Further, treated learners were 6% more likely to report new employment within a year, with an 8% increase in jobs related to their certificates. This effect was more pronounced among LinkedIn users with lower baseline employability. Across the entire sample, the treated group received a higher number of certificate views, indicating an increased interest in their profiles. These results suggest that facilitating credential sharing and reminding learners of the value of skill signaling can yield significant gains. When the experiment is viewed as an encouragement design for credential sharing, we can estimate the local average treatment effect (LATE) of credential sharing (that is, the impact of credential sharing on the workers induced to share by the intervention). The LATE estimates are imprecise but large in magnitude; they suggest that credential sharing more than doubles the baseline probability of getting a new job in scope for the credential.

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1 Introduction

In today's educational landscape, non-traditional credentials, frequently acquired through online courses, have become increasingly popular. In 2021, more than 40 million learners signed up for a Massive Open Online Course (MOOC) (Shah, 2021). Many learners gain these credentials with the intention of signaling specific skills to potential employers (Laryea et al., 2021). Despite their prevalence, there remains a significant gap in high-quality evidence demonstrating their actual value in the labor market. This raises important questions: To what extent do these non-traditional credentials help learners secure new employment? Moreover, who benefits the most from them?

In this paper, we study whether showcasing a credential acquired from a MOOC on a business networking platform increases learners' chances of finding new employment and whether light-touch platform policies encouraging doing that can be effective. In particular, we conducted a randomized experiment in the context of Coursera, a prominent MOOC provider, in which learners were encouraged to add their newly gained credentials to their LinkedIn profiles. We focus on a sample of learners who have recently graduated from a career-oriented certificate program and who do not have a college degree or come from a developing country. These learners often lack access to traditional credentials or to internationally renowned educational institutions, which makes them more likely to benefit from signaling skills through non-traditional credentials (Hansen and Reich, 2015; Moura et al., 2017).

A randomly selected subset of these learners received access to the *Credential Feature*. This feature provided an enhanced process for showcasing Coursera credentials on learners' LinkedIn profiles, along with targeted notifications that encouraged this action. The control group, in contrast, did not receive access to the feature. In our primary analysis, access to *Credential Feature* is the treatment of interest, and the reporting of new employment on LinkedIn (*New Job*) is the outcome. Additionally, we define *Credential Shared* as the inclusion of the MOOC credential on a LinkedIn profile by the learners. *Credential Shared* is an outcome from the perspective of evaluating the *Credential Feature* intervention, but when the experiment is viewed as an encouragement design for sharing, we study the impact of *Credential Shared* (now considered as a treatment) on employment outcomes.

The primary analysis focuses on the approximately 40,000 subjects who included their LinkedIn profile URLs in their Coursera accounts before randomization. For these learners, we analyze data from their LinkedIn profiles to assess if they reported new employment after their exposure to the *Credential Feature*, especially in a role related to their MOOC credentials.

Within this sample, we estimate that the learners in the treatment group are 6% (S.E. 2%) more likely to report new employment within a year after the treatment, representing a 1 percentage point (p.p.) increase from the baseline of 17%. Furthermore, there is a 9% (S.E. 3%) higher likelihood that the treated learners report a new job directly related to the certificate they earned, an increase of 1.2 p.p. (S.E. 0.6 p.p.) from the baseline of 13%. These results remain robust even when excluding new jobs reported with a starting date within the first four months after the randomization, which could potentially reflect jobs found earlier and reported on LinkedIn due to treatment. Furthermore, this effect does not appear to be driven by an increased engagement with LinkedIn, as evidenced by a comparative analysis of the completeness of LinkedIn profiles between groups. Instead, the effect of the treatment appears to be primarily mediated by the presence of credentials in learners' profiles: we estimate that the treatment group is 17% (2.8 p.p. S.E. 0.4 p.p.) more likely to share their credentials on LinkedIn.

Credential Shared, which is the act of sharing the credential on LinkedIn, is another treatment of interest. In this case, the random assignment of the *Credential Feature* works as an encouragement for adding the credential to LinkedIn, and the effect of *Credential Feature* on *New Job* is then interpreted as the intent to treat (ITT) for the *Credential Shared* treatment. The local average treatment effect (LATE) of *Credential Shared* on *New Job*, which is the effect for the type of learner induced to share credentials by exposure to the *Credential Feature*, is 24 p.p. (S.E. 13 p.p.) and 36 p.p. (S.E. 12 p.p.) when considering only jobs directly related to the certificate they earned.

Previous literature has documented that participants of MOOCs are predominantly highly educated individuals often employed in high-quality jobs, leading to the conclusion that MOOCs can exacerbate outcome disparities (Christensen et al., 2013; Zhenghao et al., 2015). Our study focuses on learners without college degrees and those from developing countries. Thus, we focus on learners with lower baseline employability as compared to the general population of learners participating in MOOCs. To better understand whether our treatments contribute to or mitigate disparities in outcomes within the population of our interest, we analyze heterogeneity in the effects of both the *Credential Feature* and the *Credential Shared* with respect to predicted baseline employability. We leverage data on educational and employment backgrounds from learners' LinkedIn profiles to build a predictive model for the outcome of finding a job in the absence of the intervention. Our analysis reveals that among learners who shared their LinkedIn accounts, those with a lower baseline predicted probability of finding a new job have higher treatment effects from the *Credential Feature* and *Credential Shared*

than learners with high baseline employability. This suggests that platform policies that facilitate and encourage the sharing of credentials particularly benefit learners in groups with the lowest chance of reporting new jobs. Furthermore, our results show that signaling skills with non-traditional credentials benefits LinkedIn users with lower baseline employability and could be an effective strategy for these learners to increase their chances of finding new jobs.

A secondary analysis relies on surrogate outcomes for the entire experimental population of over 800,000 learners. Although we do not observe the details of the LinkedIn profiles for most of these learners, we can still measure whether the learner placed the credential on their profile and received a click on it from another LinkedIn user. Clicking on the credential redirects to the certificate page on Coursera and reveals more information about it, specifically concerning the skills learned by the individual. This click may indicate increased interest from potential employers, and we show in the subsample with employment outcomes that clicks on the certificate are strongly correlated with new job reporting. We refer to this surrogate outcome as *Credential View*. Adjusted for the characteristics of the learners, we estimate that the assignment of the *Credential Feature* increases the probability of *Credential View* by 2% to 4% of the baseline probability of receiving a view, which is about 0.13. This evidence suggests that the impact of the intervention extended beyond the sub-sample where we observed employment outcomes.

2 Literature review

This paper engages with several strands of literature. It primarily contributes to research on the perception and value of non-traditional credentials among employers and the impact of MOOC credentials on learners' employability. It further connects with literature on skill signaling and credential signaling. Our study offers evidence from a randomized experiment, isolating the impact of skill signaling with MOOC credentials and separating it from the skill level or job search motivation of learners.

Using randomized audit studies (sending fictitious resumes to job openings posted online), Deming et al. (2016) and Lennon (2021) showed that online degrees have a lower impact on employability than traditional degrees. Rivas et al. (2020), using a recruited experiment where mechanical Turk workers were asked to select among alternative hypothetical worker profiles, demonstrated that MOOC credentials increase the chances of being selected for a job as compared to having no credentials at all. Hadavand et al. (2018) compared outcomes of completers to non-completers of a large

data science specialization and estimates a salary increase and a higher likelihood of job mobility for completers. Zhenghao et al. (2015), using a survey carried out after course completion, found that a significant majority of learners report that their MOOC courses helped them achieve career objectives. Novella et al. (2024) and Majerowicz and Zárate (2023) leverage randomized experiments that provide financial incentives to enroll in a MOOC to study their impact on labor market outcomes. In both cases, low course completion rates reduce statistical power, rendering the estimates of the average treatment effect on employment outcomes inconclusive. Our work adds to this discussion by using a larger randomized experiment that focuses on course completers to investigate the impact of MOOC credentials on actual labor market outcomes, particularly in the context of developing countries and learners without college degrees.

A related research agenda studies employers' perception of MOOC credentials. Rosendale (2016) surveyed 202 employers about their perceptions of MOOC credentials, showing a general preference for traditional degrees. Radford et al. (2014), surveying 103 human resources professionals, found that while MOOCs were viewed favorably on a resume, they were perceived as less likely to demonstrate specific skills than traditional credentials. Kizilcec et al. (2019) revealed that respondents believed that online degree programs are less legitimate and respected than conventional degrees. Our study contributes to this literature by providing experimental evidence of the positive impact of MOOC credentials on employer interest and real-world employment outcomes, suggesting a positive perception of these credentials by employers.

We also engage with the broader literature on skill signaling and educational credential signaling, as outlined in works such as Spence (1978), Tyler et al. (2000), and Hussey (2012). Our research adds to this body of work by examining the career outcomes of learners who add MOOC certificates to their professional profiles, thereby contributing to a more comprehensive understanding of the role of online education in the modern labor market.

Finally, our study aligns with research on the value of signaling capability through non-traditional credentials. Pallais (2014) examined the value of signals in the form of educational credentials and work history on online freelancing platforms, while Kässi and Lehdonvirta (2019) explored the impact of self-certification and client reviews on freelancers' success. Abebe et al. (2020) evaluated the effects of a job application workshop that provides certificates in various skills, leading to improvements in employment and a significant increase in earnings. Carranza et al. (2020) found that certificates improved job search outcomes and increased callbacks from firms. Athey and Palikot (2022) reported

high impacts of a program focused on developing portfolios that helped women signal technical skills in their search for technology jobs. Bassi and Nansamba (2022) showed that soft skills certificates in Uganda increased employability and earnings. Piopiunik et al. (2020) demonstrated the significant effect of different skill signals on job interview invitations in Germany. Our contribution to this literature is the focus on the value of signals across various levels of employability and skills, particularly in the context of MOOCs.

3 Empirical setting and randomized experiment

Coursera, one of the largest online platforms hosting MOOCs, is characterized by its extensive course offerings and partnerships with global universities and organizations (Coursera, Inc., 2023). In 2022, it had over 100 million users, adding more than 21 million new learners during the year (ThinkImpact, 2021; Learnopoly, 2022; Coursera, 2022). Most courses can be audited for free. Obtaining a certificate typically involves a fee, which varies depending on the course and the institution, and ranges from $29 to $99 for individual courses. Specializations and professional certificates, which consist of a series of related courses, usually cost between $39 and $79 per month, with the total expense depending on the time taken to complete the series.[1] The affordability and flexibility of Coursera's offerings are central to its appeal, particularly for learners from economically disadvantaged regions or marginalized groups (Kizilcec et al., 2017; Chirikov et al., 2020).

Many courses offered by Coursera allow learners to obtain completion certificates. In addition to paying for them, obtaining certificates typically requires completing coursework and passing assessments. These certificates are often valued for their focus on practical skills relevant to career advancement, and observational data studies and recruited experiments suggest that, indeed, credentials obtained through such courses can positively impact career progression (Hadavand et al., 2018; Rivas et al., 2020; Castaño-Muñoz and Rodrigues, 2021). Many Coursera courses are thus career-oriented, and some of the most popular domains include *Information Technology*, *Computer Science*, *Data Science*, and *Business*.

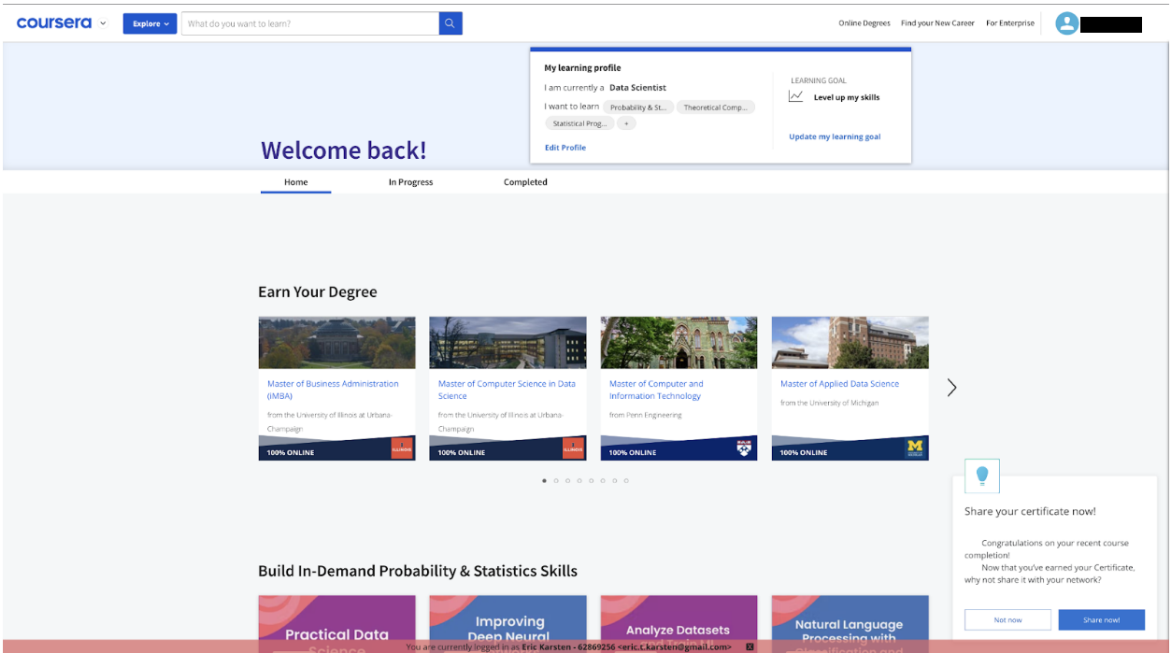
3.1 Randomized experiment

In the experiment, the treatment group was randomized to receive access to the *Credential Feature*, a new feature composed of notifications that encouraged the sharing of credentials on LinkedIn and

[1] Coursera also offers online degrees with significantly higher costs, but individuals graduating with online degrees are not part of this study.

provided a simplified process to do so. The first notification was sent on the learner's first visit to the Coursera app after the credential was granted, with the message: *"Do you want to boost your career? Only [XYZ]% of learners manage to complete [course name] on Coursera and get a certificate. Let everyone know you did it! Add the certificate to your LinkedIn profile in just two clicks."*[2] If the learner did not click the "Share now" button in the first notification, they received a second notification during their subsequent visit to the app, stating: *"Looking to boost your career? LinkedIn profiles with credentials receive 6x more views! Don't waste your hard-earned certificate! Add the certificate to your LinkedIn profile in just two clicks. PS. This is your last reminder."* These notifications highlighted a streamlined process to add certificates to LinkedIn profiles, which required only two clicks, compared to the baseline case, where learners had to manually copy a link from their credential page and paste it into their LinkedIn profile. Figure 1 shows how a notification looks on a web app. The control group did not receive these notifications or the streamlined credential-sharing process.

Figure 1: Screenshot of Coursera web app with a notification



The in-app notification is in the bottom right corner

The experimental sample was restricted to learners from developing countries and learners without college degrees who graduated with credentials in the selected primary domains (Information Technology, Data Science, Computer Science, and Business) between September 2022 and March 2023. All Coursera learners in these target groups were recruited into the experiment. The experimental

[2]This message included the corresponding course name and the percentage of learners completing it.

population consisted of 880,000 learners, with 37% in Business, 25% in Computer Science, 24% in Data Science, and 14% in Information Technology. The credentials were issued from 7,355 unique courses, ranging from shorter formats such as Courses (82%) and Guided Projects (16%) to longer ones such as Specializations (1.6%) and Professional Certificates (1%).

Randomization was carried out in monthly batches from September 2022 to March 2023. Each batch included learners who received the certificate between the first and last day of the month. The size of the batches varied from 130,000 to 160,000 learners. At the end of each month, the learners in a given batch were randomized to treatment and control. Randomization was stratified based on the learners' primary domain, whether they came from a developing country, and whether they had a college degree. Each learner was randomized to the treatment or control group with equal probability within these strata.

Learners who did not launch the Coursera app within 30 days of being assigned to the treatment group did not receive any notification. However, we continue to consider these users to be part of the treatment group. The percentage of learners who launched the app after graduation varied between batches, with the second batch having the highest percentage (96% of learners) and the fifth batch having the lowest (82%). Note that the batch is defined on the basis of graduation date rather than on visit dates to the app. Thus, a learner who graduated in September (the first batch) but visited the Coursera app and saw the notification in October is still classified as batch 1.

3.2 Data

To analyze the results of the experiment, we combined data from two sources. The first is the *Coursera Internal Data*, which includes data that describes user engagement with Coursera apps and user registration surveys. For each learner, we observe the name and dates of granted certificates and the level of engagement (which may come from potential employers) on the certificate pages, including the number of views (page visits) on the certificate page. Each view is categorized by its origin, including whether or not the view came from LinkedIn (the referral page was LinkedIn) and whether the view came from the associated learner. The last metric is inferred by Coursera from several signals and might have both type I and type II errors. Each certificate is associated with a primary domain and skills (e.g., "project management", "digital marketing", "web development"). In our dataset, we observe 462 different skills. For each learner, Coursera assesses skill mastery and assigns a score (Reddick, 2019). Additionally, we compute a max-mean standardization of the learners' skill level. We also

observe the country where the learner registered for the course. Following the OECD classification, we use this information to group countries into developing and developed. Finally, we also observe the information provided by the learners in their registration survey. Specifically, we have information about the level of education and gender. The response to the study is voluntary; thus, we do not observe these characteristics for some learners.

The second source of data is the *LinkedIn Matched Sample*. Upon enrolling in the course, learners were asked to provide their LinkedIn profile URLs. In September 2023, we collected LinkedIn profiles of approximately 40,000 learners who provided this information. As a result, there was a 12-month gap between randomization and LinkedIn data collection for learners in the first batch and an 8-month gap for those in the last batch. The dataset includes additional information on educational background, work experience, and LinkedIn activity. Details about the construction of features using LinkedIn data are provided in Appendix A.1.

The primary outcome of interest is whether learners reported new employment on their LinkedIn profiles—termed *New Job*. This outcome is observed exclusively within the *LinkedIn Matched Sample*. We define *New Jobs* as positions that had a reported starting date at least one month after randomization.[3] This category includes positions with the same employer. Additionally, to better align with the career aspirations of learners in our sample, we limit our analysis to positions in the technology sector or managerial roles. Relevant positions are identified by job titles containing keywords such as *software*, *data*, and *manager*. Consequently, *New Job in Scope* is assigned a value of 1 if the job starts at least one month after the randomization and fits these job title criteria. Moreover, *Credential Shared* is valued at 1 if the credential appears on the learner's LinkedIn profile and zero otherwise.[4]

Finally, for all learners in *Coursera Internal Data*, we observe the number of visits to the credential page and the referring page. Based on this data, we construct four indicator variables. Specifically, *All Views* takes the value of 1 when the certificate received any view; *All Views by Others* takes the value of 1 when the certificate page has been viewed at least once by someone other than the learner; and *Views LinkedIn* and *Views LinkedIn by Others* take the value of 1 for views originating only from LinkedIn by anyone or by someone other than the learner, respectively.

Summary statistics are presented in Table 1, and the balance of covariates between experimental groups is assessed in Appendix B.1. We do not find statistically significant differences in the covariate

[3] Additionally, a robustness check restricts our analysis to positions starting four months or more after randomization.

[4] Credentials are identified by their unique ID, provided by Coursera and displayed next to the credential's name on LinkedIn profiles.

Table 1: Summary statistics pretreatment and outcome variables

Variable name	Coursera Internal Data Mean	S.E.	LinkedIn Matched Sample Mean	S.E.
Treatment	0.499	0.001	0.500	0.003
Panel A: Pre-treatment covariates				
Professional Experience Years	–	–	3.040	0.028
Past Tech Job	–	–	0.127	0.002
Past Managerial Job	–	–	0.064	0.001
Main Skill Absolute	0.099	0.001	2.074	0.010
Main Skill Standardized	0.000	<0.001	0.000	0.001
Computer Science	0.252	0.001	0.230	0.002
Data Science	0.236	0.001	0.300	0.002
Information Technology	0.140	0.001	0.138	0.002
Guided Project	0.168	0.001	0.097	0.002
Professional Certificate	0.005	<0.001	0.005	<0.001
Specialization	0.009	<0.001	0.009	0.001
Developing Country	0.896	0.001	0.850	0.002
Associate Degree	0.029	<0.001	0.062	0.001
Bachelor Degree	0.127	0.001	0.367	0.003
Some College	0.072	0.001	0.130	0.002
Doctorate Degree	0.004	<0.001	0.012	0.001
High School Diploma	0.059	0.001	0.097	0.002
Less than High School	0.009	<0.001	0.012	0.001
Masters Degree	0.050	0.001	0.146	0.002
No Education Mentioned	0.645	0.002	0.164	0.002
Professional Degree	0.004	<0.001	0.010	0.001
Male	0.302	0.002	0.674	0.002
Gender Not Mentioned	0.533	0.002	0.101	0.002
Panel B: Outcome variables				
New Job	–	–	0.177	0.002
New Job in Scope	–	–	0.133	0.002
Credential Shared	–	–	0.181	0.002
All Views	0.191	0.001	0.429	0.003
All Views by Others	0.143	0.001	0.318	0.002
Views LinkedIn	0.165	0.001	0.409	0.003
Views LinkedIn by Others	0.124	0.001	0.296	0.002

Note: Professional Experience Years is the number of years between the starting date of the first job and August 2023. Past Tech Job takes the value of 1 when the learner had a job title related to technology before randomization and zero otherwise. Analogously, Past Managerial Job for jobs with managerial titles.

values between the treatment and control groups. Comparing the average covariate values in *Coursera Internal Data* and the *LinkedIn Matched Sample*, we find that the learners in the *LinkedIn Matched Sample* are more likely to have graduated with a certificate in Data Science (the difference is 0.067 p.p. with S.E. <0.001), less likely to participate in a Guided Project (the difference is - 0.074 p.p. with S.E. 0.002) and less likely to be from a developing country (the difference is -0.048 p.p. with S.E. 0.002). Recall that gender and level of education are provided voluntarily through the registration survey, similar to the LinkedIn URLs. We observe that in the *LinkedIn Matched Sample*, learners are more likely to report their gender or level of education.

Panel B of Table 1 presents the summary statistics of the outcome variables. In the *LinkedIn Matched Sample*, 18% of the learners found new jobs during the considered period, and 13% of all the learners found jobs that we consider in scope, indicating that most of the new jobs reported were related to certificates. However, most learners did not receive views on their credentials. In the *LinkedIn Matched Sample*, these shares were 43% and 30%, respectively. In the *Coursera Internal Data*, 19% of learners received any views and only 12% of them received views from others originating from LinkedIn. Finally, we find that 18% of learners in the *LinkedIn Matched Sample* had certificates in their profiles.[5]

4 Treatment effects in the LinkedIn Matched Sample

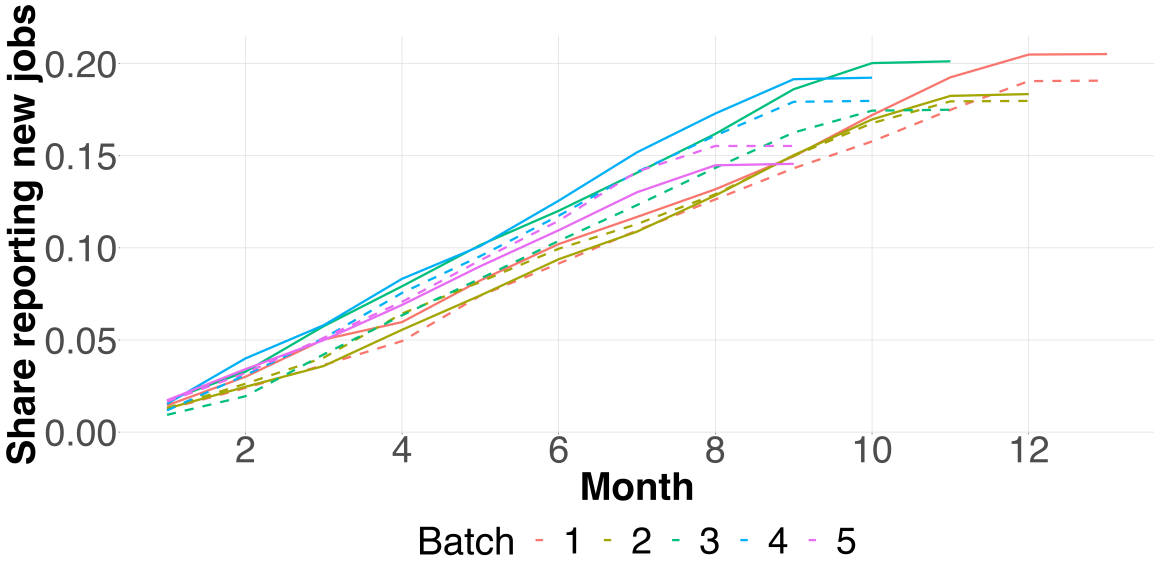
Using the randomized experiment, we first explore the effect of the *Credential Feature* on the average rate at which Coursera learners report new jobs, and second, we consider the Local Average Treatment Effect (LATE) (Imbens and Angrist, 1994) of *Credential Shared* on job outcomes, which is the effect on learners who added credentials due to the intervention. From a managerial perspective, the evaluation of the *Credential Feature* yields the overall benefit of the intervention—a combination of encouragement to share credentials and a streamlined process—to all Coursera learners. This evaluation would be relevant for a cost-benefit analysis of the development of the feature (where, in this case, the development costs of the feature were low). The second analysis is relevant to understanding the impact of showcasing course completion on LinkedIn on the likelihood of securing new employment. This analysis focuses on the outcomes of learners who adhered to the treatment, highlighting the potential value of adding these credentials to their LinkedIn profiles. Both questions are examined using the *LinkedIn Matched Sample*.

[5]Note that approximately 10% of learners received views from LinkedIn on their credentials even though they do not have the credentials in their profile. This can happen, for example, when a learner shares the credential as a post in their feed instead of adding it to their profile.

4.1 Average Impact of a Credential-Sharing Intervention

Figure 2 shows the share of subjects per experimental group and batch that reported a new job since the date of randomization. Month 0 corresponds to the month in which the batch was randomized into treatment or control groups, which is a different calendar month for each batch. Earlier batches are followed for longer than the later cohorts, with the first batch being followed for 12 months and the last one for 8. We notice that each batch followed a similar trend in reporting new jobs, with approximately 10% of learners reporting a new job after six months. In all batches, except for the fifth batch, more users in the treatment group reported new jobs than users in the control group. In that batch, there was also a negligible treatment effect on credential sharing (see Appendix C).

Figure 2: Share of learners reporting new jobs in treatment and control groups



Note: For each batch, the figure presents the share of learners by treatment and control groups who have reported a new job. Solid lines treatment groups. Dashed lines control groups.

In Table 2, we present the estimates of the average effect of the *Credential Feature* on the probability of reporting a new job. We use the Cox proportional hazard model in all six models and use censoring as defined by the duration between randomization and data collection for each batch. Models 1, 2, and 3 consider new jobs reported with a starting date at least one month after the randomization. Models 4, 5, and 6 restrict attention to jobs with a starting date at least 4 months after the randomization. Models 1 and 4 consider *New Job* outcome, and all other models *New Job in Scope*. Models 3 and 6 are based on the subsample of *LinkedIn Matched Sample* of learners whose previous job was not in scope. All models are adjusted for learners' covariates.

Table 2: Effect of *Credential Feature* on New Job and New Job in Scope

	Cox Prop. Hazards Overall			*Cox Prop. Hazards Exclude 4 months*		
	New Job	New Job in Scope	New Job in Scope & Old Not in Scope	New Job	New Job in Scope	New Job in Scope & Old Not in Scope
ATE	1.006	1.187	0.906	0.612	0.668	0.633
	(0.452)	(0.397)	(0.363)	(0.329)	(0.274)	(0.353)
ATE % baseline	5.815	9.320	10.451	6.785	11.341	7.301
	(2.611)	(3.118)	(4.184)	(3.646)	(4.659)	(4.072)
Baseline	17.303	12.736	8.666	9.020	5.889	8.666
	(0.067)	(0.058)	(0.238)	(0.048)	(0.039)	(0.238)
No. of obs.	36,946	36,946	30,607	36,946	36,946	30,607
Learners covariates	Yes	Yes	Yes	Yes	Yes	Yes

Note: Estimates of the impact of Credential Feature on New Job and New Job in Scope using Cox proportional hazards models. The first three columns based on new employment reported with a start date at least one month after randomization. The baseline is the share of learners in the control group that reported new jobs or jobs in scope. ATE is reported as a percentage point increase. Standard errors in parantheses.

We estimate a statistically significant difference in the probability of reporting a new job between treatment and control in all specifications. Considering *New Job* outcome we find a 5.8% (S.E. 2.6%) increase from baseline and 6.8% (S.E. 3.6%) when restricting to employment with a reported starting date at least 4 months after the treatment. Point estimates are higher when focusing on *New Job in Scope*, we estimate a 9.3% (S.E. 3.1%) and 11.3% (S.E. 4.7%) respectively. When we additionally restrict the sample to learners whose employment prior to the experiment was not in scope, we find that the *Credential Feature* increases the probably of reporting *New Job in Scope* with a starting date at least 1 month after the randomization by 10.5% (S.E. 4.2%) and 7.3% (S.E. 4.1%) with jobs starting 4 months after the randomization.

Groups based on certificate sharing and new employment We classify learners into four outcome-based groups based on the combination of the outcomes *New job* and *Credential Shared*: *Group 1* consists of learners who neither added the certificate nor reported a new job, *Group 2* includes those who did not add the certificate but reported a new job, *Group 3* comprises learners who added the certificate but did not report a new job, and *Group 4* consists of learners who both added the certificate and reported a new job. In the control group, the distribution of learners is as follows: 63% in Group 1, 7% in Group 2, 19% in Group 3, and 10% in Group 4.

Table 3 presents estimates of multinomial logistic models with the group indicators as dependent variables. Model 1 only has the Credential Feature indicator on the left-hand side; it takes the value of 1 for learners in the treatment group and 0 for control group learners. We find that among those treated, there are more learners in all groups except *Group 1* (reference group, not displayed); however, the difference is particularly pronounced for *Group 4*. Model 2 also accounts for the low employability

Table 3: Impact of *Credential Feature* on combined Credential Shared and New Job indicators

	Model 1			*Model 2*		
	New Job No certificate	No new job Certificate	New Job Certificate	New Job No certificate	No new job Certificate	New Job Certificate
Credential Feature	0.034	0.050	0.116	−0.071	−0.002	−0.035
	(0.041)	(0.027)	(0.034)	(0.053)	(0.038)	(0.044)
Low employability				−1.113	−0.513	−1.245
				(0.063)	(0.039)	(0.054)
Credential Feature * Low employability				0.266	0.098	0.415
				(0.087)	(0.054)	(0.073)
Baseline	0.0696	0.193	0.103	0.0696	0.193	0.103
	(0.0019)	(0.0029)	(0.0022)	(0.0019)	(0.0029)	(0.0022)
Observations	36,946	36,946	36,946	36,946	36,946	36,946

Note: Multinomial logistic regression with outcome variable equal to the group indicator. Model 1 includes only the Credential Feature indicator as a covariate, and Model 2 includes the Credential Feature indicator and the interaction term with a low employability indicator. No learners covariates. Low employability is the lowest tertile, as predicted by the GBM model trained on the control group. Standard errors in parentheses.

indicator and the interaction between treatment and employability. We predict baseline employability following the methodology described in Athey et al. (2025). We initially train a Gradient Boosted Machine (GBM) model using data from the control group. This model predicts the likelihood of a learner reporting a new job based on pre-treatment characteristics. We then apply this model to participants in both the treatment and control groups and classify them into tertiles according to their predicted employability. We find that controlling for the interaction term, the treatment is statistically insignificant and the interaction term is statistically different from zero for *Group 2* and *Group 4*. This result suggests that the effect of *Credential Feature* is present amongst the learners with low baseline employability (we analyze this further in Section 4.3).

4.2 The impact of *Credential Shared* on the probability of reporting a new job

The results presented in Tables 2 correspond to the average increase in the probability of reporting a new job among all treated learners. Now, we estimate the Local Average Treatment Effect of *Credential Shared* treatment. In the first stage, we consider the impact of the *Credential Feature* on *Credential Shared*, and in the second stage, the impact of *Credential Shared* on *New Job* and *New Job in Scope*. Results are presented in Table 4.

Columns 1 and 2 of Table 4 show estimates from the first-stage regression. We find that treatment increases the probability of sharing credentials by 2.8 p.p. (S.E. 0.4 p.p.), which corresponds to a 17% increase from baseline. The remaining columns present estimates from the instrumental variable

Table 4: Local Average Treatment Effects of Credential Sharing: First and Second Stage

	First Stage		*Second Stage Overall*			*Second Stage Exclude 4 months*		
	Cred. Shared	*Cred. Shared & Past Not In Scope*	*New Job*	*New Job in Scope*	*New Job in Scope & Past Not in Scope*	*New Job*	*New Job in Scope*	*New Job in Scope & Past Not in Scope*
Cred. Feature	0.028	0.023						
	(0.004)	(0.004)						
Cred. Shared			0.242	0.360	0.287	0.188	0.217	0.166
			(0.130)	(0.117)	(0.132)	(0.105)	(0.090)	(0.101)
No. of obs.	36,946	30,607	36,946	36,946	30,607	36,946	36,946	30,607
Learners covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: The first two Columns show the results from the first-stage regression. The estimates in Column 1 are based on the entire LinkedIn Matched Sample, in Column 2 we restrict the sample to learners whose past jobs were not in scope. Columns 3 to 8 present results of the second stage regressions. Columns 3 to 5 consider all jobs. The last three columns restrict attention to jobs reported with a starting date at least 4 months after randomization. Columns 3 and 6 New Job outcome; Columns 4, 5, 7, 8 New Job in Scope. Columns 5 and 8 restrict to subsample of learners with past jobs out of scope. Standard errors in parantheses.

regression with *New Job* and *New Job in Scope* as outcomes. In Columns 6, 7, and 8, we restrict attention to jobs reported with a starting date at least four months after treatment. We estimate positive and statistically significant effects. Specifically, we estimate the local average treatment effect of 0.24 (S.E. 0.13) for any new job starting at least one month after treatment and 0.36 (S.E. 0.12) when restricting attention to jobs with a starting date at least four months after the treatment.

4.3 Effect of *Credential Feature* and *Credential Shared* on Employment Across Levels of Employability.

In this section, we examine the impact of the *Credential Feature* and *Credential Shared* on the probability that workers with varying levels of baseline employability report a new job. Our analysis aims to determine whether our intervention and credential sharing more broadly increase or reduce disparities in outcomes.

Table 5: Effect of Credential Intervention and Credential Sharing on Employment by Tertile of Predicted Employability

	Impact of Credential Feature: Proportional Hazard Model			*Impact of credential sharing: Instrumental Variable Model*		
	High Employ.	Medium Employ.	Low Employ.	High Employ.	Medium Employ.	Low Employ.
Credential Feature/Shared Credential (pp)	0.382	0.671	1.265	0.074	0.193	0.622
	(1.141)	(0.640)	(0.529)	(0.207)	(0.190)	(0.296)
Credential Feature (%)	0.012	0.054	0.109			
	(0.037)	(0.053)	(0.048)			
Baseline in employability group	0.316	0.120	0.110	0.316	0.120	0.110
	(0.005)	(0.003)	(0.002)	(0.005)	(0.003)	(0.002)
Observations	9,432	11,817	15,697	9,432	11,817	15,697

Note: Estimates of the heterogeneous treatment effects across tertiles of predicted employability from the GBM model. The first three columns show the estimate from the proportional hazard model of the average treatment effect of the Credential Feature. Standard errors are in parentheses.

The results of this analysis are presented in Table 5. The baseline probability of reporting employment is 32% for the upper tertile, 12% for the middle tertile, and 11% for the lower tertile. The first

three columns of the table show the estimates from the Cox proportional hazard model of the impact of *Credential Feature* on *New Job*. For the upper and middle tertiles, the effects are statistically insignificant, with estimates of 0.382 p.p. (S.E. 1.141) and 0.671 p.p. (S.E. 0.640), respectively. However, for the bottom tertile, we find a statistically significant effect of 1.265 p.p. (S.E. 0.529). When comparing the effects between the bottom and top tertiles, the difference is 0.1 p.p. (S.E. 0.06).

Columns 4 through 6 of Table 5 present the heterogeneity in LATE estimates across tertiles of baseline employability. The estimate is statistically significant only in the lower tertile. Therefore, the impact of both the *Credential Feature* and *Credential Shared* observed in the entire experimental population appears to be driven by improved outcomes among learners with lower baseline chances of finding a new job, thus reducing the disparity in outcomes across learners.[6]

First, these findings suggest that prioritizing access to the feature for learners with low baseline employability may be advantageous when the feature cannot be rolled out to all learners. Second, we find that credential sharing, for example, due to encouragement with *Credential Feature*, can particularly benefit learners with low baseline outcomes.

4.4 Change in the pattern of LinkedIn engagement

The *Credential Feature* emphasized the importance of having up-to-date LinkedIn profiles. Thus, it is not implausible that the feature drove treated learners to complete their LinkedIn profiles in addition to sharing their credentials. We consider two mechanisms that, if true, would upwardly bias our results.

First, treated learners who found a job between graduating from the course and receiving treatment but have not yet added the new job to their LinkedIn profile might update their profiles due to the nudge. Thus, the jobs added in the first month or two after treatment reflect the difference in the probability of having an up-to-date profile rather than getting a new job. In Columns 2 and 3 of Table 2, we consider the impact of treatment on the probability of reporting a new job with a start date of at least four months after the randomization's date (we find qualitatively the same results for 3 and 5 months). Taking into account only such jobs, we estimate the treatment effect of 7.1% (SE 3.1%). There were no differences in reminders or other Coursera services between the treatment and control groups after the initial treatment. Thus, it is unlikely that at the time of treatment, many learners would add jobs with a start date four months later. Thus, while we cannot rule out that some learn-

[6]We analyze the impact of *Credential Shared* on finer employability groups (deciles) in Appendix E. We show that the treatment effect is particularly pronounced in the bottom two deciles.

ers updated their profiles because of the treatment, the difference in the probability of reporting jobs starting several months after the treatment is suggestive of an impact from the treatment.

Second, treated learners could also become more active on LinkedIn and have more complete profiles. If that were the case, the treatment effect could combine the effect of signaling skills with the impact of a more complete LinkedIn profile. To test for this mechanism, we compute the number of characters in the learner's LinkedIn profile, excluding fields related to credentials and new jobs. We find that, on average, learners in the treated group have 1362 characters, and learners in the control group have 1356. The effect of treatment on this outcome is, therefore, 6 characters (S.E. 6). Thus, we do not find that the profiles of treated learners are more complete.

5 Impact of the *Credential Feature* on Certificate Views

In this section, we consider the impact of the *Credential Feature* on the probability that learners' certificates were viewed. In this analysis, we consider the entire experimental group, which includes learners in the *LinkedIn Matched Sample*, all of whom have LinkedIn accounts, and other learners, including those who might not have LinkedIn accounts. In Appendix D, we show that there is a high correlation between certificate views and the probability of reporting a new job; thus, we treat certificate views as a proxy for employment outcome.

Table 6 shows the estimates of the average effect of *Credential Feature* on the probability of getting a click on LinkedIn from the OLS estimator. Models 3 and 4 restrict attention to views where the referral page was LinkedIn. Models 2 and 4 restrict attention to views by someone other than the learner. All estimates are adjusted for learners' characteristics.

Table 6: Impact of Credential Feature on the probability of receiving views

	OLS			
	All views	All views by others	Views LinkedIn	Views LinkedIn by others
ATE	0.00619	0.00246	0.00600	0.00214
	(0.00090)	(0.00080)	(0.00085)	(0.00075)
ATE % baseline	3.371	1.8041	3.8036	1.8278
	(0.5473)	(0.4894)	(0.5152)	(0.4596)
Baseline	0.1884	0.1421	0.1621	0.1228
	(0.00063)	(0.00056)	(0.00059)	(0.00053)
Observations	765,616	765,616	765,616	765,616
Learners covariates	Yes	Yes	Yes	Yes

Note: Estimates of the average treatment effect on the probability of receiving views from LinkedIn. Columns 1 and 3 have all LinkedIn views as outcomes, and Columns 2 and 4 restrict attention to views not by the user. Estimates in Columns 1 and 2 are from the OLS estimator, and in Columns 3 and 4, they are with logit regression. Each estimate is adjusted using learners' characteristics as controls.

We estimate that *Credential Feature* increases the probability of having at least one view on the certificate by 0.7 p.p. (S.E. 0.1 p.p.) to 0.3 p.p. (SE 0.1 p.p.) corresponding to a 4% to 2% increase from the baseline levels.

6 Conclusion

This study provides insights into the impact of non-traditional credentials, specifically MOOC certificates, on labor market outcomes. Our randomized experiment first shows that features that encourage and simplify credential sharing can improve job outcomes for learners. Second, we show that learners who showcased their Coursera certificates on LinkedIn experienced a significant increase in the likelihood of reporting new employment, particularly in roles related to their MOOC credentials. This effect was most pronounced among learners with lower baseline employability, suggesting that signaling skills through non-traditional credentials can be particularly beneficial for this group and may contribute to more equitable employment outcomes. The findings also highlight the importance of the visibility of credentials on professional networking platforms, as the treatment effect was mediated by the presence of certificates on learners' LinkedIn profiles. This underscores the value of online platforms in facilitating skill signaling and enhancing employability.

For further research, it would be valuable to explore the longitudinal impact of showcasing MOOC credentials on career advancement and income growth, providing a more comprehensive understanding of their value over time. Investigating employers' perceptions of non-traditional credentials in more depth, including the factors that influence their recognition and acceptance, would provide valuable insights for both learners and MOOC providers. Furthermore, examining the impact of MOOC credentials in different cultural and economic contexts could shed light on the differences in the applicability of these findings. Further research could also assess the extent to which MOOCs contribute to skill development and how this relates to employability, exploring the balance between signaling and skill acquisition.

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Appendix

A Sample of courses included in the experiment

In Table 7, we show a sample of 50 courses of 7355 from which the learners included in the experiment graduated.

Table 7: Sample of course included in the experiment

Primary domain	Credential Type	Certificate Name
Information Technology	Course	Fundamentos do Suporte Técnico
Business	Guided Project	Develop a Company Website with Wix
Data Science	Course	SQL for Data Science
Information Technology	Course	Fundamentals of Red Hat Enterprise Linux
Data Science	Course	Neural Networks and Deep Learning
Information Technology	Course	Introduction to Cloud Computing
Information Technology	Course	AWS Cloud Practitioner Essentials
Business	Course	Capital-investissement et capital-risque
Data Science	Specialization	Introduction to Data Science
Business	Course	Teamwork Skills: Communicating Effectively in Groups
Information Technology	Course	Crash Course on Python
Business	Course	Excel Skills for Business: Advanced
Data Science	Guided Project	Introduction to Business Analysis Using Spreadsheets: Basics
Business	Course	Foundations of Project Management
Business	Course	Assess for Success: Marketing Analytics and Measurement
Business	Course	Bookkeeping Basics
Computer Science	Course	Introduction to Front-End Development
Business	Guided Project	Create a Project Charter with Google Docs
Data Science	Professional Certificate	Google Data Analytics
Information Technology	Course	Technical Support Fundamentals
Computer Science	Course	Python Programming: A Concise Introduction
Information Technology	Course	Introduction to Web Development with HTML, CSS, JavaScript
Computer Science	Guided Project	Get Started with Figma
Computer Science	Course	Foundations of User Experience (UX) Design
Computer Science	Course	Programming for Everybody (Getting Started with Python)
Data Science	Professional Certificate	IBM Data Analyst
Computer Science	Course	JavaScript Basics
Business	Course	Foundations of Digital Marketing and E-commerce
Data Science	Course	Foundations: Data, Data, Everywhere
Information Technology	Course	AWS Cloud Technical Essentials
Computer Science	Course	Blockchain: Foundations and Use Cases
Computer Science	Course	HTML, CSS, and Javascript for Web Developers
Business	Course	Developing Innovative Ideas for Product Leaders
Business	Guided Project	Introduction to Microsoft Excel
Business	Course	Construction Project Management
Data Science	Course	Introduction to Genomic Technologies
Information Technology	Course	Explore Core Data Concepts in Microsoft Azure
Computer Science	Course	Responsive Website Basics: Code with HTML, CSS, and JavaScript
Business	Course	Esports Teams and Professional Players
Computer Science	Guided Project	Build a mobile app with Google Sheets on Glide and no coding
Business	Guided Project	Designing and Formatting a Presentation in PowerPoint

Note: A sample of courses in which learners' included in the experiment graduated from.

A.1 LinkedIn Feature Engineering

- **Current Enrollment in Educational Program**: This binary feature is set to *TRUE* if the end date of the participant's educational program is later than 2022. It is important to note that only the year of the start and end dates of the educational programs are available in our dataset.
- **Level of Education**: This categorical feature classifies the participant's highest level of education based on keywords found in the title of their degree. The classifications are as follows:
  - *Master's Degree*: Identified through keywords such as 'master', 'msc', 'maestría', or 'ma'.
  - *Bachelor's Degree*: Identified through keywords like 'bsc', 'bs', 'bachillerato', or 'bachelor'.
  - *Doctor's Degree*:Identified through keywords such as 'doctor', 'doutorado', or 'docteur'.
  - *Degree*: This is marked as *TRUE* if any of the above conditions are satisfied.
- **University Ranking of the Latest Academic Degree**: Utilizing the national rankings provided by a public Kaggle dataset (https://www.kaggle.com/datasets/mylesoneill/world-university-rankings), we assigned rankings based on the latest available data, predominantly from 2015. Note that rankings may vary annually, and institutions may hold different positions in different years.
- **Years Since Latest Academic Degree**: This feature calculates the difference in years between 2023 and the year of the participant's most recent academic degree. If the result is negative, indicating that the participant has not yet graduated, the value is set to 0.

Additionally, to discern career outcomes from the LinkedIn scraped data, the following methodology was applied:

1. **Internship Identification**: Initially, we extracted the current job position from the profile to ascertain whether the term "Intern" was present, which would indicate an internship role.
2. **Time Difference Calculation**: Subsequently, we calculated the time difference in months between the start date of the most recent experience and September 2022, when our experiment started.
3. **Career Outcome Determination**: Based on the computed time difference, we categorized the career outcomes as follows:

- If the time difference is greater than or equal to 0 months, it implies a recent career development, leading to further analysis:
  - If "Intern" is found in the current job title, the outcome is classified as a *new internship*.
  - If the employer of the current job differs from the employer of the previous job, it indicates a change in job roles, leading to the classification of *new job*.
  - Otherwise, the outcome is classified as a *promotion*.

B Descriptive statistics

Table 8 presents summary statistics for the covariates provided by the Coursera internal dataset.

Table 8: Summary Statistics for Internal Coursera Covariates

Variable	Group	Count	Min	Max	Mean	SD
gender	unknown	470459	0.00	1.00	0.53	0.50
gender	male	269836	0.00	1.00	0.30	0.46
gender	female	146897	0.00	1.00	0.17	0.37
gender	other	1027	0.00	1.00	0.00	0.03
education level	unknown	570268	0.00	1.00	0.64	0.48
education level	associate degree	25298	0.00	1.00	0.03	0.17
education level	masters degree	44975	0.00	1.00	0.05	0.22
education level	bachelor degree	114926	0.00	1.00	0.13	0.34
education level	professional degree	3540	0.00	1.00	0.00	0.06
education level	college no degree	64078	0.00	1.00	0.07	0.26
education level	high school diploma	53155	0.00	1.00	0.06	0.24
education level	doctorate degree	3963	0.00	1.00	0.00	0.07
education level	less than high school diploma	8016	0.00	1.00	0.01	0.09
primary domain	business	330462	0.00	1.00	0.37	0.48
primary domain	data science	208819	0.00	1.00	0.24	0.42
primary domain	computer science	222335	0.00	1.00	0.25	0.43
primary domain	information technology	126603	0.00	1.00	0.14	0.35
credential type	course	727602	0.00	1.00	0.82	0.38
credential type	guided project	147540	0.00	1.00	0.17	0.37
credential type	specialization	8278	0.00	1.00	0.01	0.10
credential type	professional certificate	4799	0.00	1.00	0.01	0.07
developed country	-	888219	0.00	1.00	0.10	0.30
certificate has page views	-	888219	0.00	1.00	0.20	0.40
certificate has page views from linkedin	-	888219	0.00	1.00	0.17	0.38
count all views	-	888219	0.00	726.00	0.71	3.09
count all views not by user	-	888219	0.00	725.00	0.60	3.03
count linkedin views	-	888219	0.00	411.00	0.58	2.37
count linkedin views not by user	-	888219	0.00	411.00	0.49	2.31
has degree linkedin	-	20396	0.00	1.00	0.62	0.48
has bachelor linkedin	-	20396	0.00	1.00	0.43	0.49
has master linkedin	-	20396	0.00	1.00	0.18	0.38
has doctor linkedin	-	20396	0.00	1.00	0.02	0.13
yearsSinceEnrollment	-	20396	0.00	46.00	3.97	5.43
new internship linkedin	-	20396	0.00	1.00	0.05	0.22
new job linkedin	-	20396	0.00	1.00	0.31	0.46
promotion linkedin	-	20396	0.00	1.00	0.08	0.27
new job or promotion linkedin	-	20396	0.00	1.00	0.39	0.49
any outcome linkedin	-	20396	0.00	1.00	0.44	0.50

B.1 Balance check analysis

Table 9 presents a balance check analysis for the total population of the experiment participants. Results show no significant differences between treatment and control groups.

Table 9: Covariate balance between treatment and control

Variable	Mean Difference	Standard Error	Treatment Mean	Control Mean	Treatment N	Control N
first_skill_score_1	3e-04	0.0014	0.1002	0.0999	381815	383801
first_skill_score_3	0	1e-04	0	0	381815	383801
associate_degree	3e-04	4e-04	0.029	0.0287	381815	383801
bachelor_degree	-8e-04	8e-04	0.1269	0.1278	381815	383801
some_college	-5e-04	6e-04	0.0721	0.0726	381815	383801
doctorate_degree	-2e-04	2e-04	0.0043	0.0045	381815	383801
high_school_diploma	-4e-04	5e-04	0.0592	0.0596	381815	383801
less_than_high_school	0	2e-04	0.0089	0.009	381815	383801
masters_degree	-7e-04	5e-04	0.0496	0.0503	381815	383801
no_education_mentioned	0.0022	0.0011	0.6458	0.6436	381815	383801
professional_degree	2e-04	1e-04	0.0041	0.0038	381815	383801
male	-8e-04	0.001	0.3014	0.3022	381815	383801
gender_not_mentioned	9e-04	0.0011	0.5336	0.5328	381815	383801
primary_domain_computer_science	0.0015	0.001	0.2529	0.2514	381815	383801
primary_domain_data_science	-0.001	0.001	0.2353	0.2363	381815	383801
primary_domain_information_technology	-6e-04	8e-04	0.1398	0.1404	381815	383801
credential_type_guided_project	1e-04	9e-04	0.1679	0.1678	381815	383801
credential_type_professional_certificate	-1e-04	2e-04	0.0054	0.0055	381815	383801
credential_type_specialization	-3e-04	2e-04	0.0084	0.0087	381815	383801
developing_country	5e-04	7e-04	0.8962	0.8957	381815	383801
professional_exp_years	0.0464	0.0609	3.6122	3.5658	18487	18459
past_business_job	-0.0014	0.0026	0.0641	0.0655	18487	18459
past_tech_job	0.0034	0.0035	0.1308	0.1274	18487	18459

Note: Averages of covariate values across treatment and control groups.

C Impact of Credential Feature on Credential Sharing

Panel A of Table 10 presents the average treatment effect estimates on *credential sharing* per batch. We can observe differences in the baseline shares of learners who shared their credentials, as well as in the average treatment effect estimates. Notably, the final batch exhibited a significantly lower treatment effect compared to other batches. Various factors may contribute to these discrepancies, including the baseline propensity to respond to treatment and the number of learners effectively exposed to the treatment.

Notifications aimed at encouraging credential sharing were displayed within the Coursera apps, hence only those learners who logged into the platform post-randomization were targeted. The percentage of learners who did so varied, with the second batch having the highest share (96%) and the final batch having the lowest share (82%). Furthermore, in instances where Coursera was sending additional notifications to learners, depending on their priority level, they might be shown before our notifications. In such cases, treated learners would encounter the notification during their subsequent visit to the Coursera app. Panel B of Table 10 illustrates the average treatment effect on credential sharing limited to learners who logged into the app post-randomization (the restriction is applied to both treatment and control groups). We observe a higher treatment effect across all batches, including

batch 5, compared to the unrestricted sample.

Table 10: Average treatment effect of Credential Feature on Credential Shared by Batch

Batch	Mean Control	Mean Treatment	ATE	ATE (%)
Panel A: LinkedIn Matched Sample				
1	17.832	20.074	2.242	12.571
	(0.617)	(0.650)	(0.896)	(5.025)
2	14.992	18.255	3.262	21.759
	(0.569)	(0.601)	(0.828)	(5.521)
3	16.398	19.382	2.984	18.196
	(0.579)	(0.627)	(0.853)	(5.203)
4	17.533	21.794	4.261	24.303
	(0.616)	(0.669)	(0.909)	(5.185)
5	16.546	18.123	1.577	9.528
	(0.706)	(0.732)	(1.017)	(6.147)
Panel B: Sample of learners that logged in after randomization				
1	18.007	20.203	2.195	12.191
	(0.623)	(0.655)	(0.904)	(5.022)
2	15.259	18.679	3.420	22.410
	(0.579)	(0.614)	(0.844)	(5.531)
3	16.853	19.917	3.064	18.183
	(0.596)	(0.644)	(0.877)	(5.206)
4	17.749	22.292	4.543	25.594
	(0.628)	(0.686)	(0.930)	(5.241)
5	16.829	18.581	1.752	10.411
	(0.724)	(0.754)	(1.045)	(6.211)

Note: Estimates of the average treatment effect obtained using a difference-in-means estimator. Standard errors in parentheses.

D Correlation between views and new jobs

Table 11 shows the estimates from the linear probability regressions of *New job* on the four types of credential views using LinkedIn Matched Sample. We find that there is a strong correlation between receiving credential views and reporting a new job.

Table 11: Correlation between views and new jobs

	Dependent variable:			
	All views	All views by others	Views LinkedIn	Views LinkedIn by others
	(1)	(2)	(3)	(4)
New job	0.513***	0.400***	0.497***	0.379***
	(0.008)	(0.007)	(0.007)	(0.006)
Observations	36,946	36,946	36,946	36,946
R^2	0.109	0.090	0.107	0.086
Adjusted R^2	0.109	0.090	0.107	0.086
Residual Std. Error (df = 36945)	0.618	0.538	0.604	0.520
F Statistic (df = 1; 36945)	4,538.226***	3,641.660***	4,446.666***	3,492.890***

Note: *p<0.1; **p<0.05; ***p<0.01

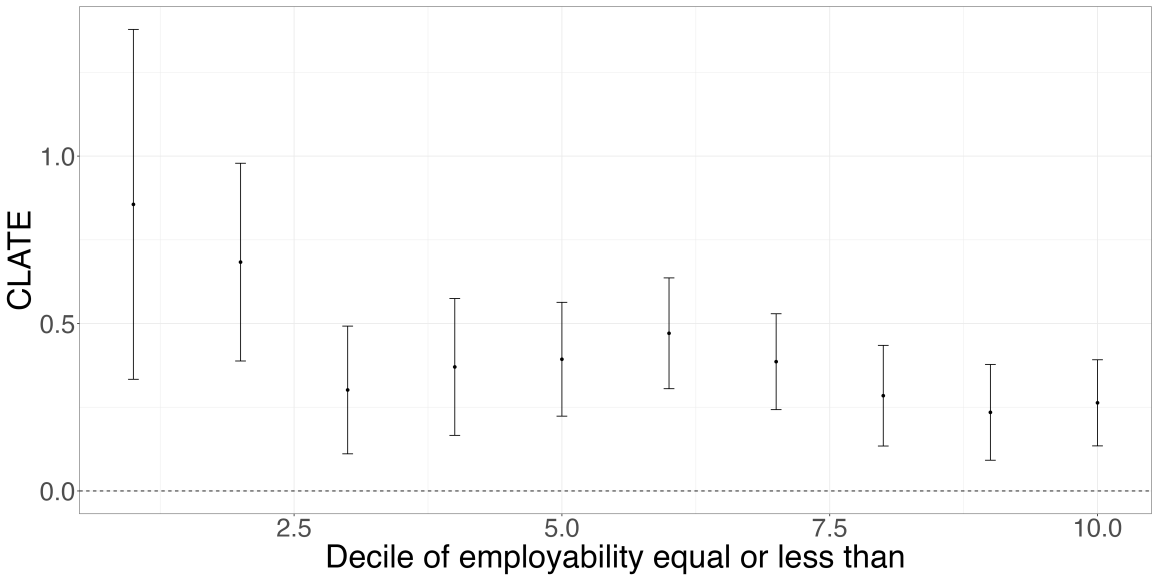
Note: Estimate from linear probability models regressing new jobs on the four types of views outcomes. Estimates based on the LinkedIn Matched Sample.

E Local average treatment effect across deciles

To analyze the impact of *Credential Shared* across various levels of employability as predicted by our models, we predict baseline employability using a Gradient Boosting Machine (GBM) with cross-fitting on a LinkedIn Matched Sample. The GBM was trained on nine of these folds to predict employability scores, which were then utilized to assign each observation into deciles based on predicted employability levels. Next, we compute indicators of deciles of baseline employability.

Using these declines, we estimate LATE within the groups defined by cumulative deciles (e.g., the first model includes only the lowest decile, the second model spans the first and second deciles, etc.). Results are presented in Figure 3. Our analysis shows a higher LATE in the two lowest deciles, suggesting that interventions might be most effective within these groups.

Figure 3: Conditional Local Average Treatment Effects



Note: Estimates of the Local Average Treatment Effects of sharing the credential conditional on the baseline level of employability. Estimates from models estimated with data on learners with an increasing baseline employability.