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Skill Signals in a Digital Job Search Market and Duration in Employment Gaps

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ABSTRACT⁴

With the rise of the digital job search market, new opportunities for signaling skills and competencies to employers have emerged. In this paper, we examine listed skills on individuals' LinkedIn profiles in the United States between 2015 and 2021, both those members add themselves and skills for which they are endorsed from others in their network. We use an inverse probability weighted proportional hazards model with time varying covariates to estimate the impact of profile-listed skills on shortening employment gaps (time between jobs). We find that, for both self-added and peer-endorsed skills, an additional ten skills on the profile decreases median employment gap duration by about one month (from an average of 7 months). Individuals with no education listed on their profile have the largest benefit from listed skills in terms of reducing employment gaps. When education is listed, workers with lower educational attainment have larger reductions in median employment gaps from more endorsed skills on the profile.

Keywords: unemployment, human capital, signaling, labor, skills JEL classifications: J24, J64, J28, I26

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1. Introduction

There are important information asymmetries in the job matching market. In deciding interviews to extend and job offers to make, firms must form beliefs about the competencies and abilities of potential employees (Altonji & Pierret, 2001). In deciding which jobs to apply to and offers to accept, job seekers attempt to determine characteristics of the job and how well they would fit into the firm. In this paper, we examine one set of signals—listed skills on a LinkedIn member's profile—that potential employers can use to form beliefs about worker productivity and how that translates into ending employment gaps, and thus offer insights into how technology may be transforming the signaling landscape for job matching in terms of employment gap duration. Employers may rely on several signals of competencies include education degrees, job history, and occupational certifications and licenses, all of which have been shown to be related to positive employment history in prior work (Albert, 2017; Baird et al., 2022; Card, 1999; Pallais, 2014). With the rise of the digital job search market, new formalized mechanisms for signaling have emerged (Agrawal et al., 2015).

We examine the relationship between listed skills on individuals' LinkedIn profiles and the duration of employment gaps in the United States between 2015 and 2021, exploring both skills the members list themselves and skills for which they are endorsed from others in their network. Listed skills serve as signals of competencies and may improve likelihood of career progression and improve job match quality between workers and firms. Workers with differing levels of educational attainment may benefit differently from such signals; we contrast how the estimated impact of skills varies by educational attainment. In this paper, we examine the return to ending employment gaps. In future work, we will expand the work to examine the impact on recruiter outreach to job seekers as well as worker promotion and cross-job upward transitions.

Our research documents several important findings. First, workers with higher educational attainment are generally more likely to add skills to their profiles and be endorsed for skills. All workers are more likely to add and be endorsed for skills early on in employment and non-employment spells. However, the probability of new endorsed skills during employment spells does not begin declining until after a few

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months. We estimate that each additional 10 skills added to a profile (approximately one standard deviation in our sample) increases the probability of finding a job match each month by approximately ten percent, both for self-added and endorsed skills. This translates to shortening the median employment gap by one month, from 7 to 6 months. Those with no education listed on the platform (which may include those with no post-secondary education as well as those with college degrees who have incomplete profiles) have the largest marginal difference for each skill added on ending non-employment. The results comparing sub-baccalaureate workers and workers with a bachelor's or higher are more mixed, with lower education workers having a larger reduction in median employment gap for additional endorsed skills compared to higher education workers, with the reverse approximately holding for self-added skills.

1.1. Related Literature

This paper is most closely connected to the literature on the returns to education, signaling, and sheepskin effects. Years of education not only increase human capital (making workers more productive and employers more willing to hire and pay higher wages), but signal to the employers a host of proficiencies (Altonji & Pierret, 2001). There is a rich literature on the returns to the completion of an educational degree. The sheepskin effect, named after the historical material on which diplomas were sometimes printed, are associated with increases in employment and earnings (Hungerford & Solon, 1987; Jaeger & Page, 1996). While often discussed with respect to college degrees in the United States, there is also an estimated positive return to a high school degree (in a meta-analysis, the return was estimated at around 8 percent in Mora & Muro, 2014).

Sheepskin effects have also been found to vary by subgroups, relevant to our context of variation by educational attainment. Compared to White male workers, women and minority workers had smaller returns to degrees for lower education years, but larger returns at higher education levels (Belman and Heywood 1991). Bitzan (2009) found similar results between White and Black workers and concludes the presence of both signaling and statistical discrimination in the White-Black wage gap.

The return to skills goes beyond formal educational degrees. Occupational credentials, such as licenses and certificates, have been found to improve employment outcomes (Albert, 2017; Ingram, 2019). Baird et al. (2022) found a similar positive return from credentials on employment and earnings, with women in particular in terms of being employed, conditional on being in the labor force. They conclude that credentials serve as an important signal for women regarding commitment to the labor force.

2. Conceptual Framework

Employment gaps—which may include either unemployment spells or voluntary separation from the labor force, or both—end when a worker and a firm agree to a contractual job arrangement. In creating this match, workers must gauge their benefit from working in that job, which depends on pay, non-wage benefits, potential for career progression, and other factors (Baird, 2017). At the same time, firms form beliefs regarding how good of a match a given worker would be for the job (Altonji & Pierret, 2001). The match quality—from the employer side, primarily regarding how productive the worker would be at the job—is both occupation and industry specific, and given that, context depends on the skills and proficiencies of a job candidate. Firms form beliefs regarding the worker's productivity based on several information sources, including educational degrees, employment history, references, and interviews. Each of these signals may serve to increase the likelihood of an offer being made to a candidate and thus the end of an employment gap upward transitions between employers (outcomes we hope to explore in future work).

Digital job searching has allowed for an expansion of potential signals that job candidates can use (Agrawal et al., 2015). In LinkedIn profiles, candidates can list specific skills they have. They can also be endorsed for skills by peers. This information provides firms with additional signals about skills workers may have.

In this paper, we examine the impact of listed skills on shortening employment gaps across two dimensions: educational attainment and source of skill listing (self-added vs. endorsement). Self-added skills are skills that a member has added to their profile themselves. Endorsed skills are those that have been suggested by someone in the member's network, or a skill that was added by the member and then later endorsed by someone in their network (functionality on that has changed over time). Workers with higher education, such as bachelor's or graduate degrees, may have clearer signals of some of their competencies. Aside from the general sheepskin effect that may inform employers about the bundle of worker's soft skills such as determination, the specific field of study contains information about skills. Likewise, the reputation of the degreegranting college may also increase information that the employers have. Workers with high school or associate degrees may thus benefit more from skills on profiles compared to their bachelor's degree holding peers, as they lack the spotlight of the university degree. In addition, a turn towards skills-first hiring may help weaken the so-called paper ceiling wherein sub-baccalaureate workers are filtered out of job searches solely due to their educational attainments. Workers with higher education from lower ranked institutions may also benefit from a move to more skills-first hiring.

As for source of skill information, self-added skills may be a fuller representation of skills for a worker but may suffer from credibility barriers if firms are uncertain about how accurate that added skill reflects productivity gains. Social endorsement from others in their social network allows for a certain degree of vetting. Thus, we hypothesize that the return to endorsed skills would be greater than self-added, and that degree-granting programs confer additional credibility to self-listed skills. Meanwhile, individuals without college providing evidence of a skill may receive a larger benefit from social proof such as receiving endorsements from their social networks on having a skill. We would see this if lower education workers had larger benefits from endorsed skills than higher education workers.

3. Methods

3.1. Data and Context

We use data from individuals who have profiles on LinkedIn in the United States who experience at least one employment gap spell between 2015 and 2021. We use both public and private profiles. As of 2022, there are over 191 million LinkedIn members in the United States. While not a perfectly representative sample of the overall US workforce

(with somewhat higher representation among higher education workers), the membership constitutes a large and important population of the labor force, and one likely more representative of those using digital job search technologies. We define an employment gap spell as one that starts after the end of a job listed on the profile that ended after their graduation date (when graduation date is known) and ends at the date of the start of a new job listed on the profile.

Given the nature of the LinkedIn data, which allows for month to be recorded, we classify an employment gap when there is at least one month gap between jobs. If an individual ended a job at the start of February for instance, and started a new job at the end of March, we would not record this as an employment gap, as there would be no month in between jobs. Further, to account for known profile update lag (wherein individuals do not immediately update their profile when they lose or add a job), we limit the sample to ending with recorded employment status as of December 2021, instead of through the current date. We are assuming that 10 months is sufficient time for the large majority of workers to have listed the end of employment gap by recording a new job.

We have millions of observations in the sample, both for unique individuals and employment gaps (our sample of those with at least one employment gap average 1.2 employment gaps total in the time span). Bachelor's degree holders account for approximately one third of our analytic sample. Another quarter of the observations are those with a graduate degree. The smallest two groups are those with associate's degree and those with high school or less, with each of the groups forming under ten percent of our sample (with more in the associate's degree group). Nearly 30 percent of the total sample have no listed education. Those whose education is missing may have disproportionately lower educational attainment, but for the purpose of this analysis we cannot determine that. Additionally, we might suspect that this group who have no listed education would benefit most from skills listed on their profiles.

Table 1 shows the average skills added and being endorsed by education group for our analytic sample. Higher education workers tend to add more skills and be endorsed for more skills, on average. One standard deviation for both measures is around 10 skills (and a bit larger when conditioning on having positive skills), which we will use later as a benchmark when interpreting the estimated impacts of the skills. While not shown here, just under half of the sample do not have any skills on their profile.

	Sel	lf-added	Endorsed		
	Mean			Std. Dev.	
All	5.910	8.962	7.949	9.886	
HS or less	4.806	7.971	3.753	7.596	
AA	5.949	8.794	6.807	9.426	
BA	7.129	9.575	9.152	9.914	
Grad	6.599	9.524	9.955	10.387	
Missing	3.98	7.383	5.551	9.055	

Table 1: Summary Statistics on Skills on Profiles in Sample

Note: Std. Dev: standard deviation; HS or less: High school or less; AA: associate's degree; BA: bachelor's degree; Grad: graduate degree

We next examine the probability that a person adds a skill or is endorsed for a skill in a given month. Note that this is unadjusted and reflects platform activity as well. Figure 1 shows the overall averages. There is still the general positive relationship between higher educational attainment and more skills, with the exception being that bachelor's degree holders are consistently the highest group. The gap between educational groups is smallest for self-added skills during employment spells.

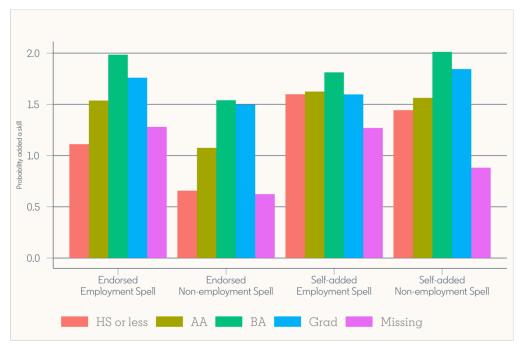


Figure 1: Probability of a skill being added to a profile in one month

3.2. Trends in Skills Added

In Figure 2, we examine how these probabilities of adding skills have changed over time. For endorsed skills, there are strong temporal shifts, with a spike in 2017 followed by a steep drop-off. These are due to changes in the platform functionalities and experience. For all four cases, we see an overall downward trend over time, with people being less likely to add skills. We also note that the orderings observed in Figure 1 across educational groups are consistent over time, suggesting that it is not just statistical noise wherein we note higher educational group's higher propensity to have skills added.

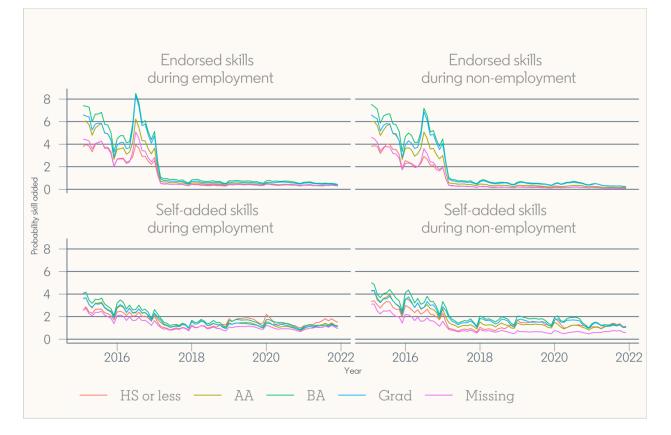
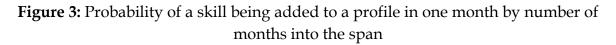


Figure 2: Probability of a skill being added to a profile in one month across time

Figure 3 again examines the trends shown in Figure 2 of the probability of adding a skill in a month, but now breaks it down by how many months into the (employment or non-employment) span the individual is. Thus for example, a bachelor's degree holder in the first month of an employment gap has a probability of adding a skill of around 4 percent; this drops to below 2 percent by one year into the span. Overall, we still find consistent orderings by educational groups across time. We also see that there is an overall decline in the probability of skills being added and skills being endorsed the further into an employment gap spell a person is, which is particularly acute for selfadded skills during employment gaps.

For Figure 3, the composition of workers in a given time period change depending on how far into the span it goes. Thus, at one month for non-employment spells, everyone in the sample is included in the average. By 12 months, only those who have had an nonemployment spell lasting at least a year are included. To account for this, appendix Figure A.1 repeats the calculations, but limits the sample to employment gaps lasting at least one year so that the composition does not change. The trends are not meaningfully different.





3.3 *Empirical Strategy*

In this paper, we use a Cox Proportional Hazards Model with time varying covariates to account for skills that may have been added during the employment gap spell. Survival regression models are standard for examining the predictors of ending employment gaps, and also account for differences in timing between when skills are added and when employment gap spells end. The methodology is described in more detail in the appendix.

We additionally control for several covariates that may be related to the propensity to add or be endorsed for skills, and we generate continuous inverse probability weights to better control for non-random selection into higher and lower skill counts. In this paper, we control for and weight on the following covariates: gender, potential work experience (number of years elapsed since graduation), age, a standardized z-score of how recently they have logged into the LinkedIn platform (more recent log-ins would have higher scores and be related to more active users who would also be more likely to add skills), and the local LinkedIn Hiring Rate (LHR), a measure of local labor demand.

As a demonstration of the role of the weighting and to show the means of the covariates, Table 2 provides the averages and proportions both unweighted and weighted, after splitting the sample between those with no skills on their profile and those with skills. As we expect, those with skills (self-added or endorsed) on their profile are much more likely to have logged in more recently (z-scores of 0.287 and 0.407 standard deviations, respectively); with the weighting, those differences reduce to approximately 0.1. Additionally, those with skills on their profile tend to be older and have more experience (especially for endorsed skills), but here as well, weighting narrows the gap between those with skills on their profile and those with no skills. Thus, it is important for us to include these inverse probability weights to help account for the non-random propensity to add skills to profiles that likely would be correlated with ending employment gap spells (as we later show).

		Unweight	ed	Weighted			
	No	Has		No	Has		
	skills	skills	Difference	skills	skills	Difference	
Self-added skills							
Woman	49%	48.3%	0.7%	48.7%	48%	0.7%	
Potential experience	9.309	11.711	-2.402	9.752	11.449	-1.697	
Age	33.554	35.338	-1.784	34.065	35.613	-1.548	
Std. time since last log-in	-0.149	0.138	-0.287	-0.082	0.028	-0.11	
LHR	1.002	1.002	< 0.001	1.002	0.993	0.009	
Endorsed skills							
Women	49.8%	47.3%	2.5%	49%	48%	1.0%	
Potential experience	6.817	13.396	-6.579	10.048	11.933	-1.885	
Age	30.883	37.142	-6.259	34.708	35.839	-1.131	
Std. time since last log-in	-0.239	0.168	-0.407	-0.122	-0.023	-0.099	
LHR	0.984	1.012	-0.028	0.988	1.001	-0.013	

Table 2: Unweighted and Weighted Covariate Means

4. Results

4.1. Impact of Added Skills on Shortening Employment Gaps

Table 3 presents the hazard ratios from the survival models for self-added skills, and Table 4 for endorsed skills. All hazard ratios are greater than one across all educational groups, which implies that skills on profiles (either self-added or endorsed) shorten employment gaps. For example, for the overall population for self-added skills in the unadjusted model, the hazard ratio is 1.0202, which implies that an additional skill selfadded to a profile is associated with approximately a 2 percent higher probability that the employment gap spell ends in a given month. Adding 10 skills is related to approximately a 20 percent higher probability of ending an employment gap spell in a given month relative to adding no skills. We also find, as expected, that controlling for covariates decreases the hazard ratios in almost all cases, and additionally weighting using the inverse probability weights decreases the hazard ratios further.

Examining self-added skills in the adjusted and weighted model, we estimate an additional skill increases the probability of ending an employment gap spell in a given month by around 1.3 percent. We also find that the largest return to skills in reducing non-employment spells is for those with no education listed on their profiles, consistent

with our hypothesis. Across those who do list their education, workers with higher educational attainment have larger returns than those with lower educational attainment, although all are statistically significant.

Model	Unadjusted	Adjusted	Adjusted and weighted
All	1.0202	1.0145	1.0127
	(1.0202-1.0203)	(1.0144-1.0146)	(1.0123-1.0131)
High school or less	1.0057	1.0074	1.0044
	(1.0053-1.006)	(1.007 - 1.0078)	(1.0021-1.0066)
Associates degree	1.0101	1.011	1.0097
	(1.0098 - 1.0103)	(1.0107-1.0112)	(1.0087 - 1.0106)
Bachelor's degree	1.0154	1.0141	1.0129
	(1.0153-1.0155)	(1.014-1.0142)	(1.0125-1.0133)
Graduate degree	1.0144	1.0127	1.0112
	(1.0143-1.0145)	(1.0126-1.0129)	(1.0106 - 1.0117)
Education not listed	1.0261	1.0185	1.0151
	(1.0259-1.0262)	(1.0184-1.0187)	(1.014-1.0163)

Table 3: Survival Model Hazard Ratios for self-added skills on shortening employmentgap spells

Note: each cell is from a different regression, and reports the hazard ratio from a Cox Proportion Hazards model with time-varying covariates. 95% confidence intervals are presented in parentheses.

When examining self-endorsed skills, the overall return is around 1 percent higher probability of ending employment gap spells per skill added, slightly lower than the return we estimate for self-added skills. We again see that those with no education listed on their profile have the largest returns. Beyond this, the returns are roughly similar across educational groups.

	8"P 5	I	Adjusted and
Model	Unadjusted	Adjusted	weighted
All	1.0182	1.0125	1.0111
	(1.0181-1.0182)	(1.0125-1.0126)	(1.0107-1.0116)
High school or less	1.0176	1.0144	1.0087
	(1.0172-1.0179)	(1.014 - 1.0148)	(1.0041-1.0134)
Associates degree	1.0128	1.0111	1.0098
	(1.0126-1.013)	(1.0108-1.0113)	(1.0088 - 1.0108)
Bachelors degree	1.0108	1.0125	1.0107
	(1.0107 - 1.0109)	(1.0124-1.0126)	(1.0103-1.011)
Graduate degree	1.0091	1.0102	1.0084
	(1.009-1.0092)	(1.0101-1.0103)	(1.0078-1.009)
Education not listed	1.0256	1.0165	1.0144
	(1.0254-1.0257)	(1.0164-1.0166)	(1.0138-1.0151)

 Table 4: Survival Model Hazard Ratios for endorsed skills on shortening employment

 gap spells

Note: each cell is from a different regression, and reports the hazard ratio from a Cox Proportion Hazards model with time-varying covariates. 95% confidence intervals are presented in parentheses.

For interpretability of the results, we also translate these hazard ratios into the implied shortening of the employment gap spell at the median. The methodology is described in the appendix. Table 5 presents these results. Thus, for the overall sample, the median employment gap was around 7 months. For one additional skill, the median employment gap duration decreases by 0.13 months; 10 additional skills decreases the median employment gap spell by 1.17 months. Given the longer employment gap durations on average for members with lower educational attainment, we see a clear pattern now with larger reductions in the median employment gap duration for these workers for endorsed skills, with high school or less seeing a decrease of 1.15 months and graduate degree holders by approximately half that, at 0.66 months.

	Median	Median	Difference	Median	Difference
	employment	with 1	with 1	with 10	with 10
	gap	more skill	more skill	more skills	more skills
Self-added, 1 skill					
All	7.09	6.95	0.13	5.92	1.17
High school or less	8.86	8.79	0.06	8.24	0.61
Associates degree	7.77	7.66	0.11	6.73	1.05
Bachelor's degree	5.47	5.37	0.10	4.62	0.85
Graduate degree	5.52	5.44	0.09	4.72	0.80
Education not listed	13.17	12.77	0.41	10.47	2.70
Endorsed, 1 skill					
All	7.23	7.11	0.13	6.17	1.07
High school or less	8.67	8.54	0.12	7.52	1.15
Associates degree	7.83	7.72	0.11	6.76	1.08
Bachelor's degree	5.63	5.55	0.08	4.87	0.76
Graduate degree	5.68	5.61	0.07	5.02	0.66
Education not listed	13.36	12.96	0.40	10.61	2.75

Table 5: Impact of additional skills on change in median employment gap

Note: estimated change in median employment gap derived from changes in the survival curves averaged across the sample, as described in Appendix 1.

Table A.1 in the appendix repeats Table 2 but breaks out the educational groups more finely. The results are consistent—for self-added skills, the hazard ratios increase with higher education groups, whereas for endorsed skills, the hazard ratios decrease with higher education groups.

We next repeat the hazard model, but now separate out the impact of going from zero to non-zero skills (the extensive margin impact) and the marginal return for each additional skill (intensive margin). Table 6 reports the hazard ratios for the weighted and adjusted model. The intensive margin impacts are smaller than as reported in tables 3 and 4, given there is generally a larger return to the first skill listed. Appendix Table A.1 calculates the impact on median employment gap from this model for an additional skill or ten skills. Using this model, allowing for the one additional skill to move those from zero to one as well as those with positive skills on their profile from their current value to one more than that value. That is, it does not calculate only the impact on the margin, but the net impact. The results are generally slightly larger than those reported in Table 5.

Sample	Variable	Self-added	Endorsed
All	Skills	1.0087	1.0072
		(1.0082-1.0091)	(1.0066 - 1.0077)
	1(Skills>0)	1.1642	1.1658
		(1.1605 - 1.168)	(1.1613-1.1702)
High school or less	Skills	1.0061	1.0044
		(1.0032-1.0089)	(0.9984 - 1.0104)
	1(Skills>0)	0.9427	1.1752
		(0.9206-0.9653)	(1.1144-1.2393)
Associates degree	Skills	1.0071	1.007
		(1.0058 - 1.0083)	(1.0057-1.0083)
	1(Skills>0)	1.0938	1.1021
		(1.0826 - 1.1051)	(1.0887-1.1156)
Bachelor's degree	Skills	1.0086	1.007
		(1.0081-1.009)	(1.0065 - 1.0075)
	1(Skills>0)	1.1904	1.157
		(1.1859 - 1.1948)	(1.1515-1.1626)
Graduate degree	Skills	1.008	1.0061
		(1.0074 - 1.0086)	(1.0054-1.0069)
	1(Skills>0)	1.1342	1.0989
		(1.1286-1.1398)	(1.0921-1.1057)
Education not listed	Skills	1.0098	1.0082
		(1.0083-1.0113)	(1.0073-1.009)
	1(Skills>0)	1.1904	1.2533
		(1.1779-1.203)	(1.2438-1.2629)

 Table 6: Survival Model Hazard Ratios for endorsed skills on shortening employment

 gap spells, two-variable skills

Note: each education group by source of skill adding is from a different regression, and reports the hazard ratio from a Cox Proportion Hazards model with timevarying covariates. Each regression additionally controls potential work experience, age, standardized time since last log-in into the platform, local LinkedIn Hiring Rate, year dummies, and indicators for imputed variables. All odds ratios are statistically different from 1 at p<0.01.

Profile skills may benefit a member differentially depending on the tightness of the local and national labor market. We estimate the heterogeneity in the return to skills depending on labor market tightness in two ways. First, in Table 7 we interact the skills count with a standardized (mean zero, standard deviation one) version of the LinkedIn Hiring Rate (LHR). Given we control for year, this intuitively contrasts individuals who geographically live in tighter local labor markets versus individuals in less tight markets. We find small, statistically significant but diverging estimates. Self-added skills in general have a higher return in markets and months where there is a higher hiring rate, and the economy is doing well. Workers are able to leverage their skills into new positions. On the other hand, self-added skills have a higher return in markets and months where there is a lower hiring rate, suggesting that as firms have fewer job openings and there are many workers competing for fewer jobs, skills on the profiles provide a better advantage to standing out. Interestingly, HS or less are the only ones who have a larger premium when hiring is down for both self-added and endorsed skills, which may be due to them having fewer other signals and the ability to stand out from their peers being more important during those competitive times.

		• •		-	0	
	All	HS or less	AA	BA	Graduate	Missing
Self-added skills						
Skills	1.0127	1.0042	1.0097	1.0128	1.0111	1.0152
Std. LHR	1.0291	1.0432	1.0378	1.0197	1.0187	1.0409
Skills X std. LHR	1.0007	0.9993	1.0006	1.0009	1.0006	1.0010
Endorsed skills						
Skills	1.0110	1.0081	1.0097	1.0107	1.0084	1.0143
Std. LHR	1.0518	1.0800	1.0513	1.0380	1.0362	1.0655
Skills X std. LHR	0.9990	0.9970	0.9989	0.9993	1.0001	0.9990

Table 7: Heterogeneity in returns by local hiring rate

Note: each education group by source of skill adding is from a different regression. Std. LHR: standardized LinkedIn Hiring Rate. Each regression additionally controls potential work experience, age, standardized time since last log-in into the platform, local LinkedIn Hiring Rate, year dummies, and indicators for imputed variables. All odds ratios are statistically different from 1 at p<0.01.

Table 8 next attempts to view the heterogeneity with respect to the overall national trends in the economy. 2020 and 2021 had the early pandemic and the largest spike in unemployment. And indeed, we find that the largest premiums overall for both self-added and endorsed skills were during those times of economic downturns during the pandemic, when workers had to compete with each other more for fewer job postings. Thus, we conclude that there is suggestive evidence that skills on member profiles tend to be slightly more important when hiring is down and unemployment is up, especially for endorsed skills and especially for workers with lower educational attainment.

	All	HS or less	AA	BA	Graduate	Missing
Self-added skills						
Skills X 2015	1.0123	1.0049	1.0100	1.0130	1.0119	1.0130
Skills X 2016	1.0118	1.0000	1.0100	1.0124	1.0109	1.0141
Skills X 2017	1.0103	1.0032	1.0084	1.0105	1.0083	1.0130
Skills X 2018	1.0120	1.0046	1.0076	1.0120	1.0089	1.0161
Skills X 2019	1.0149	1.0063	1.0100	1.0141	1.0120	1.0197
Skills X 2020	1.0150	1.0059	1.0103	1.0141	1.0136	1.0189
Skills X 2021	1.0168	1.0109	1.0137	1.0160	1.0154	1.0230
Endorsed skills						
Skills X 2015	1.0116	1.0079	1.0116	1.0136	1.0096	1.0129
Skills X 2016	1.0124	1.0221	1.0122	1.0126	1.0099	1.0146
Skills X 2017	1.0105	0.9922	1.0086	1.0101	1.0086	1.0161
Skills X 2018	1.0094	1.0097	1.0083	1.0087	1.0049	1.0130
Skills X 2019	1.0106	1.0106	1.0070	1.0081	1.0070	1.0164
Skills X 2020	1.0124	1.0174	1.0098	1.0110	1.0096	1.0158
Skills X 2021	1.0090	1.0015	1.0099	1.0076	1.0084	1.0143

Table 8: Heterogeneity in returns by year

Note: each education group by skills interaction is from a different regression. Each regression additionally controls potential work experience, age, standardized time since last log-in into the platform, local LinkedIn Hiring Rate, year dummies, and indicators for imputed variables. All odds ratios are statistically different from 1 at p<0.01.

4.3. Sensitivity Analysis of Survival Analysis

We examine two sensitivity tests subsetting the data. The results are reported in Table 9. First, we limited the sample to 2015-2017, to account for the period where there was substantially higher endorsement activity. For self-added skills, the hazard ratios are a bit smaller with this subset of years, although not dramatically so. For endorsed skills, the hazard ratios are very similar. Thus, we conclude that the decision of which years are included is not a significant determinant of the results we find. Second, we limit to those who have logged into LinkedIn in the calendar year 2022 to get focus on more active users. Once again, the results are not meaningfully different, perhaps at least in part due to the methodology which matches and regression-adjusts for the most recent log-in. In future work, we plan to control for platform usage intensity more directly.

	Table 9: Sensitivity Analysis nazaru Katlos						
	2015	-2017	Accessed	LI in 2022			
	Self-added	Endorsed	Self-added	Endorsed			
All	1.0106	1.0104	1.0133	1.0099			
	(1.0105, 1.0106)	(1.0104, 1.0105)	(1.0132, 1.0133)	(1.0099, 1.0100)			
High school or	1.0013	1.0036	1.0099	1.009			
less	(1.0010, 1.0017)	(1.0032, 1.0039)	(1.0096, 1.0102)	(1.0087, 1.0093)			
Associates	1.0086	1.01	1.0114	1.0083			
degree	(1.0083, 1.0088)	(1.0098, 1.0103)	(1.0111, 1.0116)	(1.0081, 1.0085)			
Bachelor's	1.0114	1.0115	1.0136	1.0101			
degree	(1.0113, 1.0115)	(1.0114, 1.0116)	(1.0135, 1.0137)	(1.0101, 1.0102)			
Graduate	1.01	1.0084	1.0117	1.0083			
degree	(1.0099, 1.0102)	(1.0083, 1.0086)	(1.0116, 1.0118)	(1.0082, 1.0084)			
Education	1.0112	1.013	1.0162	1.0122			
missing	(1.0111, 1.0114)	(1.0129, 1.0131)	(1.0161, 1.0163)	(1.0121, 1.0123)			

Table 9: Sensitivity Analysis Hazard Ratios

Note: each cell is from a different regression, and reports the hazard ratio from a Cox Proportion Hazards model with time-varying covariates. All odds ratios are statistically different from 1 at p<0.01.

5. Discussion

In this paper, we show that there are important differences in skill patterns and that those with higher skill levels tend to end employment gap spells earlier. 10 skills additional on the profile is correlated with approximately 1 months shorter employment gaps (from a median of around 7 months) for self-added skills. For endorsed skills, bachelor's degree and graduate degree holders see a reduction in the median employment gap by of three quarters and two thirds of a month respectively for ten additional skills, while high school or lower decrease by 1.15 months and associates degree holders by just over one month. This is consistent with our hypothesis regarding the educational gradient across returns to endorsed skills overall, while we hypothesized endorsed skills would yield a larger return. In future work, we may investigate not only the adding of skills, but the number of endorsements to determine if additional social signaling of competencies helps align our findings with that hypothesis better.

We also found that individuals with no education on their profile see the largest return from more skills listed on their profile. This is in alignment with our hypothesis, as without the signal of education, the additional information from skills is more pertinent to hirers. Further, for self-added skills, we did not find a clear relationship of lower education workers having a higher return, as had hypothesized. This remains an area for continued exploration. Further, we found some suggestive evidence that the returns to skills are highest when hiring rates are lower, especially for endorsed skills. We find some evidence that skill signaling in tight labor markets is even more important, as employers need more ways to identify individuals and also more open to different types of backgrounds. Whereas in slack labor markets, credibility of those signals has increased importance and thus the higher return to endorsed skills.

This paper is an important contribution to the literature, by first focusing on the employment margin (whereas most papers on signaling focus on the returns to earnings) and by looking at how self-added and endorsed skills can serve as micro-signals to employers.

5.1. Limitations

While this paper provides important insights into the relationships between profile-listed skills and employment gaps, it has limitations. First, although we used a method well-suited to exploration of the causal return by both weighting and covariate-adjusting, the results are still only valid if the missing at random (that is, conditional on the covariates) assumption is met. The threat of selection bias is potentially still present here, where workers who are more likely to have and to add skills to profiles are more likely to possess other attributes, such as ambition, hard work, and social skills, that would also increase the probability of employment. Additionally, LinkedIn members most active on the profile will be more likely both to add skills and to report new jobs that would end employment gaps. Endorsed skills should not suffer as much from this issue, and our sensitivity analysis demonstrates that controlling for recent activity on the platform does not impact the relationship strongly. However, in the future we will look to add more covariates to better control for these selection biases, such as intensity of platform usage,

underlying skills, better measures of work history, and the fraction of their LinkedIn profile that is complete.

Another potential limitation of this analysis the generalizability of the findings. Our sample is limited to workers who have LinkedIn profiles and use the platform (so as to record the start and end of jobs and thus map out employment gaps). Especially as we evaluate differences by educational attainment, we recognize the differing representation of the US workforce by industry and education group, with higher education workers generally being more represented in our data.

5.2. Future Work

This paper represents only a start in better understanding how workers signal skills to potential employers in the digital economy. We hope to collect data on and leverage information about the historical timing of skills adding campaigns by LinkedIn and timing of when workers were logging into the platform (and thus being exposed to these campaigns) to create an instrumental variable of exposure to skills-adding campaigns. We will incorporate this instrumental variable into the survival model if we are able to construct these variables.

We will also investigate more deeply into the skills signal itself. We will do so in two ways. First, we will use prior work by authors on this paper to leverage a skills genome with LinkedIn data that does not limit skills to counts, but to measures of intensity and labor market relevance. Second, we will examine groupings of skills to see which have stronger relationships (such as soft skills, technical skills, industry-targeting skills, etc.).

We will also explore several dimensions of heterogeneity. We will examine how the relationship varies by age of the worker, geography and tightness of the local labor market, and by employment history. We will also extend the analysis to additional outcomes, in particular examining the relationship with skills adding and promotion as well as receiving emails from recruiters.

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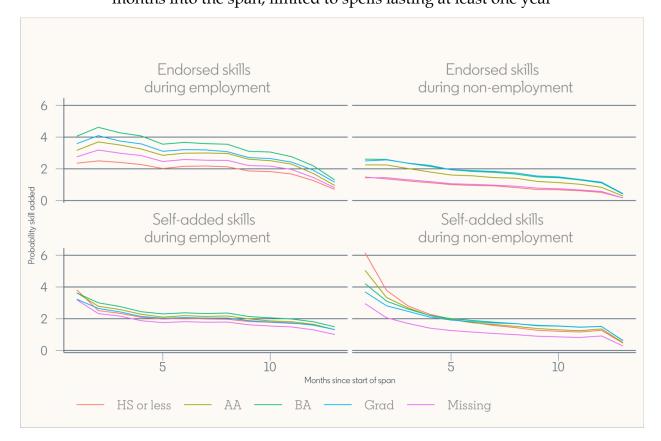
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APPENDIX

Supplementary Tables and Figures

Figure A.1: Probability of a skill being added to a profile in one month by number of months into the span, limited to spells lasting at least one year



	Tuble 1.1. Impact of adamonal skins of change in median employment gap spen						
	Median	Median	Difference	Median	Difference		
	employment	with 1	with 1	with 10	with 10		
	gap	more skill	more skill	more skills	more skills		
Self-added, 1 skill							
All	7.02	6.29	0.73	5.64	1.38		
High school or less	8.89	9.32	-0.43	8.50	0.39		
Associates degree	7.73	7.18	0.56	6.55	1.18		
Bachelors degree	5.43	4.89	0.53	4.45	0.98		
Graduate degree	5.49	5.01	0.48	4.56	0.93		
Education not listed	12.97	10.77	2.20	9.86	3.11		
Endorsed, 1 skill							
All	7.02	6.51	0.64	5.93	1.22		
High school or less	8.89	7.11	1.42	6.70	1.83		
Associates degree	7.73	7.19	0.59	6.56	1.22		
Bachelors degree	5.43	5.20	0.39	4.79	0.80		
Graduate degree	5.49	5.39	0.27	4.96	0.69		
Education not listed	12.97	10.60	2.40	9.82	3.18		

Table A.1: Impact of additional skills on change in median employment gap spell

Note: estimated change in median employment gap derived from changes in the survival curves averaged across the sample, as described in Appendix 1.

Methodology

Survival Model

The survival model we use is of the form

$$h(t) = h_0(t) \exp(\beta X_t)$$

We implement it using the R package *survival*. We use time-varying covariates, including to account for within-employment gap changes in the treatment variable, skills. Additionally, we implement inverse probability weights for continuous treatment using the *ipwpoint* R package.

Translation of Effects

To create more interpretable effects, we translate the hazard ratio to the implied shortening of the median employment gap duration. We do so by calculating the survival curve from the survival model at the mean skill rate. From this we calculate the month-by-month transition rates (that is, the proportion of the remaining sample that exit non-employment in a given month). We scale this by the hazard ratio to get new transition rates and from this calculate the counterfactual survival curve with the additional skill (or ten skills with a corresponding scaling of the hazard ratio). Figure A.2 shows the comparison of how the survival curve moves with ten additional self-added skills for all education groups. From this, we calculate the shift in the median, that is where the survival curve takes on a value of 0.5 on the y-axis.

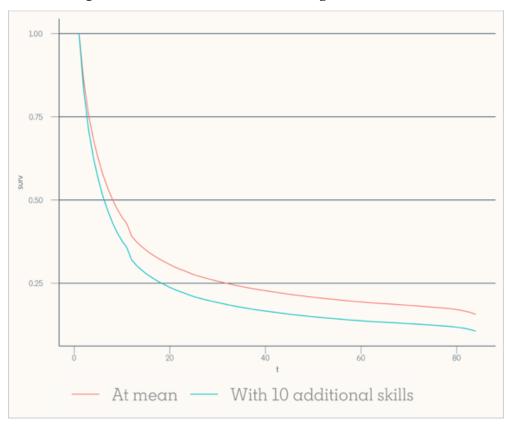


Figure A.2: Movement in the average survival curve