ifh Working Paper No. 43/2024

Risk-reward trade-offs

– Modes of innovation and economic performance of young firms

Petrik Runst [a,b,*], Jörg Thomä [a]

[a]*Institute for Small Business Economics at the Georg-August-University Göttingen, Heinrich-Düker-Weg 6, 37073 Göttingen, Germany*

[b]*Institute of Rural Economics, Thuenen Institute, Bundesallee 64, 38116 Braunschweig*

Abstract

The literature has established that young firms engaged in R&D exhibit a pronounced asymmetry in their economic performance, with high premia at the upper end of the conditional growth distribution. We argue that this binary view – i.e., R&D-oriented firms versus all others – is somewhat limited. In particular, non-R&D innovation activity should be treated as an important category in its own right, and that its sui generis mode of learning is reflected in a distinct growth pattern. We examine data from the German IAB/ZEW Start-up Panel. Our evidence suggests that young non-R&D innovators also exhibit asymmetric and improved economic performance relative to non-innovators, although less so than R&D firms. Our results also suggest that firms engaged in non-R&D innovation grow in a less risky and costly way than R&D innovators, and that a young firm's decision whether to engage in R&D for the purpose of innovation and growth can therefore usefully be understood as being driven by a specific risk-return trade-off.

JEL: D21; L11; L25; L26; O31

Keywords: Firm growth; R&D; non-R&D innovation; Modes of innovation;

* Corresponding author. petrik.runst@thuenen.de

1. Introduction

Young firms that invest heavily in research and development (R&D) are generally seen as an important source of dynamism, economic development and growth (Schneider & Veugelers, 2010; Coad, 2009; Audretsch et al., 2014a). However, previous research in this context shows an asymmetric impact of R&D on firm performance (measured by sales and/or employment growth) along the conditional growth distribution. For example, the results of Coad and Rao (2008) and Coad et al. (2016) suggest that the economic benefits of R&D-driven innovation tend to be concentrated among a small number of firms at the top of the growth spectrum, while the typical risks associated with business R&D often result in more substantial losses for those positioned lower down.[1] The asymmetric growth effect of R&D is particularly pronounced in young firms (Coad et al., 2016).

At first sight, one may infer that many young firms avoid the inherent risk of R&D activities and thus forego innovation and growth (Audretsch et al., 2014b). However, this binary view of the relationship between R&D and firm growth underlying these earlier studies – i.e., R&D-oriented firms versus all others – is somewhat limited. Audretsch et al. (2014b) have already pointed out that, depending on factors such as the nature of the market or the technological environment, young firms can be economically successful and grow without investing in risky R&D activities. This is a first indication that there are other innovating young firms with a specific risk-return profile whose economic performance has not yet been analysed in the existing literature. To the best of our knowledge, Segarra and Teruel (2014) are the first to attempt to broaden the types of innovators under consideration by separately examining the differential performance effects of internal and external R&D. What has not been considered thus far, however, is the existence of a third category alongside R&D innovators and non-innovators: companies that engage in innovation with minimal or no reliance on in-house R&D.

Several studies have shown that smaller firms can compensate for their lack of R&D by, for example, using management practices that encourage interactive learning within the company and the inflow of external knowledge – allowing them to seize innovation opportunities in a less risky and costly way (e.g., Rammer et al., 2009; Hervas-Oliver et al., 2014; 2016; Moilanen et al., 2014). However, it remains an open question whether young firms engaged in non-R&D innovation actually follow growth trajectories that are different from both non-innovating and R&D-oriented young firms. One study that provides some evidence in this respect is the paper by Thomä and Zimmermann (2020). They show that smaller firms that focus on a non-R&D innovation mode based on learning by doing, using, and interacting (DUI) have similar sales growth, labour productivity rates and higher employment growth than firms that rely more on R&D (i.e., the science, technology, innovation (STI) mode with its strong emphasis on R&D; see Jensen et al., 2007). However, the cross-sectional sample of Thomä and Zimmermann (2020) does not have a distinct R&D group, nor does it focus on young firms or business development over time. Their data also provide limited information on economic performance indicators, which means that the risk-return trade-off of innovating firms is only partially analysed. To date, the growth trajectories of young firms engaged in non-R&D innovation activities remain largely unknown.

In this paper, we seek to enrich the literature on the economic performance of young firms by providing a better understanding of the links between innovation, R&D and firm growth. Based on German panel data provided by the IAB/ZEW Start-up Panel, we empirically examine the impact of innovation on economic performance by considering a broader typology of innovating young firms. By first distinguishing between R&D, non-R&D innovators and non-innovators we provide a more comprehensive picture of the development trajectories of young firms. To further differentiate this trichotomy, we also bridge the gap between the aforementioned literature on R&D and firm growth and the literature on innovation modes (see e.g., Jensen et al., 2007; Parrilli & Elola, 2012; Parrilli & Alcalde Heras, 2016; Thomä, 2017; Runst & Thomä, 2022; Haus-Reve et al., 2022). A deeper classification allows us to distinguish between two R&D oriented innovation modes (STI and STI plus) and two less R&D oriented modes (DUI and DUI plus). By distinguishing and measuring these innovation modes, we also try to better describe the input side of R&D and non-R&D-based innovation as a prerequisite for growth and economic success. In this context, we also address the question of whether the choice of innovation mode can be understood as a young firm's decision in favour of a certain risk-return trade-off.

The remainder of this paper is organized as follows. In Section 2, we discuss the theoretical background and develop several hypotheses. Section 3 presents our data and the methods used. The empirical results are described in Section 4. Finally, in Section 6 we summarize our findings and conclude with implications for policy and further research.

[1] Other studies find positive effects of R&D at the upper end of the growth distribution, with little or no countervailing negative effects identified at the bottom (e.g. Capasso et al., 2015; Falk, 2012).

2. Theoretical Background and Hypotheses

2.1. The impact of R&D on young firm growth

A number of studies have examined the impact of R&D innovation on firm performance by using indicators such as sales or employment growth. Coad and Rao (2008) use the presence of R&D capabilities as well as the use of patenting in order to classify firms as innovative or not. Their quantile regression results reveal the skewed nature of the returns to R&D, i.e., there are strong positive effects of R&D-based innovation on sales growth at the upper end of the growth distribution, starting at the 0.8 quantile. Similarly, Falk (2012) analyzes the relationship between sales and employment growth and R&D intensity. Again, the evidence points to a skewed effect, with firms at the top of the growth distribution benefiting disproportionately from R&D, and small or no effects at lower quantiles. Segarra and Teruel (2014) go a step further by exploring heterogeneity in the relationship between R&D and growth, notably by distinguishing between internal and external R&D. The former is measured by the wages of researchers and technicians, equipment, software licenses, and others. The latter is measured by the acquisition of external R&D services through contracts. Their evidence suggests stronger growth effects of internal R&D on sales and employment at higher quantiles, and stronger growth effects of external R&D at lower quantiles (up to the median). They also find stronger R&D effects in manufacturing than in services. Capasso et al. (2015) confirm previous findings by showing that R&D investment starkly increases the likelihood of high growth rates, but does not decrease the likelihood of low growth, reiterating the asymmetric nature of the relationship under consideration. Finally, Coad et al. (2016) investigate further heterogeneities in this context by separating the impact for young and mature firms. They find that the asymmetric impact of R&D is more pronounced for younger firms, i.e., the negative impact of R&D-based innovation at lower quantiles, and the positive impact at higher quantiles becomes quantitatively stronger. This already points to the risky nature of R&D-based innovation (Ortega-Argilés et al., 2009).

Overall, it can therefore be stated that the literature shows a robust relationship between higher R&D investment and positive economic performance in the case of high-growth firms. It is striking, however, that the studies mentioned more or less equate innovation with R&D. Such a view overlooks non-R&D innovators as an important category of young firms. However, findings suggest that business activities such as design, prototyping, use of advanced machinery and equipment, training or marketing are important drivers of innovation in less R&D-oriented knowledge environments (Barge-Gil et al., 2011; Hervas-Oliver et al., 2011, 2012; Kirner et al., 2009; Santamaría et al., 2009). In addition, several studies show that the innovation performance of non-R&D performing small firms can, under certain circumstances, be quite similar to that of R&D performers (Rammer et al., 2009; Hervas-Oliver et al., 2014; 2016; Moilanen et al., 2014). This raises the question of the different ways in which young firms pursue innovation in order to be economically successful – or, in the words of Audretsch et al. (2014b), "why don't all young firms invest in R&D?".

2.2. Modes of innovation: how innovation can succeed without R&D

The growing literature on innovation modes at the firm level (see the reviews by Apanasovich, 2016; Parrilli et al., 2016, and Santos et al., 2022) provides insights into how small and young firms can benefit from innovation without investing in risky and costly R&D activities. Corresponding studies contrast the Science-Technology-Innovation (STI) mode, with its emphasis on formal processes of R&D, and the Doing-Using-Interacting (DUI) mode, characterized by informal non-R&D processes of interactive learning and experience-based know-how (Jensen et al., 2007). This mode of innovation theorizing is input-oriented in that it focuses on different kinds of knowledge and learning processes at the firm level, i.e., the how-to of generating innovation. According to this literature, an STI-oriented firm deliberately searches for new technological developments and learns through R&D, where explicit and codified knowledge is both used. The corresponding innovation output is often radical in nature. In DUI-oriented firms, learning-by-doing, by-using and by-interacting replaces the more targeted R&D-based search for new knowledge of STI firms. DUI-based knowledge is therefore, in a sense, an unintentional by-product of day-to-day activities, often held by specific individuals within the firm who gradually become better at a particular task as they gain experience, or it may be embedded in teams working on a certain application-oriented problem. Accordingly, DUI innovation is more incremental and less radical. Such learning processes also tend to involve a high degree of informal interaction within firms and between firms and external agents such as suppliers or customers. DUI knowledge is often implicit in nature with strong tacit elements (know-how and know-who) as opposed to explicit and codified knowledge (know-why and know-what) in STI-based learning processes (see Jensen et al., 2007).

Since its inception, the literature on innovation modes has also alluded to the existence of combinatorial modes (see, for example, Jensen et al., 2007; Apanasovich, 2016; Thomä, 2017; Alhusen & Bennat, 2021). In fact, the ideal types of STI and DUI do not exist in reality – innovating companies always use elements of both modes, although it is possible that they focus more on one or the other. Therefore, a dynamic continuum between the two modes can be assumed in the practice of business innovation, characterized by varying degrees of R&D intensity, ranging from no R&D at all to a strong reliance on STI-based innovation activities (Alhusen & Bennat, 2021). However, to the best of our knowledge, the performance of young STI and DUI have not been examined as of now.

2.3. Hypotheses

In line with the literature on R&D performance, we expect to find a highly skewed effect of innovation on growth in terms of sales and employment for young firms in general, but for those with a strong focus on the STI mode in particular. On the hand, their investment in risky and costly R&D activities may be compensated by particularly high financial returns in case of success. On the other hand, their quest for higher market shares and sales requires sufficient employment growth to enable them to successfully implement their growth strategy. Nevertheless, we also argue that non-R&D innovation activity should be treated as an important category in its own right, and that its sui generis mode will be reflected in a distinct growth pattern that allows young firms to benefit economically from innovation in a less risky and costly way compared to the STI mode. We therefore expect that while young non-R&D oriented firms engaged in the DUI mode of learning, and may not develop the kinds of products and services that allow them to transform themselves and the market in a Schumpeterian fashion, they will nevertheless generate genuine and commercially successful novelty. Thus, they should show an improved economic performance over non-innovating firms, but without observing the very high performance of successful R&D oriented STI firms.

H1.a Young firms engaged in R&D innovation show a pronounced asymmetry along the conditional growth distribution, with significantly higher growth than non-innovators at the upper end.

H1.b Young firms engaged in R&D innovation display higher growth rates than non-R&D firms at higher quantiles.

H1.c Young non-R&D innovators exhibit significantly higher growth rates than non-innovators.

Finally, the above studies suggest that while some young R&D-oriented innovators can achieve very high growth rates that allow them to recoup their initial investment, most do not differ from non-innovating firms in this respect, reflecting the fact that R&D activities are initially costly and risky especially for smaller firms (Ortega-Argilés et al., 2009). Young STI firms can therefore be thought of as being situated at one end of the risk-return distribution, with young non-innovators at the other pole, facing low risk but also low growth potential. Between these two extremes, however, there is another type of innovator in the form of the non- (or less) R&D-intensive innovators. As far as this group is concerned, we do not expect to see the kind of gazelle-like growth of some young STI firms. Therefore, compared to the latter, we would also expect to see some countervailing forces in terms of the risk-reward trade-off – in the form of lower initial costs and lower risk to compensate for lower economic growth prospects. In other words, we argue that young non-R&D oriented DUI firms are positioned somewhere in the middle of the risk-return spectrum, experiencing higher growth than non-innovators and lower growth than R&D-focused STI firms, but also lower costs and risks than pure R&D innovators. We hypothesize that the high costs of R&D projects may lead to lower *initial* profitability in young R&D innovating firms. In addition, the inherently risky nature of R&D projects should increase the *initial* vulnerability of young R&D innovating firms, increasing the likelihood of their exit from the market.

H2.a Young innovating firms without R&D will have higher profits/lower losses than young R&D firms in the first years after start-up.

H2.b Young innovating firms without R&D will exhibit higher survival rates than young R&D innovating firms in the first years after start-up.

3. Data and Methods

3.1. Data set

The IAB/ZEW Start-Up Panel is collected and maintained by the Institute of Employment Research (IAB), the Leibnitz Centre for European Economic Research (ZEW) and the credit rating agency Creditreform. It constitutes a nationally representative German data set of about 6,000 annual young firm observations. Besides basic questions on company size, branch, employees etc. there are additional questionnaire modules concerning specific themes. The stratification of the sample provides for a focus on high-tech start-ups in order to analyse the development of this small but economically significant group, which is of particular policy interest. However, about half of the sample composition of the IAB/ZEW Start-up Panel also includes young firms from non-high-tech sectors, which permits us to analyse and compare R&D-intensive and non-R&D-intensive development trajectories of young firms.

3.2. Identification of non-R&D innovators and different modes of innovation

Based on our data set, we classify a young firm as an R&D innovator if it is engaged in R&D activities either occasionally or continuously and has introduced product or process innovations and/or reported ongoing or abandoned innovation projects in the same year. Similarly, non-R&D innovators are young firms that did not carry out R&D but were active innovators in the year in question. The innovation definitions used in the IAB/ZEW Start-Up Panel are based on the Oslo Manual guidelines as the common standard in innovation measurement (see OECD/Eurostat 2018). This variable formation results in a panel dataset for years 2007 to 2018.

For a finer identification and differentiation of R&D and non-R&D oriented innovation modes, we follow Thomä (2017) and others (Runst & Thomä, 2022; Bischoff et al., 2023) in applying a factor analysis followed by a clustering procedure to identify and generate different modes of innovation at the firm level. As factorized variables lead to more robust clustering than using original items (Hair et al., 1998), 14 variables from the 2014 survey year known from previous literature to identify different modes of firm-level innovation (Table A1 in the Appendix) are included in a factor analysis (principal components, see all variables and factor loadings in the Appendix, Table A2).

After varimax rotation, the eigenvalue rule (>1) as well as the inspection of a scree plot indicate the existence of four factors (Table A2). The first factor shows high loadings on the *Absorption of external scientific and technological knowledge (F1)*, mainly from scientific organizations, private research consultants and scientific journals. The second one is determined by positive loadings of measures of vocational education and training (VET) and negative ones for R&D competencies, and which we therefore label *Internal knowledge base (F2)*. A positive value of F2 indicates a tendency towards VET-based skills and knowledge – which is a typical feature of the DUI mode, particularly in Germany with its pronounced VET system (Thomä, 2017; Matthies et al., 2023) – and a negative value indicates a tendency towards internal R&D capacities embedded in the STI mode of learning and innovation. The third factor, F3, is characterized by learning through interaction with external supply chain partners, such as customers and suppliers, as well as competitors, which is why we have chosen the label *Absorption of external applied knowledge (F3)*. Finally, the fourth factor relates to the internal dimension of employee freedom and participation and measures the extent to which employees are free to make their own decisions and participate in collective decision-making. It is labelled *Involvement of employees (F4)*.

We then use all four factors in a cluster analysis, choosing a hierarchical method using Ward's linkages and Euclidean squared distances. The corresponding dendrogram (see Appendix, Figure A1), in conjunction with standard cluster stopping rules (Calinski-Harabasz pseudo-F index and the Duda-Hart index), indicates a four-cluster solution, whose consistency is validated by a set of profiling variables that were not used for clustering, but which are known from previous literature to vary across different modes of innovation (see Appendix Table A3).

Cluster C1 is characterized by above-average levels of employee freedom and creativity, in addition to learning stimulated by contacts along the supply chain to absorb external applied knowledge, two DUI mode characteristics also found in a number of other studies (see the reviews by Apanasovich, 2016; Parrilli et al., 2016 and Santos et al., 2022). This cluster also shows a moderate bias towards vocational qualifications as opposed to R&D competences. The absorption of external scientific and technological knowledge, which is a typical characteristic of the STI mode, is below average. As C1 therefore combines strong internal DUI mode competences with an openness to external DUI sources, it can be described as *DUI plus*.

Compared to the other groups, the internal knowledge base of the member of cluster C2 is most strongly characterized by internal R&D competences, leading to a strong focus on the STI mode. It also shows very little employee autonomy and a medium level of learning through interaction along the supply chain. The absorption of external scientific and technological knowledge also plays a minor role. Young firms in this group seem to drive innovation processes mainly from within, based on their strong R&D competences. Cluster C2 is therefore labelled as a pure *STI type*.

Innovation processes in cluster C3 are almost exclusively driven by practice-oriented internal knowledge sourcing based on vocational qualifications. Employee autonomy is very low and learning in the supply chain is slightly below average. There is also limited openness to external sources of scientific knowledge (F1). In contrast to the first cluster (C1), C3 represents a more traditional and less open *DUI mode*. Finally, cluster C4 shows a strong tendency to absorb external scientific and technological knowledge, some employee autonomy and very little supply chain-induced learning. The internal knowledge base is clearly oriented towards R&D competences. The fourth group thus represents a more outward-looking *STI plus* mode.

Since the information used to identify these innovation modes is only available for 2014, and based on the assumption of the persistence of young firms' innovation modes, we extend the assigned modes to other survey years, resulting in a panel period from 2010 to 2017 for the regression analysis on the four innovation modes. However, this type of classification can potentially lead to a selection effect if firms from certain innovation modes are more likely to survive until 2014 than others. We mitigate this potential problem by restricting the sample to the cohort of firms founded in 2012 in certain robustness specifications at the regression stage. In addition, as mentioned above, we also use the simpler classification of R&D and non-R&D innovators, which is available for all panel years (2007 to 2018), thereby avoiding potential selection effects.

3.3. Quantile and panel regression analysis

Using quantile regression, we analyse (1) the effects of R&D and non-R&D innovator status and (2) of belonging to one of the four identified innovation modes on the economic performance of young firms, with non-innovators in the reference group in each case. Quantile regression estimates the effect of each mode conditional on the quantile of the dependent variable (see Koenker & Hallock, 2001; Parente & Santos Silva, 2016). We also use additional binary measures of economic performance. Exit equals one if the firm is active in year t but not in t+1. Our data allow us to distinguish between panel attrition and real business closures, as the dataset contains the exit years of all surveyed companies, even after they have left the sample, and thus sample attrition does not bias our results. The overall exit rate is quite low. After five years, about 75 per cent of all companies remain in the sample.[2] Profit and loss are additional binary performance indicators that are equal to one if the company earns a positive or negative profit. Table 1 shows the descriptive statistics for all variables.

We control for firm size (number of employees in full-time equivalents), export orientation (binary) and investment (in euros per person), an 11-item industry indicator, year and years since start-up fixed effects. Standard errors are clustered at the company level. Linear panel regressions are used for the binary dependent variables exit, profit and loss. However, we do not fully exploit our information on exit years in the panel regression setting, as firms that leave the sample cannot be included due to missing predictor data. To fully exploit the exit year data, we also run survival regressions (Jenkins, 1995), in particular the Cox proportional hazards model with heteroskedasticity robust standard errors, for which we report odds ratios (see also Cleves et al., 2010).

[2] The data provider has confirmed that this is indeed a feature of the data set, which deliberately oversamples R&D intensive high-tech companies (see above).

Table 1. Descriptive statistics

		Mean	**Std. dev.**
Exit	Enterprise deaths per year during the period 2010 to 2017 (1/0)	0.015	0.123
Profit	Profit in the reference year (1/0)	0.819	0.385
Loss	Loss in the reference year (1/0)	0.136	0.342
Revenue growth	Change in sales generated compared to previous year (in %)	78.623	221.101
Workforce growth	Change in number of active persons compared to previous year (in %)	28.313	113.229
No Innovation	Non-innovating firm (1/0)	0.482	0.499
R&D innovator	R&D innovating firm	0.253	0.434
Non-R&D innovator	Non-R&D innovating firm	0.264	0.441
No Innovation	Non-innovating firm (1/0)	0.525	0.499
DUI plus	Firm with DUI-plus innovation mode (1/0)	0.206	0.405
STI	Firm with STI innovation mode (1/0)	0.090	0.286
DUI	Firm with DUI innovation mode (1/0)	0.102	0.302
STI plus	Firm with STI-plus innovation mode (1/0)	0.077	0.267
Active persons	Persons active in the reference year, including owners (number)	7.426	13.031
Investment per person	Volume of investment per person in the reference year (in thousand euro)	5,237.358	48,684.190
Export orientation	Export activity in the reference year (1/0)	0.255	0.436
High-tech manufacturing		0.088	0.283
Advanced manufacturing		0.068	0.252
Technology intensive services		0.267	0.442
Software		0.074	0.262
Low-tech manufacturing		0.142	0.349
Knowledge-intensive services		0.112	0.316
Other business-related services		0.081	0.273
Consumer-related services		0.038	0.190
Construction		0.090	0.287
Trade		0.039	0.194
Others		0.000	0.017

3.4. Matching specifications

The regression analysis aims to identify differences in economic performance between innovation types/modes. However, such results cannot be interpreted as strictly causal if treatment assignment is not random, e.g., firms may self-select into certain innovation modes based on their sectoral or company characteristics. While descriptive differences in the economic performance of young firms are informative in their own right, and the antecedent literature on the impact of R&D on growth and performance follows this approach (e.g., Coad et al., 2016), we further extend the analysis. Motivated by Parrilli et al. (2020), we use matching estimators to mitigate endogeneity concerns. Based on observable characteristics, one must first estimate the probability of treatment before estimating the outcome regression on an adjusted sample in the second stage. There are a number of adjustment methods, such as nearest neighbour, entropy balancing or weighted regression. We choose inverse probability weighted regression adjustment (IPWRA), which applies the inverse of the probability of treatment selection to all covariates (see Imbens &Wooldridge, 2009). While matching estimators are commonly used in the case of binary treatment variables, Imbens (2000), Imbens and Wooldridge (2009), Cattaneo (2010) and Cattaneo et al. (2013) extend the application to multivalued treatments that can be estimated by multinomial logit regressions.[3] We implement these estimators using `teffects` in Stata. Quantile regression on the dependent variables of workforce and revenue growth is not currently supported by `teffects`. However, the user written program `rifhdreg` allows the use of matching estimators, multivalued treatment and quantile regression (see Rios-Avila & Maroto, 2022; Rios-Avila, 2020, p.70-72).

[3] Also see Rios-Avila, 2020, and references on `effects multivalued' in Stata.

4. Results

4.1. Quantile regression analysis of revenue and workforce growth

The quantile regression results for R&D and non-R&D innovating young firms are shown in Figure 1. There is a clear contrast between the two types in terms of revenue growth. At the lower quantiles (1st and 2nd), the revenue growth of R&D innovators is indistinguishable from that of non-innovators, while non-R&D innovating firms display a higher performance. At medium quantiles (3rd to 6th) the R&D and non-R&D innovating firms behave similarly, both showing higher growth rates than non-innovators (by up to 10 percentage points). It is only at the upper end of the conditional growth distribution that young R&D innovating firms outperform their non-R&D counterparts, which in turn outperform non-innovators. The maximum effect sizes at the top end are quite different, 55 and 13 percentage points respectively. This contrast between the two types of innovators is much less pronounced when it comes to workforce performance. For quantiles 1st to 6th, their respective growth rates do not differ from those of non-innovators. Only at the upper end of the conditional change in workforce distribution, does the effect size for both rise to around 12 percentage points. Both R&D innovators and non-R&D innovators therefore experience positive effects on the number of persons active in the firm compared to non-innovators, but there is little difference between them. To sum up, we find evidence for hypotheses H1.a and c. There is partial evidence for hypothesis H1.b (i.e., regarding revenue growth).

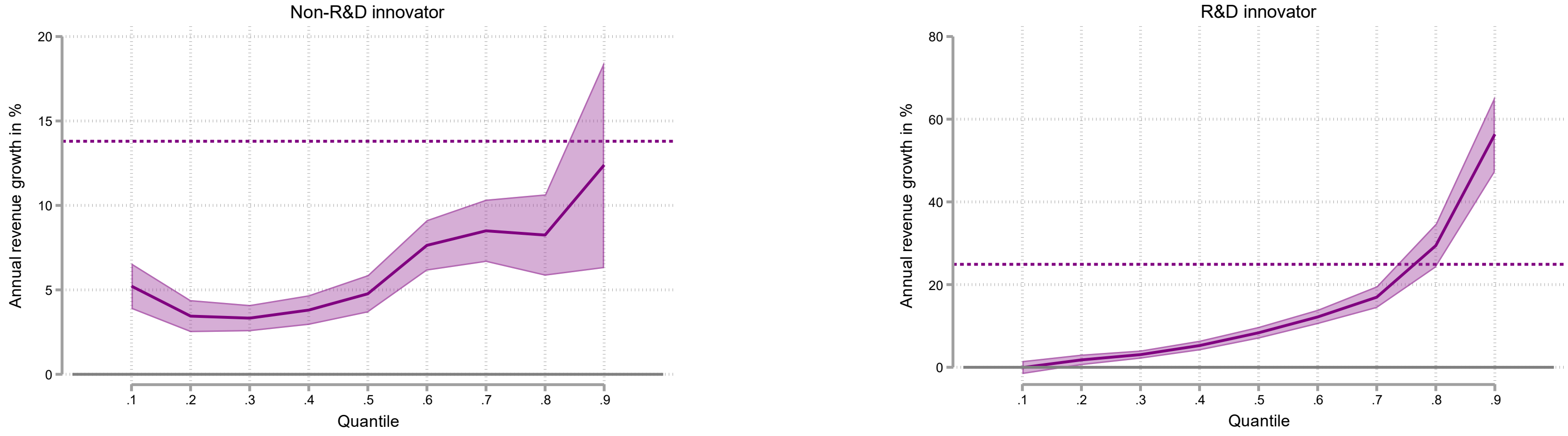
The detailed quantile regressions by mode of innovation (DUI plus, STI, DUI and STI plus) in Figure 2 and Figure 3 provide a consistent but more detailed picture compared to the simpler dichotomy of R&D and non-R&D innovators (see Figure 1). On the one hand, the results show that the different types of DUI and STI modes map onto the non-R&D and R&D innovator types, respectively. However, they also show that the simpler R&D-based dichotomy masks some underlying heterogeneities. Compared to the reference group of non-innovators, there is no evidence of an improved revenue performance of basic DUI firms at the lower end of the conditional growth distribution, and only a small positive effect at mid-level quantiles (5th to 7th; see Figure 2). In contrast, DUI plus firms have statistically significant and positive coefficients at most quantiles, although the effect sizes are small at the lower quantiles and rise to around 10 percentage points at the 6th to 8th quantile. The positive growth effect is strongest for STI and STI plus firms, both of which have large positive coefficients. However, the more outward-looking STI plus type outperforms the more inward-looking pure STI type. They show growth premia of 38 (STI) and 59 (STI plus) percentage points respectively at the 9th quantile. Overall, Figure 2 provides further evidence in favour of H1.a. The finer differentiation by innovation mode again provides evidence for the validity of hypothesis H1.b with respect to revenue growth performance. Hypothesis H1.c, on the other hand, is only confirmed in the case of the DUI-plus group. Thus, DUI and DUI plus represent categories of their own, distinct from both non-innovators and STI-oriented young firms. Both DUI groups share similarities and show moderate revenue growth rates, although the effect sizes are larger for the more advanced DUI plus type. Hence, the more open DUI-plus group performs more favourably than their counterparts in the basic DUI group. This confirms a repeated finding in innovation mode research, according to which firms that combine different internal and external sources of innovation tend to be more innovative and successful than firms with a purely internal focus (Apanasovich, 2016; Parrilli et al., 2016; Santos et al., 2022).

Figure 3 shows the results of the quantile regression for the dependent variable workforce growth across innovation modes. All four innovation modes show similar patterns compared to non-innovators. There is little to no evidence of a different growth path from the 1st to the 5th quantile and a positive premium from the 6th to the 9th quantile. However, in contrast to the results for revenue growth, the effect size is higher for basic DUI firms, with a growth premium of 35 percentage points at the 9th quantile. It seems that the labour intensity of basic DUI firms outweighs the stronger revenue growth of STI-oriented firms. In case of workforce growth, our results therefore support H1.a and H1.c, but are not consistent with H1.b.

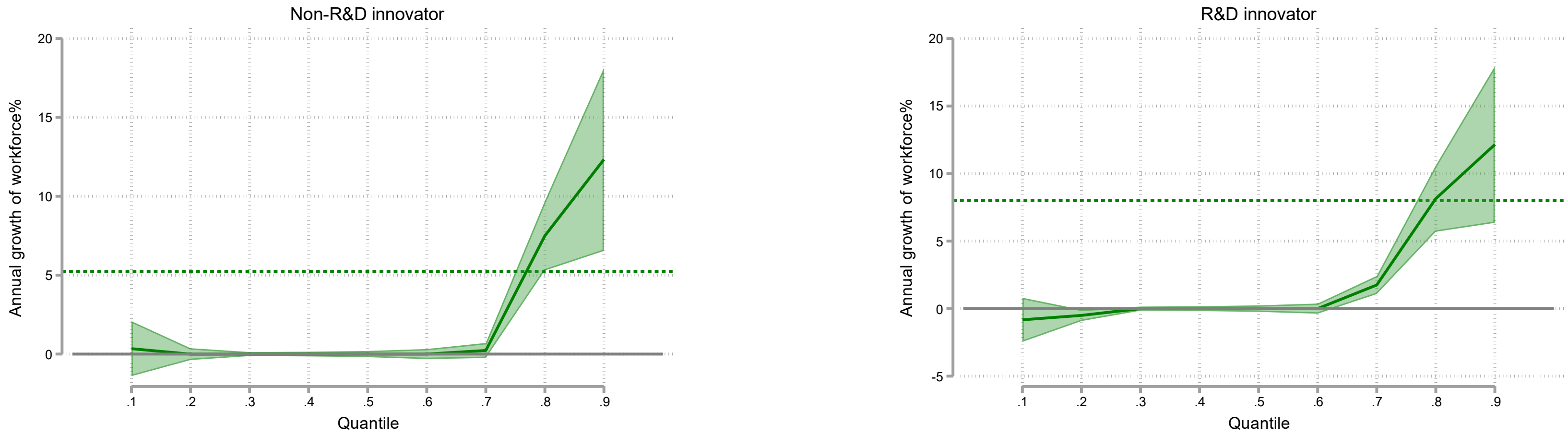
Finally, some robustness checks are presented in Figure A2 (revenue growth) and Figure A3 (workforce growth), where the sample is restricted to the 2012 cohort of start-ups only to mitigate potential selection bias. For revenue growth, the previous findings of strongly elevated STI growth at the upper quantiles and elevated DUI growth at the mid-to-high quantiles are confirmed, with one exception: When it comes to revenue growth performance, the basic DUI group is no longer distinguishable from non-innovators. The reverse is true in case of workforce growth: STI and STI plus no longer show higher performance than non-innovators. Furthermore, the increased growth for DUI firms (especially the basic DUI group) is only observed at higher quantiles. Overall, the robustness check confirms the main previous findings. Non-R&D firms that innovate on the basis of the DUI mode constitute a separate performance category. They show lower revenue growth at the top end than R&D-oriented STI innovators, but higher revenue growth than non-innovators. In addition, they show stronger workforce growth than both R&D innovating and non-innovating firms.

Figure 1. Revenue and workforce growth, quantile regressions (R&D and Non-R&D innovators)

Revenue growth

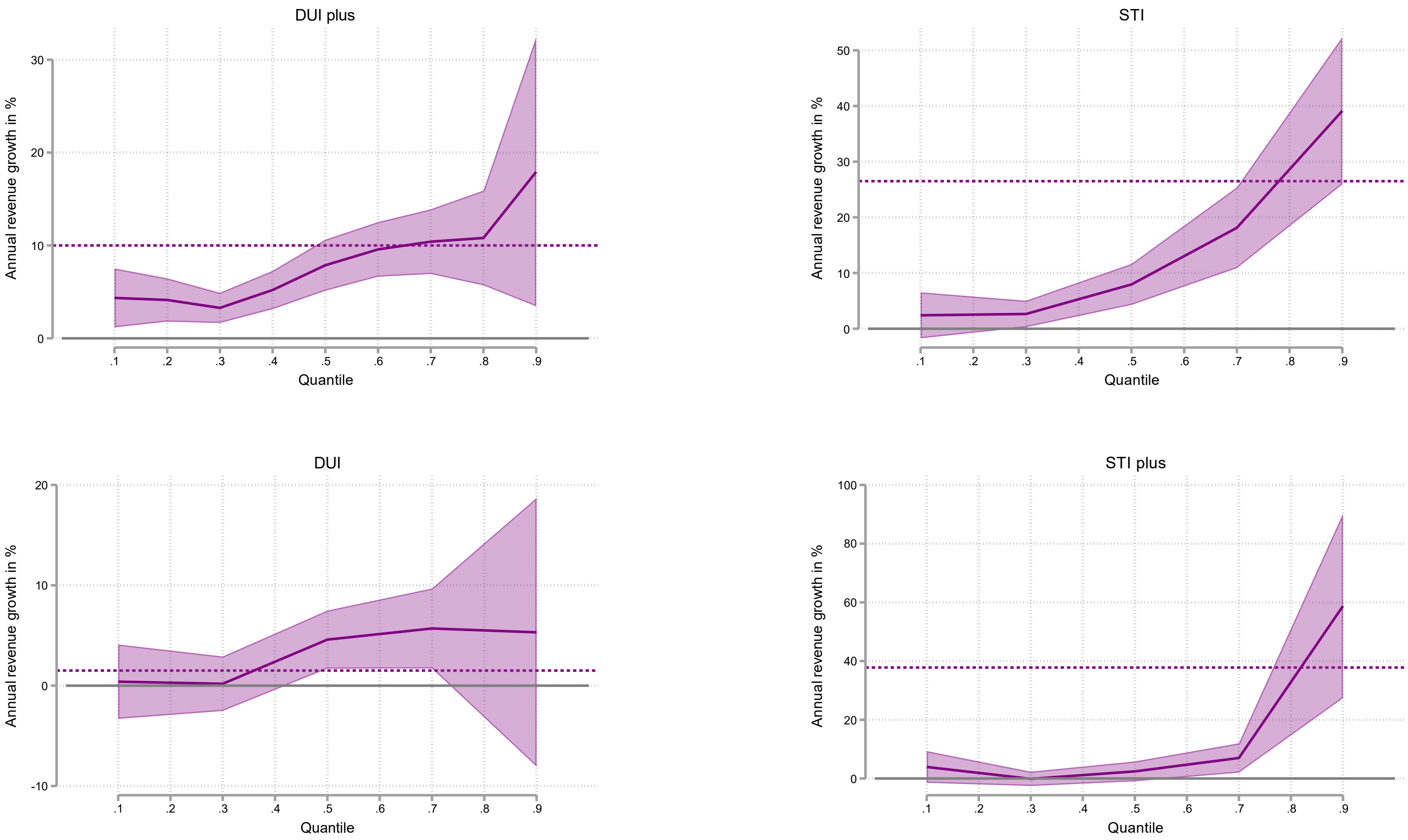


Workforce growth



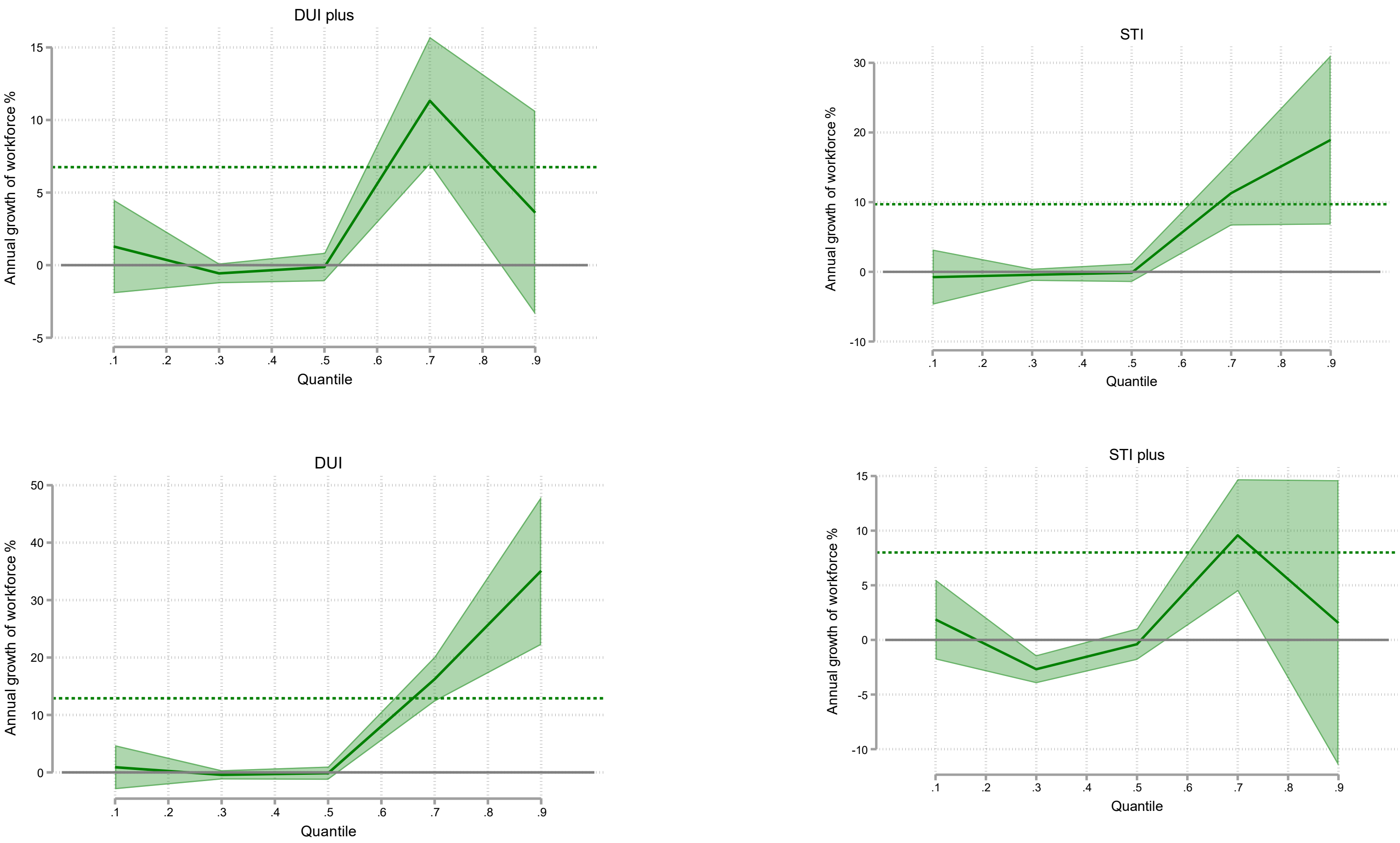
Notes: The values corresponding to each quantile can be seen in Table 4 and 5. The shaded areas correspond to the 90% confidence interval and the horizontal purple or green line represents the OLS coefficient.

Figure 2. Quantile Regressions (revenue growth)



Notes: The four innovation modes are the result of a cluster analysis (see Table A3) and the values corresponding to each quantile can be seen in Table A4 in the appendix. The shaded areas correspond to the 90% confidence interval and the horizontal purple line represents the OLS coefficient.

Figure 3. Quantile Regressions (workforce growth)



Notes: The four innovation modes are the result of a cluster analysis (see Table A3) and the values corresponding to each quantile can be seen in Table A5 in the appendix. The shaded areas correspond to the 90% confidence interval and the horizontal green line represents the OLS coefficient.

4.2. *A different risk-reward trade-off?*

In this section we analyse whether young R&D innovating firms, with their superior revenue growth performance, have a higher existential risk – in the form of lower survival rates– or experience lower initial profitability due to higher ongoing risks and costs than non-R&D innovating firms (see hypotheses H2.a and H2.b).The results of linear, random-effects panel regression can be found in Table 2. The findings suggest a distinctly lower exit rate for non-R&D innovators by about 0.5 percentage points in specification 1. Given the baseline exit probability of about 1.5 percent per year, the effect size is large. The results of a Cox survival regression confirm this finding, with a statistically significant odds ratio of less than one for non-R&D innovators and more than one for R&D innovators.

Table 2. Regression result (exit, profit, and loss, by R&D status)

	(1)	**(2)**	**(3)**	**(4)**
	exit	exit	profit	loss
Ref. no innovation				
Non-R&D innovators	-0.005***	0.916***	0.002	0.009*
R&D innovators	-0.002	1.125 ***	-0.096***	0.102***
Active persons	-0.000	1.000	0.000	-0.000
Investment per person	-0.000	1.000	-0.000***	0.000***
Export orientation	-0.005**	0.738***	0.049***	-0.030***
Ref. High-tech manufacturing				
Advanced manufacturing	0.001	1.293***	-0.038**	0.016
Technology intensive services	0.004	1.098**	0.105***	-0.093***
Software	0.006	1.276***	0.001	-0.002
Low-tech manufacturing	0.005	1.092*	0.044***	-0.055***
Knowledge-intensive services	0.008*	1.318***	0.142***	-0.116***
Other business-related services	0.005	1.510***	0.077***	-0.091***
Consumer-related services	0.004	1.491***	0.024*	-0.027**
Construction	-0.003	1.102*	0.132***	-0.129***
Trade	0.008*	1.491***	0.072***	-0.063***
Others	-0.000	1.518***	0.032**	-0.051***
Specification	*Linear Panel*	*Cox Survival*	*Linear Panel*	*Linear Panel*
Observations	48,088	52,370	51,051	51,051

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.0$; Random-effects linear panel regression in specification 1, 3, and 4. Cox survival model in specification 2 with odds ratios, i.e. coefficients less than one signify a negative impact on firm exits. Year and year-after-start-up fixed effects are included. Standard errors are clustered at the firm level.

Focusing on profits and losses in specifications 3 and 4 of Table 2, we find that non-R&D innovators are almost indistinguishable from non-innovators, although there is some weak evidence of slightly higher losses. In contrast, R&D innovators have a lower probability of profits (by about 9.6 percentage points) and a higher probability of losses (by about 10.2 percentage points), both of which are highly statistically significant. To sum up, we therefore conclude that the overall risk of exit is lower for young non-R&D innovators compared to R&D innovators, with their initial profits being higher and their losses lower. These results are thus in line with our hypotheses above, which state that young non-R&D innovating firms have higher profits/lower losses and higher survival rates than young R&D innovating firms in the first years after start-up.

In a next step, we perform the same analysis using the four innovation modes (Table 3). Columns 1 to 4 present regression results for the dependent variable exit, with panel regressions in columns 1 and 2 and Cox survival regressions in columns 3 and 4. The coefficient on the basic DUI dummy variable is the only one that shows consistent negative effects, albeit at the 10 percent significance level, except in specification 2. This finding also persists when we change the reference group to all firms other than basic DUI (see column 4). While the STI coefficient is negative and significant in column 1, this effect does not reappear in any other specification, including an unreported survival specification for the 2012 sample similar to that in column 4. Thus, while there is evidence in favour of hypothesis H2.b, i.e., that young non-R&D innovating firms are more likely to survive, these results again indicate some underlying heterogeneity in the above findings on the group of non-R&D innovators, a higher survivability is only observed for the basic DUI mode.

Table 3. Regression result (exit, profit, and loss, by innovation mode)

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
	exit	exit	exit	exit	profit	profit	loss	loss
Ref. No Innovation								
DUI plus	-0.006	-0.002	1.104		-0.080***	-0.071	0.088***	0.115***
STI	-0.014***	0.011	0.919		-0.152***	-0.204***	0.156***	0.183***
DUI	-0.009*	-0.012	0.649*	0.387*	-0.006	0.049	0.019	-0.015
STI plus	-0.008	-0.001	0.898		-0.155***	-0.069	0.143***	0.125**
Active persons	-0.000	0.000	0.997	0.996	0.001**	0.002**	-0.001*	-0.002**
Investment per person	-0.000	-0.000	1.000*	1.000	-0.000***	-0.000**	0.000***	0.000***
Export orientation	-0.007*	-0.006	0.812	1.071	0.045***	0.013	-0.025**	0.025
Ref. High-tech manufacturing								
Advanced manufacturing	0.013*	0.003	1.744	1.695	-0.049	-0.023	0.013	0.012
Technology intensive services	0.010**	0.014	1.549	1.519	0.084***	0.093	-0.075***	-0.075
Software	0.009	-0.001	1.224	0.434	-0.013	-0.056	-0.009	0.071
Low-tech manufacturing	0.008	0.028**	1.926**	1.690	0.041	0.065	-0.061**	-0.095
Knowledge-intensive services	0.002	0.012	1.724	1.625	0.119***	0.142**	-0.098***	-0.105*
Other business-related services	0.009	0.010	2.357**	1.427	0.091***	0.129*	-0.098***	-0.123*
Consumer-related services	0.014	0.005	2.822***	2.898*	0.005	0.043	-0.054	-0.070
Construction	0.005	0.007	1.837*	1.330	0.130***	0.188***	-0.114***	-0.138**
Trade	0.011	0.000	-	-	0.088***	0.153**	-0.082***	-0.127**
Others	0.464	-0.002	-	-	0.344	0.060	-0.320	-0.022
Specification	*Linear Panel*	*Linear Panel*	*Cox Survival*	*Cox Survival*	*Linear Panel*	*Linear Panel*	*Linear Panel*	*Linear Panel*
Cohort restriction	none	2012 only	none	2012 only	none	2012 only	none	2012 only
Observations	9,572	1,838	1,576	3,68	9,372	1,802	9,372	1802

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.0$; Random-effects linear panel regression in all specifications except 3 and 4. Cox survival model in specification 3 and 4 with odds ratios, i.e. coefficients less than one signify a negative impact on firm exits. Year and year-after-start-up fixed effects are included. Standard errors are clustered at the firm level.

4.3. Further robustness specifications

The results of a matching estimator of the weighted quantile regressions for the dependent variable 'revenue growth' are presented in Table 4. Similar to Figure 1, we see that R&D innovating young firms clearly outperform non-innovators in terms of revenue growth, especially at higher quantiles by 60 to 73 percentage points. Non-R&D innovators also display higher revenue growth but their growth premium is somewhat smaller (up to about 19 percentage points). Table 5 shows that, as before, R&D innovators and non-R&D innovators behave rather similarly with respect to the growth in the number of active persons. The former group has a growth premium of up to 16 percentage points and the latter up to 20 percentage points above non-innovators at the 7th and 8th quantiles.

Table 4: Quantile Regression results (IPWRA, dep. var. revenue growth, by R&D status)

		(1)		(2)	
Quantile	Value	Non-R&D innovator	p	R&D innovator	p
10	-0.25	4.69	0.38	10.11	0.10
20	-0.05	9.61	0.01	9.85	0.01
30	0.00	6.86	0.06	8.52	0.02
40	0.14	6.13	0.10	14.34	0.00
50	0.25	11.44	0.01	21.98	0.00
60	0.47	15.53	0.03	34.87	0.00
70	0.75	19.28	0.09	59.72	0.00
80	1.33	21.92	0.24	73.34	0.00
90	3.00	13.56	0.74	171.05	0.01

Notes: The columns Non-R&D innovator and R&D innovator display the coefficients along the conditional distribution, separately for each group. We use bootstrapped standard errors and run 50 iterations.

Table 5: Quantile Regression results (IPWRA, dep.var. workforce growth, by R&D status)

		(1)		(2)	
Quantile	Value	Non-R&D innovator	p	R&D innovator	p
10	-0.33	-8.54	0.09	-10.93	0.05
20	-0.08	-7.43	0.22	-5.00	0.41
30	0.00	-0.50	0.57	-0.75	0.43
40	0.00	0.50	0.55	-0.07	0.94
50	0.00	1.51	0.09	0.61	0.54
60	0.00	3.51	0.42	-5.92	0.22
70	0.29	17.99	0.00	16.39	0.01
80	0.50	20.10	0.05	8.71	0.22
90	1.00	38.64	0.19	6.59	0.59

Notes: The columns Non-R&D innovator and R&D innovator display the coefficients along the conditional distribution, separately for each group. We use bootstrapped standard errors and run 50 iterations.

In addition, the corresponding estimation results for the weighted quantile regressions for all four innovation modes are presented in Tables A4 and A5 in the appendix. For the basic DUI group, the results for revenue growth broadly confirm the previous findings of increased performance at medium to high values of revenue change, particularly at the 7th and 6th quantiles (Table A4). The growth pattern of the DUI plus group is still similar to that of the basic DUI group, but is more pronounced in that it shows increased growth in the mid-range and improved growth in the low and, to some extent, high end (7th quantile). For members of the STI group, the results are in line with previous findings and point to an improved mid to high level performance (4th to 8th quantiles). STI-plus shows improved mid to high level growth, extending into the 8th quantile.

The matching estimator results of our weighted quantile regressions for the dependent variable change in workforce are presented in Table A5. The results are very similar to those presented in Figure 3, with an improved growth at quantiles corresponding to positive values of workforce growth. Thus, we find higher workforce growth in all types of DUI and STI innovation modes compared to non-innovators. The performance is similar across modes, with perhaps a slightly lower workforce growth rate for DUI plus firms.

The panel regression analysis for the dependent variables exit, loss and profit (in Table 2 and Table 3) is complemented by matching estimations, the results of which are presented in Appendix Table A6. The coefficient on non-R&D innovators is negative and significant (column 1, bottom panel), suggesting a 1.7 percentage point reduction in exits. The coefficient of R&D innovators is also negative (-0.008), but smaller and statistically insignificant. Looking at the underlying heterogeneity of innovation modes (see upper panel), both the basic DUI and the DUI plus show a lower probability of exit, with an effect size of around 2 percentage points. The STI mode group also shows a similarly reduced exit rate, although the level of statistical significance is low. There is no evidence of a change in exit rates for STI plus. Overall, the IPWRA results on the dependent variable exit confirm the higher survival rate of non-R&D innovators compared to R&D innovators and non-innovators. They also confirm the higher survival rate of basic DUI firms compared to non-innovators.

Looking at columns 2 and 3 of Table A6, we again find that non-R&D innovators have higher initial profits than non-innovators (bottom panel). In contrast, R&D innovating firms have lower initial profits and higher losses. We also find a higher probability of profits and a lower probability of losses for basic R&D innovators compared to non-innovators. In contrast, STI and STI plus firms show lower profits and higher losses, although at a weaker level of statistical significance. Overall, the matching estimates confirm previous findings.

5. Discussion and conclusion

Starting from the well-established fact that there is an asymmetric impact of R&D on firm performance along the conditional growth distribution, this paper has used panel data from Germany to examine the growth trajectories of young firms as a function of their reliance on in-house R&D for innovation. By distinguishing non-R&D innovators from R&D innovators and non-innovators, and further differentiating this basic trichotomy by identifying different modes of firm-level innovation, we provide a better understanding of the links between innovation, R&D and growth in young firms. While the results confirm the superior performance of R&D innovators at the upper end of the conditional growth distribution, our findings suggest that young non-R&D innovators also exhibit improved growth performance compared to non-innovators, albeit at lower levels. This is particularly true for young firms that rely on the 'learning by doing, using, and interacting' (DUI) mode of innovation and are open to external sources of learning, such as suppliers or customers. Our results also indicate that R&D oriented innovators only outperform non-R&D innovators in terms of revenue growth and that there is little difference between them in terms of workforce growth. Finally, we also find some differences between innovation modes (e.g. the lower exit rates of DUI vis-à-vis DUI plus), confirming the underlying heterogeneity within non-R&D innovating firms.

We suggest that whether or not young firms employ R&D in their innovation effort can be understood as a particular risk-reward combination. We show that while young innovating firms with a non-R&D orientation may have a positive, albeit inferior, growth performance compared to young R&D firms at the higher end of the performance distribution, they also face a lower risk of failure and lower costs, and are therefore initially more profitable after entering the market. Our results therefore highlight the previously underestimated growth potential of young, non-R&D-oriented firms and their role in generating economic dynamism, albeit at a lower level than R&D-oriented young firms. As these innovator types are more numerous than R&D-intensive high performers, it can also be suspected that their moderate growth performance will nevertheless exert a positive effect on regional growth and job creation. This also raises the question of whether this type of innovator has been being given due consideration in academic research and innovation policy.

Therefore, policy makers can conclude from our study that non-R&D innovators are an independent source of growth and economic dynamism. Although their growth potential is lower than that of R&D-innovating firms, it still represents a significant improvement over non-innovators. Our findings add to previous analyses that have exclusively focussed on the R&D vs. non-innovator dichotomy, overlooking non-R&D innovators with their typical emphasis on the DUI mode.

Future research could address the question of whether successful non-R&D innovators can eventually develop into firms with R&D capabilities, thus serving as seedbeds for future high-growth firms. Moreover, one can speculate whether the existence of non-R&D innovators potentially contributes to a richer, more diverse innovation ecosystem (especially at the regional level). For example, incremental DUI mode innovators and the skills and knowledge they possess can complement the capabilities of R&D intensive firms through interaction or collaboration. By contributing tacit and experiential knowledge, the co-existence of both types of skills within a region can potentially stimulate higher-level innovation and growth. Indeed, previous studies have found a positive interaction between different sources of R&D and non-R&D sources of learning and innovation (Apanasovich, 2016; Parrilli et al., 2016 and Santos et al., 2022), and it can be plausibly hypothesized that such a positive effect extends to a situation where such capabilities are not integrated within a single firm, but exist in two different but cooperating firms within a region, where different forms of knowledge can be brought together through joint projects or other forms of interaction. However, these questions cannot be answered with the available data and therefore represent suggestions for future research.

References

Alhusen, H., & Bennat, T. (2021). Combinatorial innovation modes in SMEs: mechanisms integrating STI processes into DUI mode learning and the role of regional innovation policy. European Planning Studies, 29, 779–805. doi:10.1080/09654313.2020.1786009.

Apanasovich, N. (2016). Modes of Innovation: A Grounded Meta-Analysis. Journal of the Knowledge Economy, 7, 720–737. doi:10.1007/s13132-014-0237-0.

Audretsch, D. B., Coad, A., & Segarra, A. (2014a). Firm growth and innovation. Small Business Economics, 43, 743–749. doi:10.1007/s11187-014-9560-x.

Audretsch, D. B., Segarra, A., & Teruel, M. (2014b). Why don't all young firms invest in R&D? Small Business Economics, 43, 751–766. doi:10.1007/s11187-014-9561-9.

Barge-Gil, A., Jesús Nieto, M., & Santamaría, L. (2011). Hidden innovators: the role of non-R&D activities. Technology Analysis & Strategic Management, 23, 415–432. doi:10.1080/09537325.2011.558400.

Bischoff, T. S., Hipp, A., & Runst, P. (2023). Firm innovation and generalized trust as a regional resource. Research Policy, 52, 104813. doi:10.1016/j.respol.2023.104813.

Capasso, M., Treibich, T., & Verspagen, B. (2015). The medium-term effect of R&D on firm growth. Small Business Economics, 45, 39–62. doi:10.1007/s11187-015-9640-6.

Cattaneo, M. D. (2010). Efficient semiparametric estimation of multi-valued treatment effects under ignorability. Journal of Econometrics, 155, 138–154. doi:10.1016/j.jeconom.2009.09.023.

Cattaneo, M. D., Drukker, D. M., & Holland, A. D. (2013). Estimation of Multivalued Treatment Effects under Conditional Independence. The Stata Journal: Promoting communications on statistics and Stata, 13, 407–450. doi:10.1177/1536867X1301300301.

Cleves, M.; Gould, W.; Gutierrez, R. G., & Marchenko, Y. (2010). An introduction to survival analysis using Stata (3rd ed., A Stata Press publication). College Station, Tex.: Stata Press.

Coad, A., & Rao, R. (2008). Innovation and firm growth in high-tech sectors: A quantile regression approach. Research Policy, 37, 633–648. doi:10.1016/j.respol.2008.01.003.

Coad, A. (2009). The growth of firms: A survey of theories and empirical evidence (New perspectives on the modern corporation). Cheltenham: Edward Elgar.

Coad, A., Segarra, A., & Teruel, M. (2016). Innovation and firm growth: Does firm age play a role? Research Policy, 45, 387–400. doi:10.1016/j.respol.2015.10.015.

Falk, M. (2012). Quantile estimates of the impact of R&D intensity on firm performance. Small Business Economics, 39, 19–37. doi:10.1007/s11187-010-9290-7.

Hair, J. F., Anderson, R. E., Tatham, R. L., & Black, W. C. (1998). Multivariate data analysis (5th ed.). Prentice-Hall International, Inc.

Haus-Reve, S., Fitjar, R. D., & Rodríguez-Pose, A. (2022). DUI it yourself: Innovation and activities to promote learning by doing, using, and interacting within the firm. Industry and Innovation, 1–21. doi:10.1080/13662716.2022.2131509.

Hervas-Oliver, J.-L., Albors Garrigos, J., & Gil-Pechuan, I. (2011). Making sense of innovation by R&D and non-R&D innovators in low technology contexts: A forgotten lesson for policymakers. Technovation, 31, 427–446. doi:10.1016/j.technovation.2011.06.006.

Hervas-Oliver, J.-L., Albors-Garrigos, J., & Baixauli, J.-J. (2012). Beyond R&D activities: the determinants of firms' absorptive capacity explaining the access to scientific institutes in low–medium-tech contexts. Economics of Innovation and New Technology, 21, 55–81. doi:10.1080/10438599.2011.555113.

Hervas-Oliver, J.-L., Sempere-Ripoll, F., & Boronat-Moll, C. (2014). Process innovation strategy in SMEs, organizational innovation and performance: a misleading debate? Small Business Economics, 43, 873–886. doi:10.1007/s11187-014-9567-3.

Hervas-Oliver, J.-L., Ripoll-Sempere, F., & Moll, C. B. (2016). Does management innovation pay-off in SMEs? Empirical evidence for Spanish SMEs. Small Business Economics, 47, 507–533. doi:10.1007/s11187-016-9733-x.

Imbens, G. (2000). The role of the propensity score in estimating dose-response functions. Biometrika, 87, 706–710. doi:10.1093/biomet/87.3.706.

Imbens, G. W., & Wooldridge, J. M. (2009). Recent Developments in the Econometrics of Program Evaluation. Journal of Economic Literature, 47, 5–86. doi:10.1257/jel.47.1.5.

Jenkins, S. P. (1995). Easy Estimation Methods for Discrete-Time Duration Models. Oxford Bulletin of Economics and Statistics, 57, 129–136. doi:10.1111/j.1468-0084.1995.tb00031.x.

Jensen, M. B., Johnson, B., Lorenz, E., & Lundvall, B. Å. (2007). Forms of knowledge and modes of innovation. Research Policy, 36, 680–693. doi:10.1016/j.respol.2007.01.006.

Kirner, E., Kinkel, S., & Jaeger, A. (2009). Innovation paths and the innovation performance of low-technology firms—An empirical analysis of German industry. Research Policy, 38, 447–458. doi:10.1016/j.respol.2008.10.011.

Koenker, R., & Hallock, K. F. (2001). Quantile Regression. Journal of Economic Perspectives, 15, 143–156. doi:10.1257/jep.15.4.143.

Matthies, E., Thomä, J., & Bizer, K. (2023). A hidden source of innovation? Revisiting the impact of initial vocational training on technological innovation. Journal of Vocational Education & Training, 1–21. doi:10.1080/13636820.2023.2201602.

Moilanen, M., Østbye, S., & Woll, K. (2014). Non-R&D SMEs: external knowledge, absorptive capacity and product innovation. Small Business Economics, 43, 447–462. doi:10.1007/s11187-014-9545-9.

Ortega-Argilés, R., Vivarelli, M., & Voigt, P. (2009). R&D in SMEs: a paradox? Small Business Economics, 33, 3–11. doi:10.1007/s11187-009-9187-5.

OECD/Eurostat (2018). Guidelines for Collecting, Reporting and Using Data on Innovation, 4th Edition, The Measurement of Scientific, Technological and Innovation Activities. OECD Publishing, Paris/Eurostat, Luxembourg.

Parente, P. M., & Santos Silva, J. M. (2016). Quantile Regression with Clustered Data. Journal of Econometric Methods, 5, 1–15. doi:10.1515/jem-2014-0011.

Parrilli, M. D., & Elola, A. (2012). The strength of science and technology drivers for SME innovation. Small Business Economics, 39, 897–907. doi:10.1007/s11187-011-9319-6.

Parrilli, M. D., & Alcalde Heras, H. (2016). STI and DUI innovation modes: Scientific-technological and context-specific nuances. Research Policy, 45, 747–756. doi:10.1016/j.respol.2016.01.001.

Parrilli, M. D., Fitjar, R. D., & Rodríguez-Pose, A. (2016). Business Innovation Modes: A Review From a Country Perspective. In M. D. Parrilli, R. D. Fitjar, & A. Rodríguez-Pose (Eds.), Innovation Drivers and Regional Innovation Strategies, 197–218.

Parrilli, M. D., Balavac, M., & Radicic, D. (2020). Business innovation modes and their impact on innovation outputs: Regional variations and the nature of innovation across EU regions. Research Policy, 49, 104047. doi:10.1016/j.respol.2020.104047.

Runst, P., & Thomä, J. (2022). Does personality matter? Small business owners and modes of innovation. Small Business Economics, 58, 2235–2260. doi:10.1007/s11187-021-00509-1.

Rammer, C., Czarnitzki, D., & Spielkamp, A. (2009). Innovation success of non-R&D-performers: substituting technology by management in SMEs. Small Business Economics, 33, 35–58. doi:10.1007/s11187-009-9185-7.

Rios-Avila, F. (2020). Recentered influence functions (RIFs) in Stata: RIF regression and RIF decomposition. The Stata Journal: Promoting communications on statistics and Stata, 20, 51–94. doi:10.1177/1536867X20909690.

Rios-Avila, F., & Maroto, M. L. (2022). Moving Beyond Linear Regression: Implementing and Interpreting Quantile Regression Models With Fixed Effects. Sociological Methods & Research, 004912412110361. doi:10.1177/00491241211036165.

Santamaría, L., Nieto, M. J., & Barge-Gil, A. (2009). Beyond formal R&D: Taking advantage of other sources of innovation in low- and medium-technology industries. Research Policy, 38, 507–517. doi:10.1016/j.respol.2008.10.004.

Santos, D. M., Gonçalves, S. M., & Laranja, M. (2022). Drivers, Processes, and Outcomes of the STI and DUI Modes of Innovation: A Systematic Review. International Journal of Innovation and Technology Management. doi:10.1142/S0219877021400150.

Schneider, C., & Veugelers, R. (2010). On young highly innovative companies: why they matter and how (not) to policy support them. Industrial and Corporate Change, 19, 969–1007. doi:10.1093/icc/dtp052.

Segarra, A., & Teruel, M. (2014). High-growth firms and innovation: an empirical analysis for Spanish firms. Small Business Economics, 43, 805–821. doi:10.1007/s11187-014-9563-7.

Thomä, J. (2017). DUI mode learning and barriers to innovation—A case from Germany. Research Policy, 46, 1327–1339. doi:10.1016/j.respol.2017.06.004.

Thomä, J., & Zimmermann, V. (2020). Interactive learning — The key to innovation in non-R&D-intensive SMEs? A cluster analysis approach. Journal of Small Business Management, 58, 747–776. doi:10.1080/00472778.2019.1671702.

Appendix

Table A1. Variables for identifying the innovation mode of young firms (year 2014)

Variable	**Description**	**Mean**
R&D competency	The firm carries out in-house R&D either continuously or occasionally (1/0)	0.54
VET qualifications	Proportion of employees with vocational education and training (VET) qualification (percent)	0.50
Advanced VET	The highest professional qualification of the founder(s) is at the level of "master craftsman/civil servant/professional school", no university degree (1/0)	0.33
Participation	Employees are allowed and encouraged to actively participate in deciding which business ideas and projects the company will pursue (1/0)	0.64
Decision making freedom	Employees have the freedom to make their own decisions without having to constantly check with management (1/0)	0.44
Customers	Importance[a] of customers as a source of information for providing ideas for the company's innovation activities	3.0
Suppliers	Importance[a] of suppliers as a source of information for providing ideas for the company's innovation activities	2.2
Competitors	Importance[a] of competitors as a source of information for providing ideas for the company's innovation activities	2.2
Scientific organizations	Importance[a] of scientific organizations as a source of information for providing ideas for the company's innovation activities	1.9
Private research and consulting	Importance[a] of private research and consulting as a source of information for providing ideas for the company's innovation activities	1.5
Associations, chambers	Importance[a] of associations, and chambers as a source of information for providing ideas for the company's innovation activities	1.6
Trade fairs, conferences etc.	Importance[a] of trade fairs, conferences etc. as a source of information for providing ideas for the company's innovation activities	2.4
Scientific journals	Importance[a] of scientific journals as a source of information for providing ideas for the company's innovation activities	2.0
Patents and standards	Importance[a] of patents and standards as a source of information for providing ideas for the company's innovation activities	1.6

Source: IAB/ZEW Start-Up-Panel

[a] Significance on scale: (1=insignificant, 2=minor significance, 3=significant, 4=very significant)

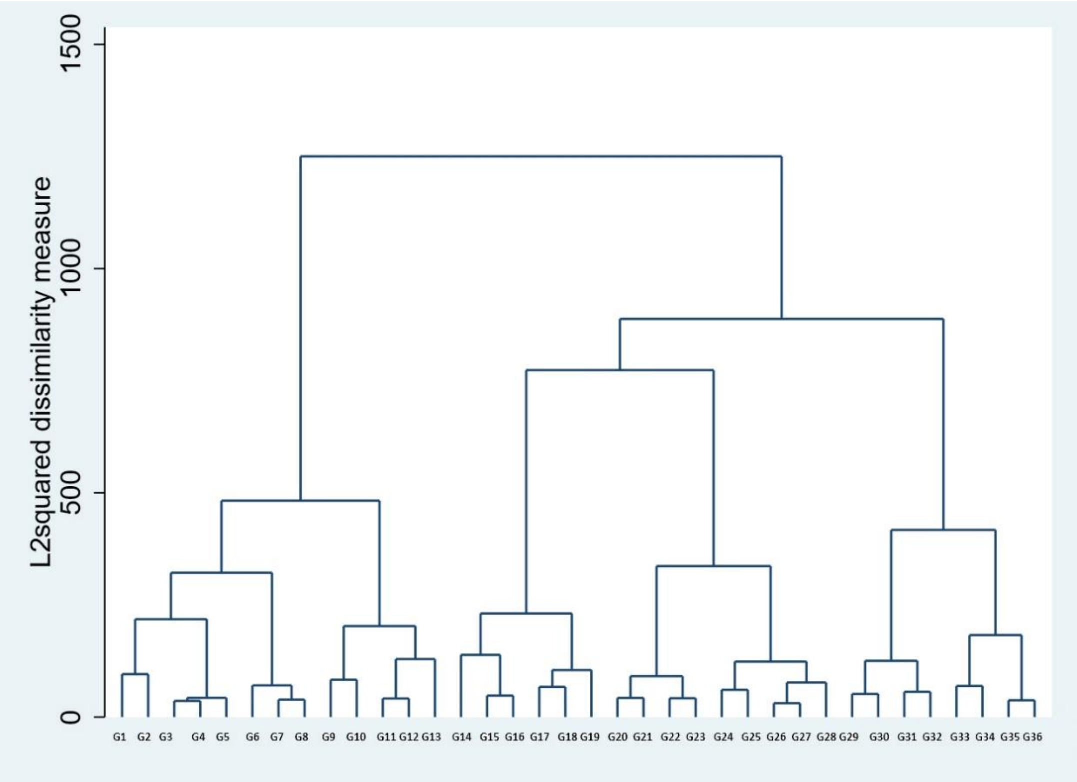
Table A2. Factor Analysis, drivers of learning and innovation (Principal Component Analysis, varimax rotated factor loadings)

	Factor 1	**Factor 2**	**Factor 3**	**Factor 4**
R&D competency	0.095	**-0.666**	0.093	0.040
VET qualifications	-0.008	**0.726**	-0.004	-0.005
Advanced VET	-0.042	**0.716**	0.026	0.010
Participation	-0.031	-0.063	0.060	**0.791**
Decision making freedom	-0.003	0.045	-0.069	**0.800**
Customers	-0.008	-0.149	**0.789**	-0.017
Suppliers	0.186	0.282	**0.629**	-0.004
Competitors	0.278	-0.020	**0.578**	0.031
Scientific organizations	**0.720**	-0.197	0.055	-0.007
Private research and consulting	**0.689**	0.039	-0.001	-0.001
Associations, chambers	**0.597**	0.288	0.134	-0.007
Trade fairs, conferences etc.	**0.441**	-0.008	**0.399**	-0.038
Scientific journals	**0.620**	-0.061	0.193	-0.038
Patents and standards	**0.512**	-0.303	0.210	-0.063
Factor description	**Absorption of external scientific and technological knowledge**	**Internal knowledge base**	**Absorption of external applied knowledge**	**Involvement of employees**
Explained variance (in %)	16.5 %	12.9 %	11.6 %	9.1 %

Source: IAB/ZEW Start-Up-Panel

Notes: N=1,057 (year=2014); Bartlett-Test: Chi² = 1900.81; p < 0.000; Kaiser-Meyer-Olkin-Criterium: KMO = 0.756

Figure A1. Cluster analysis dendrogram



Source: IAB/ZEW Start-Up-Panel

Table A3. Cluster solution (Ward's method, overall and cluster averages)

Cluster variables	**Over-all**	**Cluster**				**Chi^2**
		C1	**C2**	**C3**	**C4**	
Absorption of external scientific and technological knowledge (F1) [a]	0.00	-0.24	-0.39	0.25	0.74	151.50***
Internal knowledge base (F2) [a]	0.00	0.15	-0.79	0.96	-0.51	392.15***
Absorption of external applied knowledge (F3) [a]	0.00	0.48	0.09	-0.21	-0.98	263.44***
Involvement of employees (F4) [a]	0.00	0.73	-0.98	-0.79	0.36	546.51***
Label		**DUI plus**	**STI**	**DUI**	**STI plus**	
Profiling variables						
Share of R&D employees in %	18.7	17.3	24.9	5.4	29.6	100.19***
Customers use the company's products and services because of…						
… originality and uniqueness (%)	20.9	20.6	26.8	8.5	30.0	22.0***
… reliability and proven quality (%)	49.1	50.2	44.7	61.3	36.7	16.9***
Company creates primarily…						
… products/services tailored to individual customers (%)	51.5	45.5	48.0	60.3	58.8	11.5***
… products/services for a larger number of customers (%)	34.6	37.9	39.0	28.4	29.4	6.2*
Technological innovativeness of new products						
... proven and common technologies	16.2	17.9	9.6	22.4	14.1	
... new combinations of established technologies	33.2	34.8	36.5	34.2	22.5	
... new technologies from third parties	16.8	16.4	14.4	27.6	9.9	
... new technologies developed in-house	33.9	30.9	39.4	15.8	53.5	32.7***
Introduction of new-to-market innovations since the company was founded						
… no	68.0	66.5	60.6	81.1	65.0	
…yes, at the regional level	4.2	4.0	2.8	6.6	3.8	
…yes, at the national level	13.0	14.1	14.2	8.5	14.2	
…yes, at the global level	14.8	15.5	22.5	3.8	17.0	42.5***
Sample share in percent		41.06	21.00	20.15	17.79	

Source: IAB/ZEW Start-Up Panel

Notes: Statistical significance indicated by *** 1 % and ** 5% (Kruskal-Wallis Test; Pearson chi-square test).

[a] Average factor scores, with a mean of zero and a standard deviation of one. A negative value indicates that the importance of the innovation driver in question in the corresponding group of young firms is below average compared to the other three clusters. Conversely, a value around 0 indicates an average importance and a positive value indicates an above-average high importance. For the driver 'internal knowledge base', a negative sign indicates an above-average importance of in-house R&D competencies.

Figure A2. Quantile Regressions (revenue growth, only the 2012 start-up sample)

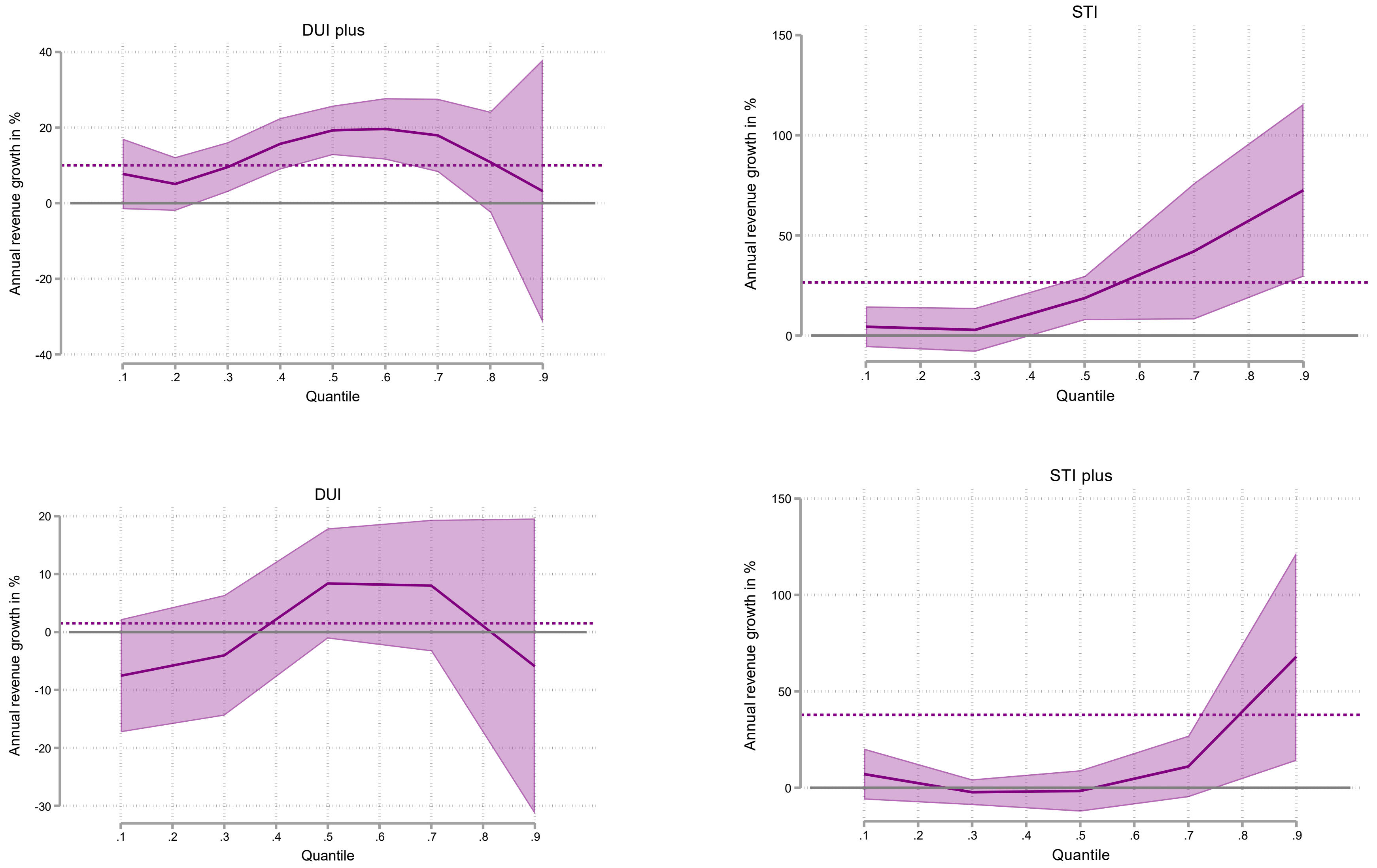


Figure A3. Quantile Regressions (workforce growth, only the 2012 start-up sample)

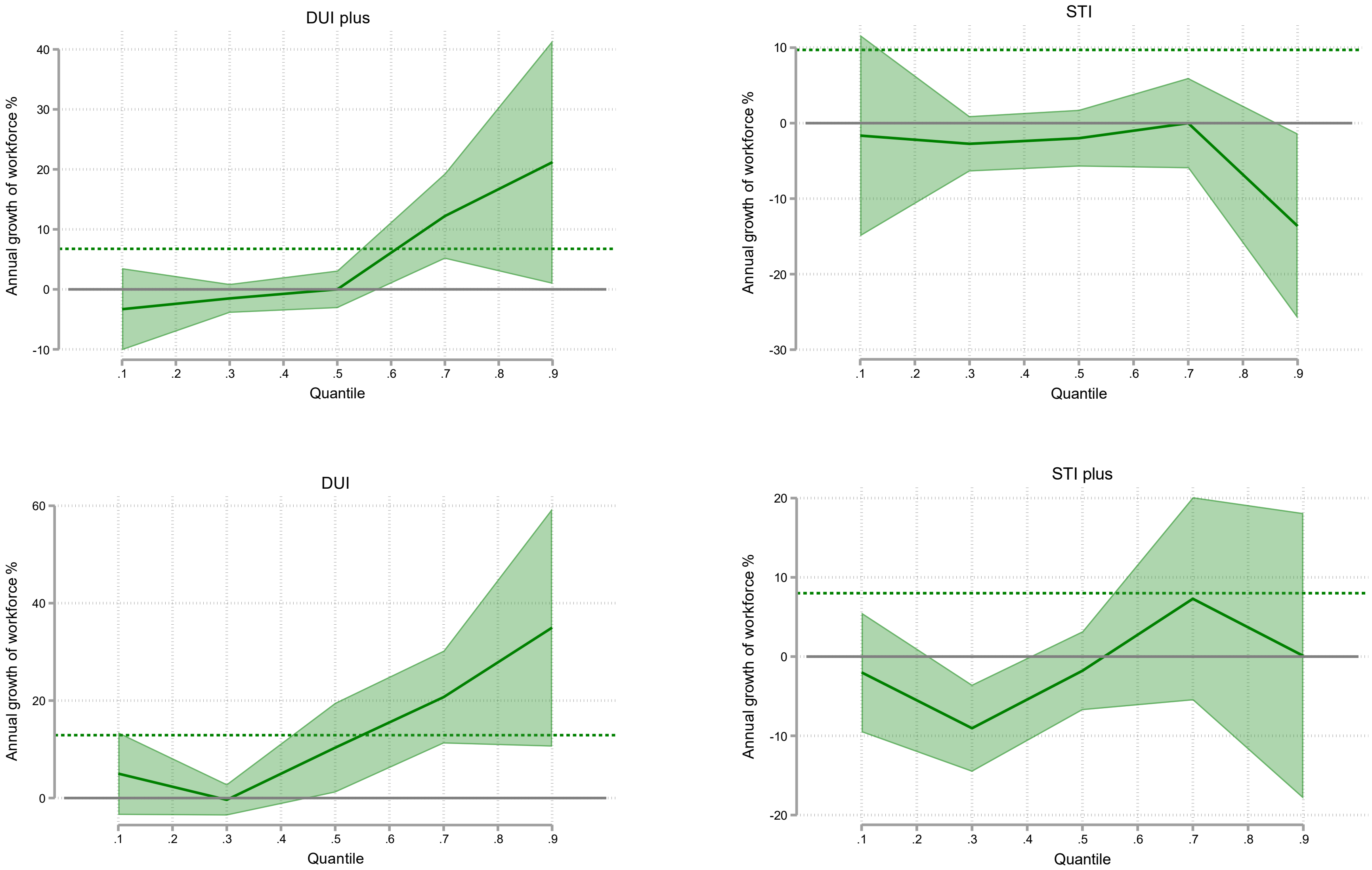


Table A4. Quantile Regression results (IPWRA, dep. var. change in revenue)

Quantile	Value	DUI plus	p	STI	p	DUI	p	STI plus	p
10	-0.25	0.20***	0.00	-0.03	0.78	0.10	0.43	0.13	0.33
20	-0.03	0.14***	0.00	0.09	0.37	0.05	0.46	0.07	0.25
30	0.00	-0.02	0.70	0.09	0.12	0.04	0.42	0.03	0.45
40	0.16	0.18***	0.00	0.17*	0.06	0.15***	0.00	0.14**	0.01
50	0.30	0.21***	0.00	0.2***	0.00	0.13	0.10	0.14	0.16
60	0.50	0.30***	0.00	0.24**	0.04	0.21**	0.05	0.32	0.25
70	0.90	0.32**	0.02	0.44	0.10	0.26	0.14	0.64*	0.05
80	1.50	0.28	0.28	0.81**	0.02	0.38	0.10	1.25**	0.01
90	3.67	1.05	0.16	1.09	0.36	0.32	0.64	2.28	0.27

Notes: The columns DUI plus, STI, DUI, and STI plus display the coefficients along the conditional distribution, separately for each innovation mode.

Table A5. Quantile Regression results (IPWRA, dep. var. change in workforce)

Quantile	Value	DUI plus	p	STI	p	DUI	p	STI plus	p
10	-0.50	0.30	0.05	0.12	0.57	0.27	0.16	0.17	0.37
20	-0.09	0.05	0.26	-0.03	0.70	0.01	0.87	0.02	0.69
30	0.00	0.02	0.24	-0.01	0.92	0.00	0.98	0.00	1.00
40	0.00	0.05**	0.01	0.04	0.24	0.02	0.35	0.04	0.15
50	0.00	0.05**	0.04	0.08*	0.07	0.01	0.74	0.06	0.18
60	0.06	0.09*	0.06	0.15**	0.02	0.07*	0.25	0.12	0.13
70	0.21	0.12**	0.02	0.20***	0.00	0.12*	0.05	0.18***	0.00
80	0.33	0.11*	0.07	0.12*	0.05	0.11	0.12	0.19***	0.00
90	0.50	0.11	0.11	0.14*	0.08	0.17**	0.01	0.15***	0.00

Notes: The columns DUI plus, STI, DUI, and STI plus display the coefficients along the conditional distribution, separately for each innovation mode.

Table A6. Matching estimator results (IPWRA regression, ATE)

	(1)		(2)		(3)	
	exit2	p-value	profit	p-value	loss	p-value
Ref. No Innovation						
DUI plus	-0.021***	0.002	-0.038	0.154	0.039	0.104
STI	-0.020*	0.053	-0.031	0.367	0.064*	0.058
DUI basic	-0.022***	0.013	0.064**	0.020	-0.053**	0.027
STI plus	-0.016	0.188	-0.068*	0.057	0.048	0.127
N	2,663		2,605		2,605	
	exit	p-value	profit	p-value	loss	p-value
Ref. No Innovation						
non-R&D	-0.017***	0.001	0.064***	0.000	-0.040**	0.014
R&D	-0.008	0.193	-0.134***	0.000	0.131***	0.000
	4,464		4,536		4,536	