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Human Capital, Innovation and the Distribution of Firm Growth Rates

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Abstract

This paper focuses on the occurrence of high-growth firms in relation to human capital and innovation. High-growth firms are rather exceptional and temporary phenomena and occur in the upper tail of the conditional firm growth distribution. Using quantile regression we study how human capital and R&D affect the probability that high-growth firms occur. The results show that both human capital and R&D increase the likelihood that a firm is a high-growth firm. Human capital appears to be positive and growth enhancing over the entire conditional growth distribution, hence also in the lower quantiles, where it reduces the likelihood of low growth. By contrast, R&D increases not only the likelihood of high-growth firms, but also the likelihood of low-growth firms and exits, underscoring the risky nature of innovation. A probit analysis for high-growth firms and low-growth firms provides corroborating evidence for this finding. From a policy perspective the results suggest the use of more integrated policies, not only focusing on stimulating R&D but also on the quality of human capital to foster the development of high-growth firms.

Keywords: firm growth, high-growth firms, R&D, human capital

JEL: L25, O32

Human Capital, Innovation and the Distribution of Firm Growth Rates

1. Introduction

High-growth firms (HGFs) have attracted a lot of interest in academic research. High-growth firms are ‘statistically’ defined as firms that have grown, in terms of sales or employment, by more than 20% per year over three consecutive years (OECD 2007).

HGFs are typically small and young firms, but only represent a small subset of all firms, usually in the range of 1% to 5% of the total population of firms (OECD 2014). However, evidence from various countries shows that HGFs create a disproportionate amount of jobs; they exhibit above average levels of innovativeness, and generate positive externalities to the region where they are located. Unsurprisingly, researchers and policy makers alike want to have a good understanding of the origin, characteristics and behaviour of HGFs.

Particularly, there is rising concern about turnover in the group of HGFs over time, i.e. changes in the composition of the HGFs group, raising questions about the persistence and long term performance of HGFs. When the growth performance of a high-growth firm is observed over a longer period of time, it is noticed that after a period of high growth, a period of regress or at best average growth is observed (Parker et al. 2010; Douglas et al. 2012; Coad et al. 2014; Hölzl 2014). Moreover, considering the relative stability of top companies in various important industries over time, one may wonder why few of the HGFs make it to the top. This raises the ontological question whether conceptually a ‘high-growth firm’, defined as a firm with long term superior growth capacities and performance, which can over time become a major player in its industry, really exists.

If, on the other hand, most HGFs are only short-lived, with different HGFs emerging in successive periods, it appears reasonable to assume that high growth is rather the result of a non-permanent shock which over the considered period positions the firm in the upper tail of the distribution of firm growth rates. Hence, to empirically analyse HGFs it becomes less

recommended to focus on a single moment of the conditional growth distribution, the conditional mean, as is done in ordinary regression models, but instead to analyse the whole conditional growth distribution. Particularly, what seems to matter is to find out if certain external factors or types of firms affect the location and shape of the conditional growth distribution such that more HGFs appear in the upper tail. This is exactly what we do in this paper. The particular focus of our paper is on the role of innovation and human capital as growth drivers and the impact these factors may have on the conditional firm growth distribution.

The paper analyses a large data set of firms based in Flanders and Brussels, two major regions in Belgium. After discussing the relevant literature, first some evidence on the persistence in the growth pattern of HGFs is presented. In line with earlier research we measure the growth of a firm in terms of the number of employees. It is shown that while HGFs are observed in each period, there is little persistence in growth performance. We next use quantile regression techniques to study the entire conditional growth distribution, and the factors that affect the location of the upper quantiles where HGFs occur. We also look at the lower quantiles where the low-growth firms occur and investigate if the factors have a similar effect on the location of these quantiles. In doing so, we find that while human capital appears to be growth enhancing over the entire conditional growth distribution, the effect of R&D switches from a negative effect in the lower end of the growth distribution to a positive effect in the higher end of the growth distribution. Corroborating evidence is provided by subsequent probit analyses for HGFs and low-growth firms, showing that, in contrast to human capital, R&D increases not only the likelihood of HGFs, but also the likelihood of low-growth firms and exits. The concluding section summarises the findings.

2. Human capital and innovation as growth drivers

Most studies recognise the stochastic nature of the growth process of a firm in which random factors play a major role. The pioneering work of Gibrat (1931) argued that growth is fundamentally unpredictable. Gibrat's 'Law of Proportionate Effect (LPE)', describes growth in its most extreme random form.

The LPE was very influential in that it led scholars to investigate growth more intensively and to find determining factors affecting the chances of growth, rejecting the LPE. Many studies find that small firms grow faster than large ones and young firms grow faster than older firms (see Coad 2009, for a review of these studies). The negative size-growth relationship is especially compelling for the smallest firms, which grow rapidly to reach the growth 'Minimum Efficient Scale (MES)' (Caves 1998; Audretsch 1995; Teruel 2010). The negative age-growth relationship is supportive to theoretical models such as those developed by Lucas (1978) and Jovanovic (1982) who argue that growth is essentially a learning process, a discovery of one's own level of efficiency. During the first years after entry, young firms discover their efficiency level and grow rapidly, adjusting their size to a scale of operations that corresponds to their level of efficiency. This is a Bayesian learning process which is stronger in the early years after start-up and explains the higher growth performance of young firms. This reasoning has further been extended to 'active' learning models (Ericson and Pakes 1995; Pakes and Ericson 1998) suggesting that firms can actively increase their efficiency level, leading to higher growth.

Building upon these insights, a growing body of literature has been looking at firm growth in relation to innovation. A theoretical model of firm growth of innovating firms is developed by Klette and Kortum (2004). In the model, the appearance of successful innovations is stochastic and depending on R&D expenditure and accumulated knowledge capital. The fundamental source of firm heterogeneity in the model is the luck of the draw in R&D outcomes. A firm grows if it innovates and shrinks if a competitor innovates by improving on one of the firm's products. Empirical studies indeed establish a positive relationship between R&D or innovation and firm growth (e.g. Geroski and Toker 1996; Roper 1997; Yasuda 2005). Others find this relationship to hold for high growth of firms (e.g. Almus 2002; Coad and Rao 2008; Stam and Wennberg 2009; Hölzl and Friesenbichler 2010; Czarnitzki and Delanote 2013). The relationship between R&D, innovation and high growth of firms appears further to be affected by interactions and combinations of firm characteristics, such as firm size, patenting and persistence in innovation (Demirel and Mazzucato 2012; Deschryvere 2014) and industry characteristics such as the competitive regime or industry life cycle (Mazzucato and Parris 2014). Alternatively, Segarra and Teruel (2014) found that not all R&D expenditures have the same effect on high growth:

Internal R&D has a positive impact among high-growth firms, whereas external R&D has a positive impact for firms with median growth.

Similar to innovation, the quality of the human capital is expected to positively stimulate efficiency and growth. A widely used measure in this context is the education level of the employees. The measure reflects the cognitive abilities and achievement motivations of the employees (Hatch and Dyer 2004). Higher levels of knowledge and skills allow employees to engage in complex and non-routine tasks and perform them efficiently while conforming to high quality standards, thus increasing the value added by the firm. These are crucial tasks in industries where businesses compete by producing new and different goods using the most sophisticated production processes (Schwab 2010). For example, Hatch and Dyer (2004) in their study on the effect of general and specific human capital on the performance of firms in the semiconductor industry found that human capital selection (education requirements and screening), development through training, and deployment significantly improve learning by doing, which in turn improves firm-level performance.

Lopez-Garcia and Puente (2012) and Arrighetti and Lasagni (2013) find evidence that human capital raises the incidence of HGFs. Coad et al. (2014) by contrast find evidence that HGFs are more likely to employ young people, poorly educated workers, immigrants, and individuals who experienced longer unemployment periods. Others find the impact of human capital to be contingent on the stage of the firm's evolution (Coad et al. 2014) or the age of the firm (Cardon 2003).

Rather than to study aggregate and average levels of human capital, which impact on growth is conditioned by firm and industry characteristics, some of the recent work has zoomed in on the human capital of persons occupying decisive positions in the company, such as the individual entrepreneur, the founding team or top managers, a strand summarised by Wennberg (2013). The empirical literature on new firm growth shows that managerial competencies, commonly approximated through the founder team or CEO's knowledge and education, are crucial determinants for new firm growth (McKelvie et al. 2006; Colombo and Grilli 2007 and 2009; Unger et al. 2011; Wennberg 2013). In the context of HGFs, the core competences of the management team may be even more important, as the managerial challenges of rapidly growing

firms require a specific set of leadership competencies (Wennberg 2013). Both theory and empirical studies indicate that major changes in systems, structures, and capabilities are required to cope with the increased complexity that accompanies high growth (Garnsey et al. 2006; Nicholls-Nixon 2005; Penrose 1959).

While most of the above studies looked at the impact of innovation and human capital separately, our study is the first to focus on the joint, but differentiated role of both factors in relation to firm growth. This will be done by an empirical study focusing on the occurrence of HGFs in the Flemish region of Belgium.

3. HGFs in Flanders

3.1. Data and prevalence of HGFs

For this study we use data from the BELFIRST database covering all firms that reported accounts in the 2008-2011 period¹.

For the selection of sectors we follow the guidelines spelled out by OECD (2007, p.13). It recommends including all sectors and types of firms in the data, including the service sector which is becoming increasingly important in the economy. We thus withhold all observations from NACEBEL2008 sections B to N and P to S. Within this population there is a multitude of firms to be found with a wide variety of legal forms. For example it includes organisations which are active in non-commercial services, often non-profit, with associated legal forms like non-profit organisations. These are often found in the sector of non-commercial services, but also in other sectors.

¹ Firms whose headquarters are located in the Flemish Region or in the Brussels-Capital Region are initially included in the dataset. Brussels was added to the dataset because there are many firms that have their main activity in Flanders, but for administrative reasons have their headquarters in Brussels, and therefore they are registered as located in Brussels.

Subsequently, we made a selection of firms according to size and age. Only those firms that were active in 2008 and reported an average employment of 10 or more employees were selected. This selection generated a total of 27 522 firms for Flanders and Brussels. However, due to missing values for some key variables, the sample is reduced in some of the estimated models.

The prevalence of HGFs is presented in Figure 1. For identifying HGFs the definition of OECD (2007) is applied here: a firm is a high-growth firm in year x if it had at least 10 employees in year $x - 3$ and has increased the number of employees by a factor of 1.728 over the three year period increase (OECD 2007)². Figure 1 shows the proportion of HGFs for manufacturing, services and non-commercial services separately; and following the EUROSTAT classification according to global technological intensity for manufacturing; and knowledge intensity for services (EUROSTAT 2014).

For the whole sample, 2.3% of the firms are HGFs. This proportion is highest in non-commercial services, which include activities such as education, health care, public administration, arts and entertainment, where 3.4% are HGFs, followed by commercial services (2.3%) and manufacturing (1.8%). From the technology and knowledge intensity classification of industries, it becomes clear that knowledge intensive services (KIS) have the highest proportion of HGFs (4%), followed by medium-high tech (MHT) manufacturing and knowledge less-intensive services (KLIS) with 2.4% and 2.1% each. High tech (HT) and low tech (LT) have the smallest prevalence of HGFs, respectively 0.8% and 1.5%. These proportions are similar to findings from the UK, where it was found that HGFs exist in all industries, but their chances to occur are higher in services (Anyadike-Danes et al. 2009).

FIG 1

3.2. Growth persistence

² This corresponds to an average annual growth rate of 20%.

Table 1 shows in column (1) the number of HGFs from different years. Column (2) shows how many of the HGFs from column (1) are still a high-growth firm in the subsequent the three-year period. It is clear, past growth appears not to be a good predictor of future growth. Although every year one can find a number of HGFs, these are mostly not the same firms. We see that in 2006 a total of 642 enterprises meet the definition of high-growth firm and thus achieved high growth over the period 2003-2006. However, in the subsequent three-year period, 2006-2009, only 63 of them are still a high-growth firm. For the other years, we observe a similarly low persistence in high growth and the proportion of persistent HGFs becomes even smaller, an evolution that could be traced back to the years of crisis. In sum, the table shows that only a small fraction of the HGFs manages to sustain its high growth over a longer period; most of the firms regress in terms of growth performance.

TABLE 1

Table 2 shows the growth rates of the group of HGFs versus other firms in the *first* year following the observation window over which the firm was defined as a high-growth firm. The table show that the average HGFs observed over the period 2003-2006, had a growth rate of 5.4% in 2006-07 and an average annual growth rate of 1.3% over the period 2006-2009. The control group of other firms grew in the same periods by 8.2% and 4.7% respectively. In many cases, this difference in average growth is statistically significant. Hence, HGFs perform worse in the subsequent period than the control group of firms that were not HGFs in the observation period.

TABLE 2

The evidence shown in table 2 suggests that high growth is subject to regression-to-the-mean³, or even subject to negative auto-correlation. Negative auto-correlation implies a systematically lower growth rate in the next period and was found in Goddard et al. (2002), Coad et al. (2013) and in a majority of industries in Bottazzi et al. (2007), Bottazzi et al. (2011).

³ 'Regression to the mean' implies a return to the average 'normal' value of the distribution in an observation period, after one observes an extreme value during a previous period of observation.

A more general way to present the evidence on possible auto-correlation in growth rates consists of looking at the growth performance of all firms in the sample jointly, and investigating the correlation matrix of growth rates on a year-to-year basis. The correlations in growth rates between the different periods, shown in Table 3, are extremely low, and tend to zero. Hence they do not suggest a systematic negative correlation. Conversely, the correlations do not show a significant positive correlation either, excluding the persistence of sustained growth over time (unlike evidence presented in Kumar 1985; Wagner 1992, Bottazzi et al. 2001, Bottazzi and Secchi 2003).

TABLE 3

This basic evidence presented here suggests that high growth is largely a transient stochastic process, subject to many unsystematic temporal shocks, echoing the findings of Almus and Nerlinger (2000), Bottazzi et al (2007), Lotti, et al (2003). This evidence calls for a particular empirical approach if we want to study drivers of growth and high growth of firms, which takes into account the largely stochastic nature of growth.

4. Empirical approach: quantile regression

HGFs are typically found the upper tails of the conditional distributions of firm growth rates. Hence, ordinary regression models explaining the ‘conditional mean’ are not fit to study the occurrence of HGFs. Instead, quantile regression methods which provide an estimation of the whole conditional growth distribution by means of its quantiles appear more appropriate. Recent research along this line pointed out that the conditional growth distribution is not invariant with respect to certain industry and firm specific factors (Coad and Rao 2008; Goedhuys and Sleuwaegen 2010; Segarra and Teruel 2014; Mazzucato and Parris 2014).

Firm age and size have been found to act on the expected ‘average’ growth of firms. Rooted in the evolutionary leaning approach, young and small firms were found on average to grow faster than other firms. Using quantile regression, we can analyse if these effects are concentrated

around the mean, or have a wider impact on the conditional growth distributions. More closely related to the focus of this study, there is also growing evidence that innovation and R&D expenditures have a significant impact on the growth distribution.

However, recent work has also shown that the use of standard indicators, such as R&D intensities, is not straightforward and without problems (e.g. Mazzucato and Parris 2014). Especially for large samples composed of many small firms, measures of R&D may be less reliable and unstable over time. In order to account for these measurement problems, we have adopted a conservative approach and investigated if R&D active firms (R&D =1) grow faster than other firms and are more likely to be HGFs. Next, we checked if scale effects are present and substituted the dummy of ‘doing R&D’ by the log of R&D expenditures for each firm.

We adopted a similar procedure for ‘Human Capital’ and investigated whether firms that employ higher educated employees, with a college or university degree, show better growth performance. This procedure aligns well with the focus on the human capital of managers and founder team on firm growth on the one hand, as well as with the recent findings that many successful HGFs are built around a small highly educated management team who hire a disproportionately large amounts of low skilled individuals to execute routine type of tasks (Coad et al. 2014).

Finally, we included industry dummies as extra control variables to account for specific industry effects.

5. Results

The results of the first basic quantile regression are shown in Table 4. The estimated quantiles are respectively the 10th, 25th, 50th (or median), 75th and 90th quantile.

In line with earlier results, we find that the negative effect of age and size on ‘average’ firm growth mainly results from the impact the factors have in the upper quantiles (Mazzucato and Parris 2014).

TABLE 4

More revealing in the context of particular growth drivers are the results with respect to R&D and human capital. Figure 2 plots the estimated marginal effects of R&D, respectively R&D intensity, on the different quantiles, estimated jointly with the human capital dummy variable. Figure 2a shows a steady increase in the effect of R&D effect as one moves from the lower to the upper side of the conditional growth distribution, turning from negative to positive above the median firm. The results presented above are in line with Freel (2000) and Coad and Rao (2008) who argue and show that innovators are not necessarily more likely to grow, but those who do are more likely to experience rapid growth. These results suggest that R&D is a risky process, generating winners and losers. Among those who win there are more that experience high growth, in a comparison with non R&D investors. Among those who lose, there are more who display poor growth. Replacing R&D by the (log of) R&D expenditures to account for possible scale effects does not really affect the results, as shown in Figure 2b, except for widening the confidence intervals.

FIGURE 2

The results for human capital show a completely different picture (Figure 3). The coefficients of the human capital variable are positive for all quantiles, but larger for the lower quantiles. As a consequence, human capital increases the growth rate at the lower quantiles, thereby decreasing the likelihood of low growth. The effect for the upper quantiles is smaller, but remains positive, implying that education will raise growth in the upper quantiles, but to a lesser extent than it does reduce the likelihood of low growth.

Replacing the human capital binary variable by a human capital intensity variable, measuring the (log of) the number of highly educated employees, did not produce any statistically significant results (not shown⁴).

⁴ Not reported, available upon request

FIGURE 3

In Figure 4, the human capital variable is further split for university education and ‘other higher education’. The results show that the positive influence of university educated human capital exceeds the positive effect of other higher education on firm growth in every quantile, with much stronger effects in the upper quantiles. Hence, university education helps to generate HGFs, which are typically positioned in the upper quantile regions.

FIGURE 4

6. Probit regression: the likelihood of being a high-growth firm

An alternative, but closely related approach to study the occurrence of HGFs, is probit regression. Instead of estimating the conditional distribution of growth rates, probit assumes that the probability that a firm is a high-growth firm is related to firm and industry characteristics following a cumulative standard normal distribution. In a probit analysis of HGFs - starting from a definition in which HGFs are firms with a growth rate are above a certain (arbitrary) value - the probability that a firm is a high-growth firm is related to firm and industry characteristics.

Using the same covariates as explanatory variables as in table 4, table 5 shows the results of two probit estimations: for the probability that a firm is a high-growth firm (HGF) in 2011, according to the OECD definition, and thus had an average 20% growth over the period 2008-2011 (column 1); for the probability that a firm is a low-growth firm (LGF) in 2011 witnessing an average 20% reduction in employment or exit over the observed period (column 2);

The results are corroborating the results of the quantile regression. R&D raises the probability of HGFs, but also raises the probability of being a low-growth firm. Highly educated human resources also raise the probability of being a HGFs, but more substantially lowers the probability a being a low-growth firm. The result is more marked for university trained collaborators.

TABLE 5

Robustness checks

So far we have been mute about the fact that our growth equations may be affected by selection bias. Obviously, in the growth equations, only surviving firms were included. However, it is likely that some unsystematic factors that affect survival and selection into the sample are also those affecting growth. To determine the robustness of our result when accounting for this possible bias, we estimated a two equation (selection and outcome) Heckman model. The results of this model suggested that the two equations are independent and that our findings are unbiased and robust.

Finally we did the probit estimation also on a split sample, for manufacturing and services separately. The literature survey in section 2 raised evidence on the possibility that important industry effects and interactions with growth driving factors may exist. We tested whether the findings of our analysis would be strongly affected or only hold in either manufacturing or services. The findings showed that this is not the case. We found no significant differences in regime between manufacturing or services industries.

7. Discussion and conclusion

HGFs are not easy to predict. They are typically located in the upper tail of the conditional growth distribution, and hence tend to be ‘exceptional’ phenomena. Their positions are also not stable over time and show no auto-regressive pattern. Most firms that experience high growth in a given period see their growth rates severely reduced in the subsequent periods. Hence, the relevant question becomes whether, over a given period, there are factors that affect the conditional growth distribution in such a way that more HGFs occur in the upper tail.

Using quantile regression, we find that the location and shape of the conditional growth distributions are indeed affected by certain industry wide and firm-specific factors. Among these

factors, R&D expenditures have a positive effect in the upper quantiles and a negative effect in the lower quantiles of the growth distribution. They thus increase the chances of very high growth, but also very low growth. This is a remarkable finding, showing that the 'average' zero impact of R&D hides the actual effects of R&D on growth. This can be explained by the nature of the innovation process, which is a complex process by which valuable knowledge translates into successful products and production processes, procedures and routines and further into superior economic performance. The process is difficult and risky and the positive effects on the growth performance of the firm are often only observable with a time lag. There is uncertainty at every stage of the innovation process and the economic result depends on success at every stage of the process. For Mansfield et al. (1977) success of innovative activities is the product of three conditional probabilities: the probability that technical objectives of the project are met; the probability that, given technical success, the product or process is commercialised; and finally the probability that, given commercialisation, the project yields a satisfactory return on the investment. If a firm fails in one of these phases, it will not be able to recover the costs incurred, which makes the firm particularly vulnerable, mortgaging its growth opportunities. If, on the other hand firms succeed, they will enjoy a first-mover or related strategic advantages, which get translated into rapid growth over a certain period of time.

Conversely, we find human capital to be growth-enhancing over the entire distribution, and to significantly reduce the chances of low growth (shifting of quantiles to the right). The mechanisms underlying these relationships have been the subject of other studies, which show that superior managerial human capital leverages and facilitates the deployment of other resources in the firm. For instance, Colombo and Grilli (2009) and Gimmon and Levie (2010) show that founder or manager human capital have a direct effect on growth but also an indirect effect through attracting venture capital and external investment. For low-growth firms facing limited access to capital, the signalling effect of highly skilled management is instrumental in smoothing the binding constraints.

The results have some clear policy implications. First and foremost, it is difficult to work out policies directly targeting sustained growth champions. Growth tends to be erratic, sporadic and short-term. As a consequence, HGFs are difficult to predict and their growth performance

changes quickly over time. A ‘picking the winner’ strategy seems unjustified in this regard. In most countries, assistance is largely focused on support for R&D and targeted at certain types of firms, especially firms at start-up stage. However, policies that stimulate R&D efforts industry- or economy wide will not only raise the likelihood that HGFs will occur but will also raise also likelihood that more firms experience a strong growth decline and possibly exit over time.

More encouraging are the results with respect to human capital. Firms employing a highly educated managerial team or work force have a higher chance to grow, and are more likely to be a high-growth firm. More importantly, firms with a strong human capital team fail less. Hence, our results highlight the need for a more integrated policy towards HGFs. Such a policy should not only provide stimulating framework conditions (tax systems, regulations), stimulate R&D, but should also encourage a more intensive and better use of well-educated teams to support the growth of firms, especially the growth of young, dynamic innovative firms.

To be able to reinforce our claim with respect to policy implications, future research should analyse the effect innovation and human capital on firm growth over a longer time span and using panel data. This would allow controlling for firm fixed effects and studying whether the findings are specific to the period studied here, which is a period of severe crisis, or by contrast hold more generally.

Table 1: Persistence in growth of high-growth firms (HGF)

	(1) # HGF	Of which in:	(2) # HGF
2006	642	2009	63
2007	749	2010	45
2008	805	2011	29

Table 2: Growth performance (employment), HGF versus other firms, over the period of one year and three years following the year of definition of HGF

Year T	Growth rate over T- (T+1)		Growth rate over T-(T+3)	
	HGF _T	Other _T	HGF	Other
2006	.054	.082	0.013	0.047
2007	0.062	.073	0.003	0.029
2008	-0.019	0.019	-0.008	0.018
2009	0.011	0.021	-	-
2010	0.035	0.026	-	-

Notes: The growth rates shown are calculated as $\ln(\text{employment } t+1) - \ln(\text{employment } t)$ and $(\ln(\text{employment } t+3) - \ln(\text{employment } t)) / 3$;

Table 3: Correlation matrix of annual growth rates, full sample

Correlation	Growth 06-07	Growth 07-08	Growth 08-09	Growth 09-10	Growth 10-11
Growth 06-07	1				
Growth 07-08	0.1387	1			
Growth 08-09	0.0391	0.0498	1		
Growth 09-10	0.0255	0.0310	0.0322	1	
Growth 10-11	0.0338	0.0354	0.0358	0.0858	1

Table 4: Results of the quantile regression, with R&D dummy

VARIABLES	q.10	q.25	q.50	q.75	q.90
<i>Firm size</i>	0.004** (0.002)	0.002** (0.001)	-0.001 (0.001)	-0.005*** (0.001)	-0.008*** (0.001)
<i>Firm age</i>	0.017*** (0.003)	0.001 (0.001)	-0.009*** (0.001)	-0.024*** (0.001)	-0.044*** (0.002)
<i>RD</i>	-0.009 (0.007)	-0.007** (0.003)	-0.001 (0.002)	0.007* (0.003)	0.016** (0.008)
<i>HumanCap</i>	0.049*** (0.005)	0.020*** (0.002)	0.008*** (0.001)	0.008*** (0.002)	0.013*** (0.002)
<i>Industry High-Tech</i>	0.010 (0.014)	0.013 (0.010)	0.012 (0.008)	0.008 (0.013)	0.016 (0.022)
<i>Industry MH-Tech</i>	-0.003 (0.009)	0.002 (0.004)	0.000 (0.004)	-0.002 (0.005)	-0.007 (0.009)
<i>Industry ML-Tech</i>	0.015* (0.008)	0.006 (0.004)	0.002 (0.003)	-0.005 (0.003)	-0.004 (0.009)
<i>Services</i>	0.016** (0.007)	0.015*** (0.002)	0.015*** (0.002)	0.012*** (0.002)	0.006 (0.005)
<i>Services*KI</i>	0.002 (0.006)	0.016*** (0.002)	0.016*** (0.001)	0.017*** (0.002)	0.024*** (0.003)
Constant	-0.225*** (0.012)	-0.083*** (0.006)	0.010** (0.004)	0.115*** (0.005)	0.243*** (0.009)
Pseudo R ²	0.018	0.012	0.010	0.029	0.053
Observations	19,896				

Bootstrapped standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 5: Results of a probit regression for HGFs (1) and low-growth firms (LGFs) (2); marginal effects

VARIABLES	(1) HGF	(2) LGF
<i>Firm size</i>	-0.006*** (0.001)	0.000 (0.002)
<i>Firm age</i>	-0.024*** (0.001)	-0.023*** (0.002)
RD	0.015** (0.006)	0.024** (0.010)
<i>HC-Higher</i>	0.008*** (0.003)	-0.055*** (0.003)
<i>HC-Univ</i>	0.020*** (0.003)	-0.076*** (0.003)
Pseudo R ²	0.079	0.066
Observations	21,372	21,372

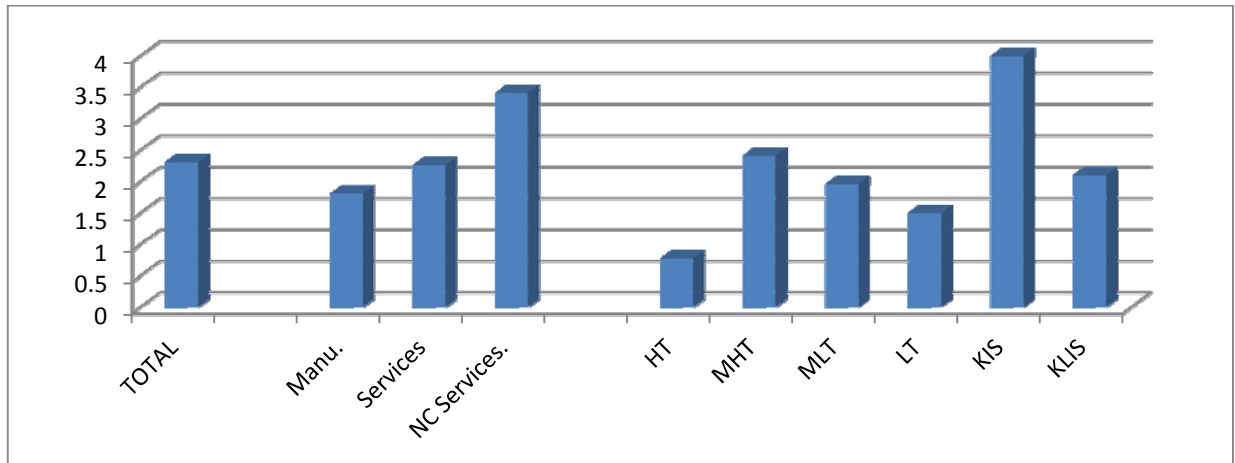
Note: Industry dummies included; Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

APPENDIX: Table A1. Definition of variables

<i>Variables</i>	Definition	Mean value (STD)
<i>Employment growth</i>	Growth over the period 2008-11, measured by $\ln(\text{employment in 2011}) - \ln(\text{employment in 2008}) / 3$	-0.011 (0.138)
<i>HGF</i>	= 1 if the firm had an average annual employment growth rate of at least 20% over the period 2008-2011 and at least 10 employees in 2008	0.03
<i>LGF</i>	= 1 if the firm had an average annual employment decline of at least 20% or went bankrupt between 2008 and 2011, and had at least 10 employees in 2008	0.07
<i>Firm size</i>	Employment in 2008, in log.	3.32 (0.96)
<i>Firm age</i>	Firm age in 2011, in log.	3.04 (3.05)
<i>RD</i>	=1 if the firm had R&D expenditures for the period 2006-2011	0.05
<i>RD intensity</i>	Amount of R&D expenditures over 2006-2011, cumulative, per employee; in log.	2.21
<i>HumanCap</i>	=1 if the firm employs individuals with college or academic degrees	0.52
<i>HC-Higher</i>	=1 if the firm employs individuals with higher non-university (college) education	0.22
<i>HC-Univ</i>	=1 if the firm employs individuals with university education	0.30
<i>Industry High-Tech</i>	=1 if the firm is active in High-tech manufacturing, according to the EUROSTAT classification	0.01
<i>Industry MH-Tech</i>	=1 if the firm is active in Medium-high-tech manufacturing, according to the EUROSTAT classification	0.03

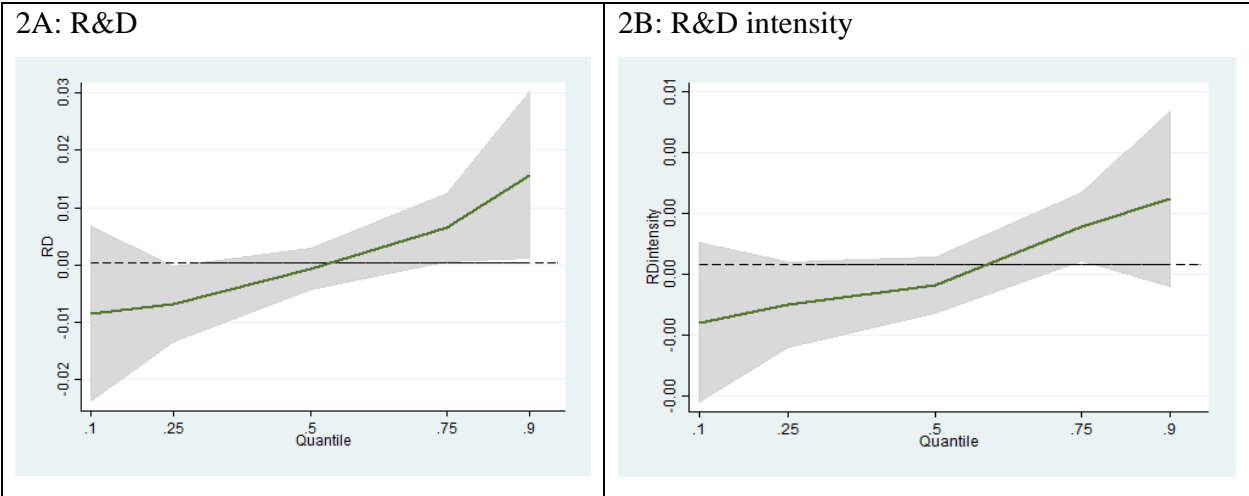
<i>Industry ML-Tech</i>	=1 if the firm is active in Medium-Low-tech manufacturing, according to the EUROSTAT classification	0.06
<i>Services</i>	=1 if the firm is active in services, NACEBEL 2008, sections D-N, P-S	0.82
<i>Services*KI</i>	=1 if the firm is active in 'Knowledge-Intensive' services, according to the EUROSTAT classification	0.23

Figure 1: Prevalence of HGFs in the sample, by industry classifications



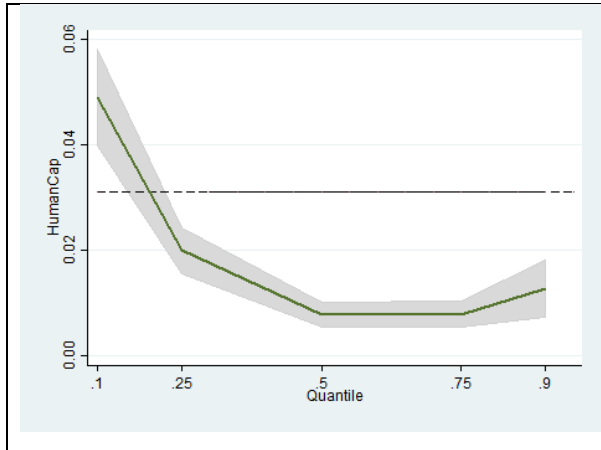
Note: Manu includes firms in NACEBEL2008 C; also 13 firms from section B mining and quarrying, are added to this group; Services includes Sections D-N and S; NC-Services includes Sections O, P, Q, R and 2-digit industry 94;

Figure 2: the impact of R&D (2A) and R&D intensity (2B) on employment growth, by quantile



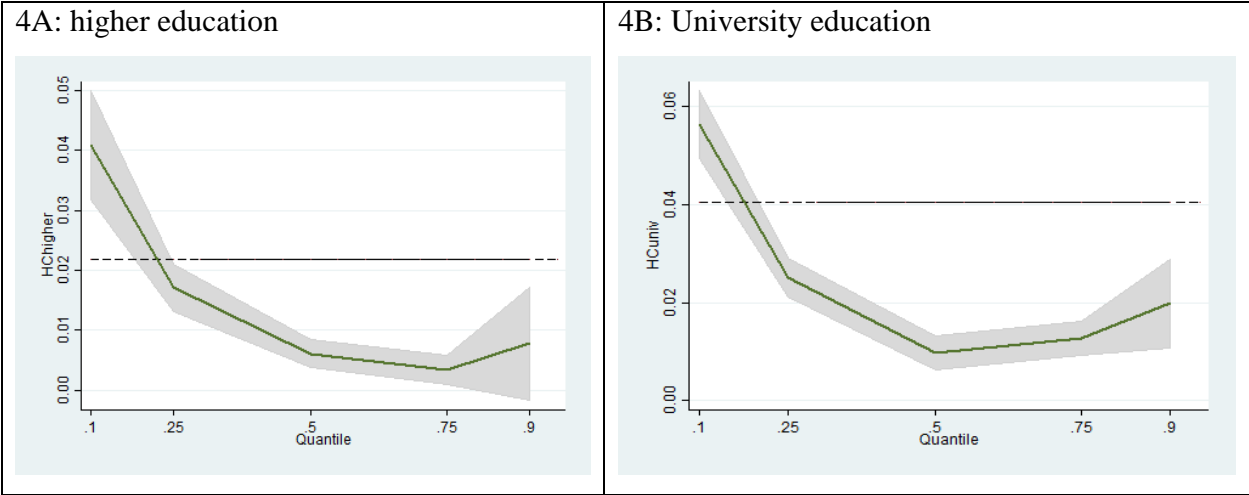
Note: a 95% confidence interval of the quantile estimation is plotted; the horizontal line represents the coefficient of the OLS estimate

Figure 3: the impact of human capital on employment growth, by quantile



Note: a 95% confidence interval of the quantile estimation is plotted; the horizontal line represents the coefficient of the OLS estimate

Figure 4: the impact of different educational levels on employment growth, by quantile



Note: a 95% confidence interval of the quantile estimation is plotted; the horizontal line represents the coefficient of the OLS estimate

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