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Entrepreneurship, human capital, and labor demand: a story of signaling and matching

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Abstract

In contrast to employee qualifications, there is no clear evidence that entrepreneurs' qualifications positively affect their income. In this study we propose that entrepreneurs can benefit from using their qualification as a signal during the process of recruiting employees. This is assumed to follow a process of matching equals among equals. We confirm a matching of qualification levels for highly skilled employees in Denmark, and an indication of this in Germany. Partial support for matching among medium-skilled employees was only found in Germany, with no consistent evidence of matching for low-skilled employees in neither country. This suggests that as skill levels of employees decrease, their probabilities of working for different founders converge. Founders' qualifications are the most reliable predictor of recruitment choices over time. Our findings are robust to numerous control variables as well as across industries and firm age.

JEL classification: J23, J24, J21.

1. Introduction

Higher qualification levels are generally associated with access to better jobs and higher earnings for employees—these facts are backed up with rich empirical evidence. However, when we turn our attention to entrepreneurs, the impacts of qualification are far more ambiguous, leaving questions about the role of human capital in nearly all stages of the entrepreneurial process.¹ For example, higher qualification levels have been demonstrated to have both positive and negative impacts on entry into entrepreneurship. Furthermore, the returns on entrepreneurial earnings are not straightforward, with different studies finding conflicting results. The positive results tend to be driven by the upper end of the distribution, since only a handful of entrepreneurs are able to achieve above-average earnings. Also, higher levels of human capital tend to positively correlate with survival and growth (Bates, 1985; Unger *et al.*, 2011;

1 See Parker and van Praag (2006), Hartog *et al.* (2010), Unger *et al.* (2011), and Åstebro and Chen (2014) to gain an impression on all these different effects.

Nielsen, 2015). Also, there are continuing efforts on the part of policymakers to understand how higher levels of qualification affect entrepreneurs' success in establishing healthy and thriving start-ups.

In this article we propose that entrepreneurs' human capital functions as a signal during the process of matching with employees. Specifically, since reliable signals of previous firm performance are not (yet) available, start-ups must attract personnel via other mechanisms (Bhidé, 2000). We argue that the qualification of the entrepreneur serves as a substitute signal for performance, making start-ups founded by more highly qualified entrepreneurs, instead of entrepreneurs with lower qualification levels, more attractive for employees. Education is considered as a subarea of qualification, but our focus is on the latter broader definition. Matching mechanisms steer the allocation of employees to firms since, for instance, not all employees can work for highly qualified entrepreneurs due to a limited number of positions. Established models predict that employing workers with similar skill levels [i.e., self-matching (Kremer, 1993)] allow firms to maximize profit. Accordingly, a matching of equals among equals should be the most promising strategy in a process that is mediated through different signals. In classic signaling theory, potential workers observe signals of firm productivity, and potential employers observe signals of worker productivity when productivity is unknown (Spence, 1973; Hopkins, 2011). However, our article is more concerned with how employees choose among entrepreneurs who lack a record of past performance.

In our empirical analysis, we investigate the existence of the signal (founders' human capital) and the matching process (self-matching) for start-ups in knowledge-intensive business services (KIBS) and manufacturing industries based on German and Danish data. The dual data setup will allow us to identify empirical regularities in employment choices across two different labor market settings: the Danish labor market, which is characterized by flexible employment with strong income security for dependent employees, and the German labor market, which involves institutionalized job protection, with the only notable exceptions being very small businesses (Brücker *et al.*, 2014). For Denmark, we rely on longitudinal data from Statistics Denmark, which provides a population perspective on the match between entrepreneurs and employees. For the German case, we assemble a unique data set for start-ups, based on our own survey of founders' personal information and data from the German Federal Employment Agency. We estimate the relationship between entrepreneurs' and employees' qualifications separately for firms of different ages, starting with a baseline model that can be estimated with either data set, and that is then extended with available country-specific variables.

In Denmark, and to a lesser extent in Germany, we find that highly skilled employees are more likely to work for medium- and highly skilled founders than for low-skilled founders. For medium-skilled employees, the suggested matching relationship can only be confirmed with German highly skilled founders. No consistent evidence is found for low-skilled employees. Extending the analysis to all industries, including various control variables, or applying alternative estimation techniques yields similar results. In sum, highly skilled employees are most likely to work for highly skilled founders. This points toward self-matching for highly skilled employees, with entrepreneurs' qualifications serving as a reliable signal for matching of this group at all investigated firm ages. In other words, no alternative signal appears to serve as replacement at later stages. Lower-skilled employees, on the other hand, have an equal chance of working for a low-, medium-, or highly skilled founder. Thus, low-skilled founders struggle most in their search for capable employees.

Previous studies have investigated the degree to which start-ups create jobs (Birch, 1979; Storey, 1994; Wagner, 1994; Sternberg and Wenckers, 2005; Fritsch and Weyh, 2006). However, the research has primarily focused on the number of jobs created, but not the type or quality of jobs (Baldwin, 1998), for example, as measured by qualification level. The importance of this topic has been stressed by small business owners who have rated labor shortages and human resource management as major obstacles, and who regret the lack of theoretical approaches and empirical evidence to address this issue (Heneman *et al.*, 2000; Katz *et al.*, 2000; Cardon and Stevens, 2004; Tansky and Henemann, 2006). Most studies disregard firm age, as, for instance, is the case with matching approaches. Due to a lack of experience and resources, the majority of start-ups do not yet have formal human resources strategies, instead relying on informal recruitment channels to attract employees (Cardon and Stevens, 2004; Aldrich and Ruef, 2006). We would like to expand this discussion with the argument that founders' human capital plays a significant role in explaining what type of employees a founder is able to attract (Dahl and Klepper, 2015). This reasoning allows us to contribute to the discussion on the entrepreneurial earnings puzzle (Roessler and Koellinger, 2012; Hyttinen *et al.*, 2013; Åstebro and Chen, 2014), in which entrepreneurs appear to earn less on average than similar employees (based on observable characteristics). Thus, it remains unknown why entrepreneurs' qualifications are not consistently positively related with income or performance.

To our knowledge, we are first to investigate (1) the matching approach for young and small firms and (2) the role of entrepreneurial human capital as a signal during the matching process. By doing so, we want to reconcile past contradictory findings in the literature on founders' human capital—thus solving the puzzle of entrepreneurial human capital—and to provide a different starting point for future research. We are aware that our analysis does not address causal relationships, but this is not required to report evidence on matching among individuals on the basis of different individual attributes. Even if qualification level proxies an underlying ability, it should not bias our results in light of the observable signal of human capital.

The remainder of the article is structured as follows. In Section 2, the theoretical background for the puzzle of entrepreneurial human capital is presented. Section 3 introduces the data, and Section 4 discusses the methodology and results. Section 5 concludes the article with a summary and implications for future research.

2. The puzzle of entrepreneurial human capital

2.1 Entrepreneurs' qualifications as a signal that reduces uncertainty

Building on the idea of signaling and the inherent uncertainty regarding start-ups, we suggest that the verifiable qualifications of the founder(s) of a start-up are crucial for attracting employees. Employees working for large, established firms receive higher earnings and enjoy more job security, making it difficult for start-ups to meet their own labor demand. For instance, Schnabel *et al.* (2011) demonstrate that employment stability is lower in start-ups than in incumbent firms, confirming the notion that job quality varies based on firm size and age. Also, a lack of financial resources and other benefits for employees, combined with low employment stability, might make it difficult to attract employees—particularly highly skilled ones—to new ventures (Brixy *et al.*, 2006; 2007). In addition, entrepreneurs are capital constrained (Van Praag *et al.*, 2005) due to information asymmetry between the founder and financier (Shane, 2003), and around half of all start-ups close down within 3 years (Van Praag, 2005). This makes employment opportunities in these ventures less attractive, as assessed by extrinsic work characteristics (i.e., factors not related to the work tasks). However, the existing literature suggests the opposite regarding intrinsic work characteristics (i.e., those related to the work tasks). Although entrepreneurs are found to earn less than employees (Hamilton, 2000), they report a higher degree of work satisfaction (Hundley, 2001). This can be explained by the difference in intrinsic work characteristics like independence, flexibility, and stimulation of skills between the two occupations. Based on the same logic, employees would prefer to work at start-ups if they offered more attractive intrinsic work characteristics and sufficient extrinsic ones. However, since the extrinsic work characteristics vary between large and small firms, entrepreneurs find it difficult to hire employees, a finding that is supported by Bhidé (2000) with regards to founders that have limited verifiable human capital and/or a novel business idea.

This leads to the question of what other approaches could be used to explain labor demand of start-ups. In the economics literature, the simplifying assumption of perfect information can be problematic, as “the labour market is replete with imperfect and asymmetric information” (Autor, 2001: 25). For start-ups, asymmetric information can be especially pronounced, since these firms have no or little history to use as a signal to potential workers. In fact, most start-ups still need to learn about their (endogenous) productivity, and inefficient job matches can be costly for such firms, since their productivity potential cannot be reached. In this case, the qualification of the entrepreneur can be considered an important signal for use in reducing information asymmetry. As highlighted by Devine and Kiefer (1993: 8–9), “[t]he basic hypothesis of ‘matching’ models is that employers and workers continue to learn about each other [...]”. In general, many characteristics of a specific job–worker combination are not observable, and only the realization of the job–worker combination will provide additional information about the match (Jovanovic 1979a,b). In the case of start-ups, initial observation error in the job–worker match is likely to be larger for younger firms than for older ones. For example, workers' future earning streams are more difficult to assess because of the higher failure rates of young firms. When the observation error is large, alternative signals like the entrepreneur's formal education may be relevant for informing workers about the potential job–worker match. Another interesting aspect can be derived from models that introduce different search costs for workers (Albrecht and Axell, 1984) and that allow search costs to vary by type of firm. In the case of young firms, workers will most likely face higher search costs as compared to older firms. However, information on the qualifications of entrepreneurs may reduce these search costs.

In sum, the uncertainty inherent to start-ups and the information asymmetry between the founder(s) and stakeholders (financiers, employees, etc.) regarding the ability, work ethics, and future decisions of the founder, make it

hard for the founder to obtain resources like capital and labor. However, the verifiable qualifications of the founder, like formal education and training, previous work experience and performance, could act as a signal to potential stakeholders that reduces uncertainty regarding the future performance of the new venture. Previous research has investigated the role of founders in the process of firm creation and growth, looking, for instance, at how founders' existing human capital influences their recognition and exploitation of opportunities (Shane and Venkataraman, 2000). Studies have found that both education (Unger *et al.*, 2011; Nielsen, 2015) and industry experience (Phillips, 2002; Van Praag, 2005) have a positive effect on start-up performance. If the firm survives the critical first 3 years, the survival curve continues to flatten. This implies that for surviving firms, the signal of entrepreneur qualification becomes less important, since the (job) uncertainty is heavily reduced.

2.2 Sorting of employees and entrepreneurs

A prominent approach to explain the sorting of employees and employers is matching models. Most models of job matching build on the premise that labor markets consist of heterogeneous firms. These firms offer a variety of jobs that require different skill sets and experience, and thus, heterogeneous workers who possess various skill sets and experience. Ideally, workers with the highest qualification levels will hold positions that require the most skills. Under conditions of perfect information, workers will theoretically be sorted into jobs that allow aggregate output to be maximized (Mortensen, 1978). Differences in firm productivity then allow for variations in wage offers (Mortensen, 1990), moderating the matching process. For firms, a suitable match between the skills of workers and the positions available allows the workers' skills to be utilized in a way that maximizes productivity (Jovanovic, 1979a). This also allows employees to find better-paid jobs (Sørensen and Kalleberg, 1981). A mismatch may occur, however, if the supply of skilled workers exceeds that of skilled jobs and vice versa (Jovanovic 1979a; Sørensen and Kalleberg, 1981). Although information asymmetries may impede perfect matching and maximizing output, the sorting processes are still in place. However, the open question remains as to what types of jobs are matched with which types of workers.

Milgrom and Roberts (1990) put forward the idea that firms decide whether to group together complementary activities. This is described as a supermodular function, where employees with similar skills are matched, as opposed to a submodular function, in which skills are cross-matched. A popular study of the submodular function was introduced by Rosen (1981), who investigated the reasons for large wage differentials between highly talented persons, superstars, and other individuals. Possible explanations for such a phenomenon include, first, imperfect substitution. This means that lesser talent cannot substitute for greater talent, which is why talented individuals earn significantly more money. As a second explanatory mechanism, Rosen (1981) suggests the effects of technology, whereby the production costs do not rise in proportion to the market. Kremer (1993) introduced the O-ring production function, which provides an example of a supermodular function. The idea is that workers of similar skills need to be matched together to generate a valuable product and decrease the chances of failure. In such an environment, quantity cannot substitute for quality. Similar to Rosen (1981), this implies that hiring several low-skilled workers to substitute for one highly skilled worker is not effective. Kremer gives the example of a construction firm looking for bricklayers that match the skills of its carpenters, electricians, and plumbers. A similar approach was suggested in the entrepreneurship literature by Lazear (2004, 2005) to address the skill balance of entrepreneurs. Since entrepreneurs need to fulfill a variety of tasks, their success depends on the skill that is weakest. That is why they invest in improving their weakest skill to avoid it limiting their success. Lazear's idea was empirically confirmed by comparing the generalized skill sets of entrepreneurs and the specialized skill sets of employed persons, with the result being that entrepreneurs are, on average, more balanced in terms of skills than employees (Wagner 2003, 2006; Hyttinen and Ilmakunnas, 2007; Bublitz and Noseleit, 2014). It appears that Lazear's skill balance approach is a specific example of a one-man enterprise, where the O-ring production function works through all of the skills embodied by one individual. Taking into account the previous empirical evidence and the peculiarities of start-ups, we believe that the same production, and thus matching, function should hold when the first employees are hired. Against this backdrop, it appears reasonable to assume that entrepreneurs will try to hire employees that match their own entrepreneurial skill level (self-matching) rather than hiring less or more highly skilled individuals (cross-matching).

In a simple framework, our main ideas can be summarized as follows: while the employees' income is a function of their own human capital, entrepreneurs' income (a measure of firm performance) is a function of both the entrepreneurs' and their employees' human capital. During the matching process, the expected income of workers is thus determined by (1) the founder's human capital and (2) the firm's past performance, where the signaling value of (1) decreases and that of (2) increases over the life span of the start-up. In the empirical analysis, we will not focus on

determining the conditions under which firms and employees maximize output, but rather on the importance attached to human capital during the matching process.

3. Data on start-ups and employees

To investigate whether qualification of the founder acts as a signal during the matching process with employees, we rely on detailed information from administrative databases in Germany and Denmark.

For Germany, we use the GAW-ADIAB², which consists of a survey that is linked with the Establishment History Panel (BHP) at the Institute for Employment Research of the German Federal Employment Agency (see [Fritsch et al., 2015](#)). This merged data set is unique in Germany and is suitable for use in addressing our research question regarding the labor demand of start-ups because it allows us to observe the development of the employees by qualification category and relate it to the characteristics of the founder. The latter information became available for the first time in conjunction with the BHP employment statistics with the release of the GAW-ADIAB. The BHP data set is collected via an administrative process, whereby employers are legally required to report information about all employees who are obliged to be part of the social security system. However, despite its reliability, the data set lacks information on firm and employer characteristics. To compensate for this shortcoming, we collected additional data from founders in Germany who are listed in the BHP as having employed at least one worker subject to social security—but no more than 20 upon entering the sample—between 2002 and 2008.³ Interviews were conducted using a computer-assisted telephone interviewing software, producing a response rate of 31%. Based on this survey, we are able to include personal information about founders—for example, their educational attainment, work experience, and psychological traits—along with information about the firm.

The businesses in our German sample were founded between 1990 and 2008 and are active in manufacturing and KIBS in six different regions.⁴ The founders in our sample started to hire employees in 2002 at the earliest, with subsequent employment growth observed until 2008. In the baseline specification, we observe 1033 establishments for at least 1 year. The GAW-ADIAB therefore reliably captures firms that are small and emerging—attributes that are indispensable prerequisites for our research question.

To construct the Danish sample of start-ups and employees, we identify all start-ups during the period of 2001–2011 from the Danish entrepreneurship registry administered by Statistics Denmark. Start-ups founded before 2001 are not included because of a structural break in the entrepreneurship registry; the upper boundary of 2011 is chosen due to data availability.⁵ This entrepreneurship database allows us to isolate newly registered firms and the (primary) founder of the new venture. To identify the employees in these new ventures, the information from the entrepreneurship register is merged with data from the Integrated Database for Labor Market Research (IDA), a longitudinal data set also administered by Statistics Denmark, containing detailed information on all firms and individuals in the labor force from 1980 onward (for more information, see [Timmermans, 2010](#)). It is possible to identify employees many years after the founding, provided that the new firms survive. Given the level of detail in the data set, it is frequently

2 This abbreviation is short for survey data from “Gründungsgeschehen und Arbeitsmarkt in ost- und westdeutschen Wachstumsregimen” (GAW, new business formation and the labor market in East and West German growth regimes) and registry data from “Administrative Daten des Instituts für Arbeitsmarkt- und Berufsforschung” (ADIAB, administrative data from the German Institute for Employment Research).

3 The fixed time frame was implemented to avoid the problem of perforated establishment IDs (cf. [Fritsch and Brixy, 2004](#)) and to ensure that entrepreneurs were available for interviews at their firm addresses.

4 In a different analysis of the data, only a negligible selection bias was found in the sample ([Bublitz et al., 2015](#)). All manufacturing establishments were contacted if they had newly entered the BHP between 2003 and 2008 and were active in 2010 in the sample regions. Our original sample covered 75–80% of all firms that had newly emerged between 2003 and 2008 in these industries. The restriction to two industries and six regions was necessary due to financial constraints, but allowed us to achieve high coverage rates within the chosen industries and regions. The regions were chosen to represent three different agglomeration levels in both East and West Germany.

5 Compared to the German data, the Danish data have more years available for the analysis. We take advantage of the data availability by using the entire period at our disposal. Since the additional years also include periods of crises, which might bias some of our results, we later run additional robustness checks on the Danish data that only include the years 2002–2008 (i.e. the same hiring years included in the German sample).

used in entrepreneurship research (Nanda and Sørensen, 2010; Dahl and Sorenson, 2012). To assure that we identify start-ups and not corporate spin-offs or new economic activities other than the establishment of a new independent business, start-ups with more than 20 employees in their founding year are excluded. These specifications result in 152,596 start-ups; with 41,252 active in manufacturing and KIBS.

Using the German and Danish data allows us to capitalize on specific strengths of the two data sets. The German data, due to its distinct survey design, permit us to identify true founders and exclude corporate spin-offs and other new economic activity that would not be classified as a start-up. Furthermore, the German sample contains information on founder characteristics, such as psychological variables and motivation, and on knowledge variables, such as employee experience, skill balance, and founder teams. In the Danish sample, we have data that cover all industries, rather than only manufacturing and KIBS, allowing the identified matching mechanisms to potentially be generalized. In addition, the data include information on regional experience, wealth, income, and personal ownership.

A detailed overview of the two data sets, including the construction of variables, can be found in Table A1. For a baseline specification, we use the same main variables for the two samples, allowing a cross-national comparison of labor demand in start-ups. Differences between the data sources are then used for unique sensitivity analyses in the extended models.

3.1 Dependent variables

The dependent variables consist of three count variables that measure the number of employees in the categories of low-skilled, medium-skilled, and highly skilled, during three stages of start-up development (3, 6, and 9 years). Low-skilled employees are defined as employees who have not completed secondary school or who have no vocational qualification. Medium-skilled employees consist of graduates of upper secondary school or those who have completed a vocational qualification. Highly skilled employees are those workers who have obtained, at a minimum, a degree from a specialized college of higher education or a university.

3.2 Independent variables

In the analysis we create a baseline model that allows us to compare the results of the Danish and German samples. In addition to this baseline model, we develop extended models to analyze founder and firm characteristics that are available exclusively in either the German or the Danish data.

The main independent variables featured in the baseline model are the signals founders use to attract employees. First, we create a series of dummy variables indicating the formal qualification of the founder at the time of founding. Formal qualifications of the founder follow the same categorization as the qualifications of employees (i.e., low, medium, and high). Experience can act as another signal, which we measure along four dimensions:

- previous self-employment experience or serial entrepreneurship (measured in number of years, and a count variable for the number of ventures founded, respectively), by which prospective employees can evaluate the entrepreneur's previous success as a founder;
- previous industry experience (a dummy variable or the number of years of work experience in the same industry), by which a prospective employee can evaluate the industry-specific knowledge of the entrepreneur;
- a dummy variable indicating whether the founder was unemployed prior to founding the start-up; and
- a dummy variable indicating whether the founder had self-employed parents.

In addition to these labor market signals, we control for sociodemographic variables that might determine the ability to attract employees, like the age of the founder (including age squared) and dummy variables indicating sex and marital status. Finally, control dummies for industry, region, and year complete the set of independent variables in the baseline model. Some variables differ slightly between the two data sets (see Table A1 for more details).

In the extended model, we include a series of country-specific variables for the knowledge and experience of the founder. In the case of Germany, we add variables such as the number of years the person has been working as an employee, a dummy variable indicating whether the start-up was founded by a team, entrepreneurial balance as measured by the number of professional fields in which the founder was active before start-up, psychological traits of the founder that are often associated with entrepreneurship, and a range of start-up motivations, including both intrinsic and extrinsic factors (e.g., creating something new and earning money). From the IDA, we include the following founder-specific measures: founder's pre-start-up income, regional experience in years, measures of household wealth for the founder and the founder's parents, and the ownership type for the new venture (a dummy for personal

Figure 1. Development of employees' qualification levels in start-ups in Germany (manufacturing and KIBS).

ownership). In addition, we test whether the results hold across all industries. See [Table A1](#) for the specific categories in the German and Danish data and [Table A2](#) for summary statistics. The correlations of the variables are provided in Supplementary Tables S1–S4 online.

4. Employment decisions of founders in Germany and Denmark

4.1 Employee development over time

[Figure 1](#) plots the average number of employees in manufacturing and KIBS start-ups in Germany with high (HQ), medium (MQ), and low (LQ) qualification levels over the life span of the start-up. These averages are based on all firm-year observations available in the data set, which means that the number of observations declines over the period. At founding, the average start-up in the German sample employs 1.28 medium-skilled workers, making this employee group by far the largest labor input. Highly skilled employees are the second-largest group, with an average of 0.33, making low-skilled employees the smallest labor input, with 0.12. Furthermore, the distribution of qualification groups is relatively stable for start-ups over time in the German case.

[Figure 2](#) shows how the qualification levels of employees in Danish manufacturing and KIBS start-ups develop. Similar to the German case, the average number of employees with a medium qualification level is larger than the average number with low or high qualification levels, regardless of firm age. In the founding year, the average number of medium-skilled employees is 0.3, compared to 0.1 for both low- and highly skilled employees. In contrast to the German data, the average number of employees with high, medium, and low qualification levels increases as the firm gets older, to the values 0.8 (HQ), 1.1 (MQ), and 0.5 (LQ) in the ninth year.

When including all industries in Denmark, there are some noticeable differences (see [Figure 3](#)). First, medium-skilled workers remain the largest group, but the average number of medium-skilled workers is higher and grows faster, although in a decreasing rate, over the 9-year life span. High-skilled workers are the smallest category and also experience the lowest growth rate; but the growth rate appears to be constant. On average, and unsurprisingly, low-skilled employees are more common in this larger sample and similar as medium-skilled workers grow with a decreasing rate over the 9-year life span. In sum, firms operating in manufacturing and KIBS require more skilled labor when compared to labor inputs in all industries, and, over time, the share of high-skilled employees continuously increases in the full industry sample.

4.2 Matching of employees' and founders' qualifications

To assess the relevance of founders' qualifications as a signal for subsequent matching of employees with similar skill levels, we regress the number of highly, medium-, and low-skilled employees on the formal qualification of the founder at three points in time—3, 6, and 9 years after founding.⁶ Focusing on these periods allows us to identify potential

⁶ Here, we would like to make the reader aware that due to relatively high mortality rates of young firms, there exists a survivor bias for the firms we select. Consequently, the sample will underrepresent unsuccessful new ventures, particularly in the samples with firms that are older. Since we do not know whether a lack of available employees played a role, we also cannot make any statements on the role of matching in firm success.

Figure 2. Development of employees' qualification levels in start-ups in Denmark (manufacturing and KIBS).

Notes: ***, **, * significant at the 1%, 5%, 10% level. The number of signs reflects the magnitude of the association, with + < ++. LQ is a low, MQ is a medium, HQ is a high qualification level. Dark grey describes the suggested matching relationship. Light grey (white) stands for HQ (MQ) founders. The numbers are the marginal effects of 18 separate negative binomial regressions for each country (see Annex).

Figure 3. Relationship between founder's qualification level and the number of employees by qualification level and firm age for firms in Denmark and Germany (based on baseline regression results in Tables A3 and A4).

changes in the importance of founders' formal qualifications over time. The data are restricted to those founders for whom information is available on all relevant variables. Thus, since the majority of firms are relatively young, they can only be observed for a short time. The models are estimated with the following equation:

$$Emp_i^{Q,t} = \beta_1^t MQE_i + \beta_2^t HQE_i + \gamma X_i^t + \epsilon_i^{Q,t},$$

(with $t = 3, 6, 9$ years and $Q = \text{low, medium, and high qualification level}$)

Where Emp is the number of employees with qualification Q for all firms i in the sample that are t years old. MQE represents a dummy variable indicating that the founder of firm i has a medium qualification level. HQE represents a dummy variable that identifies founders with high levels of formal qualification. Founders with low levels of formal qualification form the reference group. Additional control variables in the baseline and extended models are represented by the vector X . Our dependent variables are positive count variables. We prefer to use the number of employees over an employment share because shares are subject to extreme changes when employment figures tend to be rather low—as in our case of relatively young businesses. Thus, estimations of count data using ordinary least squares (OLS) would result in biased estimates. Moreover, we aim to compare predictions and therefore require an estimator that allows prediction on the scale of the data. Also, the negative binomial regression model is more suitable than Poisson regressions because of overdispersion. We always report marginal effects. In the German data, standard errors are bootstrapped to provide more reliable standard errors in light of the small sample. Tables A3 and A4 in the Annex report the regression results for Germany and Denmark, respectively, sorted by employee qualification level and firm age.

For illustrative purposes, Figure 3 provides an overview of on the main findings from the 18 regressions. More specifically, the figure shows whether the qualification level of the entrepreneur is related to the number of employees with different formal qualification levels, and whether this relationship changes over time. The color code of the figure reads as follows. White and light grey boxes (□ □) show the empirical results of medium-skilled founders and highly skilled founders, respectively. The dark grey boxes (■) indicate the expected matching relationships. An empty box with dotted lines (□) shows instances where no significant differences are identified, while boxes with solid lines highlight significant differences. The number of signs inside the boxes with solid lines reflects the magnitude of the association between employees' and founders' qualifications. The results should be interpreted against the reference group of low-skilled entrepreneurs. For example, a positive sign in a box with solid lines indicates that, relative to founders with low qualification levels, a medium or high formal qualification level of founders is associated with a significantly higher number of employees in the same employee qualification group. The results for Germany are shown in the top box and for Denmark in the box directly below. Following the argument of a matching of equals among equals, the basic idea is that start-ups primarily employ workers that have the same qualification level as the entrepreneur. As the difference between the founder's and the employees' qualifications increases, less employees in the founder's qualification levels are found in the firm. In the case that founders are less qualified than prospective workers, it becomes more difficult to attract these potential employees to come work for the firm. If founders are more highly qualified than employees, this prospective worker group is of less interest to the entrepreneur than more qualified personnel. The relationships between founders' qualifications and the number of employees by qualification level thus become weaker or even negative with an increasing difference between the qualification levels. Accordingly, for low-skilled employees, Column 1 shows negative signs (with a larger negative association for highly skilled than for low-skilled founders). For highly skilled employees, Column 3 is positive (with a larger positive association for highly skilled than for medium-skilled founders). Finally, for medium-skilled employees, Column 2 displays positive signs for medium-skilled founders and no significant difference between the other qualification levels.

Concerning low-skilled employees, Column 1 shows that German founders with different qualification levels employ a similar number of low-skilled employees when their businesses are 3 years old, while in Denmark, only founders with high qualification levels employ fewer low-skilled employees (see also Columns 1–3 in Table A3 for Germany and in Table A4 for Denmark). However, in Denmark, which has an average of 0.07 fewer employees relative to the reference group of low-qualified founders, the estimated difference is rather small. There are no significant relationships between founder qualification and recruitment of low-skilled workers in Denmark and Germany after 6 and 9 years. Thus, for this employee group, very limited support for matching is found in Denmark in year 3 and no support for matching is found in Germany in general.

Column 2 in Figure 3 shows partial support for the matching idea (see also Columns 4–6 in Table A3 for Germany and in Table A4 for Denmark). The insignificant results for highly skilled entrepreneurs in Germany and, in one case, Denmark, are in line with the matching approach. However, there is no evidence for a significant positive

relationship between entrepreneurs and employees with medium levels of qualification in Germany, which contradicts the matching idea. Instead, the suggested positive relationship is only present in Denmark in year 6; here, founders with medium levels of qualification have an average of 0.31 more medium-qualified employees. Interestingly, and contrary to the matching prediction, we also find a positive relationship between entrepreneurs that are highly skilled and employees with medium qualifications in years 6 and 9. Thus, the matching idea is partially supported in Denmark and Germany for medium-qualified employees.

Column 3 provides robust evidence for matching of qualification levels for highly skilled employees in the Danish data (see Columns 7–9 in Table A4). We find that medium- and highly skilled founders run businesses that employ, on average, more employees with high levels of formal qualification than founders with low formal qualification. The magnitude of this relationship is significantly larger for highly skilled than for medium-skilled founders, and this result holds regardless of firm age. For instance, after 9 years, highly skilled founders employ around 1.5 more highly qualified employees compared to low-skilled founders. For medium-skilled founders, this difference in highly skilled employment—relative to low-skilled founders—is only 0.54 on average. While the marginal effects in the German data point in the same direction, the results are only significant in a few cases (see Columns 7–9 in Table A3). Most prominently, after 3 years, German highly skilled founders have, on average, around 0.52 more highly skilled employees than their low-skilled counterparts.

4.3 Extended analyses

4.3.1 Robustness checks for baseline models

To test the robustness of the baseline model, which focuses on the manufacturing and KIBS industries, we use the Danish data to estimate OLS as well as negative binomial panel estimation with random effects (using information from all years, i.e., 1–10). The baseline results are confirmed. The OLS results support the matching of highly qualified founders with highly qualified employees (only the coefficient for highly qualified founder is significant), and partially support matching of medium qualifications (the coefficient for medium-qualified founders is significant in years 3 and 6), but do not support matching of low qualifications, since highly qualified founders do not hire fewer low-skilled employees. The results of the negative binomial panel estimation with random effects can be found in Table 1; because founder qualification is held constant, a fixed effects model is inappropriate. As previously reported, matching is fully supported for highly skilled entrepreneurs and employees, is not supported for medium employee qualifications, and is fully supported for low employee qualification, since both medium- and highly skilled founders hire fewer low-skilled employees, although the magnitude of the coefficient being larger for the highly skilled founders.

Regarding the German baseline estimates, none of the other explanatory variables show a robust or systematic relationship with the employment structure. Very few variables are significant and if so, only for one employee qualification group and a certain firm age. For Denmark, several of the control variables in the baseline model are significant. In general, male founders and founders with more industry experience are more likely to hire employees, regardless of their qualification level, while the opposite is true for founders who were unemployed before starting up. In addition, serial entrepreneurs in Denmark recruit more employees within all three qualification categories in the first years of operation, while their German counterparts only recruit more medium-skilled employees.

Table 1. Results from negative binomial panel estimations with random effects for the number of highly, medium-, and low-skilled employees (Denmark, manufacturing and KIBS)

	High	Medium	Low
Medium-skilled founder	0.143** (0.064)	0.029 (0.048)	−0.225*** (0.058)
Highly skilled founder	0.760*** (0.065)	−0.224*** (0.050)	−0.493*** (0.061)
Log-likelihood	−66,221	−98,952	−60,510
Observations	148,440	148,440	148,440

Note: Marginal effects with standard errors in parentheses. Significant at *** $P < 0.01$, ** $P < 0.05$, * $P < 0.1$. All models include control variables from the baseline regression and a full set of region, year, and two-digit NACE dummies, which are not reported for brevity.

4.3.2 Results from extended models

To test the robustness of the results, we introduce a set of extended models that include additional control variables (see Section 3.2 for details). For Germany, the results of the extended model are reported in Supplementary Table S5. With the exception of work satisfaction in year 3, these additional variables are always insignificant. Adding these variables hardly alters the relationships between the qualification levels of founders and employees, with the exception of medium-skilled founders and highly skilled employees in firms that are 3 years old. These differences in the results do not change our main story.

As another alternative, we test whether replacing firm age with a different time measure would affect the results. One could argue that successful matching depends more on whether founders have already successfully recruited their first employee. In that case, the focus shifts to the development of the workforce, and thus, we use the number of years since the first hire as a proxy for recruiting or human resource experience. However, the results do not change substantially but continue to confirm the importance of founder qualification (results are available upon request).

Turning to Denmark, the robustness tests are carried out in two steps. First, the baseline model is extended with different control variables (for the extended model, see Supplementary Table S6). Second, the baseline and extended models are repeated on a sample that includes all industries rather than limiting the analysis to manufacturing and KIBS (see Supplementary Tables S7 and S8). In the extended models, regional experience and personal ownership show a consistently negative relationship with the recruitment of employees, irrespective of qualification level, while in most cases, previous income exhibits a positive correlation with hiring. Household and parent wealth show no systematic associations with hiring. The associations between the qualification levels of founders and highly skilled employees are robust, that is, highly skilled founders are more likely to hire highly skilled employees than medium-skilled founders, and medium-skilled founders are more likely to hire highly skilled employees compared to low-skilled founders. Medium-qualified founders still hire more medium-skilled employees in year 6, but highly skilled founders no longer hire more medium-skilled employees in that year. In addition, highly skilled founders hire fewer low-skilled employees in years 3 and 9.

The main results from the baseline and extended models for *all industries* can be found in Supplementary Tables S7 and S8. The results indicate that the recruitment of highly qualified employees in manufacturing and KIBS is representative of the entire sample, and that matching based on qualification is supported for this employee group. The matching of medium-skilled employees is only partially supported because although medium-skilled entrepreneurs hire significantly more medium-skilled workers compared to low-skilled workers, highly skilled founders always hire the highest number of medium-skilled workers. Finally, in the baseline model, there is no significant difference between founder qualification and low-skilled employees; however, in the extended model, founders with high qualifications are significantly less likely to hire low-skilled employees. This result is in line with the expected matching relationships, but since it only works for the sample with all industries and additional control variables, it may be driven by a more heterogeneous sample, which hints at a more selective recruitment process by highly skilled founders. In general, findings concerning potential matching are in line with the previous results from the sample that included only the manufacturing and KIBS industries.

Finally, to ensure that the crisis years do not influence the main results, negative binomial regressions are conducted on a subsample for the years 2002–2008 (i.e., the same hiring years as in the German sample) for the manufacturing and KIBS industries in Denmark. Again, matching between founders and employees is fully supported for highly skilled, partially supported for medium-skilled and not supported for low-skilled individuals (results are available upon request).

5. Conclusions

Our study adds to a better understanding of the role of founders' qualification levels. While the existing research has failed to document a consistent link between schooling and income of the self-employed, we highlight that qualification may instead fulfill an important signaling function at the early stages of a new venture, allowing the firms to attract employees with different skill levels. Based on data from Germany and Denmark, we find evidence that firms' employment decisions are shaped by the qualification levels of the entrepreneurs and their prospective employees. The results provide evidence for matching by qualification level for highly skilled employees, but suggest that other factors may interfere with this relationship for lower-skilled employees. In general, as the skill level of the employees decreases, so does the propensity to observe a matching of equals among equals, an effect that is most robustly shown in the Danish sample. The qualification of the entrepreneur is the most reliable predictor of recruitment decisions when matching is observed, as we cannot identify robust alternative explanatory mechanisms among the various variables and sample specifications.

Our work aims to fill an important research gap with regard to the founding and evolution of new organizations and their labor demand. While this study does not completely solve the paradox of the schooling investments of

entrepreneurs, it does help inform future research. More specifically, we suggest that schooling is especially relevant for entrepreneurs as a signal. If investments in schooling are neither considered solely a means of increasing human capital investment nor a pure signal of unobserved ability but rather a continuum with the above options representing two idealized extremes, different labor market groups may occupy different positions in this continuum. In our case, for entrepreneurs, the relative weight is assumed to lean more toward signaling. Future research may investigate whether such differences also exist for different occupational groups by testing for signaling differences among other groups of employees (c.f. Lang and Krop, 1986; Tyler, Murnane and Willet 2000). Research could also address whether firms maximize their profits under the matching hypothesis. However, we also face problems that cannot be solved with the data made available for this study. For instance, qualification might matter on a more hidden level, at which founders might hire workers who compensate for their weaknesses (Granovetter, 1973). Further work on this topic can provide policy-makers with information about the type of labor needed by founders so as to avoid labor shortages and to encourage new venture growth. Many new businesses fail, and, so far, this has primarily been studied by focusing on founders' and founding teams' characteristics or business environments. What if part of the reason is a lack of access to adequate labor?

Supplementary Material

Supplementary material is available online.

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Table A1. Continued

	Germany	Denmark
Variable		
<i>Experience and sociodemographic characteristics</i>		
Qualification	<i>High</i> : Minimum qualification a degree from specialized colleges of higher education or universities <i>Medium</i> : Graduates from upper secondary school or with completed vocational qualification <i>Low</i> : Not completed secondary school or have no vocational qualification	See left
Industry experience	Number of years active in the industry before start-up	Binary variable taking the value 1 if the founder worked in the same two-digit NACE industry the year before founding the new venture
Self-employment experience	Number of years in self-employment before start-up	Not included
Number of previous start-ups	Number of firms that the founder has started before (excluding the present one)	Number of firms that the founder has started (including the present one)
Unemployment	Binary variable taking the value 1 if the founder was unemployed the year before founding the new venture	See left
Self-employed parents	Binary variable: Had a self-employed parent at the age of 15 years (1 = yes, 0 = no)	Binary variable taking the value 1 if one of the founder's parents is present in the entrepreneurship register or had a status as self-employed (personal ownership) before the founding year
Male	1 = male, 0 = female	See left
Age	Number of years	See left
Married	1 = married, 0 = not married	See left
<i>Firm variables</i>		
Firm age	Number of years that passed since first revenues	Number of years that passed since registration year
Human resource experience	Number of years passed since first hire	Not included
<i>Controls</i>		
Industry	Six dummies (one-digit NACE 2008)	19 Dummies (two-digit NACE)
Region	Six dummies (see above)	12 Dummies (see above)
Year	Six dummies for year of first hire (2003–2008)	11 Dummies for year of hire (2001–2011)
<i>Personality</i>		
Openness	“In my daily actions I act according to new ideas and experiments instead of established procedures.” (1 = does not apply, 7 = fully applies)	
Extraversion	“I am communicative.” (1 = does not apply, 7 = fully applies)	
Work satisfaction	“I am very satisfied with my work.” (1 = does not apply, 7 = fully applies)	
Locus of control	“What happens in my life depends on me.” (1 = does not apply, 7 = fully applies)	
Life satisfaction	“Overall, I am very satisfied with my life.” (1 = does not apply, 7 = fully applies)	

(Continued)

Table A1. Continued

	Germany	Denmark
General risk	“Are you in general a risk-loving or risk-averse person?” (1 = very risk-averse, 7 = very risk-loving)	
Private risk	“Assume that you have won 100,000 € in a lottery. You may use this money for your private benefit but you cannot invest it in your firm. Now you receive the chance to double the money. However, the risk to lose half of the invested money is equally high. How much of your money would you be willing to invest for this risky, but potentially rewarding lottery? 100,000, 80,000, 60,000, 40,000, 20,000 or nothing?” (1 = very risk-averse (invest nothing), 6 = very risk-loving (invest everything))	
<i>Motivation</i>		
Independence	“I want to be independent” (1 = does not apply, 7 = fully applies)	
Create something new	“I want to change something in the world, create something new.” (1 = does not apply, 7 = fully applies)	
Make money	“I want to make money.” (1 = does not apply, 7 = fully applies)	
Market niche	“I want to use a market opportunity, fill a gap in the market.” (1 = does not apply, 7 = fully applies)	
<i>Knowledge experience</i>		
Founding team	1 = yes, 0 = no	
Skill balance	Number of professional fields in which self-employed was active before start-up	
Employee experience	Number of years worked as dependently employed before start-up	
Region experience		Number of years that the entrepreneur lived in the municipality (categorization after the 2007 reform) of the new venture going 20 years back
<i>Wealth and income</i>		
Previous income		Natural logarithm of the wage income the year before founding the new venture
Household wealth		Natural logarithm to the wealth of the founder and spouse (partner) if married (in registered partnership) the year before founding the new venture
Parents wealth		Natural logarithm to the wealth of the founder's parent the year before founding the new venture
Personal ownership		Binary variable taking the value 1 if the new venture is personally owned and zero if it is a limited liability company

Table A2. Summary statistics

	Germany				Denmark			
	N	Mean	Median	S.D.	N	Mean	Median	S.D.
<i>GAW-ADIAB</i>					<i>IDA</i>			
Low-skilled founder (1=yes)	1033	0.028	0	0.165	152,596	0.187		0.390
Medium-skilled founder (1=yes)	1033	0.343	0	0.475	152,596	0.560		0.496
Highly skilled founder (1=yes)	1033	0.629	1	0.483	152,596	0.252		0.434
Self-employed experience	1033	2.528	0	4.943				
Industry experience	1033	10.617	10	9.232	152,596	0.359		0.480
Number of previous start-ups	1033	0.424	0	1.382	152,596	1.222		0.618
Self-employed parent	1033	0.203	0	0.403	152,596	0.236		0.424
Unemployment	1033	0.045	0	0.208	152,596	0.175		0.380
Male (1=yes)	1033	0.845	1	0.362	152,596	0.733		0.442
Age	1033	46.770	46	9.152	152,596	39.182		10.624
Age^2	1033	2271.077	2116	893.515	152,596	1648.095		892.516
Married (1=yes)	1033	0.717	1	0.451	152,596	0.536		0.499
Skill balance	1001	2.639	2	2.162				
Founding team	1001	0.351	0	0.477				
Employee experience	1001	12.546	10	9.658				
General risk	1001	4.644	5	1.237				
Private risk	1001	1.322	1	1.521				
Openness	1001	4.261	4	1.350				
Extraversion	1001	5.519	6	1.291				
Locus of control	1001	6.254	7	1.090				
Work satisfaction	1001	5.899	6	1.094				
Life satisfaction	1001	5.900	6	0.971				
Motivation independence	1001	6.079	6	1.204				
Motivation create something new	1001	4.218	4	1.802				
Motivation make money	1001	5.464	6	1.456				
Motivation market niche	1001	4.278	5	1.871				
Low-skilled employees	3311	0.354	0	0.919	584,881	0.541		1.894
Medium-skilled employees	3311	1.363	1	2.416	584,881	0.756		2.310
Highly skilled employees	3311	0.159	0	0.562	584,881	0.187		1.087
Regional experience					152,596	10.764		7.558
Personal ownership					152,596	0.622		0.485
Previous income					152,596	260,704.200		319,824.200
Household wealth					152,596	2,002,203.000		9,815,151.000
Parents wealth					152,596	1,419,839.000		11,800,000.000

Table A3. Regression results for Germany using the baseline model (manufacturing and KIBS)

	Low-skilled employees			Medium-skilled employees			Highly skilled employees		
	[1] 3 years	[2] 6 years	[3] 9 years	[4] 3 years	[5] 6 years	[6] 9 years	[7] 3 years	[8] 6 years	[9] 9 years
Medium-skilled founder	0.081 (1.192)	0.187 (0.663)	0.093 (2.437)	0.282 (2.050)	0.293 (2.617)	-1.524 (6.553)	0.097** (0.039)	0.129 (0.109)	0.135 (1.405)
Highly skilled founder	0.007 (1.197)	0.115 (0.398)	0.137 (3.386)	0.683 (2.080)	0.785 (2.630)	-0.964 (6.357)	0.523*** (0.131)	0.510 (0.354)	0.445 (2.502)
Self-employed experience	0.009 (0.008)	0.014 (0.047)	0.006 (0.749)	0.056** (0.022)	0.076* (0.041)	0.123 (0.104)	0.014 (0.01)	0.011 (0.017)	-0.020 (0.188)
Industry experience	-0.001 (0.004)	0.001 (0.009)	0.008 (0.384)	0.014 (0.015)	-0.001 (0.020)	0.028 (0.040)	-0.010 (0.007)	-0.006 (0.009)	-0.006 (0.037)
Number of previous start-ups	-0.003 (0.032)	0.008 (0.069)	0.072 (4.103)	0.029 (0.128)	-0.080 (0.190)	-0.170 (0.593)	-0.043 (0.063)	0.110 (0.093)	0.152 (0.965)
Self-employed parent	0.109 (0.099)	-0.018 (0.931)	0.127 (5.873)	0.533** (0.256)	-0.095 (0.330)	-0.375 (0.661)	0.015 (0.13)	-0.066 (0.147)	-0.123 (4.673)
Unemployment	-4.407 (4.291)	-2.290 (7.000)	0.378 (10.714)	-1.716 (4.049)	-0.717 (0.754)	-0.525 (4.604)	-5.668 (5.055)	-5.467 (6.193)	-0.167 (5.652)
Male	-0.182 (0.120)	-0.119 (0.702)	-0.080 (3.162)	-0.859** (0.355)	-0.558 (0.414)	-0.384 (0.771)	-0.091 (0.187)	-0.107 (0.186)	0.225 (1.578)
Age	0.003 (0.03)	-0.008 (0.085)	0.105 (3.886)	0.012 (0.096)	-0.113 (0.149)	-0.071 (0.392)	0.078 (0.057)	-0.041 (0.066)	-0.013 (0.191)
Age^2	0.000 (0.000)	0.000 (0.001)	-0.001 (0.045)	0.000 (0.001)	0.001 (0.002)	0.000 (0.004)	-0.001 (0.001)	0.000 (0.001)	0.000 (0.002)
Married	0.100 (0.106)	0.062 (0.255)	1.925 (42.533)	0.391* (0.219)	0.496 (0.340)	-0.466 (0.868)	0.142 (0.140)	0.295 (0.262)	0.174 (0.891)
Log pseudolikelihood	-182.987	-92.109	-26.863	-605.885	-370.691	-165.731	-282.311	-144.648	-69.594
Observations	413	250	122	413	250	122	413	250	122

Note: Negative binominal regression with marginal effects. The dependent variables are the number low-skilled employees (Columns 1–3), medium-skilled employees (Columns 4–6), or highly skilled employees (Columns 7–9). Estimations are done separately for firm age 3 years (Columns 1, 4, and 7), 6 years (Columns 2, 5, and 8), or 9 years (Columns 3, 6, and 9). Bootstrapped standard errors in parentheses (100 replications). Significant at *** $P < 0.01$, ** $P < 0.05$, * $P < 0.1$. All models include a full set of region, year, and 1-digit NACE dummies, which are not reported for brevity.

Table A4. Regression results for Denmark using the baseline model (manufacturing and KIBS)

	Low-skilled employees			Medium-skilled employees			Highly skilled employees		
	[1] 3 yrs	[2] 6 yrs	[3] 9 yrs	[4] 3 yrs	[5] 6 yrs	[6] 9 yrs	[7] 3 yrs	[8] 6 yrs	[9] 9 yrs
Medium-skilled founder	−0.009 (0.022)	0.083* (0.045)	0.044 (0.086)	0.061 (0.043)	0.310*** (0.090)	0.227 (0.163)	0.089*** (0.031)	0.176** (0.070)	0.544*** (0.176)
Highly skilled founder	−0.069*** (0.023)	0.010 (0.048)	0.031 (0.093)	0.018 (0.045)	0.316*** (0.103)	0.494** (0.197)	0.470*** (0.048)	0.767*** (0.112)	1.535*** (0.320)
Industry experience	0.062*** (0.015)	0.038 (0.028)	0.123** (0.057)	0.168*** (0.028)	0.233*** (0.057)	0.252** (0.105)	0.050*** (0.017)	0.103** (0.040)	0.239** (0.099)
No. of previous start-ups	0.088*** (0.013)	0.125*** (0.027)	0.063 (0.060)	0.216*** (0.025)	0.306*** (0.051)	0.053 (0.107)	0.097*** (0.016)	0.167*** (0.038)	0.101 (0.105)
Self-employed parent	−0.042*** (0.016)	−0.021 (0.033)	0.022 (0.075)	0.006 (0.032)	−0.062 (0.066)	0.004 (0.135)	0.010 (0.021)	0.012 (0.050)	−0.103 (0.112)
Unemployment	−0.122*** (0.015)	−0.230*** (0.027)	0.368** (0.164)	−0.355*** (0.026)	−0.536*** (0.051)	0.112 (0.193)	−0.182*** (0.017)	−0.333*** (0.036)	−0.447*** (0.094)
Male	0.089*** (0.015)	0.129*** (0.030)	0.209*** (0.057)	0.240*** (0.027)	0.423*** (0.053)	0.371*** (0.103)	0.160*** (0.017)	0.238*** (0.039)	0.261*** (0.101)
Age	−0.026*** (0.005)	−0.004 (0.010)	−0.038* (0.021)	0.008 (0.010)	0.018 (0.020)	−0.034 (0.040)	0.012* (0.006)	−0.028* (0.015)	−0.035 (0.038)
Age^2	0.000*** (0.000)	−0.000 (0.000)	0.000 (0.000)	−0.000 (0.000)	−0.000* (0.000)	0.000 (0.000)	−0.000*** (0.000)	0.000 (0.000)	0.000 (0.000)
Married	0.033** (0.015)	0.044 (0.030)	0.034 (0.061)	0.133*** (0.028)	0.176*** (0.058)	0.099 (0.111)	0.093*** (0.018)	0.206*** (0.041)	0.386*** (0.104)
Log-likelihood	−10,273	−5592	−1904	−16,936	−8575	−2734	−11,625	−6240	−2366
Observations	16,549	7287	2297	16,549	7287	2297	16,549	7287	2297

Note: Negative binomial regression with marginal effects. The dependent variables are the number low-skilled employees (Columns 1–3), medium-skilled employees (Columns 4–6), or highly skilled employees (Columns 7–9). Estimations are done separately for firm age 3 years (Columns 1, 4, and 7), 6 years (Columns 2, 5, and 8), or 9 years (Columns 3, 6, and 9). Standard errors in parentheses. Significant at *** $P < 0.01$, ** $P < 0.05$, * $P < 0.1$. All models include a full set of region, year, and two-digit NACE dummies, which are not reported for brevity.