# Effect of Firms' Age on Their Use of Highly Skilled Workers

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*Abstract.* We aim to contribute to the literature on entrepreneurship by examining the relationship between firms' age and their use of highly skilled workers, measured by employees with higher education. A panel data set of Norwegian firms is used. Based on population-averaged panel data regression, we find that newly established firms have a higher proportion of highly skilled workers than incumbent firms. A sensitivity analysis shows that this result holds for different correlation structures in the panel data, different calculations of employees' age, and whether the explanatory variables are lagged in order to reduce the potential endogeneity of these variables. The result can be explained by the fact that the capital intensity is higher in newly founded firms than in incumbent firms and that the proportion of highly skilled workers is positively correlated with the capital intensity in firms.

## 1. Introduction

In this study, we focus on firms' use of highly skilled workers. Using a linked employer–employee data set for Germany, Brixy *et al.* (2006) find descriptive evidence that newly founded firms, on average, have a higher proportion of low-skilled employees than incumbent firms.[1] We may, therefore, expect that the proportion of highly skilled workers is correlated with the age of firms. Regarding the empirical literature, very few previously published studies have, to our knowledge, examined and estimated the relationship between firms' age and their use of highly skilled workers. One exception is Bartel and Lichtenberg (1987). They analyse the group of highly educated workers.[2] Their empirical results are consistent with the implication of the hypothesis that this group has a comparative advantage with respect to the adjustment to, and implementation of, new technologies: The relative demand for educated workers declines as the age of plant and equipment increases, but the education distribution of employment depends more strongly on the age of equipment than on the age of plant. In line with their analysis, the definition of 'highly skilled workers' used in our study is based on workers' educational level. However, we use a much larger set of firms than that used in the Bartel and Lichtenberg study.

We examine the relationship between firms' age and their use of highly skilled workers. The approach used is as follows: in the descriptive analysis, we compare the proportion of

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such workers between newly founded and incumbent firms. Then, we estimate the effects of firms' age on the proportion of highly skilled workers, where firm age is used as a categorical variable. In the analysis, we use a panel data set of Norwegian firms, which is based on matched employer–employee data and financial data.

This article aims to contribute to the literature on entrepreneurship because the empirical literature is fairly limited when it comes to discussing the relationship between firm age and the use of highly skilled workers. There are several arguments in the theoretical literature for expecting differences in the use of highly skilled workers among newly founded and incumbent firms. Some studies suggest that new firms will employ more highly skilled employees than incumbent firms, whereas others suggest the opposite. Hypotheses regarding a firm age–skill relationship are formulated and tested in the analysis.

The rest of the article is organized as follows. Section 2 gives an overview of previous studies on entrepreneurial activity, firm age, and firm size. Theoretical links between firms' age and their use of highly skilled workers, including the hypotheses that will be tested in the analysis, are presented in Section 3. The data set and the variables are described in Section 4, where we also define the group of 'highly skilled workers'. Section 5 presents the econometric approach. Descriptive statistics are given in Section 6. In Section 7, we present the estimation results and conduct a sensitivity analysis in order to examine whether the estimated effects of firm age are sensitive to the econometric approach and how employees' age is calculated. Section 8 provides some concluding remarks.

## 2. Previous studies on entrepreneurial activity, firm age, and firm size

Several studies on entrepreneurial activity have found that firm size and age are negatively related to firm growth (Evans, 1987; Dunne and Hughes, 1994; McPherson, 1996; Liu *et al.*, 1999; Yasuda, 2005; Park *et al.*, 2010) and positively related to firm survival (Park *et al.*, 2010; Yasuda, 2005). Other studies have found empirical support for the argument that younger firms are better able to capture the value from entrepreneurial strategies in the form of higher organizational growth rates than their older peers (Anderson and Eshima, 2013). Furthermore, some studies emphasize that entrepreneurial activities in knowledge-intensive sectors have been recognized as having potentially considerable economic value (Delmar and Wennberg, 2010).

Haltiwanger *et al.* (2013) show that if one controls for firm age, then there is no systematic relationship between firm size and growth. Regarding the relationship between firm growth and firm size, many studies have related their results to Gibrat's law of proportionate effect (see Coad, 2009; Sutton, 1997), i.e. the prediction that the growth rate of a given firm is independent of its size at the beginning of the period examined (Lotti *et al.*, 2009). For example, Mansfield (1962), Hart and Oulton (1996), and Yasuda (2005) find no strong evidence that Gibrat's law holds. Evans (1987) and Calvo (2006) conclude that Gibrat's law fails, and the results in Liu *et al.* (1999) and Park *et al.* (2010) suggest that the law does not hold, whereas McPherson (1996) finds little evidence that the law holds. Some studies have found that Gibrat's law is weakly rejected for the smaller firms and accepted for the larger firms (Hall, 1987) and that the law does not hold among smaller firms (Dunne and Hughes, 1994), whereas other studies have found that the law cannot be rejected (Audretsch *et al.*, 2004; Lotti *et al.*, 2003). Moreover, Lotti *et al.* (2009) find that Gibrat's law has to be rejected ex ante, but that a significant convergence towards Gibrat-like behaviour can be detected ex post.

The concept of 'entrepreneurship' has been discussed in several studies, including the concept of the so-called 'defensive entrepreneurship'. Baumol (2010) distinguishes between the innovative entrepreneur who comes up with new ideas and puts them into practice and the replicative entrepreneur who instead starts a new business regardless of whether similar firms already exist in the market (see also Vivarelli, 2011).[3] 'Schumpeterian innovative entrepreneurs', therefore, coexist with 'defensive and necessity entrepreneurs' (Quatraro and Vivarelli, 2015; Vivarelli, 2013). Vivarelli (2013) explains that the latter does not enter a new business because of market opportunities and innovative ideas, 'but merely because they need an income to survive' (p. 1454). In line with this, Ensign and Robinson (2016) emphasize that defensive entrepreneurship is often undertaken in order to survive. Founding a new firm can thus be motivated by a defensive attitude such as the fear of becoming unemployed (Storey, 1991).

Focusing on the motivation for becoming self-employed, Caliendo and Kritikos (2010) find that formerly unemployed founders are motivated by both push and pull factors: they both want and have to become self-employed. Related to this, Van der Zwan *et al.* (2016) find important differences between opportunity and necessity business ownership in terms of their socioeconomic characteristics, personality, and entrepreneurial perceptions. The start-up motivation also has consequences for how a business is managed, e.g. in terms of business performance (Arrighetti and Vivarelli, 1999; Vivarelli, 2004).

Mueller (2006) argues that knowledge is transformed into economically useful knowledge by either incumbent or new firms. According to Acs *et al.* (2004), incumbent firms incorporate new knowledge into their firm-specific knowledge, whereas new firms are assumed to transmit knowledge and transform it via knowledge spillovers into economically relevant knowledge. In line with this, Audretsch and Keilbach (2004) argue that entrepreneurship is an important source of diversity in that it transforms knowledge into economic knowledge and that the process of entrepreneurship is a mechanism that generates diversity and the spillover of knowledge. Other studies have suggested that knowledge spillovers come from the stock of knowledge and that there is a strong relationship between such spillovers and entrepreneurial activity (Acs *et al.*, 2009) and that knowledge spillovers can be viewed as involving either the creation of new entrepreneurial opportunities or the discovery of entrepreneurial opportunities not previously recognized (Agarwal *et al.*, 2010). Furthermore, Mueller (2006) emphasizes that new firms in knowledge- or technology-intensive industries are most likely founded because of opportunities and that new firms in innovative industries are an important mechanism for knowledge spillovers.

According to Swart and Kinnie (2003), the phrase 'knowledge-intensive' can be used in at least three contexts: knowledge-intensive work, knowledge workers, and knowledge-intensive firms. They point out that 'knowledge-intensive firms' refer to firms where most work is said to be intellectual and where well-educated, qualified employees form the major part of the workforce. However, the idea of knowledge-intensive firms and related concepts such as knowledge work is problematic (Alvesson, 2001). Alvesson (2011) emphasizes that a key aspect of knowledge work is the ambiguity of what it stands for, what people working with 'knowledge' are doing, and what they accomplish. It is also difficult to substantiate knowledge-intensive firms and knowledge workers as distinct, uniform categories, and 'the distinction between these and non- (or less) knowledge-intensive organization/non-knowledge workers is not self-evident, as all organizations and work involve "knowledge" and any evaluation of "intensiveness" is likely to be contestable' (Alvesson, 2001, p. 864).

## 3. Explanations for a firm age–skill relationship and the hypotheses

There are several arguments for expecting that incumbent firms use more highly skilled workers than newly founded firms. First, if old firms are more capital-intensive than new firms, and capital–skill complementarities exist, old firms will employ more highly skilled workers (Hamermesh, 1980). Second, if the capital intensity is relatively higher in old firms and they use technologies relying on standardization and teamwork, old firms will demand more highly skilled workers (Oi, 1983). As a consequence of this, there is a systematic sorting of highly skilled workers into older firms, which in most cases are larger firms (Heyman, 2007). Third, older firms may have more highly skilled managers who employ more highly skilled workers with relatively higher wages (Oi, 1983). Fourth, Brixy *et al.* (2006, p. 103) show that newly founded firms have higher labour turnover rates than incumbent firms. Risk aversion may thus lead to an overrepresentation of low-skilled employees in new firms.

It may also be the case that new firms employ more highly skilled workers than old firms. Brixy *et al.* (2006, p. 99) point out that new firms are more likely to fail than incumbent firms, and both passive learning models (Hopenhayn, 1992; Jovanovic, 1982) and active learning models (Ericson and Pakes, 1995; Pakes and Ericson, 1998) suggest that smaller and younger firms have a higher likelihood of exit than larger and older firms (Carreira and Teixeira, 2011). These results are in line with the study by Cefis and Marsili (2006), which finds that small and young firms are the most exposed to the risk of exit. Esteve Pérez et al. (2004) find that both the youngest and the oldest firms bear a significantly higher risk of failure, whereas this risk is significantly higher among small firms than among large firms. Therefore, new firms may avoid large capital investments and use highly skilled labour as a substitute for such investments.

Furthermore, new firms may have a higher proportion of highly skilled workers than incumbent firms because entrepreneurial firms, at least in some industries, contribute substantially to innovation (Audretsch, 1995; Audretsch and Keilbach, ). In this context, the results in Olivari (2016) suggest the importance of entrepreneurial traits in explaining the propensity of firm innovation and that different entrepreneurial profiles and firm innovation propensities are related to each other.

Newly founded firms may, however, have insufficient knowledge about the 'best' skill combination and may thus need some time to find the optimal value of their skills composition. Also, because firm size is related to firm age, incumbent firms probably have more R&D departments with highly skilled employees relative to newly founded firms but may also have more administrative departments with low- or medium-skilled employees.

The life cycle concept (Klepper, 1997) may affect the need for skilled or 'knowledgeable' workers in firms. In phases of paradigm shifts in the technology life cycle, new firms may, to a larger degree, use new technologies compared with incumbent firms. One would thus expect that new firms will employ more highly skilled workers in such phases.

Based on these explanations for a firm age–skill relationship, we are unable to draw any unambiguous conclusions about the impact of firms' age on their use of highly skilled workers. It is also difficult to test each of the explanations, and thus find definitive support for any of them, because the data set used in this study does not contain enough information to perform such tests.

To find a plausible explanation for a firm age–skill relationship, we will use a modified version of the first explanation in this section by replacing the assumption that capital–skill complementarities exist. There are three reasons for this. The first reason is that the evidence does not strongly support the capital–skill complementarity hypothesis (Correa *et al.*, 2019). The second reason is that the production function in our econometric approach is of the Cobb–Douglas form, which is a too restrictive form when testing whether such complementarities exist (see Duffy *et al.*, 2004). The third reason is that we lack, e.g., information about a worker's occupation, and it will, therefore, be difficult to differentiate fully between skilled and unskilled workers.

Instead of trying to test whether capital–skill complementarities exist, we will test whether there is a positive correlation between the proportion of highly skilled workers and the capital intensity at the firm level (or negative correlation). The following hypotheses are formulated:

H1: *The proportion of highly skilled workers and the capital intensity are positively correlated.*

H2a: *If old firms are more capital-intensive than new firms, and H1 is supported, old firms will employ more highly skilled workers than new firms.*

H2b: *If new firms are more capital-intensive than old firms, and H1 is supported, new firms will employ more highly skilled workers than old firms.*

The three hypotheses are tested using regression techniques.

## 4. Data

We use a panel data set of Norwegian firms, which comprises annual administrative files from Statistics Norway. This data set is based on two data sources, where both cover the period 2000–16. The first data source is matched employer–employee register data that contain yearly information on all employees and all plants and enterprises, in Norway. In the employer–employee data, both plants and enterprises are identified by unique codes. There is a corresponding unique enterprise code to each plant's unique code, where an enterprise consists of at least one plant.

The second data source is financial register data that contain yearly information on total assets for all enterprises in Norway. For each year, the capital stock is equal to total assets, which is the sum of current and long-term assets. Total assets are measured in 1000 NOK. A firm's capital intensity is measured as the capital stock per employee.

Firms are identified at the enterprise level in the financial data, where enterprises are identified by unique codes. The enterprise codes in the financial data correspond to the enterprise codes in the employer–employee data. It is, therefore, possible to link the employer–employee data to the financial data at the enterprise level based on the enterprise codes.

Firms are defined at the plant level in the analysis. There are two reasons for this. One reason is to account for potential firm heterogeneity at this level. The other reason is that a firm's capital stock is the only variable that is defined at the enterprise level, whereas all other variables are defined at the plant level. We match the two data sources together by linking the financial register data to the matched employer–employee register data at the enterprise level based on the enterprise codes. As a result, firms within the same enterprise will have the same (monetary value of the) capital stock.

### *4.1. Sample of firms*

There are two challenges to using the combined matched employer–employee and financial register data. First, many firms in these data have a one-year period of deregistration. By 'a deregistration period', we mean that a firm is not registered in the data in this period. This may be related to statistical errors or temporary exit, rather than a permanent exit. If we assume that a firm makes a final exit in a one-year deregistration period, we may underestimate its age.

Second, for many observations in the combined data, firms are registered with a non-positive turnover or a non-positive capital stock (i.e. total assets). Because the log of the productivity level and the log of the capital intensity are used as control variables in the regression, the sample of firms only includes observations where a firm is 'registered as active', which is defined as being registered with both a positive turnover and a positive capital stock. This reduces the number of observations in the combined data from 3,099,653 to 1,613,321.

A firm's final exit year is defined as the last year a firm is registered as active. We use a gap period of at least two years to define a firm's founding year. A 'gap period' is a deregistration period or a period where a firm is not registered as active (or a combination of these two types of periods). If a firm does not have a gap period of at least two years, its founding year is defined as the first year it is registered as active. If a firm instead has one or more gap periods of at least two years, its founding year is defined as the first year it is registered as active after the last gap period. We exclude observations from the sample where a firm is registered in an earlier year than its founding year. The number of observations in the combined data is thus reduced to 1,544,016.

We include in the sample only firms with a final exit year in the period 2010–16 in order to obtain an appropriate categorization of the firm age variable (measured in number of years), which reduces the number of observations in the combined data to 1,332,734. Thus, the period in the panel data is 2010–16. The whole period 2000–16 is used to establish each firm's age.

According to Crespi *et al.* (2006), service sector data are particularly problematic for use in productivity calculations. We will, therefore, basically only include manufacturing firms in the sample. However, because we use panel data, a firm's industrial sector affiliation can vary between different years in the period 2010–16. Thus, the sample of firms includes all firms that are registered as manufacturing firms for at least one of the years in 2010–16. The final sample consists of 57,450 observations. For 96 per cent of these observations, a firm is registered as a manufacturing firm. There are 11,718 unique firms in the final sample.

### *4.2. Definition of highly skilled workers*

The dependent variable measures the proportion of highly skilled workers, which is a continuous variable. 'Highly skilled workers' are defined as employees with tertiary education as their highest attained educational level.[4] Educational level is based on the

Norwegian Standard Classification of Education (NUS2000). Tertiary education includes either the first stage (undergraduate or graduate level) or the second stage (postgraduate education) of tertiary education.[5]

### *4.3. Explanatory variables*

The explanatory variables are firm's age, log of the productivity level, log of the capital intensity, log of the firm size, industrial sectors, a firm's geographical location according to county, the proportion of females of total employees, the proportion of employees with unknown gender, the average age of employees, unknown average age of employees, and the proportion of employees participating in further education. Firm age is the key regressor, whereas the other explanatory variables are the control variables. The firm age variable, industrial sectors, location, and the variable 'unknown average age of employees' are represented by dummy variables, whereas the other explanatory variables are continuous.

Firm age refers to the number of years in business and is calculated as the consecutive number of years from a firm's final exit year back to its founding year. This implies that a firm's age can include at least a one-year gap period. Due to the definition of a firm's founding year, no firms have a gap period of at least two years from their final exit year back to their founding year. The data provide information on the exact age for firms founded in 2002 or later, but not if they are founded in 2000 or 2001. For firms founded in 2000 or 2001, the data only provide information that they are at least 10 years old in 2010–16. For this reason, firm age is used as a categorical variable and not as a continuous variable, where '10 years or older' is one of the categories. Because as many as 65 per cent of the observations are included in this category, we only use three categories for the firm age variable in order to include an appropriate number of observations in each category. The following categories are used: '1–4 years', '5–9 years' (the reference category), and '10 years or older'. Twenty per cent of the observations are included in the '1–4 years' category, whereas 16 per cent are included in the '5–9 years' category.

The productivity level is defined as the firm's production value per employee, where the production value is measured by the turnover given in 1000 NOK. Turnover is the sum of payment of sales to customers, sales of goods for resale, and gross income from other business activity. Turnover includes income from rent and commission income, but not government subsidies or profit from the disposal of fixed assets. Value added tax is not included in the turnover either.

Firm size measures the number of employees in each firm and is included in the regression in order to take into account that in most cases larger firms are older firms. The classification of industrial sectors is based on the Standard Industrial Classification (SIC2007), two-digit NACE code level.

An employee's age is based on his or her year of birth. Unfortunately, we do not have information about a person's exact year of birth, only that the person is born in one of a series of three-year intervals: 2002–04, 1999–2001, 1996–98, and so forth. In the empirical analysis in Sections 6 and 7, we have calculated a person's age by using the middle year in each interval. Section 7 also examines whether the estimated firm age effects are sensitive to the use of the middle year.

For very few observations, the average age of employees is unknown, and for these observations, we use the average age of the industries in which the firms are included. The average age by industry (two-digit NACE code level) is calculated among firms with a known average age of employees.

We use information about ongoing education in the combined data to calculate participation in further education. Ongoing education is based on the Norwegian Standard Classification of Education (NUS2000). Our definition of further education is the same as the one used in Børing and Skule (2013) (in Norwegian). Persons aged 35 years or older who are registered in an ongoing education are defined as participants in further education because we assume that they have completed their initial education. For persons who are registered in an ongoing education in a particular year, where they are at least 22 years but not more than 34 years of age in this year, they are defined as participants in further education this year if they are not registered in any ongoing education in the previous two years. Otherwise, we assume that ongoing education is part of the initial education, and not defined as further education.

## 5. Econometric approach

The empirical model is based on the productivity models used in Børing (2014). We use the following Cobb–Douglas form of the production function:

$$Y_{it} = F_i(K_{it}, L_{it}, T_{it}) = A_{it}K_{it}^{p}L_{it}^{q}T_{it}, \qquad [1]$$

where

$$T_{it} = \exp(bX_{it} + \mathbf{Z}_{it}\mathbf{c}). \qquad [2]$$

Here, $Y_{it}$ is the monetary value of the production, $K_{it}$ is the monetary value of the capital stock, $L_{it}$ is the number of employees, $T_{it}$ is the state of technology, $X_{it}$ is the proportion of highly skilled workers, and $\boldsymbol{Z}_{it}$ is a row vector of explanatory variables other than the log of the productivity level and the log of the capital intensity (In($Y_{it}/L_{it}$), In($K_{it}/L_{it}$)), in firm $i$ in year $t$, $i$ = 1,2,. . .,n. $A_{it}$ represents the Hicksian neutral efficiency level, which is not observable. **c** is a column vector of coefficients, and $b$ is a coefficient. The function in (1) has non-constant returns to scale in ($K_{it}$, $L_{it}$) if the sum of the parameters, $d = p + q$, is not equal to 1.

If we set $\ln A_{it} = a + \varepsilon_{it}$ and use (1) and (2), then we get the following expression for the labour productivity:

$$\ln\left(\frac{Y_{it}}{L_{it}}\right) = a + p\ln\left(\frac{K_{it}}{L_{it}}\right) + (d-1)\ln L_{it} + bX_{it} + \mathbf{Z}_{it}\mathbf{c} + \varepsilon_{it}, \qquad [3]$$

where $a$ measures the mean efficiency level across firms and over time and $\varepsilon_{it}$ is the time- and firm-specific deviation from this mean. It follows from (3) that.

$$X_{it} = \tilde{a} + \tilde{b}\ln\left(\frac{Y_{it}}{L_{it}}\right) + \tilde{p}\ln\left(\frac{K_{it}}{L_{it}}\right) + \tilde{d}\ln L_{it} + \mathbf{Z}_{it}\tilde{\mathbf{c}} + \tilde{\varepsilon}_{it}, \qquad [4]$$

which is the basic equation to be estimated. In this equation, we define the coefficients $\tilde{a} = -a/b$, $\tilde{b} = 1/b$, $\tilde{p} = -p/b$ and $\tilde{d} = -(d-1)/b$, and, the deviation $\tilde{\varepsilon}_{it} = -\varepsilon_{it}/b$, and the column vector of coefficients $\tilde{\mathbf{c}} = -\mathbf{c}/b$.

We may have an endogeneity problem. If firms want to improve their production process, they may choose to employ highly skilled workers. Therefore, we suspect In($Y_{it}/L_{it}$) and probably also (In($K_{it}/L_{it}$), ln $L_{it}$, $\boldsymbol{Z}_{it}$) to be endogenous variables.[6] As a consequence of this, the deviation $\varepsilon_{it}$, and thus $\tilde{\varepsilon}_{it}$, cannot be assumed to be statistically independent of all explanatory variables. Because we cannot find any suitable excluded instruments in the analysis, it is not possible to use IV techniques. In Section 7, we will instead examine whether the estimated firm age effects are sensitive to the econometric approach outlined above by lagging the explanatory variables:

$$X_{it} = \tilde{a} + \tilde{b}\ln\left(\frac{Y_{i,t-j}}{L_{i,t-j}}\right) + \tilde{p}\ln\left(\frac{K_{i,t-j}}{L_{i,t-j}}\right) + \tilde{d}\ln L_{i,t-j} + \mathbf{Z}_{i,t-j}\tilde{\mathbf{c}} + \tilde{\varepsilon}_{it}, \qquad [5]$$

where $j$ = 1 if $t$ − 1 is not a gap period, and $j$ = 2 if $t$ − 1 is a gap period.

## 6. Descriptive statistics

In Table 1, we present descriptive statistics by firm age. About two-thirds of the observations concern the oldest firms in the final sample, i.e. those that are 10 years old or older. One-fifth of the observations concern the youngest firms (1–4 years old), whereas 16 per cent concern the middle-aged firms (5–9 years old).

We see from Table 1 that there are small differences in the proportion of highly skilled workers between the three firm age groups. This proportion is highest among the youngest firms (18 per cent) and lowest among the oldest firms (14 per cent). The proportion is 16 per cent among the middle-aged firms.

**Table 1.** Mean values of variables used in the regression by firm age

| | **1–4 years** | **5–9 years** | **10 years old or older** | **Total** |
|---|---|---|---|---|
| Firm characteristics | | | | |
| Firm size | | | | |
| 1–9 persons | 0.769 | 0.621 | 0.435 | 0.530 |
| 10–24 persons | 0.143 | 0.219 | 0.267 | 0.235 |
| 25–99 persons | 0.071 | 0.130 | 0.224 | 0.179 |
| 100 persons or more | 0.016 | 0.031 | 0.073 | 0.055 |
| Total | 1.000 | 1.000 | 1.000 | 1.000 |
| Average number of employees in each firm | 9 | 16 | 30 | 24 |
| Productivity level | 1,872 | 2,146 | 2,314 | 2,200 |
| Capital intensity | 18,275 | 12,253 | 10,991 | 12,628 |
| Employee characteristics | | | | |
| Proportion of highly skilled workers | 0.183 | 0.163 | 0.138 | 0.151 |
| Proportion of females of total employees | 0.228 | 0.222 | 0.230 | 0.228 |
| Proportion of employees with unknown gender | 0.037 | 0.029 | 0.017 | 0.023 |
| Average age of employees | 42 | 43 | 45 | 44 |
| Unknown average age of employees | 0.007 | 0.003 | 0.001 | 0.002 |
| Proportion of employees participating in further education | 0.011 | 0.010 | 0.009 | 0.009 |
| Total number of observations | 11,358 | 8,969 | 37,123 | 57,450 |

The productivity level is highest among the oldest firms and lowest among the youngest firms. We also find that the firm size is largest among the oldest firms and smallest among the youngest firms. This follows from the fact that the average number of employees in each firm is highest among the oldest firms (30 persons) and lowest among the youngest firms (9 persons). The corresponding average number is 16 persons among the middle-aged firms. We see that 44 per cent of the oldest firms have 1–9 employees, 27 per cent have 10–24 employees, and 22 per cent have 25–99 employees, whereas 7 per cent of the firms have at least 100 employees. In contrast, 77 per cent of the youngest firms have 1–9 employees, 14 per cent have 10–24 employees, and 7 per cent have 25–99 employees, whereas only 2 per cent have at least 100 employees.

Table 1 shows that there are small differences in the proportion of females between the firm age groups, which is 22–23 per cent for each group. For some observations, we lack information on the employees' gender, and the proportion of employees with unknown gender is somewhat higher among the youngest firms (4 per cent) than among the oldest firms (2 per cent). Furthermore, the average age of the employees is somewhat higher among the oldest firms (45 years) than among the two other age groups (42–43 years). There are very few observations where the average age of employees is unknown.

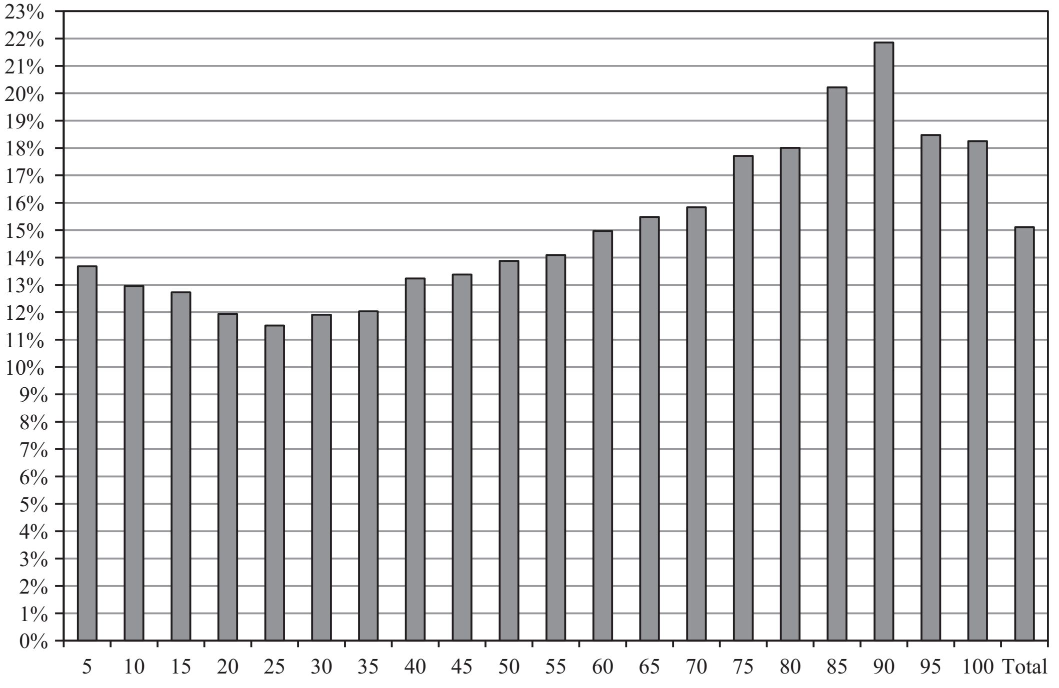
We found above that the proportion of highly skilled workers is higher among the youngest firms than among the oldest firms. Because highly skilled workers are defined as employees with tertiary education, we expect that the employees in the youngest firms participate more in further education than among those in the oldest firms. The basis for this expectation is that several studies have documented that participation in adult learning increases with increasing educational level (Boeren *et al.*, 2010; Knipprath and De Rick, 2015). However, very few of the employees participate in further education, and there are marginal differences in this participation between the three firm age groups. Nevertheless, the participation is marginally higher among the youngest firms (1.1 per cent) than among the oldest firms (0.9 per cent).

Finally, we find from Table 1 that the average capital intensity is highest among the youngest firms and lowest among the oldest firms. Because the proportion of highly skilled workers is highest among the youngest firms and lowest among the oldest firms, we expect (as formulated in hypothesis H1) that there is a positive correlation between this proportion and the average capital intensity. This is also seen in Figure 1, but the proportion is not a monotonically increasing function of the capital intensity. We see that the proportion of highly skilled workers first decreases with increasing average capital intensity and then increases up to the 90th percentile of the average capital intensities (based on the percentiles in the figure), and decreases for firms with average intensities beyond this percentile. From the data set, we find a positive and significant correlation between this proportion and the capital intensity for Spearman's and Kendall's rank correlation tests for the firms in the final sample (at the 1 per cent level), but the correlation is not significant for the pairwise correlation test (even at the 10 per cent level). These results give support to hypothesis H1. The two other hypotheses are tested in the next section.

## 7. Estimation results

The descriptive analysis in Section 6 showed that the proportion of highly skilled workers is highest among the youngest firms and lowest among the oldest firms. A firm's proportion of highly skilled workers may depend on not only firm age but also other firm

**Figure 1.** Proportion of highly skilled workers in the final sample by capital intensity.




*Note*: The average capital intensity in the figure is measured along the horizontal axis in percentiles

characteristics as well as employee characteristics. In this section, we examine how this proportion is related to firm age if we account for such characteristics.

Table 2 shows the results from population-averaged panel data regression, where we use the unstructured correlation structure. In particular, this regression fits generalized linear models and allows us to specify the within-group correlation structure for the panel data. We use the proportion of highly skilled workers as the dependent variable in the regression. Due to space limitations, the results from the effects of the dummies for industrial sectors and a firm's location are not shown in the table.

### *7.1. Effect of firm age*

From Table 2, we see that firms' proportion of highly skilled workers is significantly higher among the youngest firms and significantly lower among the oldest firms than among the middle-aged firms, which are in line with the results in the descriptive analysis. We conclude that newly established firms have a higher proportion of highly skilled workers than incumbent firms when accounting for employee characteristics and other firm characteristics. This indicates that there is a negative relationship between the proportion of highly skilled workers and firm age.

In the descriptive analysis, we found that the average capital intensity is highest among the youngest firms and lowest among the oldest firms. Newly founded firms are thus more capital-intensive than incumbent firms, on average. We also found support for hypothesis H1 in Section 6, i.e. that the proportion of highly skilled workers is positively correlated

**Table 2.** Estimates of population-averaged panel data regression: the proportion of highly skilled workers

| | Coeff. | St.err. |
|---|---|---|
| Firm age | | |
| 1–4 years | 0.009*** | 0.002 |
| 10 years or older | 0.014*** | 0.002 |
| Log of the productivity level | −0.007*** | 0.001 |
| Log of the capital intensity | 0.010*** | 0.001 |
| Log of the firm size | −0.006*** | 0.001 |
| Proportion of females of total employees | 0.059*** | 0.005 |
| Proportion of employees with unknown gender | −0.115*** | 0.010 |
| Average age of employees | 0.000*** | 0.000 |
| Unknown average age of employees | −0.014 | 0.015 |
| Proportion of employees participating in further education | 0.039*** | 0.010 |
| Constant | 0.085*** | 0.012 |
| Wald chi2(90) | | 2804.510 |
| Scale parameter | | 0.044 |
| Prob> chi2 | | 0.000 |
| Total number of observations | | 57,450 |
| Number of groups | | 11,718 |

*Notes:* (1) Estimated results from model (4). (2) The estimates in the table are based on a GEE population-averaged panel data model, where we use the identity link function, the Gaussian family function, and the unstructured correlation structure. (3) *** Significant at the 1 per cent level, ** significant at the 5 per cent level, and * significant at the 10 per cent level. (4) In the regression, we have also controlled for dummies for industrial sectors and dummies for a firm's location according to county. These results are not shown in the table. (5) The reference firm is included in the following industrial group: manufacture of fabricated metal products, except machinery and equipment (NACE code 25).

with the capital intensity in firms. These results give support to hypothesis H2b but not to hypothesis H2a.

We have conducted a sensitivity analysis in order to examine whether the estimated effects of firm age are sensitive to the econometric approach and the calculation of employees' age. First, we have examined whether these estimated effects are sensitive to the specification of the unstructured correlation structure because the estimates are based on this structure. We have tested for two alternative correlation structures: exchangeable and independent. If we use the same dependent and explanatory variables as in Table 2 but specify a correlation structure that is either exchangeable or independent instead of unstructured, we still find that the proportion of highly skilled workers is significantly higher among the youngest firms and significantly lower among the oldest firms than among the middle-aged firms. Therefore, the estimated effects of firm age are relatively robust for how the correlation structure is specified.

Second, as emphasized in Section 5, we have a potential endogeneity problem. The estimation results are based on the modelling strategy in equation (4). To reduce the potential endogeneity of the explanatory variables, we instead estimate equation (5), where the explanatory variables are lagged one year or two years. The one-year lag is used if the previous year is not a one-year gap. We use the two-year lag instead if the previous year is a one-year gap. In this case, the final sample reduces to 45,732 observations. Using this subset of the final sample and the same dependent variable as in Table 2, we still find that the youngest firms have a significantly higher proportion of highly skilled workers than the middle-aged firms and that this proportion is significantly lower among the oldest firms than among the middle-aged. Thus, the estimated firm age effects are qualitatively the same if we compare the results from this modelling strategy of accounting for potential endogeneity with the results from the basic model.

Third, we have examined whether the estimated effects of firm age are sensitive to the use of the middle year when calculating employees' age (see Section 4.3). We have performed four regressions. In two of the regressions, all variables are the same as in Table 2, except that a person's age is calculated by using either the minimum or maximum year in each birth interval (instead of the middle year). In the other two regressions, we use the subset of the final sample where the explanatory variables are lagged one year or two years, and by using either the minimum or maximum year in each birth interval. For all regressions (which are based on the unstructured correlation structure), we still find that the proportion of highly skilled workers is significantly higher among the youngest firms and significantly lower among the oldest firms than among the middle-aged firms.

### *7.2. Effects of employee and other firm characteristics*

Table 2 shows that the proportion of highly skilled workers increases with an increasing proportion of females of total employees. The proportion of employees with unknown gender has a negative effect on the proportion of highly skilled workers. The pairwise, Spearman's rank and Kendall's rank correlation tests show that there is a positive and significant correlation between the proportion of females and the dependent variable (the correlation is significant at the 1 per cent level for all three correlation tests). This can explain the positive effect of the 'females' variable on the proportion of highly skilled workers. There is a negative and significant correlation between the proportion of employees with unknown gender and the dependent variable for the pairwise correlation test and a positive and significant correlation for Spearman's and Kendall's rank correlation tests (1 per cent level for all three tests).

The proportion of highly skilled workers is estimated to increase with increasing average age of employees. We find that this proportion is not significantly affected due to unknown average age of employees (even at the 10 per cent level). There is a positive relationship between the proportion of highly skilled workers and the proportion of employees participating in further education, which is not surprising because the participation in adult learning is expected to increase with increasing educational level (see Section 6).

We find that the productivity level affects the proportion of highly skilled workers negatively. Spearman's and Kendall's rank correlation tests show a positive and significant correlation between the productivity level and the dependent variable (at the 1 per cent level), but there is a nonsignificant correlation for the pairwise correlation test (even at the 10 per cent level). Furthermore, the capital intensity is found to have a positive effect on the proportion of highly skilled workers, which is in line with the descriptive analysis.

Firm size is included in the regression in order to take into account that larger firms are generally older firms. We see from Table 2 that the effect of firm size is negative and significant. The pairwise correlation test shows a negative and significant correlation between firm size and the proportion of highly skilled workers, whereas Spearman's and Kendall's rank correlation tests show a positive and significant correlation (at the 1 per cent level for all three tests).

Using the estimates of the coefficients and standard errors of the productivity level and the firm size variable, we find that the estimate of the parameter $d = p + q$ is significantly different from one because $d = 1 - \tilde{d}/\tilde{b} < 1$ (at the 1 per cent level). We can, therefore, reject the hypothesis that the production function has constant returns to scale with respect to capital and labour.

## 8. Concluding remarks

We focus on firms' use of highly skilled workers. Brixy *et al.* (2006) found that new firms have a higher proportion of low-skilled employees than incumbent firms, on average. Therefore, we may expect that the proportion of highly skilled workers is correlated with firms' age. As far as we know, very few previously published studies have examined and estimated the relationship between firm age and the proportion of highly skilled workers in the firms. There are arguments for expecting differences in this proportion between newly founded and incumbent firms, and we have addressed a variety of possible explanations for the firm age effect. However, no clear conclusion follows about how firms' use of highly skilled workers is affected by their age.

In our study, we have investigated the effect of firms' age on their use of highly skilled workers by using a panel data set of Norwegian firms. The data set consists of matched employer–employee register data for the period 2000–16, which are linked to financial register data for the same period. Because the data set does not contain enough information to perform tests of the explanations that we have addressed for a firm age–skill relationship, we have used a modified version of one of the explanations.

Descriptive statistics show that both the proportion of highly skilled workers and the average capital intensity are highest among the youngest firms and lowest among the oldest firms. We also find that there is a positive correlation between this proportion and the capital intensity (based on Spearman's and Kendall's rank correlation tests), which gives support to our hypothesis that there is a positive correlation between these variables.

The estimation results show that firms' proportion of highly skilled workers is significantly higher among the youngest firms and significantly lower among the oldest firms than among the middle-aged firms. These results give support to our hypothesis that new firms will employ more highly skilled workers than old firms and are in line with the results in the descriptive analysis. We conclude that, on average, new firms have a lower proportion of low-skilled employees than incumbent firms. Therefore, the results give no support to the analysis in Brixy *et al.* (2006).

Firm size is included in the regression in order to take into account that larger firms in most cases are older firms. The firm size effect is found to be negative and significant. The interaction between firms' age and size is especially interesting in this analysis, given that the dependent variable is the proportion of highly skilled workers in employment, and size is defined in terms of numbers employed. Both the effects of firm age (used as a categorical variable) and size are statistically significant.

A sensitivity analysis is carried out to examine whether the estimated effects of firm age are sensitive to the specification of different correlation structures in the panel data, to the use of our modelling strategy where we do not try to account for potential endogeneity, and to the use of the middle year in each birth interval when calculating employees' age. We test for potential endogeneity by lagging the explanatory variables. The conclusion is that the estimated firm age effects are relatively robust for how the correlation structure is specified, and whether we either use the minimum or maximum year instead of the middle year. These estimated effects are also qualitatively the same if we compare the results from the modelling strategy of accounting for potential endogeneity with the results from our strategy where we do not try to account for this.

## Notes

[1] The sample in Brixy *et al.* (2006) is restricted to firms with fewer than 200 employees.

[2] Bartel and Lichtenberg (1987) define highly educated workers 'as those with greater than a high school education' (p. 7).

[3] Baumol (1990) classifies entrepreneurship as being productive, unproductive, and destructive.

[4] Because we have no information about a worker's occupation in the combined data, we use only information about educational level to define 'highly skilled workers'.

[5] Employees with tertiary education include those with either a bachelor, master, or PhD degree.

[6] (In($K_{it}/L_{it}$), ln $L_{it}$) are probably endogenous variables because they directly affect the productivity level via the production function in (1). Furthermore, each element in $\boldsymbol{Z}_{it}$ is probably an endogenous variable because it indirectly affects the productivity level via (2) and also because some of the explanatory variables in this vector either are measured as a percentage of the number of employees or are a function of the number of employees.

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