

## Fast as a gazelle – young firms gaining from educational diversity

Carita Eklund & Kristof van Criekingen

To cite this article: Carita Eklund & Kristof van Criekingen (2022) Fast as a gazelle – young firms gaining from educational diversity, *Industry and Innovation*, 29:8, 927-947, DOI: [10.1080/13662716.2022.2044764](https://doi.org/10.1080/13662716.2022.2044764)

To link to this article: <https://doi.org/10.1080/13662716.2022.2044764>



© 2022 The Author(s). Published by Informa UK Limited, trading as Taylor & Francis Group.



Published online: 27 Feb 2022.



Submit your article to this journal [↗](#)



Article views: 3511




View related articles [↗](#)



View Crossmark data [↗](#)

# Fast as a gazelle – young firms gaining from educational diversity

Carita Eklund <sup>a,b</sup> and Kristof van Criekingen<sup>a</sup>

<sup>a</sup>The Danish Centre for Studies in Research and Research Policy, Aarhus University, Denmark; <sup>b</sup>School of Accounting and Finance, University of Vaasa, Finland

## ABSTRACT



Young, high-growth firms, so-called gazelles, are an important source of growth and industry dynamics. However, our understanding is lacking on how knowledge competences support high growth among young firms. This article aims to fill this gap by utilising firm and employee knowledge stocks, and diversity in educational backgrounds. The firm's stock of knowledge capital is measured by intangible capital that is calculated from organisational, product development and ICT investments. The employees' knowledge stock is approximated by their completed educational degrees. Our data originate from Danish registers and covers 2000–2016. The findings indicate that intangible capital has the potential to increase the likelihood of becoming a gazelle. We further find that educational diversity is beneficial but is moderated by firms' knowledge intensity.

## KEYWORDS

High education; gazelle; intangible capital; high growth; fast growth; employment; knowledge competences

## 1. Introduction

Interest in gazelles or high (fast) growth firms has been increasing in recent years due to their role in industry dynamics (Coad et al. 2014, p. 93). For example, Bos and Stam (2014) relate gazelles to Schumpeterian creative destruction and show that the rise in the number of gazelles in an industry is an indicator for future growth. Furthermore, they play a role in generating new jobs (Birch 1979). However, understanding what factors contribute to the high growth remains a challenging exercise (Coad and Srhoj 2019). Studies have used different measures of high growth and found consistently that young firms tend to grow faster than the older ones (Henrekson and Johansson 2010). Yet, as stated by Coad and Srhoj (2019, p. 16), the prediction success is modest across studies. Given that knowledge and innovation competences are increasingly the source of competitive advantage, knowledge capital may play an important role in firm growth. Knowledge capital is what helps the firm to readjust, re-evaluate and innovate new products, processes and brands. At the same time, the diversity of knowledge resources may also be important for firm growth, as firms develop the need for a broader set of competences. We contribute to this gap in the literature by looking at how knowledge capital and its diversity support the probability of becoming a young high growth firm, a gazelle.

**CONTACT** Carita Eklund  [ceklund@uwasa.fi](mailto:ceklund@uwasa.fi)  The Danish Centre for Studies in Research and Research Policy, Aarhus University, Denmark

© 2022 The Author(s). Published by Informa UK Limited, trading as Taylor & Francis Group.  
This is an Open Access article distributed under the terms of the Creative Commons Attribution-NonCommercial-NoDerivatives License (<http://creativecommons.org/licenses/by-nc-nd/4.0/>), which permits non-commercial re-use, distribution, and reproduction in any medium, provided the original work is properly cited, and is not altered, transformed, or built upon in any way.

The literature has discussed whether technology-intensive industries dominate in high growth. Daunfeldt, Elert, and Johansson (2016) find that especially in knowledge-intensive services, high growth firms are overrepresented compared to other sectors and posit that the main reason for this observation is the abundance of human capital that is deployed in these industries. In fact, many highly educated employees might self-select themselves into knowledge-intensive services, such as consultancy. Thus, we expect that knowledge capital could be the hidden factor behind high growth in the knowledge-intensive sector. In our approach, we will conceptually split knowledge capital into two parts based on ownership of the asset. Employees own the human capital (HC) and firms own intangible capital (IC). Intangible capital consists of knowledge created by the employees in knowledge-intensive positions and knowledge bought from outside of the firm, such as consultancy.

We focus the analyses on how the level and diversity of human capital contribute to the probability of becoming a gazelle. There are arguments both for and against positive contributions of diversity in human capital (see Horwitz and Horwitz 2007; Williams and O'Reilly 1998). Human capital can provide access to diverse ideas and understanding. This can result in a new way to advertise the product that will speak to different kinds of customers or in improved efficiency of business processes. The hindering part of diverse knowledge is that the employees might talk in different terminologies and hence misunderstandings can be common. Another possibility is 'homophily' (Byrne 1971; Golub and Jackson 2012), where employees prefer teammates similar to themselves. In our analysis, we will argue that this ambiguity can largely be resolved when accounting for the cognitive abilities of the employees.

This research broadens the knowledge of gazelles by investigating gains from human capital and intangible capital towards high growth. High growth can be a path to survival (Almus 2002), and it can, in some cases, renew itself (Eklund 2020). Hence, our research question is *how can firms' and employees' knowledge competences act as a route towards sustained growth for young firms?* We measure high growth within a three-year period, using the Eurostat-OECD (2008) definition. The firm's knowledge base is measured by intangible capital (consisting of three parts: organisational, ICT and research & development capital) that assumes that in certain positions a share of employees' worktime builds up the knowledge stock of the firm and that s/he uses some share of outside services in the process. However, since human and intangible capitals are intimately intertwined for value creation, it is important to treat them in tandem. As such, we aim to investigate the contribution of human capital together with intangible capital for young high-growth firms to become gazelles. Employees' knowledge competences, human capital, are measured with the highest completed education. To complement this measure, we calculate a measure on diversity in education. We hypothesise that employees with master's degrees or higher might be more able to benefit from this diversity. We approach this with an interaction analysis. The analysis is based on a linked employer–employee dataset covering all employees and employers in the Danish business sector during 2000–2016.

The birth of a gazelle in Denmark is especially interesting given the market conditions. The economy is a small and open with expensive labour, high taxation and high price level. Meanwhile, foreign firms with lower price levels challenge the domestic firms. For

economic growth, young firms bring disturbances and are one important route for gross domestic product growth. Gazelles provide support for labour market dynamics, options for funders and even macroeconomic growth. Yet, Calvino, Criscuolo, and Menon (2015) state that young Danish firms experience a *growth trap* and many young firms exit the market as a result. One reason for this trap can be sub-optimal size, when firms exit before reaching minimum efficient level (Almus 2002). Cefis and Marsili (2006) stress the importance of innovation with regard to firms' survival probabilities. Moreover, they find that while small firms are especially at exit risk, small firms also benefit the most from innovation to increase their chances of survival. Further, Czarnitzki and Delanote (2013) investigate the role of innovation for high-growth and find that young and innovative firms grow faster than the other, already fast-growing firms grow.

We find that diverse human capital is beneficial towards high growth. Additionally, the findings show that the firm's intangible capital usually supports the probability of young firm's high growth: especially research and development capital supports high growth. Taken together, the current state-of-the art makes a strong case for knowledge capital being a driver of high growth among young firms. However, less has been said about the role of – upfront – education of the workforce in this regard. The contribution to the literature consists of widening the understanding of gazelles' benefits from knowledge capital and knowledge diversity.

The next section reviews related literature and develops the hypotheses that we will be examined in the paper. Section 3 describes the methods and data used, while section 4 presents the results of the analysis. Section 5 concludes.

## 2. Literature review and hypothesis development

While large firms have the majority of existing jobs, Birch (1979) shows that most of the new jobs originate from small firms instead of large firms in the United States. Since then, small firms have been in the spotlight when it comes to new job creation. However, Haltiwanger, Jarmin, and Miranda (2013) show that this pattern between small size and job creation disappears once firm age is controlled for suggesting that it is not the small but the young firms that drive the job creation. Furthermore, Lawless (2014) finds that young firms create the majority of new jobs irrespective of their size.

Lotti, Santarelli, and Vivarelli (2003) show with Italian data that small new firms grow faster a year after their entry than larger ones. They reason that the small entrants need to grow quickly in order to survive, as suggested by the theoretical model of Jovanovic (1982). In other words, they need to achieve minimum efficient scale in production. Also, Geurts and Van Biesebroeck (2016) find support for Jovanovic (1982) with Belgian data: the exit and growth rates of new firms decline with size and age.

In practice, sub-optimal size could mean a pizzeria with only one employee. In this example, the only employee would need to serve the food, clean and make the pizzas. Hence, the firm could not serve as many tables as it could with three employees. With more employees, the new firm is able to draw more gains out of the (physical) capital. Another example is an ice cream stand, where the second employee could be selling ice cream when the other one is off work. Hence, Almus (2002) reasons that the firm might rush the growth so that production quickly reaches the minimum efficient level. This rush might result in a faster growth status. For small young firms, growth can be a matter

of necessity – many new firms do not survive their youth. Calvino, Criscuolo, and Menon (2015) state that a *growth trap* of young Danish firms is at age three when a large share of young firms exit the market. One route out of this trap is greater knowledge competences that can foster innovation and growth.

However, the high growth literature has some critiques. Zhou and van der Zwan (2019) hypothesises that there might be a dark side of growing fast and find an inverse U-relationship from growth to survival. As theorised by Pierce and Aguinis (2013), a Too Much of a Good Thing (TMGT) effect might apply here too. In our pizzeria example, TMGT could be realised as a lack of human resource management skills or the quality of pizza suffering from inadequately trained cooks.

Coad, Frankish, and Storey (2020) investigate the relationship between survival and high growth with a sample of almost 6600 new firms with bank account data. They approach high growth a bit differently than we do in this paper. First, they measure high growth by yearly sales growth. They justified this by a high exit rate: half of the new firms did not survive the three-year period.<sup>1</sup> Second, with their measurement, the focus remains on the ‘intense burst of potentially excessive growth’ (Coad, Frankish, and Storey 2020, p. 553). Third, they focus on sales as the expenses of growth are realised well in advance of the revenues, hence underlying the importance of cash instead of employees. Additionally, Coad, Frankish, and Storey (2020) argue that high growth might be a signal of high risk taking which also means a larger probability of failing than with risk neutrality.

Nonetheless, young firms that grow especially fast are an important and interesting group of firms to investigate as they, by definition, have just exceeded expectations. These fast-growth firms, gazelles, are important for the dynamics of the economy. They might be a result of the entrepreneur’s braveness or a strong vision. To achieve innovative growth, the potential gazelle needs innovation capabilities and intellectual capital. Innovation capabilities are important for innovation as shown by Eklund (2019), who shows a link between intangible capital and future innovations: new products and processes. The firm first needs innovation before it can gain growth through them. Hence, we test if intangible capital can increase the probability of high growth.

H1: Young firms with a higher investment in intangible assets are more likely to become gazelles.

Knowledge assets are characterised by spillovers, synergies and increasing returns, unlike physical assets that tend to be governed by diminishing returns to scale (Tece 1998). Knowledge assets are more likely to confer a strategic advantage given that they are largely intangible and thus harder to imitate by competitors. Empirically it has been shown that in knowledge-intensive industries, high growth firms are overrepresented (Daunfeldt, Elert, and Johansson 2016), and investment into intangibles is beneficial to firm growth (Denicolai, Cotta Ramusino, and Sotti 2015). Thus, start-ups aiming to build a competitive edge might benefit especially from investment in intangible assets. For example, with regard to innovation, Santi and Santoleri (2017)

---

<sup>1</sup>The first year survival problem is also recognised by Eurostat-OECD (2008), who hence separate young high growth firms from the others.

find that process innovations support high (sales) growth. They find no gains from product innovations to high growth. Their data consists of Chilean firms that report very low shares of world novelties (Santi and Santoleri 2017, p. 446) and can thus be seen as a limit case. Meanwhile, Bianchini and Pellegrino (2019) find that constant product innovation affects job creation, while constant process innovation remains statistically insignificant. We expect that in the Danish context, more generally, higher investments into intangible capital correspond with a greater chance for a firm to become a gazelle.

However, intangible capital is only one form of intellectual capital. Matricano (2016) inspects the impact of intellectual capital on start-up expectations. Following previous research, he places human capital at the centre of intellectual capital. 'By definition, human capital entails competences (knowledge and personal capabilities), attitudes (motivation and leadership) and intellectual agility (originality or flexibility)' (Matricano 2016, p. 656). The main difference between human (HC) and intangible capital (IC) is that HC leaves the firm when the employee heads home and IC accumulates at the firm from employees in certain, knowledge building, positions. Manyika et al. (2018) report that high growing sectors tend to have both a high level of intangible assets and skilled labour, i.e. human capital. Additionally, human capital (HC) accumulation has been shown to be an important driver of firm growth. For example, Goedhuys and Sleuwaegen (2010) find for a representative sample of Belgian firms that HC is an important driver of growth, i.e. HC decreases the chances of low growth performance or failure. HC is thus especially important for firms in the start-up phase given that their survival often depends on growth. For high-tech ventures, Siepel, Cowling, and Coad (2017) find that 'access to workforce skills and human capital appears to be a prerequisite for growth'. However, whereas IC is owned by the company, measures certain knowledge aspects and is non-mobile, HC can include knowledge from multiple fields and social capital. Human capital usually also means access and ability to follow recent scientific findings in the educational area and having contacts, who might be a source of inspiration for new solutions. We hypothesise, more generally but in line with the above that:

H2: Young firms with a higher share of knowledge workers, i.e. employees with a higher educational attainment, are more likely to become gazelles.

While the existing literature has mainly measured HC quality by looking at the educational attainment of the workforce (e.g. Arrighetti & Lasagni, 2013), less attention has been given to the diversity in educational backgrounds of the workforce. Diversity is interesting because it can support the firm's competitive edge. For example, Østergaard, Timmermans, and Kristinsson (2011) find a positive relation between educational diversity and innovation. Related to the survival problems presented by Coad, Frankish, and Storey (2020), diverse competences might help the firm to answer to the demands of managing high growth, such as human resource management, knowing how the industry works, and keeping the finances in balance.

Diversity has been shown to give biotech university spinoffs in Germany and Switzerland greater access to resources and even to credibility (Moog and Soost 2020). While university spinoffs are a special case of new firms, educational diversity might still

open doors to different groups of experts. Diverse human capital can also be a proxy for diverse social capital: Maurer and Ebers (2006) find in a case study of German biotechnology start-ups that successful start-ups had managed to keep their ties to the scientific community and to establish new ones.

Coad and Timmermans (2014, pp. 117–118) investigate entrepreneurial pairs and investigate diversity with hierarchy. They say that the order matters; e.g. an engineer inviting a business administrator is a different case than a business administrator inviting an engineer (Coad and Timmermans 2014, p. 118). Hence, they use the difference in starting time to approximate the power dynamics hierarchy. Coad and Timmermans (2014, p. 133) find that hierarchy moderates how diversity affects new businesses' outcomes.

Strategic management is heavily focused on diversity in top management teams (Schubert and Tavassoli 2020, p. 272). However, Schubert and Tavassoli (2020) argue that diversity matters also for middle management because top management has the power to decide whether the company says yes to an idea but middle management decides how the decision is executed. In other words, top management can make the entry (or exit) decision, but middle management makes it happen, thus affecting the outcome enormously. In a similar manner, the lower managerial 'levels' of employees also matter for the outcome. In fact, Backman and Kohlhasse (2020) investigated Swedish firms' rates of exit finding that educational diversity has a negative relation to the probability of exit, while cultural diversity relates to it positively.

We test if educational diversity could support the rare event of a young firm becoming a gazelle, i.e. a young high growth firm.<sup>2</sup> The route to becoming a gazelle could be through an innovation enabled by educational diversity. Another possible route is utilising diverse knowledge to identify rising (otherwise hidden) market potential, e.g. finding a niche market. Third, knowledge diversity might just be a factor enabling a promising business to make it in the markets with diverse social capital possibly attracting credibility and supporting an access to (scientific) communities (Maurer and Ebers 2006; Moog and Soost 2020). However, managing high growth sets new demands for the firm within, for example, human resource management, finance and accounting. In managing these demands, a diverse set of knowledge could be crucial.

Consequently, this paper empirically investigates whether educational diversity<sup>3</sup> and level are good additional predictors for becoming a gazelle. Diversity has several effects on teams as discussed by Golub and Jackson (2012) and Williams and O'Reilly (1998). For example, in the start-up phase, when firms are figuring out the best way to conduct their business, having a more diverse set of knowledge to draw upon could increase chances to come up with new and better ways of doing business, as the knowledge base to draw from is larger. On the other hand, reconciling opposing views takes time and effort. Groups of people with similar educational backgrounds can reach consensus faster than groups with diverse knowledge (Golub and Jackson 2012).

---

<sup>2</sup>Testing how diverse education affects survival prior and after high growth status is left for future research.

<sup>3</sup>One should also note that educational diversity might correlate with the timing in innovation process: A firm at the start of innovation process might have less diverse workforce than a firm, who already markets its new product. Yet, in this case, the firm is assumed to have only one product or being heavily concentrated into one.

Team diversity has attracted considerable interest in the literature. Horwitz and Horwitz (2007) performed a meta-analytic review of the literature on team diversity in performance. There exists a lot of evidence for and against diversity enhancing performance, but Horwitz and Horwitz (2007, p. 1008) note that there are two paradigms of diversity, inverted U and upright U models, and call for more research with longitudinal data to study the dynamics. A more recent study by Parrotta, Pozzoli, and Pytlikova (2014) investigate gender, ethnicity and educational differences, and productivity with Danish linked employee-employer data. Their results on educational diversity are dependent on the estimation method. Their reduced-form analyses suggest a positive variation, but structural estimation finds no benefits of mixing highly educated employees with low-educated ones (Parrotta, Pozzoli, and Pytlikova 2014, p. 170). Moreover, Parrotta, Pozzoli, and Pytlikova (2014, p. 171) find that with (two digits) control on industries, educational diversity within highly educated employees positively correlates with productivity in half of the industries. However, there might be a relationship between education and diversity. For example, Kaiser and Müller (2015, p. 800) find that in knowledge-intensive industries, start-ups become more diverse as they age – except for start-ups founded by graduates, possibly classmates. Accordingly, we assume that the tension between gains and costs of diversity could largely be eased when the capacities of individuals to reconcile opposing views are strong or when the benefit from inter-individual spillovers is larger than the cost of longer negotiation. We hypothesise that this is the case when the agents in the workforce have acquired better cognitive capabilities through higher education:

H3: Young firms having a more diverse workforce are more likely to become gazelles, if the workforce is highly educated.

Research uses several definitions for gazelles that are a group of exceptionally fast growing *young* firms. In fact, the used fast growth definitions differ enormously – and the definition affects the selected high growth firms. While for example Hölzl (2014) uses a size neutral Birch (1979) index approach to measure high growth, Eurostat-OECD (2008, p. 62) recommends looking at annualised three-year growth, excluding firms born three years ago. The strength of the measure compared to Birch index is that the selected high growth firms are unaffected by addition or deletion of other firms in the data. We follow the Eurostat-OECD (2008, p. 63) *gazelle* definition:

All enterprises up to 5 years old with average annualized growth greater than 20% per annum, over a three year period, should be considered as gazelles.

Another commonly used definition follows from the growth of sales. An example is Coad, Frankish, and Storey (2020), who focus on yearly sales growth, where also many fast growers exit the markets. Following Hölzl (2014) our focus is on the change of employees as hiring decisions are more future oriented than sales. The literature has many names for these firms, such as high growth firms (Coad and Srhoj 2019; Megaravalli and Sampagnaro 2019), who have no age limit, fast growth firms (Calvino 2019) and superstars (Autor et al. 2017; Manyika et al. 2018). The choice to focus on gazelles follows first from an interest in young firms that are interested in economic growth reasons. One route to macroeconomic growth from gazelles is creative



destruction. Lentz and Mortensen (2008) model creative destruction where resources are reallocated to better performing production. This production could be in a young firm. Second, gazelles are interesting due to the forward-looking nature of employment decisions, as Hölzl (2014) discusses. Third, when measuring high growth with employees, we are counting the numbers of true new jobs and not just occupations that are replacing old ones. As a result, one could expect there to be positive spillovers of employment to society. The following section elaborates on the measurement of dependent variables and presents methods to predict high growth firms.

### 3. Methods and Data

We follow the Eurostat-OECD (2008, p. 63) definition of gazelles according to which gazelles are at most 5 years old firms with 20% annual growth during three subsequent years. Thus, the sample generated from the Danish register data consists of firms between three and five years of age. To measure high growth, we use the number of full-time equivalents of employees. However, to account for educated employees we use the number of employees registered, with a master's degree or higher, at the firm. Employee education is measured as the highest achieved degree. We include a measure of human capital in order to capture knowledge competences and intellectual agility (Matricano 2016, p. 656) – as knowledge resides in the employees (Harris and Moffat 2013).

Diversity in knowledge is measured with the Blau index (Gini-Simpson index), assuming that 'members differ from one another qualitatively' (Harrison and Klein 2007, p. 1204) and it does not reflect the distance between categories.<sup>4</sup> To assure a focus on the field of education, the Blau index consists of employees with at least a bachelor's degree. The Danish statistics identify education field with a six-digit ISCED code.<sup>5</sup> The Blau index is calculated as in equation (1), where  $p_k$  is the share of employees with a degree in field  $k$ . Unlike in the estimation of gazelles, the number of employees is a head count, not a count of the full-time equivalents. This means that a person working at 20% capacity is weighted evenly to a full-time employee in the Blau index.<sup>6</sup>

$$blau = 1 - \sum_{k=1}^K p_k^2 \quad (1)$$

The data are from the Danish registers, 2000–2016. The estimation sample starts at 2003 as the gazelle measure uses three previous years. Control variables include year and sector dummies and size.<sup>7</sup> Sector dummies can be interpreted as a proxy measure for trends. Parker, Storey, and Van Witteloostuijn (2010) report that the sector of a firm cannot

<sup>4</sup>An underlying simplifying assumption here is that an employee is a representative only of one area, based on the most recent highest achieved education.

<sup>5</sup>[https://ec.europa.eu/eurostat/statistics-explained/index.php?title=International\\_Standard\\_Classification\\_of\\_Education\\_\(ISCED\)](https://ec.europa.eu/eurostat/statistics-explained/index.php?title=International_Standard_Classification_of_Education_(ISCED)).

<sup>6</sup>The index values are dependent on the size of the firm. Kaiser and Müller (2015, p. 792) point out that the minimum value for a firm of size  $N$  is  $1/N$  and hence use a scaled version of Blau index. We have a separate control variable for size and we also recognise size dependence of diversity.

<sup>7</sup>Size and sector controls were also used in Moschella, Tamagni, and Yu (2019)

sufficiently predict high growth: different industries produce high growth at different times. As discussed previously, firm size might have a negative impact on the probability of high growth. The data includes several interesting time events, such as financial crises (that can be expected to hit young firms harder when the funders act to reduce risk in their investment decisions) and the recovery period. For a better picture on drivers of young firms to high growth, we include year dummies.

The measures of intangible capital are based on employee occupation data, where it is assumed that knowledge-intensive employees within organisational, R&D and ICT-based positions generate intangible capital through their work. Following Görzig, Piekkola, and Riley (2010), the intangible capital construction assumes that a fraction of knowledge-intensive employees' worktime is of investment nature and that intangible investments also involve non-labour inputs. In other words, intangible investments equal a fraction of knowledge-intensive employment expenses multiplied by the investment nature share of worktime multiplied by the assumed amount of average intermediate input usage. These investments form intangible capital together with the previous year's intangible capital stock minus the depreciation. Organisational capital depreciates 20% (25% in service industries), research & development 15 %, and ICT capital 33% (Görzig, Piekkola, and Riley 2010). An advantage with this intangible capital measure is the wide coverage of the sample compared to an innovation survey. Thus, we are not limited by the random sampling of small firms into the survey, and we have an estimate of their innovation spending for each year.

The estimation method is logit because of the binary nature of the outcome variable. We make a logarithmic transformation for the explanatory variables, which are not between zero and one. *Gazelle* is a dependent variable equalling one when a firm meets the requirement for gazelle high growth and zero when it does not. In equation 2, *SH* stands for the share of highly educated employees, i.e. employees with a master's degree or higher. *BSH* is the interaction of the Blau index and the share of highly educated employees. Intangible capital is captured by three types: RD (research and development capital), OC (organisational capital), and ICT (information communication technology capital).

$$\begin{aligned} \text{Gazelle}_{i,t} = & \beta_0 + \beta_1 \text{Blau}_{i,t-3} + \beta_2 \text{SH}_{i,t-3} + \beta_3 \text{BSH}_{i,t-3} + \beta_4 \ln \text{emp}_{i,t-3} + \beta_5 \ln \text{RD}_{i,t-3} \\ & + \beta_6 \ln \text{OC}_{i,t-3} + \beta_7 \ln \text{ICT}_{i,t-3} + \varepsilon_{i,t} \end{aligned} \quad (2)$$

Table 1 documents the variable names and descriptions. Table 2a contains descriptive statistics and Table 2b shows the distribution of observations, gazelles and other young firms over the sectors, i.e. 2-digit NACE codes.<sup>8</sup> Table 2c contains the pairwise correlations.

About 14% of firms in our estimation sample are labelled as gazelles by the Denmark Statistics' definition. The number of gazelles identified per year fluctuates around 400 in the early years of our sample. It drops substantially during the period of the financial crisis and never fully recovers as demonstrated by Figure 1. The Blau (knowledge diversity) index is on average around 0.2. Yet, its gazelles' average is about 25% times higher than for non-gazelle firms, whose average blau value is

<sup>8</sup>For information on the NACE classification, see <https://ec.europa.eu/eurostat/web/nace-rev2>.

**Table 1.** Variable descriptions.

| Variable           | Description   |
|--------------------|---|
| Gazelle            | Young high-growth firms, aged less than 5 years and having average growth of at least 20 pct. Over a 5 year period (starting from an initial size of at least 5 employees) – DST definition |
| OC <sub>t-3</sub>  | Organisational assets, in analyses this is in logarithm and lagged by 3 years   |
| ICT <sub>t-3</sub> | ICT (information communication technology) assets, in analyses this is in logarithm and lagged by 3 years   |
| RD <sub>t-3</sub>  | R&D (research and development) assets, in analyses this is in logarithm and lagged by 3 years   |
| age                | Age of the firm in number of years  |
| blau               | Blau educational diversity index, calculated on the basis of all employees in the firm with at least bachelor level education   |
| SH                 | Share of employees with a master level education  |
| BSH                | Interaction term of blau and SH   |
| emp                | Number of employees, in analyses this is in logarithm   |

**Table 2a.** Descriptive statistics for full sample.

| Variable | Full sample (N = 31,869) |       |        | Gazelles (N = 4570) |       |       | Other young firms (N = 27,299) |       |        |
|----------|--------------------------|-------|--------|---------------------|-------|-------|--------------------------------|-------|--------|
|          | $\mu$                    | p50   | sd     | $\mu$               | p50   | sd    | $\mu$                          | p50   | sd     |
| Gazelle  | 0.14                     | 0     | 0.35   | 1                   | 1     | 0     | 0                              | 0     | 0      |
| OC       | 241                      | 0     | 3453   | 158                 | 0     | 1244  | 255                            | 0     | 3694   |
| ICT      | 269                      | 0     | 5452   | 376                 | 0     | 3955  | 251                            | 0     | 5664   |
| RD       | 1180                     | 0     | 27,272 | 898                 | 0     | 9390  | 1226                           | 0     | 29,215 |
| blau     | 0.2                      | 0.19  | 0.21   | 0.25                | 0.19  | 0.25  | 0.19                           | 0.19  | 0.2    |
| SH       | 0.06                     | 0     | 0.13   | 0.08                | 0     | 0.15  | 0.05                           | 0     | 0.13   |
| BSH      | 0.03                     | 0     | 0.08   | 0.05                | 0     | 0.11  | 0.3                            | 0     | 0.08   |
| Emp      | 31.20                    | 11.49 | 290.62 | 37.11               | 20.71 | 92.21 | 30.21                          | 10.25 | 311.72 |
| Age      | 4.23                     | 4     | 0.75   | 4.05                | 4     | 0.8   | 4.26                           | 4     | 0.74   |

**Table 2b.** Distributions of observations over sectors.

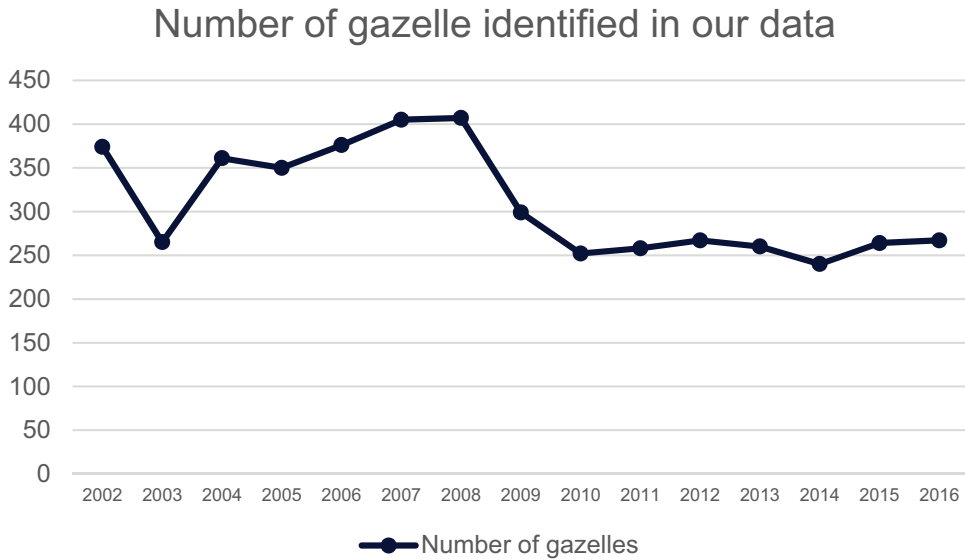
| Sector | Nace codes   | N      | #Gazelles | #other young firms |
|--------|--|--------|-----------|--------------------|
| B      | Mining and quarrying   | 49     | 7         | 42                 |
| C      | Manufacturing  | 5890   | 750       | 5140               |
| E      | Water supply; sewerage, waste management and remediation activities  | 17     | 2         | 15                 |
| G      | Wholesale and retail trade; repair of motor vehicles and motorcycles | 11,020 | 1186      | 9834               |
| H      | Transportation and storage   | 2220   | 400       | 1820               |
| I      | Accommodation and food service activities                            | 3341   | 372       | 2969               |
| J      | Information and communication  | 2000   | 559       | 1441               |
| K      | Financial and insurance activities                                   | 120    | 5         | 115                |
| L      | Real estate activities   | 858    | 103       | 755                |
| M      | Professional, scientific and technical activities                    | 3788   | 600       | 3188               |
| N      | Administrative and support service activities                        | 2548   | 585       | 1963               |
| R      | Arts, entertainment and recreation                                   | 18     | 1         | 17                 |

Note: We excluded sectors A, D and F due to their 'mixed' nature in terms of service vs. manufacturing content. Also, the public sectors O-Q, S-U are excluded from the sample.

somewhat lower at 0.19. Firms in the estimation sample have on average about 6% of masters amongst their employees, rising to just about 8% for the gazelles and being somewhat lower for the non-gazelles at 5%. The firms in our sample have an average of about 31 employees; the gazelles are on average larger than the other young firms are. The intangible assets follow a natural pattern where on average RD assets are the largest, trailed by Organizational and ICT assets. This pattern is visible for both gazelle status and other young firms.

**Table 2c.** Correlations (N = 31,869).

| Correlations in estimation sample | gazelle | OC    | ICT   | RD    | blau  | SM    | blauSM | emp |
|-----------------------------------|---------|-------|-------|-------|-------|-------|--------|-----|
| <b>gazelle</b>                    | 1       |       |       |       |       |       |        |     |
| <b>OC</b>                         | -0.009  | 1     |       |       |       |       |        |     |
| <b>ICT</b>                        | 0.008   | 0.22  | 1     |       |       |       |        |     |
| <b>RD</b>                         | -0.004  | 0.35  | 0.18  | 1     |       |       |        |     |
| <b>blau</b>                       | 0.11    | 0.081 | 0.087 | 0.054 | 1     |       |        |     |
| <b>SH</b>                         | 0.074   | 0.047 | 0.051 | 0.028 | 0.054 | 1     |        |     |
| <b>BSH</b>                        | 0.096   | 0.055 | 0.059 | 0.029 | 0.72  | 0.90  | 1      |     |
| <b>emp</b>                        | 0.008   | 0.56  | 0.21  | 0.36  | 0.052 | 0.004 | 0.007  | 1   |

**Figure 1.** Evolution of the number of gazelles.

The following section presents the results based on equation (2). The robustness is then tested by separating the sample from firms having a share of highly educated employees higher than or below the full sample mean.

## 4. Results & discussion

Based on probability estimation performed as discussed in the previous section, we report here our estimation results on how knowledge stocks affect young firms' likelihood of becoming a gazelle. Section 4.1 presents the main analyses and 4.2 presents robustness analyses. Table 3 presents the results with the full sample, while Table 4 separates the sample by the mean share of master educated employees.

### 4.1. Main analyses

Table 3 reports the main results. Regression (1) includes OC (organisational capital assets), ICT (information communication technology assets), RD (research and development assets), blau (blau index), and the number of (full-time equivalent) employees.

**Table 3.** Logit models explaining the probability of becoming a gazelle.

|                        | (1)                  | (2)                  | (3)                  | (4)                  | (5)                  | (6)                  |
|------------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|
| VARIABLES              | Gazelle              | Gazelle              | Gazelle              | Gazelle              | Gazelle              | Gazelle              |
| ln OC <sub>t-3</sub>   | 0.077***<br>(0.0083) | 0.078***<br>(0.0083) | 0.076***<br>(0.0083) | 0.074***<br>(0.0083) | 0.073***<br>(0.0083) | 0.072***<br>(0.0083) |
| ln ICT <sub>t-3</sub>  | 0.049***<br>(0.011)  | 0.048***<br>(0.011)  | 0.047***<br>(0.011)  | 0.044***<br>(0.011)  | 0.045***<br>(0.011)  | 0.044***<br>(0.011)  |
| ln RD <sub>t-3</sub>   | 0.076***<br>(0.0066) | 0.074***<br>(0.0066) | 0.074***<br>(0.0067) | 0.072***<br>(0.0066) | 0.074***<br>(0.0067) | 0.071***<br>(0.0067) |
| ln emp <sub>t-3</sub>  | -0.90***<br>(0.033)  | -0.89***<br>(0.033)  | -0.89***<br>(0.033)  | -0.91***<br>(0.033)  | -0.92***<br>(0.034)  | -0.92***<br>(0.034)  |
| blau <sub>t-3</sub>    | 0.43***<br>(0.087)   | 0.29***<br>(0.11)    | 0.051<br>(0.12)      | -1.42***<br>(0.21)   | -1.50***<br>(0.22)   | -2.13***<br>(0.27)   |
| blau2 <sub>t-3</sub>   |                      |                      |                      | 3.11***<br>(0.33)    | 3.57***<br>(0.38)    | 4.78***<br>(0.53)    |
| SH <sub>t-3</sub>      |                      | 0.37**<br>(0.17)     | -0.97***<br>(0.33)   |                      | -0.52**<br>(0.21)    | -1.13***<br>(0.42)   |
| blauSH <sub>t-3</sub>  |                      |                      | 2.64***<br>(0.52)    |                      |                      | 6.19***<br>(1.87)    |
| blau2SH <sub>t-3</sub> |                      |                      |                      |                      |                      | -8.16***<br>(2.02)   |
| Constant               | -0.73<br>(1.03)      | -0.74<br>(1.03)      | -0.71<br>(1.03)      | -0.68<br>(1.03)      | -0.66<br>(1.03)      | -0.63<br>(1.04)      |
| Observations           | 31,869               | 31,869               | 31,869               | 31,869               | 31,869               | 31,869               |
| Year & Sector dummies  | yes                  | yes                  | yes                  | yes                  | yes                  | yes                  |
| pseudo R-squared       | 0.0655               | 0.0656               | 0.0667               | 0.0688               | 0.0690               | 0.0697               |
| Log Lik                | -12,243              | -12,241              | -12,227              | -12,200              | -12,196              | -12,187              |

All of these variables date back to  $t-3$ , i.e. the year at which the start of the high growth period is defined. As controls, all the regressions have year dummies, 2003 as base. Regression (2) further has the SH variable that is the share of master educated employees. Regression (3) additionally includes an interaction term between blau and SH. Regression (4) and (5) add the square of blau to the model. Regression (6) interacts both the linear and squared blau variable with SH.

The results in Table 3, regression (1), suggest that diversity in education (blau) is in itself a predictor for gazelles. In addition, when it is interacted with high-education share (SH), the overall effect is positive and significant, regression (3). The share of highly educated employees has a negative coefficient and is significant in when the share (BSH) is included.

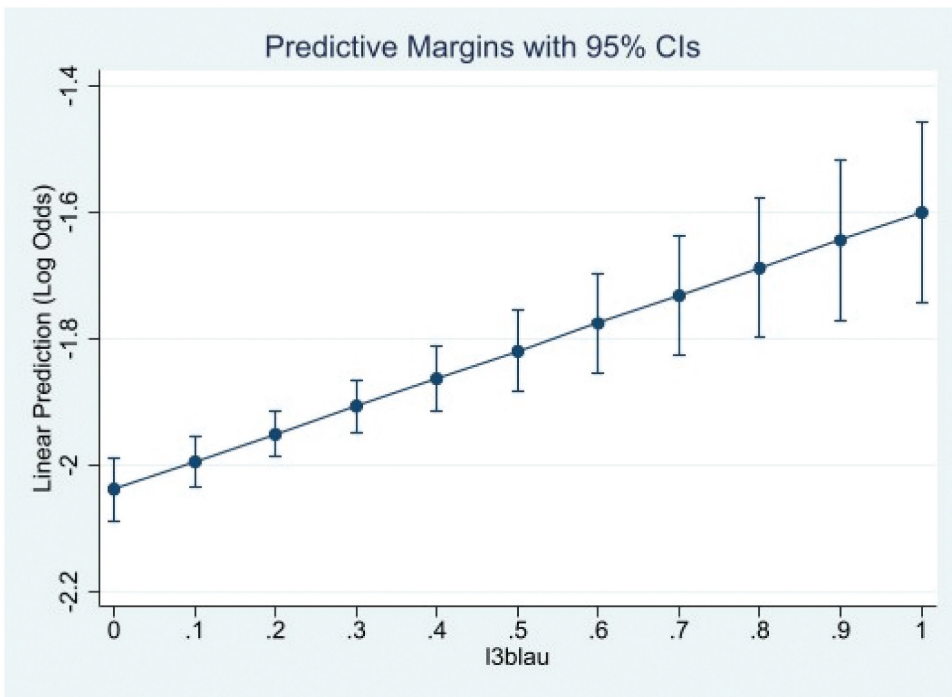
To gauge the magnitude of the effect, we calculate the predictive margins of the lagged blau coefficient at fixed intervals and at the mean values of the other covariates (except sector and year dummies, which we keep at actual values). Table 3b shows these results for regression (1), and indicates that the effects are indeed sizeable. Going from minimum to maximum diversity increases the likelihood of having a gazelle status by over 35% ( $0.1688/0.1237 = 1.3645$ ).

Figure 2 shows the predictive margins of the lagged blau index. One can notice a clear overlap between the predictive margins, especially for lagged blau values close to 1. There is some overlap also for values close to zero, but it is not as evident as for the larger values.

Regressions (4)–(6) in Table 3 check for the nonlinearity of the effect. We find evidence of a non-linear U-shaped relationship. Again, to gauge the magnitude of the effect, we calculate the predictive margins of the lagged blau coefficient at fixed intervals and at the mean values of the other covariates (except sector and year dummies, which we keep at

**Table 3b.** Predictive margins for the effect of educational diversity on achieving gazelle status.

| Delta-method |        |           |         |      |                      |       |
|--------------|--------|-----------|---------|------|----------------------|-------|
|              | Margin | Std. Err. | Z       | P> z | [95% Conf. Interval] |       |
| 1            | -2.03  | 0.025     | -80.74  | 0    | -2.08                | -1.98 |
| 2            | -1.99  | 0.02      | -98.34  | 0    | -2.03                | -1.95 |
| 3            | -1.95  | 0.018     | -105.81 | 0    | -1.98                | -1.91 |
| 4            | -1.9   | 0.02      | -92.71  | 0    | -1.94                | -1.86 |
| 5            | -1.86  | 0.025     | -72.48  | 0    | -1.91                | -1.81 |
| 6            | -1.81  | 0.032     | -56.07  | 0    | -1.88                | -1.75 |
| 7            | -1.77  | 0.04      | -44.39  | 0    | -1.85                | -1.69 |
| 8            | -1.73  | 0.047     | -36.1   | 0    | -1.82                | -1.63 |
| 9            | -1.68  | 0.056     | -30.04  | 0    | -1.79                | -1.57 |
| 10           | -1.64  | 0.064     | -25.47  | 0    | -1.77                | -1.51 |
| 11           | -1.6   | 0.073     | -21.92  | 0    | -1.74                | -1.45 |

**Figure 2.** Predictive margins for the effect of educational diversity on achieving gazelle status.

actual values). Table 3c shows these results for regression (4) of Table 3. We find that the nonlinear model estimates the increases at lower blau values to be smaller, but larger for the higher values. Figure 3 visualise the nonlinearity in blau diversity index. Here, predictive margins at values 0 and 0.1 do not overlap with each other. Predictive margins at lagged blau values 1 and 0.9 do overlap, but 1 and 0.8 do not, unlike in Figure 2.

Further, based on the significant coefficients of intangible capital assets, it seems that innovation capabilities are important for high growth. Our estimations thus provide support for hypothesis 1 (Young firms with a higher investment into intangible assets are more likely to become gazelles) and support for hypothesis 3 (Young firms having a more

**Table 3c.** Predictive margins for the effect of educational diversity on achieving gazelle status – model with squared term.

| Delta-method |        |           |        |      |                      |       |
|--------------|--------|-----------|--------|------|----------------------|-------|
|              | Margin | Std. Err. | Z      | P> z | [95% Conf. Interval] |       |
| 1            | -1.93  | 0.027     | -71.11 | 0    | -1.98                | -1.87 |
| 2            | -2.04  | 0.02      | -97.67 | 0    | -2.08                | -2    |
| 3            | -2.09  | 0.024     | -86.16 | 0    | -2.13                | -2.04 |
| 4            | -2.07  | 0.028     | -73.84 | 0    | -2.13                | -2.02 |
| 5            | -2     | 0.03      | -66.42 | 0    | -2.06                | -1.94 |
| 6            | -1.86  | 0.032     | -57.08 | 0    | -1.92                | -1.8  |
| 7            | -1.66  | 0.04      | -40.9  | 0    | -1.74                | -1.58 |
| 8            | -1.4   | 0.057     | -24.3  | 0    | -1.51                | -1.29 |
| 9            | -1.07  | 0.083     | -12.89 | 0    | -1.24                | -0.91 |
| 10           | -0.69  | 0.11      | -5.88  | 0    | -0.92                | -0.46 |
| 11           | -0.24  | 0.15      | -1.53  | 0.12 | -0.55                | 0.067 |

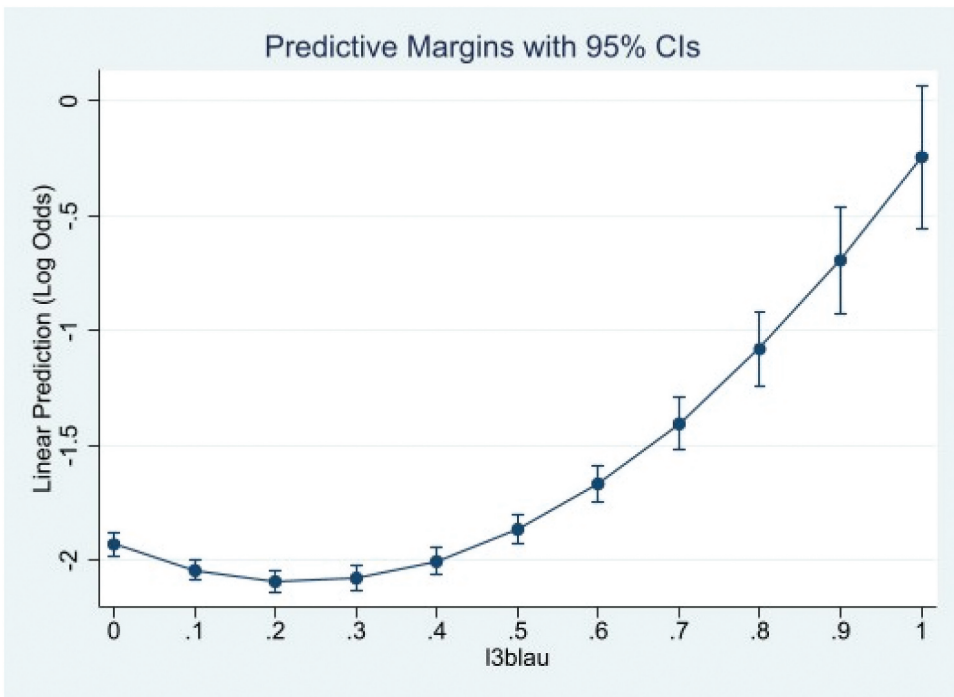
**Table 4.** Logit model and knowledge intensity.

| Variables             | (1)                                 | (2)                                 | (3)                                 | (4)                                 |
|-----------------------|-------------------------------------|-------------------------------------|-------------------------------------|-------------------------------------|
|                       | Gazelle<br>SH <sub>t-3</sub> ≥ Mean | Gazelle<br>SH <sub>t-3</sub> ≥ Mean | Gazelle<br>SH <sub>t-3</sub> < Mean | Gazelle<br>SH <sub>t-3</sub> < Mean |
| ln OC <sub>t-3</sub>  | 0.0099***<br>(0.0020)               | 0.010***<br>(0.0020)                | 0.0087***<br>(0.0011)               | 0.0084***<br>(0.0011)               |
| ln ICT <sub>t-3</sub> | 0.0057***<br>(0.0021)               | 0.0055***<br>(0.0021)               | 0.0097***<br>(0.0019)               | 0.010***<br>(0.0019)                |
| ln RD <sub>t-3</sub>  | 0.0088***<br>(0.0014)               | 0.0089***<br>(0.0014)               | 0.0089***<br>(0.001)                | 0.0083***<br>(0.001)                |
| blau <sub>t-3</sub>   | 0.18***<br>(0.023)                  | 0.027<br>(0.067)                    | -0.040**<br>(0.019)                 | -0.38***<br>(0.038)                 |
| blau2 <sub>t-3</sub>  |                                     | 0.18**<br>(0.078)                   |                                     | 1.08***<br>(0.101)                  |
| ln emp <sub>t-3</sub> | -0.17***<br>(0.0093)                | -0.17***<br>(0.0093)                | -0.087***<br>(0.0042)               | -0.097***<br>(0.0043)               |
| Observations          | 7,005                               | 7,005                               | 24,845                              | 24,845                              |
| Year & Sector dummies | yes                                 | yes                                 | yes                                 | yes                                 |
| Pseudo R2             | 0.0983                              | 0.099                               | 0.0548                              | 0.0602                              |
| Log Lik.              | -3062                               | -3060                               | -9102                               | -9051                               |

diverse workforce are more likely to become gazelles, if the workforce is highly educated). In the interaction analysis, we do not find evidence for an unconditional education-level-effect as put forward in hypothesis 2.

#### 4.2. Robustness checks

This section discusses robustness analyses of sample construction and knowledge intensity. First, one might be concerned that some larger and older firms could enter the data with a new firm tax ID-number due to a re-start, merger or acquisition. As such, they could potentially be identified as a gazelle, whereas they are actually an ‘old’ firm under a new ID-number. We made an additional check to see whether our results are robust to removing the largest firms from the sample. Our results are robust to cutting the 5 pct. largest firms from the sample, see [appendix 1](#) for the regression table. Thus, re-starting, merged or acquisition is not driving the analyses.



**Figure 3.** Predictive margins for the effect of educational diversity on achieving gazelle status – model with squared term.

Second, we checked the results for knowledge intensity. While [Table 3](#) supports the hypothesis of intangible capital and educational diversity, the following [Table 4](#) provides a robustness check. [Table 4](#) inspects how the intensity of knowledge affects the likelihood of becoming a gazelle. Hence, [Table 4](#) splits the sample into two parts, below and above the mean sample share of master educated employees. In [Table 4](#), regressions (1) and (2) consist of firms with above the mean and regressions (3) and (4) below the mean.

As the regressions in [Table 4](#) demonstrate, the significance of intangibles remains, supporting hypothesis 1. All three types of intangible capital remain statistically significant and positive in all the four regressions. Inspecting the coefficient of Blau diversity index and its squared term (blau2) indicates that the effects are purely positive for firms with the above average share of highly educated employees (SH, share of highly educated employees), whereas for firms with below the average share of highly educated employees (SH), the effect is U-shaped. Blau has a statistically significant and negative coefficient in regressions (3) and (4) and its squared term in (4) has statistically significant, positive coefficient. Meanwhile, for the sample of above the mean, regression (2) has even positive coefficient for Blau squared. We thus find robust evidence for hypothesis 3: Young firms having a more diverse workforce are more likely to become gazelles, if the workforce is highly educated.

Overall, our analysis supports hypothesis 1 that young firms with a higher investment into intangible assets are more likely to become gazelles, and hypothesis 3 that young firms having a more diverse workforce are more likely to become gazelles, if the workforce is highly educated.



## 5. Conclusions & Limitations

While high growth is a rare event, it is significant for industry dynamics for several reasons. First, high growth firms generate the majority of new jobs (Birch 1979). Second, high growth might be a result from a young firm reaching the minimum efficient scale for staying in the markets (Almus 2002) and, thus, increasing competition in their market. Also, high growth can be a sign of a firm escaping from a growth trap, a problem particular in Denmark (Calvino, Criscuolo, and Menon 2015). Further, high growth can be a result of innovation (Santi and Santoleri 2017). This research focuses on young high growth firms, applying the definition from Eurostat-OECD (2008).

Our findings contribute to the importance of crossing the boundaries of educational fields<sup>9</sup> in order to stand out in a dynamic economy and to become a gazelle firm. Our results imply that innovation capabilities are important factors in our context (following the results of Eklund 2020; Matricano 2016) and that educational diversity – a dimension that is currently still understudied – relates positively to high growth. We also find that educational diversity robustly predicts high growth for young firms, specifically for those that possess higher shares of master-level employees.

However, sectorial differences affect high growth firms' potential based on macro-economic trends (Parker, Storey, and Van Witteloostuijn 2010). We use sector (and size) dummies as controls following Moschella, Tamagni, and Yu (2019) who find, however, that the industries have no prediction power for high growth. Yet, Daunfeldt, Elert, and Johansson (2016) showed that high growth firms are overrepresented in knowledge-intensive industries. Our sample covers many new firms in each sector every year and a fraction of 'intellectual property economy' or 'knowledge economy' period. Thus, the importance of innovation capabilities should not be unexpected. The results are in line with Denicolai, Cotta Ramusino, and Sotti (2015), who show that investments in intangibles support firm growth. We take a step further and show that intangibles are important for the extreme event of becoming a gazelle.

The analyses have its limitations. The first is survival bias. Following the Eurostat-OECD definition, the sample consists of young firms that have survived three years. Thus, the estimation does not capture firms that exit the market either by being bought out (i.e. entering into the so-called 'kill zone') or bankruptcy (not achieving the minimum efficient scale in production or not achieving enough demand from the markets (Almus 2002)). Second, the focus on high growth is a narrow analysis of entrepreneurship. It is important to highlight that we focus on the top of the class in job creation during three subsequent years. Nightingale and Coad (2014) highlight that gazelles are a small fraction of all entrepreneurial firms. One group left behind is social entrepreneurship, where the owner tends to be highly educated, and the firm aims to promote social change in addition to traditional business values (Terjesen, Bosma, and Stam 2016). Also, it is possible that firms with knowledge diverse workforce are already different from the other firms and, hence, knowledge diversity is a signal of, say, different company values or management practice. Social entrepreneurship is an example of evaluating other goals than (in addition to) traditional business success. Furthermore, firms with diverse knowledge base can differ from firms with homogenous employment base. These diverse

---

<sup>9</sup>Employee diversity has been shown to be beneficial for innovation in Østergaard, Timmermans, and Kristinsson (2011).

firms might have different activities than the homogenous firms. The difference in activities is an omitted variable in our sample that we can control a bit with sector dummies. The driving forces for diverse employment base is left for further research.

A third possible limitation in our approach is what might happen after the high growth – does high growth support the firm's survival later on? Zhou and van der Zwan (2019) hypothesised, following Pierce and Aguinis (2013), that there might be a Too Much of a Good Thing (TMGT) effect. In other words, there might also be a dark side of growing too fast. For example, the company needs a different organisational strategy and structure to handle a larger workforce. This is in line with Zhou and van der Zwan (2019), who find an inverse U-relationship between survival and employment growth. We would expect that firms that are more diverse would experience a flatter inverse U-relationship between survival and employment growth than the other firms would. The gains to survival from employees' diversity after high growth is left for future research.

There is some research on survival after high growth by sales. Coad, Frankish, and Storey (2020) investigated the survival of almost 6600 new firms from customer bank records and measured growth by annual sales growth. The yearly focus was chosen as 50% of new firms did not survive after three years. They hence focused on the 'intense burst of potentially excessive growth' (Coad, Frankish, and Storey 2020, p. 553). They pointed out that the costs associated with high growth are realised well in advance of the revenue and that the firm needs to have 'the ability to manage this access to credit without incurring penalty costs' (Coad, Frankish, and Storey 2020, p. 553). Furthermore, Rostamkalaei and Freel (2016) find that firms that have experienced recent high growth are paying higher interest on their loans. One can see their results as a further call for diverse knowledge of management given the need for a broad risk assessment when the cost of external funds is high. Coad, Frankish, and Storey (2020) further identify that the price on rushed projects tends to be higher than on normally conducted projects, time pressure tends to weaken the quality of decision-making, and high growth might be a signal of high risk taking that can also lead to big losses. Yet, our definition of high growth uses a period of three years, the rush and riskiness should be lower than in Coad, Frankish, and Storey (2020).

Focusing on employment instead of sales is a more stable measure than sales. Yet, we value the future orientation of the employment measure (Hözl, 2013) and as showed by a control variable in Eklund (2020), high growth firms measured by employment do renew exceptional growth. Hence, survival after high growth is not as worrisome in our analyses using an employment measure instead of sales. Future research could also investigate whether gazelles as defined by employee growth have a high level of sales from the start to support the new large size. Even though high growth might not have survival benefits in all cases, at least high growth supports a lively business environment by challenging stagnant firms.

## Acknowledgments

The authors want to thank great colleagues at CFA for support, professors Ebbe Krogh Graversen & Carter Bloch for mentorship and conference participants at DRUID21, RADMA21 and seminar participants at Circle, Lund University, for constructive comments.

## Disclosure statement

No potential conflict of interest was reported by the author(s).

## Funding

This project has received funding from Aarhus University and from the European Union's Horizon 2020 programme under grant agreement no. 822259.

## ORCID

Carita Eklund  <http://orcid.org/0000-0002-4217-0927>

## References

- Almus, M. 2002. "What Characterizes a Fast-growing Firm?" *Applied Economics* 34 (12): 1497–1508. doi:10.1080/00036840110105010.
- Arrighetti, A., and A. Lasagni. 2013. "Assessing the Determinants of High-growth Manufacturing Firms in Italy." *International Journal of the Economics of Business* 20 (2): 245–267. doi:10.1080/13571516.2013.783456.
- Autor, D., D. Dorn, L. F. Katz, C. Patterson, and J. Van Reenen. 2017. "The Fall of the Labor Share and the Rise of Superstar Firms". NPR working paper, 23396.
- Backman, M., and J. E. Kohlhase. 2020. "Labor Force Diversity and Firm Survival." *Journal of Regional Science* 60 (5): 903–928. doi:10.1111/jors.12488.
- Bianchini, S., and G. Pellegrino. 2019. "Innovation Persistence and Employment Dynamics." *Research Policy* 48 (5): 1171–1186. doi:10.1016/j.respol.2018.12.008.
- Birch. 1979. "The job Generation Process". Vol.302. Cambridge, MA: MIT Program on Neighborhood and Regional Change.
- Bos, J. W., and E. Stam. 2014. "Gazelles and Industry Growth: A Study of Young High-growth Firms in the Netherlands." *Industrial and Corporate Change* 23 (1): 145–169. doi:10.1093/icc/dtt050.
- Byrne, D. E. 1971. *The Attraction Paradigm*. Vol. 462. New York: Academic press.
- Calvino, F. 2019. "Technological Innovation and the Distribution of Employment Growth: A Firm-level Analysis." *Industrial and Corporate Change* 28 (1): 177–202. doi:10.1093/icc/dty003.
- Calvino, F., C. Criscuolo, and C. Menon. 2015. "Cross-country Evidence on Start-up Dynamics". OECD Science, Technology and Industry Working Papers, 2015. 06
- Cefis, E., and O. Marsili. 2006. "Survivor: The Role of Innovation in Firms' Survival." *Research Policy* 35 (5): 626–641. doi:10.1016/j.respol.2006.02.006.
- Coad, A., S.-O. Daunfeldt, W. Hözl, D. Johansson, and P. Nightingale. 2014. "High-growth Firms: Introduction to the Special Section." *Industrial and Corporate Change* 23 (1): 91–112. doi:10.1093/icc/dtt052.
- Coad, A., J. S. Frankish, and D. J. Storey. 2020. "Too Fast to Live? Effects of Growth on Survival across the Growth Distribution." *Journal of Small Business Management* 58 (3): 544–571. doi:10.1080/00472778.2019.1662265.
- Coad, A., and S. Srhoj. 2019. "Catching Gazelles with a Lasso: Big Data Techniques for the Prediction of High-growth Firms." *Small Business Economics*. doi:10.1007/s11187-019-00203-3.
- Coad, A., and B. Timmermans. 2014. "Two's Company: Composition, Structure and Performance of Entrepreneurial Pairs." *European Management Review* 11 (2): 117–138. doi:10.1111/emre.12030.
- Czarnitzki, D., and J. Delanote. 2013. "Young Innovative Companies: The New High-growth Firms?" *Industrial and Corporate Change* 22 (5): 1315–1340. doi:10.1093/icc/dts039.

- Daunfeldt, S.-O., N. Elert, and D. Johansson. 2016. "Are High-growth Firms Overrepresented in High-tech Industries?" *Industrial and Corporate Change* 25 (1): 1–21. doi:10.1093/icc/dtv035.
- Denicolai, S., E. Cotta Ramusino, and F. Sotti. 2015. "The Impact of Intangibles on Firm Growth." *Technology Analysis & Strategic Management* 27 (2): 219–236. doi:10.1080/09537325.2014.959484.
- Eklund. 2019. "Innovation Capability from Intangible Assets." In *Innovation Capabilities, Design and Cutting Edge: Innovative Growth in the 21st Century* Vol. 426, Vaasa, Finland: Acta Wasaensia, pp.44–61. Retrieved from <https://osuva.uwasa.fi/handle/10024/8204>.
- Eklund, 2020. "Why Some SME's Become High Growth Firms? the Role of Employee Competences." *Journal of Intellectual Capital* 21 (5): 691–707. doi:10.1108/JIC-07-2019-0188.
- Eurostat-OECD. 2008. *Eurostat-OECD Manual on Business*. Paris: Demography Statistics.
- Geurts, K., and J. Van Biesebroeck. 2016. "Firm Creation and Post-entry Dynamics of de Novo Entrants." *International Journal of Industrial Organization* 49: 59–104. doi:10.1016/j.ijindorg.2016.08.002.
- Goedhuys, M., and L. Sleuwaegen. 2010. "High-growth Entrepreneurial Firms in Africa: A Quantile Regression Approach." *Small Business Economics* 34 (1): 31–51. doi:10.1007/s11187-009-9193-7.
- Golub, B., and M. O. Jackson. 2012. "How Homophily Affects the Speed of Learning and Best-response Dynamics." *The Quarterly Journal of Economics* 127 (3): 1287–1338. doi:10.1093/qje/qjs021.
- Görzig, B., H. Piekkola, and R. Riley. 2010. "Production of Own Account Intangible Investment: Methodology in Innodrive Project".
- Haltiwanger, J., R. Jarmin, and J. Miranda. 2013. "Who Creates Jobs? Small versus Large versus Young." *Review of Economics and Statistics* 95 (2): 347–361. doi:10.1162/REST\_a\_00288.
- Harris, R., and J. Moffat. 2013. "Intangible Assets, Absorbing Knowledge and Its Impact on Firm Performance: Theory, Measurement and Policy Implications." *Contemporary Social Science* 8 (3): 346–361. doi:10.1080/21582041.2012.751498.
- Harrison, D. A., and K. J. Klein. 2007. "What's the Difference? Diversity Constructs as Separation, Variety, or Disparity in Organizations." *Academy of Management Review* 32 (4): 1199–1228. doi:10.5465/amr.2007.26586096.
- Henrekson, M., and D. Johansson. 2010. "Gazelles as Job Creators: A Survey and Interpretation of the Evidence." *Small Business Economics* 35 (2): 227–244. doi:10.1007/s11187-009-9172-z.
- Hözl, W. 2014. "Persistence, Survival, and Growth: A Closer Look at 20 Years of Fast-growing Firms in Austria." *Industrial and Corporate Change* 23 (1): 199–231. doi:10.1093/icc/dtt054.
- Horwitz, S. K., and I. B. Horwitz. 2007. "The Effects of Team Diversity on Team Outcomes: A Meta-analytic Review of Team Demography." *Journal of Management* 33 (6): 987–1015. doi:10.1177/0149206307308587.
- Jovanovic, B. 1982. "Selection and the Evolution of Industry." *Econometrica: Journal of the Econometric Society* 50 (3): 649–670. doi:10.2307/1912606.
- Kaiser, U., and B. Müller. 2015. "Skill Heterogeneity in Startups and Its Development over Time." *Small Business Economics* 45 (4): 787–804. doi:10.1007/s11187-015-9667-8.
- Lawless, M. 2014. "Age or Size? Contributions to Job Creation." *Small Business Economics* 42 (4): 815–830. doi:10.1007/s11187-013-9513-9.
- Lentz, R., and D. T. Mortensen. 2008. "An Empirical Model of Growth through Product Innovation." *Econometrica* 76 (6): 1317–1373.
- Lotti, F., E. Santarelli, and M. Vivarelli. 2003. "Does Gibrat's Law Hold among Young, Small Firms?" *Journal of Evolutionary Economics* 13 (3): 213–235. doi:10.1007/s00191-003-0153-0.
- Manyika, J., S. Ramaswamy, J. Bughin, J. Woetzel, M. Birshan, and Z. Nagpal. 2018. "Superstars': The Dynamics of Firms, Sectors, and Cities Leading the Global Economy." McKinsey Global Institute Discussion Paper.
- Matricano, D. 2016. "The Impact of Intellectual Capital on Start-up Expectations." *Journal of Intellectual Capital* 17 (4): 654–674. doi:10.1108/JIC-04-2016-0040.

- Maurer, I., and M. Ebers. 2006. "Dynamics of Social Capital and Their Performance Implications: Lessons from Biotechnology Start-ups." *Administrative Science Quarterly* 51 (2): 262–292. doi:10.2189/asqu.51.2.262.
- Megaravalli, A. V., and G. Sampagnaro. 2019. "Predicting the Growth of High-growth SMEs: Evidence from Family Business Firms." *Journal of Family Business Management* 9 (1): 98–109. doi:10.1108/JFBM-09-2017-0029.
- Moog, P., and C. Soost. 2020. "Does Team Diversity Really Matter? the Connection between Networks, Access to Financial Resources, and Performance in the Context of University Spin-offs." *Small Business Economics* 26 (6): 1–29.
- Moschella, D., F. Tamagni, and X. Yu. 2019. "Persistent High-growth Firms in China's Manufacturing." *Small Business Economics* 52 (3): 573–594. doi:10.1007/s11187-017-9973-4.
- Nightingale, P., and A. Coad. 2014. "Muppets and Gazelles: Political and Methodological Biases in Entrepreneurship Research." *Industrial and Corporate Change* 23 (1): 113–143. doi:10.1093/icc/dtt057.
- Østergaard, C. R., B. Timmermans, and K. Kristinsson. 2011. "Does a Different View Create Something New? the Effect of Employee Diversity on Innovation." *Research Policy* 40 (3): 500–509.
- Parker, S. C., D. J. Storey, and A. Van Witteloostuijn. 2010. "What Happens to Gazelles? the Importance of Dynamic Management Strategy." *Small Business Economics* 35 (2): 203–226. doi:10.1007/s11187-009-9250-2.
- Parrotta, P., D. Pozzoli, and M. Pytlikova. 2014. "Labor Diversity and Firm Productivity." *European Economic Review* 66: 144–179. doi:10.1016/j.eurocorev.2013.12.002.
- Pierce, J. R., and H. Aguinis. 2013. "The Too-much-of-a-good-thing Effect in Management." *Journal of Management* 39 (2): 313–338. doi:10.1177/0149206311410060.
- Rostamkalaei, A., and M. Freel. 2016. "The Cost of Growth: Small Firms and the Pricing of Bank Loans." *Small Business Economics* 46 (2): 255–272. doi:10.1007/s11187-015-9681-x.
- Santi, C., and P. Santoleri. 2017. "Exploring the Link between Innovation and Growth in Chilean Firms." *Small Business Economics* 49 (2): 445–467. doi:10.1007/s11187-016-9836-4.
- Schubert, T., and S. Tavassoli. 2020. "Product Innovation and Educational Diversity in Top and Middle Management Teams." *Academy of Management Journal* 63 (1): 272–294. doi:10.5465/amj.2017.0741.
- Siepel, J., M. Cowling, and A. Coad. 2017. "Non-founder Human Capital and the Long-run Growth and Survival of High-tech Ventures." *Technovation* 59: 34–43. doi:10.1016/j.technovation.2016.09.001.
- Teece, D. J. 1998. "Capturing Value from Knowledge Assets: The New Economy, Markets for Know-how, and Intangible Assets." *California Management Review* 40 (3): 55–79. doi:10.2307/41165943.
- Terjesen, S., N. Bosma, and E. Stam. 2016. "Advancing Public Policy for High-growth, Female, and Social Entrepreneurs." *Public Administration Review* 76 (2): 230–239. doi:10.1111/puar.12472.
- Williams, K. Y., and C. A. O'Reilly. 1998. "Demography And." *Research in Organizational Behavior* 20: 77–140.
- Zhou, H., and P. van der Zwan. 2019. "Is There a Risk of Growing Fast? the Relationship between Organic Employment Growth and Firm Exit." *Industrial and Corporate Change* 28 (5): 1297–1320.

**Appendix 1 Estimation without the 95<sup>th</sup> percentile largest firms**

|                        | (1)                  | (2)                  | (3)                  | (4)                  | (5)                  | (6)                  |
|------------------------|----------------------|----------------------|----------------------|----------------------|----------------------|----------------------|
| <b>Variables</b>       | <b>Gazelle</b>       | <b>Gazelle</b>       | <b>Gazelle</b>       | <b>Gazelle</b>       | <b>Gazelle</b>       | <b>Gazelle</b>       |
| In OC <sub>t-3</sub>   | 0.078***<br>(0.0085) | 0.079***<br>(0.0085) | 0.077***<br>(0.0085) | 0.074***<br>(0.0085) | 0.073***<br>(0.0085) | 0.072***<br>(0.0085) |
| In ICT <sub>t-3</sub>  | 0.053***<br>(0.011)  | 0.052***<br>(0.011)  | 0.051***<br>(0.011)  | 0.047***<br>(0.011)  | 0.048***<br>(0.011)  | 0.047***<br>(0.011)  |
| In RD <sub>t-3</sub>   | 0.077***<br>(0.0067) | 0.075***<br>(0.0068) | 0.075***<br>(0.0068) | 0.073***<br>(0.0068) | 0.075***<br>(0.0068) | 0.072***<br>(0.0069) |
| In emp <sub>t-3</sub>  | -0.98***<br>(0.039)  | -0.97***<br>(0.039)  | -0.97***<br>(0.039)  | -1.00***<br>(0.039)  | -1.01***<br>(0.039)  | -1.02***<br>(0.039)  |
| Blau <sub>t-3</sub>    | 0.43***<br>(0.089)   | 0.27**<br>(0.11)     | 0.018<br>(0.12)      | -1.50***<br>(0.22)   | -1.57***<br>(0.22)   | -2.26***<br>(0.28)   |
| blau2 <sub>t-3</sub>   |                      |                      |                      | 3.24***<br>(0.33)    | 3.70***<br>(0.38)    | 5.01***<br>(0.54)    |
| SM <sub>t-3</sub>      |                      | 0.40**<br>(0.17)     | -0.96***<br>(0.33)   |                      | -0.51**<br>(0.21)    | -1.15***<br>(0.43)   |
| blauSM <sub>t-3</sub>  |                      |                      | 2.71***<br>(0.52)    |                      |                      | 6.62***<br>(1.88)    |
| blau2SM <sub>t-3</sub> |                      |                      |                      |                      |                      | -8.73***<br>(2.04)   |
| Constant               | -0.54<br>(1.03)      | -0.55<br>(1.03)      | -0.51<br>(1.03)      | -0.46<br>(1.04)      | -0.45<br>(1.04)      | -0.40<br>(1.04)      |
| Observations           | 30,276               | 30,276               | 30,276               | 30,276               | 30,276               | 30,276               |
| Year & Sector dummies  | yes                  | yes                  | yes                  | yes                  | yes                  | yes                  |
| pseudo R-squared       | 0.062                | 0.063                | 0.064                | 0.066                | 0.066                | 0.067                |
| Log Lik                | -11,875              | -11,872              | -11,858              | -11,829              | -11,826              | -11,816              |