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Does the timing of integrating new skills affect start-up growth?

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Abstract

Research Summary: Growth often requires start-ups to recruit new skills not present in the founding team. We analyze if the relationship between integrating new skills and growth depends on timing. Should new skills be recruited as early as possible, or can start-ups add them as needed along the way? Using a unique panel dataset covering Sweden's population of start-ups from 1997 to 2012, our analysis shows that (a) start-ups' growth rate is positively correlated with integrating novel skills early in their life, while adding novel skills later is associated with lower growth and (b) corporate spin-offs profit less from recruiting novel skills than de novo start-ups. We mirror our results against existing theories and develop theoretical perspectives for future research.

Managerial Summary: Entrepreneurs and managers of start-ups need to develop the competences of their company as it matures. For this, they typically need to hire qualified personnel. But when is the best time to do so? In this paper, we show that the costs of integrating new skills from recruitment increase over time. We show that in order to achieve high firm growth there is a window of opportunity for successful recruitment covering the first 3–4 years after the founding of the company. Recruiting novel skills after this period is associated with reduced firm growth. Our results are thus in favor of a hiring strategy, where needed skills are recruited as early as possible.

KEYWORDS

growth, spin-offs, start-ups, time/temporal aspects, venture teams

1 | INTRODUCTION

How to turn start-ups into scale-ups is a very important topic in strategic entrepreneurship and is deeply linked to the question of the timing of growth processes. Growth and scale-up processes require specific skills, which often need to be recruited because of limited capability sets in very young firms (Cafferata, Abatecola, & Poggesi, 2009; Kor, 2008; Politis, 2008; Shane & Khurana, 2003). Literature, however, remains inconclusive about when new skills should be recruited and how the timing affects firm performance. Some authors have argued that start-ups typically undergo a process of professionalization, during which new required skills may be recruited flexibly in order to facilitate scaling and growth processes (Boeker & Karichalil, 2002; Hellmann & Puri, 2002). Other authors instead have argued that recruiting new skills is far from a frictionless process and comes with heavy integration costs (Lockett, Wiklund, Davidsson, & Girma, 2011) due to organizational rigidities and path dependence (Beckman, 2006; Beckman & Burton, 2008), founder imprinting (Judge et al., 2015; Leung, Foo, & Chaturvedi, 2013; Marquis & Tilcsik, 2013), and the danger of threatening established routines (Beckman, 2006; Beckman & Burton, 2008; Guenther, Oertel, & Walgenbach, 2016; Hannan, Baron, Hsu, & Koçak, 2006). In fact, academic controversy on the ease of integrating novel skills is manifested in the real world, which is full of examples providing evidence for either view: Some firms appear unable to grow and scale up because they lack the necessary skills, for example qualified sales managers. Other firms fail to grow or fail completely because they find it difficult to make productive use of recruited specialized skills (Marmer et al., 2011). Because the frictions associated with recruiting new skills can be substantial and become even life-threatening for new ventures, we argue that minimizing integration costs must be a central task of strategic human capital management in new ventures.

Because new ventures undergo substantial organizational changes as they transform toward maturity, we posit that the costs of integration are likely to change over time, implying that there should be an optimal timing for recruitment. While existing theories are able to inform the question of timing to some degree (Beckman & Burton, 2008; Gjerløv-Juel & Guenther, 2019; Guenther et al., 2016; Hoang & Gimeno, 2010; Wiklund, Baker, & Shepherd, 2010), most insights are largely theoretical and lacking in empirical support. The main goal of this article is therefore to present large-scale quantitative evidence on the question of how recruiting skills not present in the founding team are associated with subsequent growth of start-ups.

For our estimations, we make use of a matched employer–employee data set on the population of all Swedish firms founded between 1997 and 2012. Employing panel data regression techniques, we provide evidence that, although recruiting new skills to the venture is positively associated with growth on average, the benefits decline over time. Specifically, adding one new skill is associated with an increase in growth of 17% for 1-year-old firms while it is associated with a decrease in growth of 18% for firms aged 15 years (the maximum in our sample). The turning point from positive to negative associations between new skills and growth occurs at about 3 to 5 years, suggesting the existence of a short window of opportunity during which new ventures are best able to add new skills. We also show that corporate spin-offs gain less from recruiting new skills. While we avoid claims to causality, we ensure an extraordinarily high degree of empirical robustness of our results: in specific, we have implemented a wide range of different empirical models using alternative measures of growth (e.g., turnover vs. employment growth), various assumptions on unobserved heterogeneity, flexible specifications about the time dependence, as well as corrections for firm survival among others. We also analyze whether results differ between de novo and spin-off firms on the one hand and smaller and larger firms on the other.

Our main contribution is an empirical one. In a situation where quantitative empirical results are still scarce, we provide strong empirical evidence about the patterns of the relationship between recruiting skills and subsequent venture growth. Because our results are based on population data covering 16 years, we believe that we run a comparably low risk that the results are driven by issues related to the sample selection prevalent for example in quantitative survey-based studies. We are therefore confident that the results of our study form a guiding post for future theory development. Our contribution to theory development is an in-depth discussion about the implications of the empirical results for theories that could inform future research about the effects of timing in scaling up new ventures. Specifically, we discuss founder imprinting theory (Judge et al., 2015; Leung et al., 2013; Marquis & Tilcsik, 2013), arguing that founders imprint their own cognitive frames onto the venture. We make the case that, as the firm matures, imprints and organizational routines become gradually more important for firms while the susceptibility to knowledge rooted in new recruits declines. We also discuss strategic life-cycle models (Alvarez, Barney, & Anderson, 2013; Choi & Shepherd, 2004), arguing that new ventures move from exploration to exploitation strategies, which again makes firms less susceptible to deviating knowledge rooted in recruits. Moreover, by showing that corporate spin-offs benefit less from recruiting new skills to the firm, we provide a more nuanced view on the implications of relying on routines inherited from the parent firm (Andersson & Klepper, 2013). While it may be true that inherited routines provide corporate spin-offs with a stock of valuable resources early on, we argue that they may also limit the spin-offs' ability to learn from their early recruitments. We emphasize that we do not interpret our results as an explicit test of these theories, because key concepts such as imprints or strategic shifts from exploration to exploitation strategies are not directly observable with our data. Our concluding discussion therefore represents a constructive proposition for future theory development.

2 | DATA AND METHODOLOGY

2.1 | Data sources

We base our empirical analysis on a linked employer-employee dataset on the population of Swedish start-ups from 1997 to 2012. The data are regularly collected and provided for research purposes by Sweden's statistical office, Statistics Sweden (SCB). SCB provides various types of firm and individual-level information in different databases, which can be flexibly merged through the use of common firm and individual identifiers. In this paper, we use the firms and establishment dynamics database (FAD) which allows the identification of new firms, the business statistics database (FEK) and business group register providing basic firm-level information, as well as the integrated longitudinal database for health insurance and labor market studies (LISA) providing detailed information on each firm's employees at individual level.

2.2 | Identifying new firms

Since we are focusing on start-ups, one particularly important task is to develop a clear definition of the term start-up. Practical obstacles are for example that merely legal or ownership changes (e.g., name changes, changes of the legal form, mergers, and acquisitions) can imply that a firm is given a new identifier and thus may appear as newly established. In our definition, legal changes, however, do not qualify as new. The FAD database provided by Statistics Sweden can help to alleviate this core problem. Because FAD provides additional information on the circumstances under which the firm was founded, it allows new firms to be identified without confusing them with legal changes in firms that are already established. The FAD database identifies new firms by combining information about employment flows and the appearance of firm identity numbers over a period of 2 years. In line with Andersson and Klepper (2013), we identify a firm as new if all of the following conditions are met:

- The firm is identified as new according to the FAD database (except new firms resulting from a merger).
- The firm's legal organization number did not exist in the previous year.
- The firm has only one establishment (site).
- The firm is not part of a corporate group.

New firms are identified in the period from 1997 to 2011 and followed until the end of the observation period (2012) or their exit. Following the identified firms poses two issues: First, a firm may exit according to the FAD while continuing to exist as a legal entity, and second, the legal entity may change while the company effectively continues (is flagged as remaining in the FAD). We solved this as follows: The legal entity for SMEs is more stable than the FAD. This is why we followed the legal organization numbers of all firms identified as new (circumventing the first issue). In order to deal with the second issue, we checked legal entity changes when firms appear to exit, checking the legal organization numbers of firms in the current and previous year. If we observed a change of the legal organization number for firms flagged as remaining in the FAD, we added the subsequent observations (same firm, new legal ID) to the respective firm.

Against this data, we match firm business statistics (FEK) as well as employment data based on labor market statistics (LISA), which allows us to construct the complete workforce of firms from the date of establishment until the end of the observation period.

Finally, we excluded firms with a founding team size of larger than 10 and firms that increase their labor force by a factor of more than 30 in a given year. This is to exclude organizational reorganizations where new firms are established and employees move in great numbers to the new entity. Hence, our study is limited to the large majority of new firms with a founding team not larger than 10 and no extreme growth patterns.

2.3 | Variables

The paper contributes to explaining the start-ups' ability to exploit entrepreneurial opportunities using firm growth as a measure (see McEvily, Jaffee, & Tortoriello, 2012; Roberts, Klepper, & Hayward, 2011). In literature, many variables of growth were proposed but the most frequent measurements of firm growth are based on sales and employment (Delmar, 2006; Rodríguez & Nieto, 2016; Stuart, 2000). Even though sales and employment growth are often correlated, they are not identical. Usually, employment growth is regarded as inferior. First, firms can meet increasing demand by hiring staff but also through other means such as subcontracting (Delmar, 2006). Second, employment growth neglects the fact that firms can have varying capital intensities. Sales data provides therefore a more direct measure of the growth of start-ups than employment. We consequently decided to use sales growth as the main dependent variable—we include employment growth as a robustness check, and calculate the growth factor for each firm *i* in year *t* as follows:

$$\mathrm{growth}_{i,t} = \log\left(\frac{sales_{i,t}}{sales_{i,t-1}}\right) \tag{1}$$

Our research question concerns the effects of adding new skills on firm growth at different points in time and under different preconditions. Adding new skills to the firm is thus the main explanatory variable, which we measure by the introduction of new educational backgrounds through recruitment. While educational backgrounds are clearly not a complete measure of work-relevant skills—work experience may be an important source, too—we regard educational backgrounds still as a reasonably good proxy capturing a substantial amount of the variation. That is likely to hold true even though the time period between obtaining the educational degree and the start-up activities can be large. Schubert and Tavassoli (2019) argue that the reason for the usefulness of educational backgrounds is that they create cognitive frameworks which not only determine what an individual currently knows or is able to perform, but rather, educational backgrounds affect and filter the information an individual perceives as useful or valid. Therefore, cognitive frameworks resulting from education develop cumulatively and are self-enforcing. As an example of such cumulative development of cognitive frameworks resulting from education, several authors have highlighted remarkable differences in competences, solution approaches, and skills between engineers and scientists, which do not vanish as individuals age (Allen, 1984; Allen & Katz, 1992; Faems & Subramanian, 2013).

In our study, an educational background (EB_m, *where* $m = 1, \ldots, M$) relates to the field of study, for example, humanities, social science, or natural science. The Swedish system for classifying education (SUN 2000), which is aligned with the International Standard Classification of Education 1997 (ISCED 1997), captures 10 major educational fields.[1] We register for each firm i in year t which of the educational backgrounds are represented through the employees. Educational backgrounds that are represented receive a value of 1, the others 0.

Adding a new educational background ($newedu_{i,t,m}$) to a firm i in year t implies that an individual is hired who has an education in a field that was neither represented among the founding team nor in the year before the hiring takes place (t-1). The new educational backgrounds are coded 1 and the others 0. Given that there are 10 major educational fields and that the founding team members need to be educated in at least one of them, the highest number of new educational backgrounds in a given year is 9. The dependent variable is a relative measure capturing the number of new educational backgrounds divided by the number of major educational fields, thus ranging from 0 to 0.9:

$$sh\_newedu_{i,t} = \frac{\sum_{n=1}^{M} newedu_{i,t,m}}{M} \tag{2}$$

The main moderating variable is age of the firm ($age_{i,t}$), which we define as the years since the founding of the firm. Given that we need to observe a firm for at least 2 years in order to be able to measure its growth, the minimum firm age in the sample is 1 and the maximum 15.

We control for a number of potentially confounding factors. A key control variable is the share of employees leaving or entering the firm each year:

$$share\ recruits_{i,t} = new\ employees_{i,t} / team\ size_{i,t} \tag{3}$$

$$\text{share leavers}_{i,t} = \text{exited employees}_{i,t} / \text{team size}_{i,t} \tag{4}$$

new employees$_{i,t}$ is the number of new employees of firm i in year t and *exited employees*$_{i,t}$ is the number of employees who were part of the workforce of firm i in year t-1 but not in year t. *team size*$_{i,t}$ is the total number of employees of firm i in year t. If we did not control for new or existing employees, the effects of adding new skills could be confounded with the effects of other changes in the workforce. Furthermore, we control for firm size (logarithm of sales), which accounts for the long debate on the relationship between firm size and firm growth. While Gibrat (1931) posited that growth is uncorrelated with size, a number of studies actually show that growth is affected by size and a number other factors (Grillitsch, Schubert, & Srholec, 2019). Furthermore, firm size may serve as a control for potential nonconstant returns to recruitment. One argument that would postulate decreasing marginal returns suggests that firms recruit new employees with descending order of urgency. Thus, larger firms generally profit less from hiring. To the degree that firm age and size are correlated, we may attribute effects of late hires with effects that are essentially due to hires in larger firms. By controlling for size, we reduce the risk of such a misattribution. Furthermore, we include other time variant firm-level variables in the model that relate to the strength and value of a firm's routines and capabilities, namely labor productivity (sales divided by the number of employees), profitability (earnings before depreciations divided by turnover), and the general level of skills of the work force (share of employees with tertiary education in total employment). Productivity would usually be expected to have a positive effect on growth, while the direction for profitability is less clear. On the one hand, profitability increases the financial resources available for growth processes. On the other hand, growth processes are typically costly and may therefore have an initially negative correlation at least in the short term. Furthermore, we account for changes in industry and national economic dynamics by introducing industry and year-fixed effects. The descriptive statistics of all variables, including a correlation matrix, can be found in Table A2.

2.4 | Identification strategy

The baseline model simply tests for the average effect of adding new skills depending on firm age and is formulated as follows:

$$growthi,t = \alpha + \beta 1sh\_newedui,t + \beta 2agei,t + \beta 3sh\_newedui,t \cdot agei,t + \gamma xi,t + \varphi zt + \mu i + \varepsilon i,t \tag{5}$$

where firm growth is explained by the share of new skills as measured by new educational backgrounds ($sh\_newedu_{i,t}$), firm age ($age_{i,t}$), and an interaction between the two ($sh\_newedu_{i,t} \cdot age_{i,t}$). The vector $x_{i,t}$ represents firm characteristics discussed above. z_t are time fixed effects and $\varepsilon_{i,t}$ is a random error term. We capture unobserved heterogeneity by the firm-specific effects (μ_i). If μ_i is uncorrelated with any of the included main explanatory variables or the control variables, we can estimate Equation (5) consistently by pooled OLS or random effects (RE). The zero-correlation assumption is however quite restrictive and typically fails as firms differ in many respects, which cannot easily be controlled because of unobservability. In our case, the data is for example largely silent about management practices and organization differences. Indeed, Hausman tests strongly rejected the zero correlation assumption. We therefore decided to use fixed effect (FE) estimations, which are able to control for time-constant unobserved heterogeneity, as our preferred choice. Nonetheless, we present pooled OLS models with panel-robust variances for comparison.[2]

In order to allow for an estimation of the age effect which is more flexible than the one in Equation (5), we created a vector of 15 age dummies for firm age = 1, …, 15 ($AGE_{i,t}$). The dummies are interacted with the share of new educational backgrounds, creating a vector of 15 interaction terms ($sh\_newedu_{i,t} \cdot AGE_{i,t}$) leading to the model in Equation (6). All other specifications are identical to the model represented in Equation (5).

$$growthi,t = \alpha + \beta 1sh\_newedui,t + \beta 2-16AGEi,t + \beta 17-31sh\_newedui,t \cdot AGEi,t + \gamma xi,t + \varphi zt + \mu i + \varepsilon i,t \tag{6}$$

As we progress to presenting the result, we will also introduce a number of variations and robustness checks, which provide more substance and support for our findings.

3 | RESULTS

3.1 | Baseline effects

This paper analyzes if firm age moderates the effect of adding new skills on firm growth. As shown in Table 1, new skills are added to start-ups in ~10% of all observations. Furthermore, it is more likely that new skills are added at a young age (14% at the age of 1 vs. 8% at the age of 15). The average number of skills is low (1.44), but firms that add new skills tend to have a larger set of skills even the year before adding a new skill. Adding new skills tends to be associated with larger and faster-growing firms. The aim of the paper, however, is not to establish how adding skills per se relates to the growth performance of new firms, but rather to analyze whether it makes a difference for firm growth when the new skill is added.

Table 2 depicts the results of the regressions for a linear moderation effect (Model 1 and 2) as well as for a flexible moderation effect (Model 3 and 4), which includes age as a vector of the dummies. Table 2 also includes all the

TABLE 1 Basic characteristics of firms adding new skills by age

Age	All firms: Observations	Number of skills	Firm size	Turnover growth	Firms with new skills: Share	Number of skills prev. year	Firm size	Turnover growth
1	354,379	1.30	1.61	21.54%	13.87%		3.77	43.94%
2	271,878	1.38	1.83	4.66%	10.90%	1.93	4.65	24.01%
3	220,017	1.43	2.01	2.84%	10.43%	2.13	5.34	18.76%
4	173,551	1.47	2.14	1.53%	9.84%	2.26	5.67	15.64%
5	138,105	1.50	2.27	0.86%	9.72%	2.34	6.06	14.28%
6	109,058	1.53	2.41	0.28%	9.64%	2.43	6.41	12.44%
7	86,219	1.56	2.51	0.67%	9.45%	2.54	6.88	12.04%
8	68,656	1.59	2.60	0.53%	9.31%	2.58	6.94	11.33%
9	55,361	1.60	2.68	−0.07%	9.42%	2.64	7.50	11.34%
10	43,354	1.61	2.77	−0.60%	8.99%	2.64	7.53	10.03%
11	33,340	1.62	2.80	−2.31%	8.57%	2.74	7.81	8.70%
12	24,705	1.62	2.92	−4.06%	8.20%	2.79	8.06	7.70%
13	16,896	1.63	2.95	−1.79%	8.23%	2.75	7.89	9.06%
14	10,791	1.63	2.91	−3.27%	7.72%	2.82	8.16	10.06%
15	5,508	1.63	2.87	−5.53%	7.72%	2.80	7.87	1.77%
Total	1,611,818	1.44	2.10	6.04%	10.79%	2.28	5.29	24.28%

control variables and information about the model quality. The main result, however, is best visible in Table 3 and Figure 1, which present how adding new skills is associated with firm growth depending on firm age. As shown in Table 3, new skills are positively related with the growth of young start-ups. However, this positive relationship soon turns negative: After 5 years in the models with a linear moderation effect and after 3 years in the models with a flexible moderation effect.

As Figure 1 shows, the moderation of firm age is not linear. It rapidly decreases the value of new skills in the first years after firm establishment but flattens off later as firms become more established. The 95% confidence intervals depicted in Figure 1 also show that the relationship between new skills and growth depending on firm age could be calculated accurately, that is, the confidence intervals are relatively narrow even though they increase with firm age. Larger confidence intervals for older start-ups may not only relate to the smaller number of observations, but also to a less clear moderation effect of age as firms become more established, which is consistent with a flattening of the relationship observed in Figure 1.

Due to the clear non-linearity of the age moderation, and due to the FE models controlling for unobserved firm-level heterogeneity, we discuss the size of the effect only in relation to Model 4 in Tables 2 and 3, which is depicted in Figure 1. Accordingly, a new skill (corresponding to a 0.1 increase in the explanatory variable) is associated with a higher turnover growth of 17 percentage points in year 1, 7 percentage points in year 2 and 1.5 percentage points in year 3. The relationship turns negative in year 4 (−2 percentage points) and year 5 (−4.6 percentage points). From then on, with each additional year of age, the relationship between adding new skills and firm growth declines on average by 1 percentage point.

Some of the controls are also worth mentioning. Profitability has a consistently negative effect (albeit nonsignificant in the case of OLS), which strengthens the costs argument of growth processes in the short term. Productivity was expected to be positively correlated with growth. This is indeed the case for the FE regressions, while the opposite appears to be true for OLS. The negative sign in OLS may, however, be the result of not accounting for

TABLE 2 Base model

	(1)	(2)	(3)	(4)
	OLS	FE	OLS	FE
Share of new skills	0.9908***	1.7251***	0.8680***	1.7394***
	(0.0290)	(0.0240)	(0.0338)	(0.0268)
Sh. new skills # firm age	−0.1974***	−0.3390***		
	(0.0043)	(0.0041)		
Firm age = 2 # Sh. new skills			−0.4082***	−1.0664***
			(0.0411)	(0.0368)
Firm age = 3 # Sh. new skills			−0.8113***	−1.5932***
			(0.0428)	(0.0398)
Firm age = 4 # Sh. New skills			−0.9719***	−1.9466***
			(0.0564)	(0.0436)
Firm age = 5 # Sh. New skills			−1.1340***	−2.1950***
			(0.0470)	(0.0480)
Firm age = 6 # Sh. new skills			−1.2402***	−2.2766***
			(0.0529)	(0.0525)
Firm age = 7 # Sh. new skills			−1.3640***	−2.4545***
			(0.0605)	(0.0584)
Firm age = 8 # Sh. new skills			−1.4369***	−2.6283***
			(0.0588)	(0.0645)
Firm age = 9 # Sh. new skills			−1.4170***	−2.7021***
			(0.0662)	(0.0701)
Firm age = 10 # Sh. new skills			−1.4618***	−2.8153***
			(0.0732)	(0.0791)
Firm age = 11 # Sh. new skills			−1.5060***	−2.8798***
			(0.0868)	(0.0915)
Firm age = 12 # Sh. new skills			−1.5132***	−3.0685***
			(0.0819)	(0.1087)
Firm age = 13 # Sh. new skills			−1.6026***	−3.1025***
			(0.1062)	(0.1311)
Firm age = 14 # Sh. new skills			−1.4472***	−3.2428***
			(0.1347)	(0.1667)
Firm age = 15 # Sh. new skills			−1.9789***	−3.5179***
			(0.1833)	(0.2371)
Share recruits	−0.0514***	0.0888***	−0.0670***	0.0644***
	(0.0056)	(0.0042)	(0.0056)	(0.0042)
Share leavers	−0.2158***	−0.1205***	−0.2108***	−0.1128***
	(0.0092)	(0.0014)	(0.0090)	(0.0014)
Log turnover	0.1745***	0.7085***	0.1780***	0.7144***
	(0.0013)	(0.0009)	(0.0013)	(0.0009)
Labor productivity	−0.0042***	0.0016***	−0.0047***	0.0008**
	(0.0013)	(0.0003)	(0.0014)	(0.0003)

TABLE 2 (Continued)

	(1)	(2)	(3)	(4)
Profitability	−1.4316	−3.9616***	−1.4508	−3.9850***
	(2.8522)	(0.2575)	(2.8459)	(0.2543)
Sh. of empl. w. tert. education	0.0124***	0.0329***	0.0115***	0.0359***
	(0.0014)	(0.0051)	(0.0014)	(0.0051)
Constant	−2.1203***	−9.1960***	−2.1003***	−9.3521***
	(0.0163)	(0.0202)	(0.0167)	(0.0186)
Industry dummies	Yes	No	Yes	No
Year dummies	Yes	Yes	Yes	Yes
Baseline age effects	Yes	Yes	Yes	Yes
Observations	1,611,818	1,611,818	1,611,818	1,611,818
Firms	434,247	434,247	434,247	434,247
R^2	0.125	0.365	0.134	0.381
AIC	3,216,663	2,064,682	3,199,159	2,025,141
BIC	3,217,093	2,064,941	3,199,909	2,025,719
F	2,144	33,909	1,377	15,746

Note: Dependent variable: log turnover growth; *SE* in parentheses; *SE* of OLS regressions are clustered at the level of the firm; ***, **, * indicate significance at the 1, 5, and 10% levels.

TABLE 3 Coefficients and standard errors of adding new skills by age

	Age as continuous variable				Age as vector of dummies			
At age	(1) OLS		(2) FE		(3) OLS		(4) FE	
1	0.793	(0.026)	1.387	(0.021)	0.872	(0.034)	1.739	(0.027)
2	0.596	(0.023)	1.048	(0.019)	0.465	(0.032)	0.673	(0.032)
3	0.398	(0.021)	0.709	(0.018)	0.064	(0.035)	0.146	(0.034)
4	0.201	(0.020)	0.370	(0.017)	−0.097	(0.051)	−0.207	(0.038)
5	0.004	(0.020)	0.031	(0.017)	−0.257	(0.039)	−0.456	(0.043)
6	−0.194	(0.020)	−0.308	(0.018)	−0.374	(0.046)	−0.537	(0.048)
7	−0.391	(0.022)	−0.647	(0.021)	−0.496	(0.054)	−0.715	(0.054)
8	−0.589	(0.024)	−0.986	(0.023)	−0.548	(0.052)	−0.889	(0.061)
9	−0.786	(0.027)	−1.326	(0.026)	−0.561	(0.060)	−0.963	(0.066)
10	−0.984	(0.030)	−1.665	(0.029)	−0.596	(0.068)	−1.076	(0.076)
11	−1.181	(0.033)	−2.004	(0.033)	−0.638	(0.082)	−1.140	(0.089)
12	−1.379	(0.037)	−2.343	(0.036)	−0.664	(0.077)	−1.329	(0.106)
13	−1.576	(0.040)	−2.682	(0.040)	−0.732	(0.102)	−1.363	(0.129)
14	−1.773	(0.044)	−3.021	(0.044)	−0.579	(0.131)	−1.503	(0.165)
15	−1.971	(0.048)	−3.360	(0.048)	−1.111	(0.178)	−1.779	(0.236)

Note: Dependent variable: log turnover growth; all control variables included as reported in Table 1; *SE* in parentheses; *SE* of OLS regressions are clustered at the level of the firm.

unobserved heterogeneity, which may bias results. We also find that the share of employees with tertiary education is positive across all specifications, which seems to be intuitive based on a human capital logic. Finally, our results show that growth is positively related to the size of the firm. Even though going against the idea of randomness of

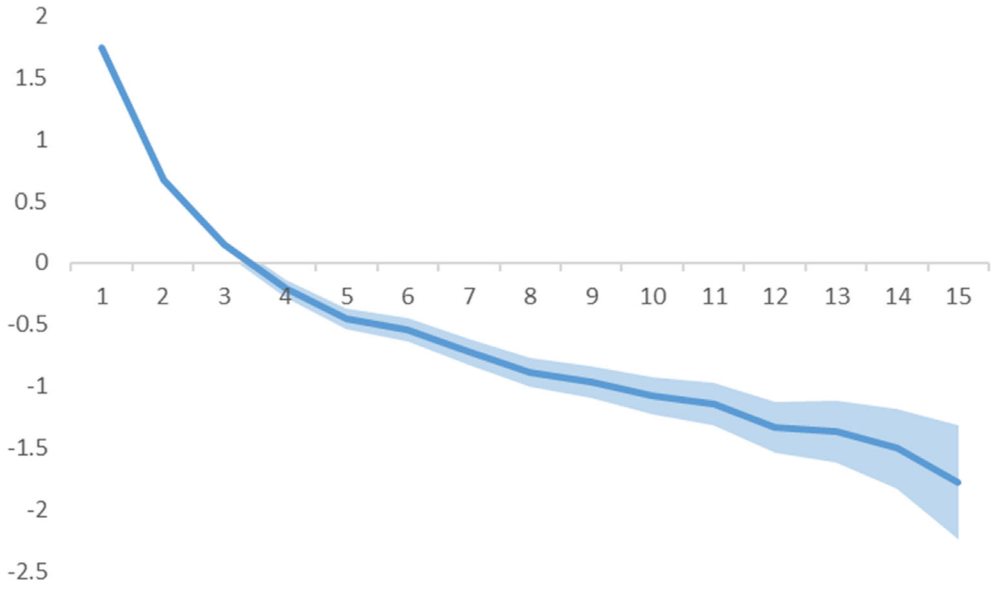

FIGURE 1 Coefficient and 95% confidence intervals of adding new skills by age

growth as summarized in Gibrat's law, this result should be interpreted with caution as it does not hold true if estimating the model with turnover in (t-1) as shown by the robustness checks in Table 8.

3.2 | Robustness checks for the baseline model

Before we proceed to the results on spin-offs, in Tables 4 to 6 we provide additional results corroborating the robustness of our assertion that the effect of the adding novel skills is a negative function of firm age. As a first robustness check, we control for region-specific industrial trends by introducing a three-way interaction composed of industry, regional, and year dummies. This allows the capture of any unobserved industry or regional trends that might correlate with firm growth and diversity in hiring at different firm ages. The results remain qualitatively unchanged, as reported in Table 4.

In Table 5, we consider the following issues that may bias our regressions. The first two checks use alternative growth variables. Model 1 uses log employment growth instead of log turnover growth. Model 2 uses the survival correction to turnover growth. The survival correction is used because growth regressions are often plagued by firm mortality: Typically, low-growth firms have higher mortality and are therefore under-represented in the sample. One way to deal with mortality is to use the following alternative growth measure:

$$growth\_Hi,t = (growthi,t - growthi,t-1)/(½growthi,t + ½growthi,t-1) \tag{7}$$

Third, our population data includes information about the legal status of firms. As a check, we include only incorporated firms in the sample, excluding all unlimited liability firms. Unlimited liability firms may be less prone to recruiting employees and may tend to have lower growth ambitions (Model 3).

Fourth, in our baseline regressions, the educational backgrounds are implicitly treated as equally distant to each other. This may not be the case, as some educational backgrounds may be more similar than others. We proxied similarity by the relative frequency of the co-occurrence of educational backgrounds in firms (Model 4). Specifically, we

TABLE 4 Robustness check 1: Including industry x year x region interactions

	(1)	(2)	(3)	(4)
	OLS	FE	OLS	FE
Share of new skills	1.0338***	1.9324***	0.8464***	1.7950***
	(0.0327)	(0.0270)	(0.0351)	(0.0280)
Sh. new comp. # firm age	−0.2284***	−0.4301***		
	(0.0054)	(0.0053)		
Firm age = 2 # Sh. new skills			−0.4272***	−1.1634***
			(0.0419)	(0.0387)
Firm age = 3 # Sh. new skills			−0.8204***	−1.7654***
			(0.0453)	(0.0432)
Firm age = 4 # Sh. new skills			−1.0063***	−2.1423***
			(0.0635)	(0.0477)
Firm age = 5 # Sh. new skills			−1.1518***	−2.4030***
			(0.0496)	(0.0529)
Firm age = 6 # Sh. new skills			−1.2677***	−2.5181***
			(0.0581)	(0.0596)
Firm age = 7 # Sh. new skills			−1.4436***	−2.7737***
			(0.0613)	(0.0681)
Firm age = 8 # Sh. new skills			−1.4814***	−2.9693***
			(0.0694)	(0.0781)
Firm age = 9 # Sh. new skills			−1.3779***	−3.0151***
			(0.0825)	(0.0880)
Firm age = 10 # Sh. new skills			−1.3915***	−3.1291***
			(0.0888)	(0.1033)
Firm age = 11 # Sh. new skills			−1.6627***	−3.3653***
			(0.0951)	(0.1223)
Firm age = 12 # Sh. new skills			−1.7236***	−3.6171***
			(0.1141)	(0.1604)
Firm age = 13 # Sh. new skills			−1.5202***	−3.6554***
			(0.2200)	(0.2554)
Share recruits	−0.0641***	0.0806***	−0.0788***	0.0567***
	(0.0065)	(0.0047)	(0.0064)	(0.0047)
Share leavers	−0.2182***	−0.1182***	−0.2132***	−0.1104***
	(0.0113)	(0.0016)	(0.0110)	(0.0015)
Log turnover	0.1841***	0.7380***	0.1874***	0.7428***
	(0.0015)	(0.0010)	(0.0015)	(0.0010)
Labor productivity	−0.0045***	0.0008**	−0.0049***	0.0001
	(0.0014)	(0.0004)	(0.0015)	(0.0004)
Profitability	−1.4743	−4.3585***	−1.4908	−4.3702***
	(3.0394)	(0.2787)	(3.0329)	(0.2754)
Sh. of empl. w. tert. education	0.0169***	0.0327***	0.0161***	0.0363***
	(0.0016)	(0.0058)	(0.0016)	(0.0058)

(Continues)

TABLE 4 (Continued)

	(1)	(2)	(3)	(4)
Constant	−2.4512***	−9.5326***	−2.5275***	−9.6512***
	(0.1379)	(0.1307)	(0.1379)	(0.1129)
Industry # year # region interactions	Yes	Yes	Yes	Yes
Industry dummies	Yes	No	Yes	No
Year dummies	Yes	Yes	Yes	Yes
Baseline age effects	Yes	Yes	Yes	Yes
Observations	1,340,821	1,340,821	1,340,821	1,340,821
Firms	384,373	384,373	384,373	384,373
R^2	0.134	0.379	0.143	0.394
AIC	2,737,133	1,734,630	2,723,267.5591	1,702,951.6972
BIC	2,781,669	1,780,159	2,768,057.9832	1,748,747.1511
F		155		164

Note: Dependent variable: log turnover growth; *SE* in parentheses; *SE* of OLS regressions are clustered at the level of the firm; ***, **, * indicate significance at the 1, 5, and 10% levels.

TABLE 5 Robustness checks 2: Different dependent variables and using similarity fields

At age	(1) Log employment growth		(2) Turnover growth (survival correction)		(3) Log turnover growth (only incorporated firms)		(4) Log turnover growth (similarity fields)	
1	**1.605**	**(0.006)**	**1.168**	**(0.021)**	**1.728**	**(0.030)**	**1.638**	**(0.029)**
2	0.779	(0.007)	0.552	(0.024)	0.646	(0.036)	0.399	(0.036)
3	0.646	(0.008)	0.153	(0.026)	0.199	(0.039)	0.027	(0.039)
4	0.532	(0.009)	−0.110	(0.029)	−0.152	(0.044)	−0.329	(0.045)
5	0.454	(0.010)	−0.295	(0.033)	−0.381	(0.049)	−0.512	(0.050)
6	0.421	(0.011)	−0.353	(0.037)	−0.425	(0.055)	−0.485	(0.056)
7	0.359	(0.012)	−0.488	(0.041)	−0.588	(0.061)	−0.661	(0.063)
8	0.321	(0.014)	−0.597	(0.046)	−0.726	(0.069)	−0.812	(0.072)
9	0.316	(0.015)	−0.635	(0.051)	−0.802	(0.075)	−0.866	(0.079)
10	0.312	(0.017)	−0.736	(0.058)	−0.868	(0.086)	−1.052	(0.095)
11	0.248	(0.020)	−0.763	(0.068)	−0.886	(0.100)	−0.951	(0.107)
12	0.190	(0.024)	−0.894	(0.081)	−1.139	(0.121)	−1.089	(0.124)
13	0.288	(0.029)	−0.932	(0.099)	−1.100	(0.146)	−1.328	(0.169)
14	0.183	(0.038)	−1.027	(0.126)	−1.100	(0.188)	−1.325	(0.214)
15	0.194	(0.054)	−1.226	(0.181)	−1.157	(0.260)	−1.360	(0.265)

Note: FE regressions; all control variables included; full table reported in Table A3; *SE* in parentheses.

create weightings for each novel educational background which decrease with the probability of co-occurrence and we use these weightings as correction factors. Mathematically, we performed the following steps:

In step one, we multiplied the row vector of new educational backgrounds of a firm i in year t ($newedu_{i,t,m}$) with the column vector of educational backgrounds existing in the founding team ($foundedu_{i,m}$), resulting in a (m × m) matrix $A_{i,t}$ for each firm i in year t. This matrix consists of 0 and 1; 1 identifies to which educational backgrounds in the founding team the new educational backgrounds relate.

$$A_{i,t} = newedu_{i,t,m} \times foundedu_{i,m} \tag{8}$$

In step two, we created a similarity index based on the covariance between educational backgrounds. The correlation between educational backgrounds is saved in the matrix *COR*. In order to receive high values for high distance, we transformed *COR* as follows:

$$D = 1 - (COR + 1)/2 \tag{9}$$

This implies a normalization such that the elements of D are equal to one if two fields never co-occur and are equal to zero if they always co-occur. Multiplying $A_{i,t}$ and D creates a weighting for each relationship between educational background in the founding team and new educational backgrounds depending on the distance between them, resulting in a (m × m) matrix $S_{i,t}$ for firm i at time t.

Finally, based on $S_{i,t}$ we define our similarity measure for adding new educational backgrounds as the sum of all elements in matrix $S_{i,t}$. This measure captures new educational backgrounds weighted by their distance to the educational backgrounds existing in the founding team:

$$w\_newedu_{i,t} = \sum_{i=1}^{M} \sum_{j=1}^{M} S_{i,j}$$

Indeed, Table 5 shows that the declining growth correlation of adding new skills over time holds for all four models with the respective robustness checks described above. For models 2–4, we even see that the effects are positive in the first years while they turn negative later on. For the employment regression, we do not see the change in sign but still corroborate decreasing effects.

In addition to the four previous checks, Table 6 provides a robustness check that takes into account different lags of adding new skills to the firm. For ease of presentation, we show how different lags influence the linear age moderation. Model 1 represents the baseline model with a 1-year lag, Model 2 with a 2-year lag, Model 3 with a 3-year lag, and Model 4 introduces all lags simultaneously. Accordingly, the coefficients for adding new skills as well as for the interaction terms tend to become weaker as lags increase. However, the general pattern remains the same, that is, providing evidence for a negative age moderation.

Finally, two robustness checks include changes to control variables, as shown in Tables 7 and 8. In Table 7, the number of skills in the year before the observed recruitment of a new skill are added to the baseline model. The age moderation remains strongly visible, yet the positive effect at a young age is less pronounced. This may have to do with the fact (as shown in Table 1) that firms adding new skills tend to have a more diverse set of skills from the outset. In Table 8, the control for firm size is replaced with turnover in (t-1) in line with the original works of Gibrat. Indeed, we find that the control variable for firm size then turns negative and is significant in the FE models. The age moderation remains negative and significant, even though the magnitude is somewhat smaller than in the baseline model.

3.3 | Effects for de novo and spin-off firms

Table 9 presents results for different types of start-up. Models 1 and 2 differentiate between de novo firms and spin-off firms. Models 3 and 4 distinguish between firms with 10 employees or fewer and firms with more than 10

TABLE 6 Robustness checks 3: Using different time lags

	(1)	(2)	(3)	(4)
	FE	FE	FE	FE
L1.Sh. of new skills	0.6188***			0.2691***
	(0.0204)			(0.0388)
L2.Sh. of new skills		0.0464**		−0.1306***
		(0.0220)		(0.0327)
L3. Sh. of new skills			0.1017***	−0.0723***
			(0.0246)	(0.0245)
L1. Sh. of new skills # L1.Firm age	−0.2047***			−0.1363***
	(0.0040)			(0.0057)
L2. Sh. of new skills # L2. Firm age		−0.1611***		−0.1381***
		(0.0045)		(0.0056)
L3. Sh. of new skills # L3. Firm age			−0.1168***	−0.1167***
			(0.0053)	(0.0053)
Share recruits	0.0900***	0.0820***	0.0905***	0.0567***
	(0.0035)	(0.0039)	(0.0044)	(0.0044)
Share leavers	−0.1033***	−0.0968***	−0.0925***	−0.0830***
	(0.0013)	(0.0014)	(0.0015)	(0.0015)
Log turnover	0.7155***	0.7171***	0.7097***	0.7295***
	(0.0010)	(0.0011)	(0.0013)	(0.0013)
Labor productivity	0.0038***	0.0044***	0.0064***	0.0042***
	(0.0004)	(0.0005)	(0.0005)	(0.0005)
Profitability	−3.5620***	−3.3197***	1.1765***	1.1199***
	(0.2638)	(0.2747)	(0.3754)	(0.3755)
Sh. of empl. w. tert. education	0.0328***	0.0238***	0.0162**	0.0233***
	(0.0052)	(0.0058)	(0.0065)	(0.0065)
Constant	−9.4779***	−9.6024***	−9.5848***	−9.7726***
	(0.0200)	(0.0212)	(0.0228)	(0.0255)
Year dummies	Yes	Yes	Yes	Yes
Baseline age effects	Yes	Yes	Yes	Yes
Observations	1,205,955	915,301	699,867	692,281
Firms	310,524	229,978	180,691	176,630
R^2	0.408	0.416	0.415	0.428
AIC	1,182,981	803,234	562,445	535,873
BIC	1,183,233	803,480	562,674	536,148
F	30,806	24,380	19,421	16,758

Note: Dependent variable: log turnover growth; standard errors in parentheses; ***, **, * indicate significance at the 1, 5, and 10% levels.

employees. The empirical pattern presented previously in Figure 1 suggests that the age moderation is less pronounced for more established firms, which would be spin-off firms or larger start-ups. However, we will discuss that observed differences between these types of firms resonate well with the potential theoretical explanations for the age moderation discussed in the next section of this article.

TABLE 7 Robustness checks 4: Including number of skills in (t-1) as control variable

	(1)	(2)	(3)	(4)
	OLS	FE	OLS	FE
Share of new skills	0.3684***	0.1498***	0.3680***	0.1407***
	(0.0285)	(0.0300)	(0.0309)	(0.0326)
Sh. new skills # firm age	−0.0667***	−0.1337***		
	(0.0041)	(0.0044)		
Firm age = 3 # Sh. new skills			−0.2548***	−0.4445***
			(0.0414)	(0.0403)
Firm age = 4 # Sh. new skills			−0.3597***	−0.6757***
			(0.0416)	(0.0431)
Firm age = 5 # Sh. new skills			−0.4313***	−0.8160***
			(0.0442)	(0.0466)
Firm age = 6 # Sh. new skills			−0.5066***	−0.8907***
			(0.0482)	(0.0501)
Firm age = 7 # Sh. new skills			−0.5356***	−0.9974***
			(0.0522)	(0.0548)
Firm age = 8 # Sh. new skills			−0.5814***	−1.0785***
			(0.0549)	(0.0598)
Firm age = 9 # Sh. new skills			−0.5909***	−1.1611***
			(0.0590)	(0.0642)
Firm age = 10 # Sh. new skills			−0.5839***	−1.2133***
			(0.0680)	(0.0715)
Firm age = 11 # Sh. new skills			−0.5987***	−1.2271***
			(0.0682)	(0.0820)
Firm age = 12 # Sh. new skills			−0.5355***	−1.3501***
			(0.0753)	(0.0962)
Firm age = 13 # Sh. new skills			−0.6628***	−1.4244***
			(0.0939)	(0.1151)
Firm age = 14 # Sh. new skills			−0.4280***	−1.4402***
			(0.1283)	(0.1450)
Firm age = 15 # Sh. new skills			−0.8013***	−1.5215***
			(0.1740)	(0.2051)
Number skills (t-1)	−0.1117***	−0.1653***	−0.1114***	−0.1627***
	(0.0016)	(0.0012)	(0.0016)	(0.0012)
Share recruits	0.0360***	0.0782***	0.0336***	0.0746***
	(0.0052)	(0.0042)	(0.0052)	(0.0042)
Share leavers	−0.1375***	−0.0534***	−0.1376***	−0.0528***
	(0.0080)	(0.0013)	(0.0080)	(0.0013)
Log turnover	0.2011***	0.7463***	0.2015***	0.7469***
	(0.0022)	(0.0010)	(0.0022)	(0.0010)
Labor productivity	−0.0144***	−0.0036***	−0.0145***	−0.0037***
	(0.0023)	(0.0004)	(0.0024)	(0.0004)

(Continues)

TABLE 7 (Continued)

	(1)	(2)	(3)	(4)
Profitability	0.8825	−3.6614***	0.8797	−3.6730***
	(3.7858)	(0.2608)	(3.7818)	(0.2604)
Share of employees w. tertiary education	0.0003	0.0349***	0.0002	0.0349***
	(0.0015)	(0.0051)	(0.0015)	(0.0051)
Constant	−2.4474***	−9.6099***	−2.4663***	−9.7033***
	(0.0260)	(0.0211)	(0.0261)	(0.0186)
Industry dummies	Yes	No	Yes	No
Year dummies	Yes	Yes	Yes	Yes
Baseline age effects	Yes	Yes	Yes	Yes
Observations	1,205,955	1,205,955	1,205,955	1,205,955
Firms	310,524	310,524	310,524	310,524
R^2	0.145	0.421	0.145	0.422
AIC	2,031,373	1,155,647	2,030,605	1,152,437
BIC	2,031,805	1,155,911	2,031,325	1,152,989
F	1,308	30,989	787	14,554

Note: Dependent variable: log turnover growth; *SE* in parentheses; *SE* of OLS regressions are clustered at the level of the firm; ***, **, * indicate significance at the 1, 5, and 10% levels.

Two conditions identify spin-offs in the population of all new firms (Andersson & Klepper, 2013). First, at least half of the employees of a new venture must have worked at the same establishment in the previous year. Second, these employees accounted for less than half of the total number of employees of the previous workplace. The FAD data includes information about the nature of the new firm and identifies corporate spin-offs. As shown in Table 5 and depicted in Figure 2, the pattern for de novo firms is very similar to the one for the whole population as presented in Figure 1. Also in line with expectations, the age moderation is less pronounced (but still exists) for spin-off firms. For these, the data provides evidence that adding new skills is associated with higher firm growth in years 1–3. For spin-offs above 3 years, the coefficient for new skills is negative but could not be estimated accurately to provide strong evidence for statistically significant relationships. Nonetheless, we do find that the results differ significantly for some periods. The pattern is that spin-offs profit less than de novo firms from hiring new employees in their early years, while they also lose less when they are older.[3]

As regards the differentiation between small (firms with 10 employees and fewer) and large (firms with more than 10 employees) start-ups, the pattern confirms a similar picture. If we interpret that large start-ups are more established than small ones, a consistent finding would be that the age moderation is less pronounced for the large start-ups than for the small ones. Figure 3 depicts the results and shows that the age moderation for small start-ups is very similar to what we have presented in Figure 1. For large start-ups, we find a positive relationship between adding new skills and firm growth in the first 3–4 years. Afterwards, adding new skills does not appear to affect the growth of large start-ups. In the case of firm size, the nonoverlapping confidence intervals show that the differences between small and large firms are significant.

3.4 | Robustness check for de novo and spin-off firms

Table 10 tests whether the results for de novo and spin-off firms are driven by differences in their original skillset. Models 1 and 2 include firms with one skill in the founder team (∼85% of all firms) whereas Models 3 and 4 include

TABLE 8 Robustness checks 5: Using turnover (t-1) as control for firm size

	(1)	(2)	(3)	(4)
	OLS	FE	OLS	FE
Share of new skills	0.9906***	0.8126***	0.9012***	0.7279***
	(0.0284)	(0.0294)	(0.0342)	(0.0330)
Sh. new comp. # firm age	−0.1146***	−0.1002***		
	(0.0041)	(0.0050)		
Firm age = 2 # Sh. new skills			−0.2130***	−0.3138***
			(0.0425)	(0.0454)
Firm age = 3 # Sh. new skills			−0.4949***	−0.5320***
			(0.0440)	(0.0490)
Firm age = 4 # Sh. new skills			−0.5692***	−0.5649***
			(0.0564)	(0.0538)
Firm age = 5 # Sh. new skills			−0.6725***	−0.5962***
			(0.0470)	(0.0591)
Firm age = 6 # Sh. new skills			−0.7302***	−0.5897***
			(0.0524)	(0.0647)
Firm age = 7 # Sh. new skills			−0.7752***	−0.6321***
			(0.0598)	(0.0720)
Firm age = 8 # Sh. new skills			−0.8153***	−0.6323***
			(0.0570)	(0.0795)
Firm age = 9 # Sh. new skills			−0.7708***	−0.6287***
			(0.0627)	(0.0863)
Firm age = 10 # Sh. new skills			−0.7837***	−0.6078***
			(0.0707)	(0.0975)
Firm age = 11 # Sh. new skills			−0.7536***	−0.5673***
			(0.0815)	(0.1128)
Firm age = 12 # Sh. new skills			−0.7066***	−0.5299***
			(0.0767)	(0.1340)
Firm age = 13 # Sh. new skills			−0.7834***	−0.5844***
			(0.0987)	(0.1616)
Firm age = 14 # Sh. new skills			−0.5733***	−0.4285**
			(0.1200)	(0.2056)
Firm age = 15 # Sh. new skills			−0.9476***	−0.6698**
			(0.1732)	(0.2924)
Share recruits	0.3622***	0.3113***	0.3565***	0.2932***
	(0.0048)	(0.0051)	(0.0047)	(0.0051)
Share leavers	−0.1567***	−0.1583***	−0.1517***	−0.1525***
	(0.0072)	(0.0017)	(0.0070)	(0.0017)
Turnover (t-1)	−0.0000	−0.0000***	−0.0000	−0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Labor productivity	0.0219***	0.0540***	0.0220***	0.0537***
	(0.0063)	(0.0004)	(0.0063)	(0.0004)

(Continues)

TABLE 8 (Continued)

	(1)	(2)	(3)	(4)
Profitability	−0.8735	−3.6117***	−0.8796	−3.6300***
	(3.4201)	(0.3154)	(3.4223)	(0.3136)
Sh. Of empl. w. Tert. Education	−0.0025*	−0.0221***	−0.0035**	−0.0201***
	(0.0014)	(0.0063)	(0.0014)	(0.0063)
Constant	0.0369***	0.5873***	0.0988***	0.4828***
	(0.0049)	(0.0192)	(0.0051)	(0.0170)
Industry dummies	Yes	No	Yes	No
Year dummies	Yes	Yes	Yes	Yes
Baseline age effects	Yes	Yes	Yes	Yes
Observations	1,611,818	1,611,818	1,611,818	1,611,818
Firms	434,247	434,247	434,247	434,247
R^2	0.038	0.048	0.044	0.058
AIC	3,369,565	2,719,240	3,359,060	2,700,823
BIC	3,369,983	2,719,485	3,359,798	2,701,389
F		2,941		1,588

Note: Dependent variable: log turnover growth; *SE* in parentheses; *SE* of OLS regressions are clustered at the level of the firm; ***, **, * indicate significance at the 1, 5, and 10% levels.

TABLE 9 Coefficients and standard errors of adding new skills by age for young versus old and de novo firms versus spinoffs

At age	(1) De novo firms		(2) Spin-off firms		(3) Firms<=10		(4) Firms<10	
1	**1.709**	**(0.028)**	**0.932**	**(0.098)**	**1.309**	**(0.030)**	**0.518**	**(0.086)**
2	0.689	(0.033)	0.493	(0.114)	0.392	(0.035)	0.247	(0.091)
3	0.147	(0.035)	0.285	(0.116)	−0.052	(0.038)	0.418	(0.087)
4	−0.195	(0.040)	−0.108	(0.136)	−0.301	(0.043)	0.259	(0.095)
5	−0.436	(0.044)	−0.428	(0.153)	−0.475	(0.048)	0.069	(0.099)
6	−0.534	(0.049)	−0.228	(0.161)	−0.521	(0.054)	0.000	(0.106)
7	−0.724	(0.056)	−0.226	(0.182)	−0.675	(0.062)	−0.045	(0.112)
8	−0.900	(0.063)	−0.342	(0.207)	−0.823	(0.069)	−0.142	(0.126)
9	−0.963	(0.068)	−0.557	(0.233)	−0.841	(0.077)	−0.079	(0.132)
10	−1.084	(0.079)	−0.316	(0.244)	−0.916	(0.088)	−0.159	(0.146)
11	−1.170	(0.092)	−0.246	(0.299)	−1.143	(0.104)	0.020	(0.168)
12	−1.355	(0.110)	−0.595	(0.349)	−1.129	(0.123)	−0.127	(0.200)
13	−1.369	(0.132)	−0.765	(0.499)	−1.190	(0.148)	−0.165	(0.254)
14	−1.527	(0.171)	−0.982	(0.563)	−1.367	(0.194)	0.101	(0.306)
15	−1.804	(0.244)	−0.509	(0.787)	−1.895	(0.285)	0.165	(0.437)

Note: FE regressions; dependent variable: log turnover growth; all control variables included; full table reported in Table A4; *SE* in parentheses.

firms with more than one skill in the founder team. The complete table in Table A5 shows that spin-off firms tend to have a more diverse skillset at foundation than de novo firms. However, this does not affect the results presented previously. De novo firms, regardless of the number of skills in the founder team, exhibit a strong age moderation.

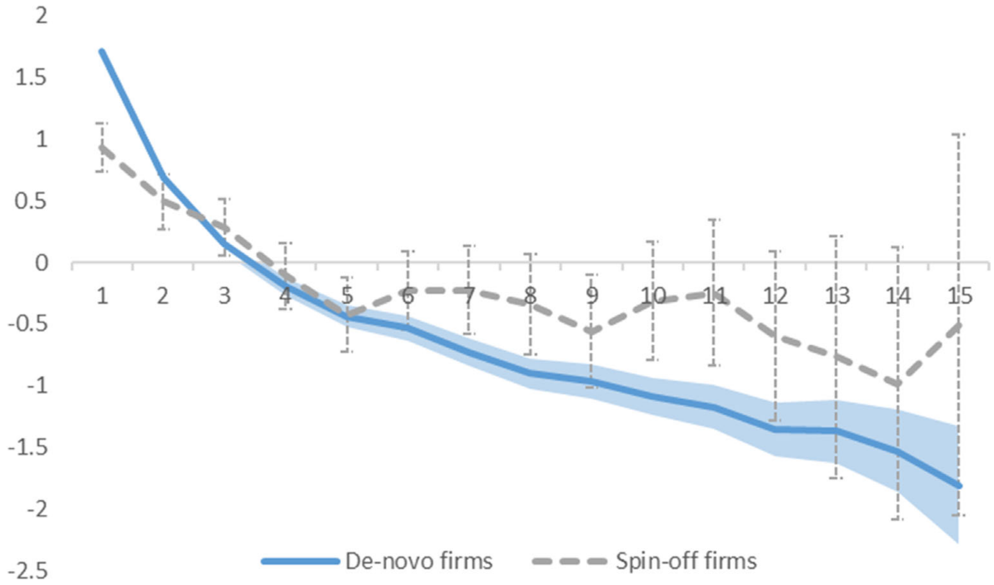

FIGURE 2 Coefficient and 95% confidence intervals of adding new skills by age for de novo and spin-off firms

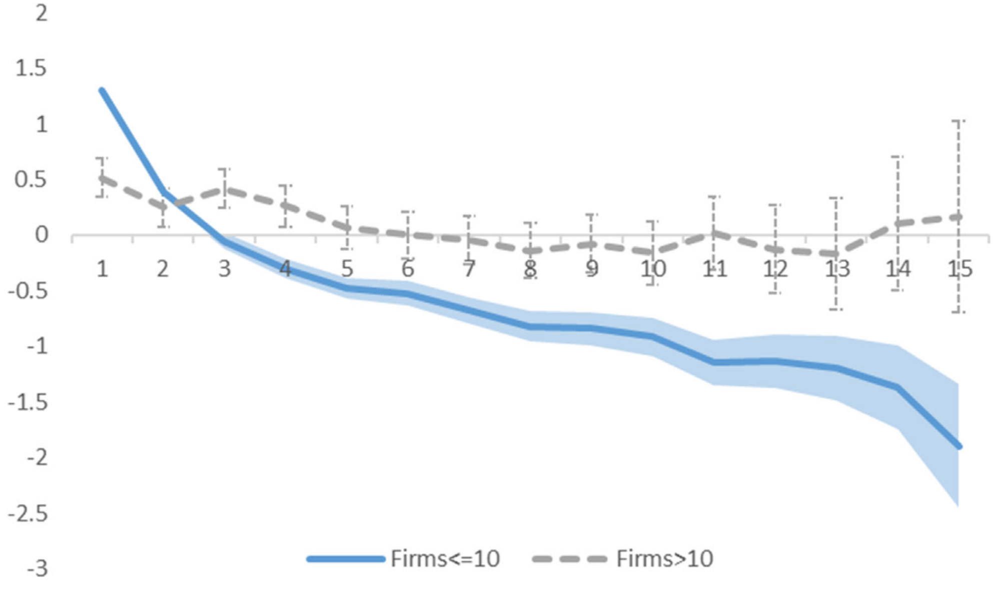

FIGURE 3 Coefficient and 95% confidence intervals of adding new skills by age for small and large start-ups (firms<=10 and firms>10)

Adding new skills at a young age correlates with higher turnover growth. This correlation becomes negative for older firms. The estimates for spin-off firms show a lower positive correlation of adding new skills at young age and also the moderation effect is weaker.

Table A6 presents a final robustness check, which estimates a model that includes a three-way interaction between age, the share of new skills, and the dummy variable for spin-off firms. This estimation provides for an additional test whether the differences between de novo firms and spin-off firms are significant. The three-way

TABLE 10 Coefficients and standard errors of adding new skills by age for de novo firms versus spinoffs and for different number of skills in founder team

	Skills in founder team = 1				Skills in founder team >1			
	(1) De novo firms		(2) Spin-off firms		(3) De novo firms		(4) Spin-off firms	
At age								
1	1.633	(0.037)	0.341	(0.237)	1.595	(0.039)	1.050	(0.107)
2	0.853	(0.043)	0.513	(0.267)	0.476	(0.046)	0.485	(0.126)
3	0.194	(0.046)	−0.022	(0.246)	0.112	(0.051)	0.345	(0.130)
4	−0.124	(0.051)	−0.134	(0.284)	−0.217	(0.057)	−0.104	(0.153)
5	−0.417	(0.057)	−0.746	(0.355)	−0.379	(0.064)	−0.334	(0.169)
6	−0.599	(0.063)	0.062	(0.358)	−0.331	(0.072)	−0.285	(0.179)
7	−0.749	(0.071)	−0.702	(0.389)	−0.576	(0.082)	−0.111	(0.204)
8	−0.979	(0.079)	−0.003	(0.446)	−0.688	(0.094)	−0.403	(0.231)
9	−1.052	(0.086)	−0.337	(0.492)	−0.680	(0.103)	−0.544	(0.263)
10	−1.148	(0.097)	−0.442	(0.506)	−0.809	(0.121)	−0.284	(0.276)
11	−1.351	(0.117)	−0.244	(0.735)	−0.709	(0.134)	−0.265	(0.327)
12	−1.518	(0.140)	−0.283	(0.750)	−0.922	(0.160)	−0.611	(0.391)
13	−1.471	(0.162)	−0.230	(1.098)	−0.956	(0.207)	−0.866	(0.556)
14	−1.707	(0.215)	−2.038	(1.110)	−1.010	(0.250)	−0.661	(0.645)
15	−1.939	(0.302)	−1.535	(1.800)	−1.133	(0.375)	−0.280	(0.871)

Note: FE regressions; dependent variable: log turnover growth; all control variables included; full table reported in Table A5; *SE* in parentheses.

interactions are positive and significant until the age of 11 even though there are some variations in the significance level. Also, the result falls slightly short of making the 10% significance level for firms with an age of 5. Yet overall, the results of this model confirm that the age moderation tends to be weaker for spin-off firms than for de novo firms. Furthermore, the two-way interaction between the share of new skills and the dummy variable for spin-off firms confirms that the baseline effect of adding new skills is lower for spin-off firms.

Overall, we find a strong and robust age moderation for the relationships between adding new skills and firm growth. The age moderation is strongest in the first few years after firm establishment but flattens off over time. The age moderation is also less pronounced for more established start-ups (for instance spin-off firms or large start-ups). The next section elaborates on potential theoretical explanations for the age moderation.

4 | DISCUSSION

The literature has highlighted that growth can be existential for new ventures in order to overcome the liabilities of smallness (Mata & Portugal, 2002) and to survive in the long-run (Cefis & Marsili, 2005; Pe'er, Vertinsky, & Keil, 2016). In order to grow, new ventures need to integrate skills and competences not yet present in the founding team. The literature so far has been keen to emphasize that integrating novel skills is fraught with costs. Our results suggest that integration costs change as the venture matures.

The stability of the findings is underpinned on the one hand by a large number of robustness checks and on the other by the population character of the data reducing concerns about selectivity. Sample selection is a particular issue in many entrepreneurship studies because population data or at least representative samples often do not exist. In our case, our results hold for the population of Swedish new ventures. A final perk of the sample is its homogeneity. By including only young firms, we effectively reduce the risk of conflating structural disadvantages, for example, in recruiting qualified staff, with causal effects. For example, if we included established firms in our sample, positive growth effects of older firms might have been overestimated if those firms also managed to attract more qualified human capital. As all firms in the sample were founded during the sample period, we reduce the risk of systematic biases. As the goal of our paper was to show stable empirical patterns, we have so far made only occasional reference to the underlying theoretical mechanisms. In this section, we will devote more attention to potential causal explanations for the observed phenomena and we will highlight how our findings may contribute to the further development and refinement of existing theoretical approaches.

Our results in Figure 1 showed that the growth benefits of adding new skills decline with the increasing age of the firm. The downward-sloping growth pattern suggests that there are costs of integrating new skills and these increase as the firm ages. Costs of change typically lead to persistence in organizational structures.

One major theoretical approach invoked to explain persistency in the organizational structures of firms is the imprinting theory (Beckman & Burton, 2008; Dobrev & Gotsopoulos, 2010). Dating back to Stinchcombe (1965), imprinting originally refers to the observation that firms founded in the same cohort tend to preserve comparable characteristics over long periods of time even in the face of considerable change in the firms' environment (Hannan, Burton, & Baron, 1996; Hannan & Freeman, 1984). Several authors have therefore argued that imprinting leads to path-dependence and organizational rigidities (Dowell & Swaminathan, 2006; Koch, 2011). At the same time, imprinting is not purely a theory of rigidities. In fact, it posits susceptibility to early environmental events and impacts (Marquis & Tilcsik, 2013) as well. That is, imprinting patterns describe a specific sequentiality, where firms are susceptible to environmental impacts early on. However, the resulting imprints become persistent over time. One explanation for this sequentiality is that two distinct learning processes in new ventures occur one after the other. Dutta and Crossan (2005) argue that accessing and integrating knowledge rests on two separate processes. The first is a process of creating mutual understanding of (often diverse) individuals to allow for coordinated action. This requires joint experience of the venture's members (Penrose, 1959). The second refers to institutionalizing successful patterns of coordinated actions in stable organizational routines. The interplay of the two learning processes allows new ventures to discover an entrepreneurial opportunity and to exploit it to its full degree (Crossan, Lane, & White, 1999; Wang & Chugh, 2014). The distinction by Dutta and Crossan (2005) suggests a specific sequentiality of the two learning processes with the institutionalization occurring later. The reason is the scarcity of stable organizational routines in new ventures, requiring firms to resort to other sources of knowledge inside and outside of the firm. As knowledge held by individuals becomes institutionalized in routines and thereby separated from the individuals, firms become less susceptible to skills not already codified in the organizational routines (Grillitsch et al., 2019). Our findings are compatible with the temporal pattern postulated by the imprinting theory, because one corollary is that costs of change, such as costs of integrating new skills, are low in young but large in older firms. This precisely mirrors our major finding of a downward-sloping growth pattern.

An alternative theoretical explanation for the negative time profile in growth lies in the notion of changes in the venture's strategic focus over time. Life-cycle models have typically argued that new ventures cycle through different phases. During the inception phase, ventures typically have not yet explored their entrepreneurial opportunity to its full extent. They are often not fully informed about the core technology underlying their products or services, the demand side, or the main competitors (Alvarez et al., 2013; Knight, 1921). In this respect, exploration activities increase the information on the potential customer value of a specific entrepreneurial opportunity (Alvarez et al., 2013) and thereby reduce the uncertainty over whether the firm's offerings will be able to compete on the market (Choi & Shepherd, 2004). Thus, during their inception phase, firms are typically more focused on exploring the characteristics of their entrepreneurial opportunity than on exploiting an opportunity, which might be premature and lock the firm into a (potentially bad) local optimum on a rugged landscape (Levinthal, 1997). As the ventures reduce technological and demand uncertainty through exploration, they become better informed about the type and value of their entrepreneurial opportunities, which allows them to develop strategies to exploit them effectively. If uncertainty is sufficiently low, firms shift their focus to exploit their entrepreneurial opportunity, which is based on tasks that aim at preserving patterns of action which have proven to be goal-efficient (Becker, 2005). Like in the case of founder imprinting, the result would be that the benefits of integrating novel skills would decline over time. While we do not directly observe the shift between exploration and exploitation with our data, in fact, Figure 1 suggests that it occurs at an age of 3–4 years, where the correlation of adding new skills and firm growth turns negative.

Apparently both the explanation of founder imprinting and of the strategic shifts during typical firm life-cycles are consistent with our finding of a negative time-profile in the benefits from recruiting new skills. Unfortunately, our dataset, although abundant in terms of demographic firm or personal-level characteristics, does not allow us to test the two explanations explicitly. The main reason is that for founder imprinting we would need to observe imprints directly. For life-cycle explanation, we would need to observe strategic shifts from exploration to exploitation. It is clear that testing any of these mechanisms directly would require quite different, probably survey-based datasets or different methodologies, in particular case study approaches.

Despite our inability to test the mechanisms underlying the life-cycle and the founder imprinting explanation directly, our results can be interpreted as delivering complementary evidence that both mechanisms might be at work simultaneously. Specifically, more than predicting just a downward-sloping pattern, life-cycle models would expect us to observe a flattening curve, which is reached when the firm enters a stable exploitation phase. Indeed, Figure 1 shows that the decline in the growth pattern is steep for the first years and becomes flatter over time. Thus, there is some evidence of the value of a life-cycle perspective.

At the same time, there is also evidence of deductions from the imprinting theory: Our results showed that, for de novo firms, recruiting new skills is initially associated with higher growth effects. However, the decline is steeper, too, when compared to spin-off firms (Figure 2). There is an established literature which argues that spin-off firms inherit valuable skills and organizational routines from their parent firms (Agarwal, Echambadi, Franco, & Sarkar, 2004; Furlan & Grandinetti, 2016; Klepper, 2009; Klepper & Sleeper, 2005). An obvious expectation resulting from the initial endowment of routines is that organizational spin-offs perform better than de novo firms—an expectation that has been corroborated empirically for a multitude of performance measures, including innovation, survival, and growth (Andersson & Klepper, 2013; Chatterji, 2009; Dahl & Sorenson, 2012). The standing agreement in the literature is that this endowment with routines, knowledge, and skills provides new ventures with advantages over de novo firms. While we agree with this reasoning, the higher degree of routinization of spin-offs as compared with de novo firms suggests that there are implications for the integration costs of new skills over time. First, if spin-offs inherit organizational routines, spin-offs will face higher costs of integrating novel skills during their inception phase than de novo firms, making them less responsive to new skills from recruitment. Second, if de novo firms develop routines over time (Dutta & Crossan, 2005), the difference between spin-off and de novo firms will diminish over time, which should manifest in a smaller negative age moderation effect for spin-offs. Our results are thus consistent with these deductions based on imprinting theory.

5 | CONCLUSION

In this paper we contribute to the fundamental question of how new firms realize entrepreneurial opportunities. The paper focuses on a key process, namely the integration of novel skills through recruitment. The empirical study is conducted on the population of Swedish start-ups from 1997 to 2012 with a founding team size of up to 10. We find that the effect of adding new skills to start-ups depends on the firm's age. Specifically, start-ups benefit strongly from adding new skills in terms of higher growth in a short period after firm formation. As the firm matures, the costs of integrating new skills increase and eventually outweigh the benefits. Moreover, we show that the institutional background of the start-up is a crucial moderator of this relationship. While spin-off firms typically benefit from operational routines inherited from their parents, these routines also reduce the ability to integrate new skills even in very young spin-off firms. This contributes to the entrepreneurship literature as well as managerial practice in several ways.

On a theoretical level, our paper contributes to an accumulating body of literature which regards entrepreneurship as a process (McMullen & Dimov, 2013). While process models differ widely in their theoretical background and explanatory scope, they have in common that time plays a fundamental role. Some recent studies have begun to analyze the role of timing and firm age for firm performance (Gjerløv-Juel & Guenther, 2019; Guenther et al., 2016). We contribute to this literature by showing how adding new skills affects the venture's growth prospect as a function of its age. The results are also interesting from the perspective of Penrosian growth theory (Lockett et al., 2011) because they demonstrate the central importance of the costs of integrating new skills. The integration of new skills and firm growth should be seen as intertwined processes, because growth necessitates the integration of new skills, while the integration of new skills causes integration costs with negative effects on growth. The findings of this paper suggest that integration costs are a function of firm age. In consequence, the timing of recruitment decisions becomes crucial.

This time-dependence has fundamental implications for practical management. While ventures almost naturally need to add new skills to their team during the scale-up phase, we show the importance of doing this early. Processes related to founder imprinting, increasing routinization, and moving from exploration to exploitation increase integration costs quickly over time. Our results show that there is a short window of opportunity to add novel skills to the firm in its very early years after foundation.

Moreover, resonating with the idea that integration costs are the result of processes related to founder imprinting, the strategic shift from exploration to exploitation and routinization, our findings show that the time profile is contingent on the institutional background of the firms. More specifically, the window of opportunity to add novel skills is considerably smaller for corporate spin-offs than for de novo firms. Thus, although spin-offs are often believed to be in an advantageous position because of inherited routines (Andersson & Klepper, 2013; Klepper, 2009; Klepper & Sleeper, 2005), our results show that spin-offs have a disadvantage in terms of integrating new skills after foundation. This finding is consistent with the proposition that integration cost disadvantages arise not despite the inherited routines, but precisely as a result of them. Thus, while so far inheritance in corporate spin-offs has been exclusively discussed as benefitting young ventures, we are the first to demonstrate some potential costs implied by inherited routines. It is interesting to note, however, that the difference between spin-offs and independent ventures with regard to the level of integration costs vanishes over time.

While our paper sheds new light on important aspects of recruitment and scaling up in the context of new ventures, our research has limitations, which open up avenues for new research.

Despite the large number of robustness checks, one empirical issue is the problem of self-selection and reverse causality. Specifically, firms which have experienced poor growth in the past may be induced to look out for new or missing skills. The opposite reaction may also be conceivable because past poor growth may make them more passive in terms of hiring. Either way, there may be endogeneity issues resulting from simultaneity, which we may have accounted for only partly through fixed-effect approaches and a careful selection of controls. Another source of issues may be due to selective survival bias, since firms with consistently negative growth face a higher hazard of leaving the sample, typically because of bankruptcy. In fact, that risk may be substantial because survival is lowest for the very small firms (Davis, Haltiwanger, & Schuh, 1996) dominating our estimation sample. We have partly controlled for that by using a potentially more robust growth measure (Table A3). Yet, more advanced techniques may use IV strategies such as unexpected deaths (cf. Choi, Goldschlag, Haltiwanger, & Kim, 2019). Potentially remaining endogeneity issues are a major reason for interpreting our findings more as correlation rather than causal effects.

Another aspect concerns the choice of the independent variable. We have chosen firm growth as our core variable of interest. While early growth and scale-up are important for the success of start-ups in the long run (Cefis & Marsili, 2005; Pe'er et al., 2016), survival may be an equally (or more) important performance dimension for many start-ups. Indeed, several of the papers that have analyzed questions closely related to ours (Gjerløv-Juel & Guenther, 2019; Guenther et al., 2016) have focused on survival as the final outcome. The focus on survival may also be driven by the notion of liabilities of newness, which are typically expressed in terms of high failure rates (Baum & Amburgey, 2002; Baum & Oliver, 1996; Sleuwaegen & Onkelinx, 2014). While, in our view, the notion of liabilities of newness could also be expressed as disadvantages in terms of firm growth, a natural extension of our work would be to analyze how the timing of recruiting novel skills affects firm survival. Moreover, such research would contribute to deepening our understanding of how growth and survival are linked to each other (Pe'er et al., 2016).

Beyond the question of how firm growth and survival are linked to each other, there is a conceptual issue for theory development. Our results consistently show that the costs of adding new skills increase as the firm ages. We have discussed this finding in terms of theory and have argued that it is consistent with imprinting and life-cycle theories. These theories however implicitly exclude the question of why firms hire and therefore do not unpack the potentially complex intertemporal relationships between growth and the recruitment of skills. Our viewpoint is consistent with supply-side views: for example, Penrosian growth theory would contend that firms with excess skills will expand (potentially into other markets), where these skills can be fruitfully applied. Demand-side views would suggest that firms meeting excess demands will recruit new skills. Here the cause-and-effect relationship may be turned around. While our data does not allow us to identify the firms' motives for recruiting new skills, the various robustness checks, in particular those relating to the lag structures, do suggest that supply-side explanations, where new skills cause growth, are playing a role—even if it is not necessarily an exclusive one. Nonetheless, exploring the causal micro-mechanisms relating growth to skill recruitment would clearly be a logical next step to further develop the ideas set out in this paper.

To implement such research, it would be imperative to develop clear measures of the theoretical core concepts. Indeed, while an increasing number of papers has resorted to imprinting theory in both empirical and theoretical settings (Bryant, 2014; Gjerløv-Juel & Guenther, 2019; Mathias, Williams, & Smith, 2015), no clear direct measures of imprints have emerged so far. Such an analysis could also zoom in on why new skills are recruited. One possible alternative explanation is that spin-off firms and old firms only recruit new skills when faced with bad growth prospects. In that respect, we believe that attempts to measure these phenomena with direct approaches could help considerably in further developing the explanatory potential of this literature.

An additional research avenue would be to delve into the effects of recruiting new skills that are related or similar to existing skills (Neffke & Henning, 2013). As widely acknowledged in the literature (Nooteboom, 2000), it is particularly difficult to integrate new skills if the cognitive distance is large. By using the broadest educational category, we have chosen to focus on the recruitment of new skills that are substantially different from existing skills. By zooming in on the lower levels of the educational hierarchy, we have been able to analyze the time effects of recruiting-related or similar skills. Following our argumentation, the more similar new skills are to existing skills, the less the cost of integrating these skills should be. Furthermore, future research may zoom in on the type of new skill recruited to the firm conditional to the existing portfolio of skills in the firm. For instance, do integration costs differ when adding a manufacturing skill to a founding team of natural scientists as compared with adding a social science skill to a founding team trained in forestry? Related to this is also the question of whether the importance of timing for adding new skills depends on the diversity of founding teams. Such more nuanced analyses could support the development of typologies with high relevance for management practice.

In summary, a necessary next step following up on our research would be to identify the causal mechanisms linking the recruitment, growth, and other measures of firm performance in an intertemporal setting. To implement that, there is a need for more in-depth theory development but also for econometric approaches which deal explicitly with the simultaneous relationships surrounding these core concepts.

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ENDNOTES

[1] The classification of educational fields follows a hierarchical structure. The detailed educational fields (3-digit levels) are grouped within broader categories (2-digit levels) by similarity. The 2-digit categories are then again grouped by similarity/relatedness under 1-digit categories, which constitute the broadest groups. This means by design (as evaluated by educational

experts) that knowledge is similar between educational fields within each 1-digit category but different between 1-digit categories. For this reason, we use the 1-digit level in our analysis. Table A1 depicts the frequency of each educational field.

[2] Please note that the POLS models include vectors for the industry of the firm, which are time-invariant.

[3] Nonoverlapping confidence intervals for independent samples provide a conservative test at the level of the confidence intervals as shown by Cumming (2009), who calls the test "inference by eye."

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APPENDIX

TABLE A1 Employees per educational field

	Employees	Share
General education	895,871	26%
Pedagogics and teaching	88,494	3%
Humanities and arts	192,387	6%
Social science, law, business, and administration	496,258	15%
Natural science, mathematics, and computer science	84,534	2%
Technology and manufacturing	932,176	28%
Agriculture, forestry, and animal care	119,091	4%
Health, medical care, and social care	207,867	6%
Services	241,685	7%
Unknown	125,627	4%
Total	3,383,990	100%

TABLE A2 Descriptive statistics

	Variables	Observations	Mean	*SD*	Min	Max	1	2	3	4	5	6	7	8	9
1	Log turnover growth	1,611,818	0.0604	0.7016	−16.16	16.23	1.000								
2	Share of new skills	1,611,818	0.0131	0.0416	0.00	0.90	0.101	1.000							
3	Share recruits	1,611,818	0.0810	0.1876	0.00	1.00	0.114	0.692	1.000						
4	Share leavers	1,611,818	0.1102	0.3954	0.00	91.00	−0.069	0.055	0.154	1.000					
5	Firm age	1,611,818	4.2178	3.1647	1.00	15.00	−0.084	−0.052	−0.059	0.026	1.000				
6	Log turnover	1,611,818	13.5107	1.4526	0.69	21.75	0.282	0.284	0.385	0.191	0.151	1.000			
7	Labor productivity	1,611,818	0.8847	2.5282	0.00	1,536.22	0.069	0.009	0.021	0.085	0.038	0.304	1.000		
8	Profitability	1,611,818	0.0000	0.0028	−1.53	1.05	−0.003	0.001	0.001	0.001	−0.001	0.007	0.000	1.000	
9	Sh. of empl. w. tert. education	1,611,818	0.2841	0.4235	0.00	6.00	−0.007	−0.030	−0.070	−0.036	−0.050	−0.091	−0.008	−0.004	1.000

TABLE A3 Robustness checks 2: Different dependent variables and using similarity fields

	(1) Log employment growth	(2) Turnover growth (survival correction)	(3) Log turnover growth (only incorporated firms)	(4) Log turnover growth (similarity fields)
Share of new skills	1.6051***	1.1676***	1.7282***	1.6377***
	(0.0061)	(0.0205)	(0.0302)	(0.0289)
Firm age = 2 # Sh. of new skills	−0.8265***	−0.6157***	−1.0824***	−1.2387***
	(0.0084)	(0.0282)	(0.0431)	(0.0420)
Firm age = 3 # Sh. of new skills	−0.9594***	−1.0149***	−1.5293***	−1.6107***
	(0.0090)	(0.0305)	(0.0462)	(0.0459)
Firm age = 4 # Sh. of new skills	−1.0730***	−1.2778***	−1.8805***	−1.9670***
	(0.0099)	(0.0334)	(0.0505)	(0.0514)
Firm age = 5 # Sh. of new skills	−1.1510***	−1.4628***	−2.1092***	−2.1500***
	(0.0109)	(0.0368)	(0.0553)	(0.0561)
Firm age = 6 # Sh. of new skills	−1.1839***	−1.5208***	−2.1535***	−2.1225***
	(0.0119)	(0.0402)	(0.0603)	(0.0613)
Firm age = 7 # Sh. of new skills	−1.2464***	−1.6560***	−2.3162***	−2.2982***
	(0.0133)	(0.0447)	(0.0667)	(0.0682)
Firm age = 8 # Sh. of new skills	−1.2842***	−1.7650***	−2.4542***	−2.4494***
	(0.0147)	(0.0494)	(0.0736)	(0.0770)
Firm age = 9 # Sh. of new skills	−1.2894***	−1.8029***	−2.5301***	−2.5036***
	(0.0159)	(0.0537)	(0.0799)	(0.0836)
Firm age = 10 # Sh. of new skills	−1.2932***	−1.9036***	−2.5963***	−2.6899***
	(0.0180)	(0.0606)	(0.0898)	(0.0983)
Firm age = 11 # Sh. of new skills	−1.3571***	−1.9311***	−2.6143***	−2.5885***
	(0.0208)	(0.0701)	(0.1032)	(0.1104)
Firm age = 12 # Sh. of new skills	−1.4149***	−2.0619***	−2.8675***	−2.7268***
	(0.0247)	(0.0833)	(0.1238)	(0.1267)
Firm age = 13 # Sh. of new skills	−1.3166***	−2.1000***	−2.8281***	−2.9654***
	(0.0298)	(0.1004)	(0.1489)	(0.1715)

(Continues)

TABLE A3 (Continued)

	(1) Log employment growth	(2) Turnover growth (survival correction)	(3) Log turnover growth (only incorporated firms)	(4) Log turnover growth (similarity fields)
Firm age = 14 # Sh. of new skills	−1.4221***	−2.1944***	−2.8279***	−2.9625***
	(0.0379)	(0.1277)	(0.1903)	(0.2156)
Firm age = 15 # Sh. of new skills	−1.4107***	−2.3933***	−2.8854***	−2.9978***
	(0.0539)	(0.1816)	(0.2614)	(0.2662)
Share recruits	1.1475***	0.1011***	0.1226***	0.0964***
	(0.0009)	(0.0032)	(0.0048)	(0.0036)
Share leavers	−0.4936***	−0.1001***	−0.0831***	−0.1161***
	(0.0003)	(0.0010)	(0.0015)	(0.0014)
Log turnover	−0.0064***	0.4907***	0.6306***	0.7118***
	(0.0002)	(0.0007)	(0.0015)	(0.0009)
Labor productivity	0.0006***	0.0056***	0.0044***	0.0012***
	(0.0001)	(0.0003)	(0.0003)	(0.0003)
Profitability	0.0143	−0.7761***	−3.3294***	−3.9912***
	(0.0578)	(0.1948)	(0.2638)	(0.2546)
Sh. of empl. w. tert. edu.	−0.0104***	0.0217***	0.0174***	0.0359***
	(0.0012)	(0.0039)	(0.0062)	(0.0051)
Constant	0.0489***	−6.3186***	−8.7339***	−9.3097***
	(0.0042)	(0.0143)	(0.0313)	(0.0186)
Year dummies	Yes	Yes	Yes	Yes
Baseline age effects	Yes	Yes	Yes	Yes
Observations	1,611,818	1,611,818	583,242	1,611,818
Firms	434,247	434,247	151,341	434,247
R^2	0.847	0.347	0.334	0.380
AIC	−2,752,707	1,165,544	659,615	2,028,284
BIC	−2,752,129	1,166,122	660,145	2,028,862
F	141,986	13,589	4,699	15,665

Note: FE regressions; standard errors in parentheses; ***, **, * indicate significance at the 1, 5, and 10% levels.

TABLE A4 Regression of firm growth on adding new skills depending on firm age (young vs. old and de novo firms vs. spinoffs)

	(1)	(2)	(3)	(4)
	Log turnover growth (de novo firms)	Log turnover growth (spinoffs)	Log turnover growth (<=10 empl.)	Log turnover growth (>10 empl.)
Share of new skills	1.7091***	0.9319***	1.3091***	0.5183***
	(0.0277)	(0.0979)	(0.0297)	(0.0862)
Firm age = 2 # Sh. of new skills	−1.0203***	−0.4385***	−0.9170***	−0.2711**
	(0.0379)	(0.1442)	(0.0406)	(0.1240)
Firm age = 3 # Sh. of new skills	−1.5618***	−0.6467***	−1.3612***	−0.1000
	(0.0410)	(0.1459)	(0.0440)	(0.1208)
Firm age = 4 # Sh. of new skills	−1.9037***	−1.0398***	−1.6099***	−0.2589**
	(0.0450)	(0.1621)	(0.0483)	(0.1259)
Firm age = 5 # Sh. of new skills	−2.1455***	−1.3595***	−1.7837***	−0.4496***
	(0.0494)	(0.1775)	(0.0535)	(0.1298)
Firm age = 6 # Sh. of new skills	−2.2430***	−1.1597***	−1.8300***	−0.5182***
	(0.0542)	(0.1847)	(0.0589)	(0.1355)
Firm age = 7 # Sh. of new skills	−2.4329***	−1.1579***	−1.9844***	−0.5636***
	(0.0603)	(0.2038)	(0.0660)	(0.1404)
Firm age = 8 # Sh. of new skills	−2.6095***	−1.2739***	−2.1321***	−0.6608***
	(0.0666)	(0.2260)	(0.0733)	(0.1510)
Firm age = 9 # Sh. of new skills	−2.6718***	−1.4885***	−2.1502***	−0.5974***
	(0.0722)	(0.2510)	(0.0803)	(0.1567)
Firm age = 10 # Sh. of new skills	−2.7933***	−1.2478***	−2.2252***	−0.6772***
	(0.0820)	(0.2614)	(0.0911)	(0.1691)
Firm age = 11 # Sh. of new skills	−2.8794***	−1.1776***	−2.4517***	−0.4979***
	(0.0946)	(0.3129)	(0.1069)	(0.1876)
Firm age = 12 # Sh. of new skills	−3.0642***	−1.5271***	−2.4376***	−0.6451***
	(0.1126)	(0.3607)	(0.1256)	(0.2176)
Firm age = 13 # Sh. of new skills	−3.0779***	−1.6967***	−2.4987***	−0.6837**
	(0.1345)	(0.5075)	(0.1502)	(0.2680)

(Continues)

TABLE A4 (Continued)

	(1)	(2)	(3)	(4)
Firm age = 14 # Sh. of new skills	−3.2359***	−1.9141***	−2.6759***	−0.4172
	(0.1722)	(0.5705)	(0.1959)	(0.3179)
Firm age = 15 # Sh. of new skills	−3.5135***	−1.4411*	−3.2039***	−0.3537
	(0.2453)	(0.7929)	(0.2859)	(0.4446)
Share recruits	0.0568***	0.2804***	0.0526***	0.6524***
	(0.0043)	(0.0170)	(0.0043)	(0.0213)
Share leavers	−0.1172***	−0.0927***	−0.1299***	−0.2899***
	(0.0014)	(0.0040)	(0.0015)	(0.0140)
Log turnover	0.7182***	0.4522***	0.7302***	0.4889***
	(0.0009)	(0.0062)	(0.0009)	(0.0086)
Labor productivity	0.0004	0.0500***	−0.0005	0.0906***
	(0.0003)	(0.0027)	(0.0003)	(0.0059)
Profitability	−4.0056***	254.8681***	−4.0037***	1870.2019***
	(0.2552)	(22.7129)	(0.2542)	(452.1976)
Sh. of empl. w. tert. education	0.0381***	−0.0341	0.0398***	0.0301
	(0.0052)	(0.0253)	(0.0051)	(0.0424)
Constant	−9.3779***	−6.4040***	−9.5381***	−6.7287***
	(0.0188)	(0.1238)	(0.0188)	(0.1616)
Year dummies	Yes	Yes	Yes	Yes
Baseline effects age	Yes	Yes	Yes	Yes
Observations	1,575,914	35,904	1,578,547	33,271
Firms	426,596	7,651	431,354	10,750
R^2	0.383	0.343	0.388	0.378
AIC	1,988,409	31,026	1,968,657	20,935
BIC	1,988,986	31,425	1,969,234	21,331
F	15,487	321	15,832	297

Note: FE regressions; standard errors in parentheses; ***, **, * indicate significance at the 1, 5, and 10% levels.

TABLE A5 Regression of firm growth on adding new skills depending on firm age (de novo firms vs. spinoffs for different number of skills in founder team)

	Skill in founder team =1		Skill in founder team >1	
	(1)	(2)	(3)	(4)
	De novo firms	Spin-off firms	De novo firms	Spin-off firms
Share of new skills	1.6327***	0.3405	1.5949***	1.0499***
	(0.0370)	(0.2369)	(0.0385)	(0.1073)
Firm age = 2 # Sh. of new skills	−0.7799***	0.1722	−1.1189***	−0.5647***
	(0.0493)	(0.3407)	(0.0560)	(0.1587)
Firm age = 3 # Sh. of new skills	−1.4383***	−0.3621	−1.4826***	−0.7051***
	(0.0530)	(0.3257)	(0.0604)	(0.1625)
Firm age = 4 # Sh. of new skills	−1.7567***	−0.4749	−1.8120***	−1.1544***
	(0.0581)	(0.3559)	(0.0658)	(0.1812)
Firm age = 5 # Sh. of new skills	−2.0492***	−1.0866***	−1.9739***	−1.3842***
	(0.0635)	(0.4158)	(0.0723)	(0.1956)
Firm age = 6 # Sh. of new skills	−2.2314***	−0.2787	−1.9260***	−1.3351***
	(0.0693)	(0.4161)	(0.0798)	(0.2051)
Firm age = 7 # Sh. of new skills	−2.3817***	−1.0427**	−2.1708***	−1.1608***
	(0.0769)	(0.4463)	(0.0888)	(0.2277)
Firm age = 8 # Sh. of new skills	−2.6113***	−0.3437	−2.2830***	−1.4525***
	(0.0839)	(0.4962)	(0.0998)	(0.2523)
Firm age = 9 # Sh. of new skills	−2.6847***	−0.6772	−2.2752***	−1.5935***
	(0.0907)	(0.5390)	(0.1089)	(0.2816)
Firm age = 10 # Sh. of new skills	−2.7809***	−0.7828	−2.4043***	−1.3336***
	(0.1018)	(0.5546)	(0.1259)	(0.2942)
Firm age = 11 # Sh. of new skills	−2.9841***	−0.5847	−2.3042***	−1.3147***
	(0.1206)	(0.7667)	(0.1381)	(0.3421)
Firm age = 12 # Sh. of new skills	−3.1502***	−0.6231	−2.5166***	−1.6614***
	(0.1436)	(0.7833)	(0.1637)	(0.4034)
Firm age = 13 # Sh. of new skills	−3.1034***	−0.5705	−2.5512***	−1.9158***
	(0.1651)	(1.1216)	(0.2104)	(0.5655)
Firm age = 14 # Sh. of new skills	−3.3401***	−2.3784**	−2.6045***	−1.7110***
	(0.2176)	(1.1325)	(0.2528)	(0.6529)
Firm age = 15 # Sh. of new skills	−3.5716***	−1.8756	−2.7275***	−1.3297
	(0.3034)	(1.8145)	(0.3769)	(0.8769)
Share recruits	0.0287***	0.4044***	0.1542***	0.2631***
	(0.0054)	(0.0399)	(0.0065)	(0.0188)
Share leavers	−0.1459***	−0.2123***	−0.1001***	−0.0827***
	(0.0020)	(0.0129)	(0.0018)	(0.0043)
Log turnover	0.7353***	0.3833***	0.5762***	0.4538***
	(0.0010)	(0.0157)	(0.0024)	(0.0070)
Labor productivity	−0.0019***	0.1351***	0.0235***	0.0439***
	(0.0004)	(0.0093)	(0.0009)	(0.0029)

(Continues)

TABLE A5 (Continued)

	Skill in founder team =1		Skill in founder team >1	
	(1)	(2)	(3)	(4)
Profitability	−3.5227***	436.9977***	−7.5490***	187.7654***
	(0.2939)	(37.3528)	(0.4679)	(29.3091)
Sh. of empl. w. tert. edu.	0.0485***	−0.0519	0.0016	−0.0366
	(0.0061)	(0.0626)	(0.0085)	(0.0276)
Constant	−9.4691***	−5.1964***	−8.1183***	−6.4757***
	(0.0205)	(0.2940)	(0.0471)	(0.1387)
Year dummies	Yes	Yes	Yes	Yes
Baseline age effects	Yes	Yes	Yes	Yes
Observations	1,346,041	5,989	229,873	29,915
Firms	367,804	1,214	58,792	6,437
R^2	0.388	0.445	0.360	0.329
AIC	1,757,369	4,167	212,828	26,610
BIC	1,757,938	4,482	213,314	27,001
F	13,458	83	2088	249

Note: FE regressions; *SE* in parentheses; ***, **, * indicate significance at the 1, 5, and 10% levels.

TABLE A6 Regression of firm growth on adding new skills depending on firm age (three-way interaction of age, share of new skills, and the dummy variable for spin-off firms)

	(1)
	Log turnover growth
Share of new skills	1.6985***
	(0.0274)
Age of company = 2	−0.2115***
	(0.0016)
Age of company = 3	−0.2803***
	(0.0018)
Age of company = 4	−0.3293***
	(0.0020)
Age of company = 5	−0.3701***
	(0.0022)
Age of company = 6	−0.4062***
	(0.0025)
Age of company = 7	−0.4337***
	(0.0028)
Age of company = 8	−0.4611***
	(0.0031)
Age of company = 9	−0.4816***
	(0.0035)
Age of company = 10	−0.5081***
	(0.0039)
Age of company = 11	−0.5267***
	(0.0043)
Age of company = 12	−0.5515***
	(0.0048)
Age of company = 13	−0.5671***
	(0.0056)
Age of company = 14	−0.5754***
	(0.0067)
Age of company = 15	−0.5738***
	(0.0088)
Age of company = 2 # share of new skills	−1.0180***
	(0.0378)
Age of company = 3 # share of new skills	−1.5578***
	(0.0409)
Age of company = 4 # share of new skills	−1.8980***
	(0.0448)
Age of company = 5 # share of new skills	−2.1391***
	(0.0492)
Age of company = 6 # share of new skills	−2.2362***
	(0.0540)

(Continues)

TABLE A6 (Continued)

	(1)
Age of company = 7 # share of new skills	−2.4251***
	(0.0601)
Age of company = 8 # share of new skills	−2.6009***
	(0.0664)
Age of company = 9 # share of new skills	−2.6632***
	(0.0719)
Age of company = 10 # share of new skills	−2.7841***
	(0.0817)
Age of company = 11 # share of new skills	−2.8693***
	(0.0942)
Age of company = 12 # share of new skills	−3.0534***
	(0.1121)
Age of company = 13 # share of new skills	−3.0672***
	(0.1339)
Age of company = 14 # share of new skills	−3.2246***
	(0.1716)
Age of company = 15 # share of new skills	−3.5018***
	(0.2443)
Spinoff = 1 # share of new skills	−0.3833***
	(0.1214)
Age of company = 2 # spinoff = 1	−0.2606***
	(0.0132)
Age of company = 3 # spinoff = 1	−0.2963***
	(0.0137)
Age of company = 4 # spinoff = 1	−0.3244***
	(0.0143)
Age of company = 5 # spinoff = 1	−0.3232***
	(0.0151)
Age of company = 6 # spinoff = 1	−0.3242***
	(0.0160)
Age of company = 7 # spinoff = 1	−0.3266***
	(0.0168)
Age of company = 8 # spinoff = 1	−0.3294***
	(0.0179)
Age of company = 9 # spinoff = 1	−0.3127***
	(0.0193)
Age of company = 10 # spinoff = 1	−0.3132***
	(0.0209)
Age of company = 11 # spinoff = 1	−0.3177***
	(0.0231)

TABLE A6 (Continued)

	(1)
Age of company = 12 # spinoff = 1	−0.2756***
	(0.0259)
Age of company = 13 # spinoff = 1	−0.2590***
	(0.0308)
Age of company = 14 # spinoff = 1	−0.2742***
	(0.0373)
Age of company = 15 # spinoff = 1	−0.3773***
	(0.0490)
Age of company = 2 # spinoff = 1 # share of new skills	0.4133**
	(0.1859)
Age of company = 3 # spinoff = 1 # share of new skills	0.6846***
	(0.1884)
Age of company = 4 # spinoff = 1 # share of new skills	0.5717***
	(0.2092)
Age of company = 5 # spinoff = 1 # share of new skills	0.3756
	(0.2290)
Age of company = 6 # spinoff = 1 # share of new skills	0.6203***
	(0.2389)
Age of company = 7 # spinoff = 1 # share of new skills	0.7817***
	(0.2636)
Age of company = 8 # spinoff = 1 # share of new skills	0.8074***
	(0.2924)
Age of company = 9 # spinoff = 1 # share of new skills	0.5383*
	(0.3243)
Age of company = 10 # spinoff = 1 # share of new skills	0.6512*
	(0.3388)
Age of company = 11 # spinoff = 1 # share of new skills	0.9969**
	(0.4055)
Age of company = 12 # spinoff = 1 # share of new skills	0.7111
	(0.4683)
Age of company = 13 # spinoff = 1 # share of new skills	0.3605
	(0.6538)
Age of company = 14 # spinoff = 1 # share of new skills	0.6258
	(0.7403)
Age of company = 15 # spinoff = 1 # share of new skills	1.1490
	(1.0302)
Share recruits	0.0637***
	(0.0042)
Share leavers	−0.1128***
	(0.0014)

(Continues)

TABLE A6 (Continued)

	(1)
Log turnover	0.7147***
	(0.0009)
Labor productivity	0.0008**
	(0.0003)
Profitability	−3.9832***
	(0.2542)
Share of employees w. tertiary education	0.0364***
	(0.0051)
Constant	−9.3231***
	(0.0125)
Year dummies	Yes
Observations	1,611,818
Firms	434,247
R^2	0.381
AIC	2,023,857
BIC	2,024,791
F	9,678

Note: FE regressions; *SE* in parentheses; ***, **, * indicate significance at the 1, 5, and 10% levels.