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The R&D Risk-Return Trade-Off: Exploring the Diversity of Young Innovative Firms

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Abstract

Previous studies have established that young innovative companies (YICs), characterized by high levels of in-house research and development (R&D), exhibit a pronounced growth premium at the upper end of the conditional growth distribution and are therefore of particular interest to policymakers. We argue that the binary view underlying this literature – i.e., the R&D vs. non-innovator dichotomy – can be meaningfully extended to provide a better understanding of the relationship between innovation and growth in young firms. To this end, this paper develops an augmented YIC categorization that also includes non-R&D innovators and young firms that conduct R&D but have not yet brought an innovation to the market. Using panel data from Germany, we examine the growth trajectories of these different types of YICs. Our evidence suggests that non-R&D-oriented YICs, typically focused on the 'Learning by Doing, Using, and Interacting' (DUI) mode of innovation, exhibit a distinct growth pattern. They show improved economic performance relative to non-innovators, though less so than R&D innovators, while growing in a less risky and costly manner. A young firm's decision to engage in R&D for innovation and growth can, therefore, be understood as a specific risk-return trade-off. The paper concludes with implications for policy and further research.

JEL: D21; L11; L25; L26; O31

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

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1. Introduction

Young innovative firms (YICs), their contribution to economic growth and development, and the removal of related barriers, are of particular interest to policymakers (Schneider & Veugelers, 2010; Mas-Tur & Simón Moya, 2015; Giraudo et al., 2019; Colombelli et al., 2020; Alperovych et al., 2020). In this context, it is usually assumed, either explicitly or implicitly, that firm-level innovativeness is determined by the intensity of internal R&D activity. Accordingly, YICs are usually defined as small, young and with a high R&D intensity (see, e.g. Schneider & Veugelers, 2010; Czarnitzki & Delanote, 2013, Dumont, 2017). And indeed, a number of studies point to a positive relationship between R&D and growth (e.g. Coad & Rao, 2008; Falk, 2012; Segarra & Teruel 2014; Capasso et al., 2015).

However, particularly in the case of YICs, the role of R&D in firm growth may be more nuanced than previously assumed. On the one hand, the results of Czarnitzki and Delanote (2013) show that YICs can be distinguished from other small, young firms by the fact that they grow faster than the others in terms of sales and employment growth – leading the authors to conclude that "the combination of the factors age, size, and R&D intensity seems to be crucial for the superior growth of YICs" (p.1335). On the other hand, the empirical findings by Coad et al. (2016) suggest that there is an asymmetric effect of R&D intensity on young firm growth. While this confirms the potential economic benefits of R&D in YICs, it also highlights that this performance premium tends to be concentrated in a small number of young firms at the top of the growth spectrum, whereas the typical risks associated with business R&D often result in losses for those YICs whose growth strategy has not been successful.

Audretsch et al. (2014) go a step further by asking why, depending on factors such as the nature of the market or the technological environment, not all economically successful and growing young firms have invested in risky R&D activities. This is a first indication that there may be other types of YICs with a specific risk-return innovation profile, whose growth trajectories have not yet been sufficiently analyzed in the existing literature. Some initial support for this conjecture can be found in the study by Pellegrino et al. (2012). According to their results, the acquisition of external technology (embodied in machinery or equipment) is a key innovative input for many YICs, pointing to the crucial role of external knowledge for innovation and growth, especially in the context of non-high-tech sectors. The study by McKelvie et al. (2017) also shows that formal processes of R&D are not the only source of innovation for YICs. According to their findings, informal, less resource- and risk-intensive innovation activities related to the effective use of external market information within the firm (in terms of informal aspects such as brainstorming, exchanging ideas, discussions and meetings on current customer needs or market trends and developments) are a more important mediator between growth orientation and actual growth in many young firms than R&D intensity. In this context, McKelvie et al. (2017) point out that innovation generally helps YICs to achieve their growth objectives. Although they do not further differentiate this with respect to different types of innovators, their findings may thus suggest that managers of YICs can choose different innovation paths with specific risk-return profiles depending on the nature of their growth orientation.

This paper builds upon these findings to address the following research question: Are there types of YICs that are economically successful with little or no R&D orientation, and if so, what are their characteristics and motivations? The present paper thus broadens the view of what can make a YIC innovative. In doing so, we aim to enrich the literature on YICs by providing a deeper understanding of the links between innovation and growth in young, small firms. From a conceptual point of view, we build on two closely related strands of the literature. First, the literature on non-R&D-based innovation shows that smaller firms can compensate for a 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 exploit innovation opportunities in a less risky and costly way (e.g., Rammer et al., 2009; Hervás-Oliver et al., 2014; 2016; Moilanen et al., 2014). However, it remains an open question whether (young) firms engaged in non-R&D based innovation actually follow growth trajectories that are different from both non-innovating and R&D-oriented innovators. In this context, we aim to examine whether the decision to engage in R&D or not can be understood as a young firm's choice in favor of a certain risk-return trade-off. We argue that the less risky and incremental nature of non-R&D innovation should be reflected in the young firm's growth trajectory. It is suggested that non-R&D innovating firms are less likely to experience top-tier growth, but will still grow significantly faster than non-innovators. We also examine the potential downsides of R&D-based innovation, such as bearing high start-up costs, risk of failure and high exit rates.

Second, to better explain what happens in YICs with little or no R&D orientation, we also bridge the gap to the literature on innovation modes (e.g., Jensen et al., 2007; Parrilli & Elola, 2012; Parrilli & Alcalde Heras, 2016; Thomä, 2017; Runst & Thomä, 2022; Haus-Reve et al., 2022), which in the case of the Learning by Doing, Using, Interacting (DUI) mode often found in smaller firms, can be understood as an in-depth description of non-R&D innovation processes. By distinguishing and measuring different innovation modes at the firm level, we provide a less parsimonious but richer typology of YICs with their specific paths to growth and economic success. This broader perspective sheds light on the underlying drivers and impulses for learning at the company level. However, the growth performance of (young) firms depending on their mode of learning and innovation has not yet been investigated in the literature on innovation modes (for an overview, see e.g. Apanasovich, 2016; Santos et al., 2022).[1] By examining firm growth from this perspective, we not only extend our findings on the growth trajectory of YICs with R&D compared to those without. The detailed differentiation made possible by categorizing YICs according to their innovation mode allows us to study a range of different R&D and non-R&D-based innovation sources and strategies, as well as their complementarities in terms of firm growth (Bianchini et al., 2018). This point is important because the literature on innovation modes has repeatedly shown that firms that are able to effectively combine different sources of learning and innovation in one form or another tend to perform better than firms that concentrate on only one mode (Apanasovich, 2016; Parrilli et al., 2016, and Santos et al., 2022).

Empirically, using German panel data from the IAB/ZEW Start-up Panel, we examine the impact of innovation on economic performance by considering a broader typology of YICs than in the previous literature. By first distinguishing between R&D and non-R&D innovators, as well as R&D and non-R&D non-innovators, we provide a holistic perspective on YICs and their respective growth trajectories. We use quantile regression to analyze the revenue and employment growth of these innovator types, as is common in the literature on the growth effects of R&D. As a robustness test, we additionally use a combination of quantile regression and a matching approach based on observable characteristics such as the YIC's industry to mitigate endogeneity concerns. Then, to examine the risk-return trade-off of the growth paths of these different types of YICs, we use linear panel regression and Cox survival regression to examine profit, loss and exit indicators. In order to gain a more nuanced understanding of the different types of YICs, to study the complementarities that arise between different sources of innovation, and also for robustness testing purposes, we then generate in a second step an empirical typology of young firms in terms of their innovation modes. A combination of factor and cluster analysis is used to do this, before the growth trajectories of the identified groups of YICs are analyzed again using the procedure of the first step.

Our results show that YICs that rely on R&D and follow a corresponding mode of innovation are indeed likely to have a better economic performance than non-innovating young firms and non-R&D-oriented YICs. However, our results also suggest that YICs engaged in non-R&D innovation also grow and experience economic success, albeit to a lesser extent than R&D innovators, but at the same time they grow in a less risky and costly way than R&D-oriented YICs. We therefore conclude that the decision of young firms to engage in R&D for the purpose of innovation and growth can usefully be understood as driven by a specific risk-return trade-off. From a policy perspective, this highlights the importance of broadening our understanding of YICs in terms of different types and their respective economic performance. Countries can vary widely in their R&D intensity, meaning that non-R&D innovation can make a larger contribution to economic growth than is often assumed (Lopez-Rodriguez & Martinez-Lopez 2017). Many countries and regions with a greater emphasis on non-R&D innovation may either be in the process of catching up (Hervás-Oliver et al., 2021; Bischoff et al., 2024; Reher et al., 2024). Alternatively, in some advanced economies, such as Germany, non-R&D innovation per se plays a larger role in the innovation system due to specific factors such as the close integration of an extensive vocational training system with the innovation system (Thomä, 2017), the higher weight of low- and medium-technology industries with their typical innovation activities (Som & Kirner, 2015), and a large number of small, non-R&D-intensive but innovation-active firms in the so-called *Mittelstand* (Pahnke & Welter, 2019; Thomä & Zimmermann, 2020).

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.

2. Theoretical Background and Hypotheses

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

Young innovative companies (or YICs), which are expected to make a significant contribution to economic development and growth, are typically defined as young, small and with a high R&D intensity (Schneider & Veugelers, 2010; Czarnitzki &Delanote, 2013). A number of studies have examined the impact of R&D 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

[1] A partial exception is the study by Thomä and Zimmermann (2020). For mature small and medium-sized enterprises (SMEs), they show on the basis of cross-sectional data that DUI-innovating firms can have similar growth rates as firms that rely more on in-house R&D (i.e. the Science, Technology, Innovation (STI) mode of innovation; see Jensen et al., 2007).

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 highlights the costly and risky nature of R&D-based innovation, which is particularly relevant in the case of smaller firms (Ortega-Argilés et al., 2009).

Overall, therefore, 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, a fact that is particularly evident in the case of YICs. Other, non-R&D sources of innovation, such as the adoption of external technologies by YICs or their internal processes for the efficient use of market information (Pellegrino et al., 2012; McKelvie et al., 2017), not to mention possible complementarities between R&D and other sources of learning and innovation in driving growth (Bianchini et al., 2018), are still largely neglected in the YIC literature. Little attention is also paid to the fact that R&D should also have a strongly asymmetric impact on the growth of young, innovating firms, and to the related question of what actually happens in the growth segment beyond the top performers. This raises the question of the different ways in which young firms pursue innovation in order to grow and to be economically successful – or, in the words of Audretsch et al. (2014), "why don't all young firms invest in R&D?".

2.2. The role of non-R&D innovation

The equation of innovation with R&D in the YIC literature overlooks the role of non-R&D innovation, either as a source of learning for innovation combined with R&D or as a distinct type of YIC in its own right. However, evidence suggests that business activities such as design, prototyping, use of advanced machinery and equipment, marketing or management practices that foster interactive learning among employees are important drivers of innovation in less R&D-oriented knowledge environments (Barge-Gil et al., 2011; Hervás-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 be quite similar to that of R&D performers under certain circumstances (Rammer et al., 2009; Hervás-Oliver et al., 2014; 2016; Moilanen et al., 2014). Given this, some selective results concerning the innovative behavior of YICs are of particular interest: For example, Pellegrino et al. (2012) analyze the sources of product innovation generation using a sample of Italian YICs. Their results show that internal R&D increases the likelihood for YICs to introduce product innovations, but that the associated innovation activity is mainly driven by the acquisition of external technology in the form of machinery and equipment.

The study by McKelvie et al. (2017) complements this picture by shedding light on the role of internal, non-R&D-based learning processes in YICs: Based on a Swedish sample, their results show that the mediating innovation activities between a YIC's growth orientation and its actual realized growth are less related to in-house R&D, but rather to informal activities in the area of efficient internal use of market information through interactive learning processes and new product launches. On the one hand, this confirms that there are sources of innovation other than R&D that play a role in YICs, but on the other hand, it also confirms that there are certain complementarities between different innovation activities in terms of YIC growth, such as those between R&D and actual innovation output (on this issue, see Bianchini 2018). Therefore, in order to better distinguish between different types of YICs in this respect, in the following empirical analysis we first separate YICs that rely on R&D from those that do not, i.e. between *R&D innovators* and *non-R&D innovators* (see Table 1). This basic categorization already takes into account the fact that R&D often does not have a direct effect on firm growth, but usually has an indirect impact via the complementary introduction of innovations to the market. For this reason, the group of *R&D non-innovators* is also considered separately (see Table 1), i.e., young firms that carry out R&D but have not yet achieved any innovation success. As a result, in the following empirical analysis the reference group is more clearly defined than in the previous literature in terms of which firm is truly 'non-innovating' – i.e., a non-R&D non-innovator, meaning a young *non-innovating company* in the strictest sense.

Table 1. Categorization of YICs by R&D activity and innovation output

R&D activity	**Innovation output**	
	Yes	No
Yes	*R&D innovator*	*R&D non-innovator*
No	*Non-R&D innovator*	*Non-innovating company (i.e. non-R&D non-innovator)*

2.3. A more differentiated picture: Modes of innovation

The four-part categorization presented in Table 1 allows us to analyze the impact of R&D on the growth of YICs in a more nuanced way than is done in the previous literature. However, it could be argued that the comparison between R&D innovators and non-R&D innovators in particular is still too simplistic, as some YICs may well have combined the use of R&D with non-R&D drivers to generate their innovation output, and on the other hand, some non-R&D innovators may also have relied on R&D-related sources of learning, such as the results of external R&D (Bianchini, 2018; Segarra & Teruel 2014). In order to sharpen the conceptual picture in this respect, we develop a more differentiated description of the two groups of R&D innovators and non-R&D innovators based on the literature on business innovation modes (see the reviews by Apanasovich, 2016; Parrilli et al., 2016, and Santos et al., 2022). 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 scientific-technological knowledge of STI firms. DUI-based knowledge is therefore, in a sense, an unintentional by-product of day-to-day business activities, characterized by a high degree of application orientation, and is often held by key 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 particular innovation-related 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). The innovation mode perspective and an associated in-depth empirical categorization thus offer two advantages for a better understanding of the different types of YICs and their respective growth trajectories: *First*, looking at the DUI mode in particular provides a deeper insight into how young firms can benefit from innovation without investing in risky and costly R&D activities. *Second*, looking at the combinatorial use of STI and DUI sources by YICs allows for the more fine-grained differentiation called for above: For example, R&D performing YICs could, in addition to their strong STI focus, also rely on DUI-related sources of learning and innovation (e.g. a culture of innovation and communication within the company that promotes learning and active employee involvement). At the same time, it can easily be assumed that a number of non-R&D innovators, with their strong emphasis on the DUI mode, receive important external innovation impulses such as STI knowledge from technology transfer channels.

2.4. Hypotheses

First, in line with the literature on the effect of R&D on firm growth, we expect to find a highly skewed effect of innovation on growth in terms of sales and employment for YICs in general, but especially for those with a strong focus on R&D (i.e. *R&D innovators*). On the one hand, their investment in risky and costly R&D activities can be rewarded with particularly high financial returns in the case of success – but can also easily lead to high losses in the case of failure (Coad et al., 2016). The latter should be particularly noticeable for the group of *R&D non-innovators*, i.e. young firms that perform R&D but have not yet generated any innovation output – as we know from the study by Bianchini et al. (2018) that in-house R&D primarily drives firm growth when it is linked to the introduction of product innovations. On the other hand, the R&D innovators' pursuit of higher market shares and sales requires sufficient employment growth to enable them to successfully implement their growth strategy. However, in light of the literature discussed above, we also expect the activity of *non-R&D innovators* to be reflected in a distinct growth pattern that allows young firms to benefit economically from innovation in a less risky and costly way than R&D innovators. This is because non-R&D learning and innovation processes are generally much less resource-intensive than R&D. At the same time, these innovation activities often take place in innovation environments characterized by less radical change and corresponding uncertainty – accordingly, innovation outcomes are often less disruptive, but also less risky from the firm's perspective (Rammer et al., 2009; Hervás-Oliver et al., 2014; 2016; Moilanen et al., 2014; Thomä & Zimmermann, 2020). We therefore expect that while non-R&D innovators among YICs 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. As a result, they should perform better than *young non-innovating companies* (i.e., non-R&D non-innovators, see Table 1). This leads to the following hypotheses:

H1: R&D innovators among YICs show a pronounced asymmetry in their economic performance, with significantly higher growth at the top of the growth distribution.

H2: The probability of low or negative growth rates is particularly high for R&D non-innovators among the YICs.

H3: Non-R&D innovators among the YICs have significantly higher growth rates than young non-innovating companies (i.e. non-R&D non-innovators).

Second, the above literature suggests that while some young R&D innovators may achieve very high growth rates that allow them to recoup their initial investment, many others may not differ from non-innovating companies in terms of growth performance, reflecting the fact that R&D activities are initially costly and risky especially for smaller firms (Ortega-Argilés et al., 2009). R&D innovators can therefore be seen as being situated at one end of the risk-reward spectrum of YICs, while young non-innovating companies are at the other end, facing low risk but also low growth potential (McKelvie et al. 2017). Between these two extremes, however, there is at least one type of innovator in the form of the non-R&D innovator. For this group, we do not expect to see the kind of gazelle-like growth of some of the R&D-intensive YICs. Therefore, compared to the latter, we would also expect to see some countervailing forces in terms of the risk-reward trade-off. In other words, we argue that non-R&D innovators among the YICs are positioned somewhere in the middle of the risk-reward spectrum, experiencing higher growth than young non-innovating companies and lower growth than R&D innovators among the YICs, but also with lower costs and risks compared to the latter. We therefore hypothesize that the high costs of R&D may lead to lower *initial* profitability for R&D performing YICs. In addition, the inherently risky nature of R&D projects should increase their *initial* vulnerability, thereby increasing the likelihood of their exit from the market:

H4: Non-R&D innovators among YICs will display higher survival rates than R&D performing YICs (i.e., R&D innovators) in the first years after start-up.

H5: Non-R&D innovators among the YICs will have higher profits/lower losses than YICs engaged in R&D (i.e., R&D innovators) in the first years after start-up.

Third, when it comes to further differentiating the innovation modes of YICs, we expect, against the background of the literature discussed above, that R&D innovators have a strong emphasis on the STI mode and non-R&D innovators have pronounced competences in the DUI mode. In this respect, hypotheses H1 to H5 will also be analyzed in the following empirical analysis from an innovation mode perspective. However, the more fine-grained differentiation of YICs according to their use and the combination of different STI- and DUI-related learning and innovation sources also allows a more detailed examination of the groups of R&D innovators and non-R&D innovators with regard to the corresponding complementarities.[2] One of the stylized facts of the innovation mode

[2] It should therefore be noted that the basic categorization of R&D vs. non-R&D innovators constitutes an approximation of the more complex categorization of innovation modes derived in the later analysis, as firms innovating based on DUI can also

literature is that a firm has a higher innovation success if it is able to combine STI and DUI mode learning effectively (Apanasovich, 2016; Parrilli et al., 2016, and Santos et al., 2022). For example, R&D performing YICs could strengthen their innovation capability by integrating DUI (e.g., through a more effective market introduction of new products or services due to greater customer proximity or through a better involvement of employees and their creativity in innovation processes). On the other hand, YICs, which are basically non-R&D innovators, could complement their distinct DUI mode competencies through targeted STI impulses, such as the absorption of external scientific-technological knowledge from universities or active participation in technology transfer activities. And indeed, there is already some indication that the combination of STI and DUI is associated not only with greater innovation success, but also with improved economic performance (Nunes & Lopes, 2015; Thomä & Zimmermann, 2020). We therefore hypothesize that:

H6: YICs that effectively combine STI and DUI mode learning (i.e. they either do DUI plus STI or STI plus DUI) are more economically successful than young firm innovators that rely only on one of these two modes.

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 Leibniz Centre for European Economic Research (ZEW) and the credit rating agency Creditreform. It is a German panel data set with about 6,000 annual observations on young firms, which may be up to seven years old. In addition to basic questions on firm size, industry, employees, etc., there are additional questionnaire modules on specific topics such as innovation in each survey wave. In the annual surveys for the IAB/ZEW Start-Up Panel, a stratified random sample is drawn based on the stratification criteria of sector and year of foundation. High-tech sectors are deliberately overweighted in order to be able to analyze the development of this small but economically important group of young firms, which is of particular policy interest, on a sound data basis. As a result, the structure of the panel sample is not fully representative of the population as a whole (Fryges et al., 2010; Gottschalk & Rodepeter, 2024). However, about half of the sample composition of the IAB/ZEW Start-up Panel also includes young firms from non-high-tech sectors, which allows us to comprehensively analyze and compare R&D-intensive and non-R&D-intensive development trajectories of young firms.

3.2. Identification of different categorizations of YICs

To empirically implement the categorization of YICs described in Table 1, we classify a young firm as an *R&D innovator* if it has introduced a product or process innovation at least once in the last four years and has reported in-house R&D activities (occasionally or continuously) during this period. Similarly, *non-R&D innovators* are young firms that have introduced at least one product or process innovation in the last four years but have not carried out any own R&D in this time. Similarly, *R&D non-innovators* are young firms that have not generated innovations in the last four years but have conducted R&D. *Non-innovating companies* are those young firms in our sample that neither had an innovation output nor actively carried out in-house R&D during the reference period. Our categorization covers the last four years to account for the time lag between innovation activity and growth, as young firms, especially those engaged in R&D, often need time to implement innovations in a way that that leads to economic success. The definitions of innovation and R&D used in the IAB/ZEW Start-Up Panel follow the guidelines of the Oslo Manual as a common standard for measuring innovation (see OECD/Eurostat 2018). This variable construction results in a panel dataset for the years 2007 to 2017.

To better identify and differentiate YIC types, an innovation mode perspective (Jensen et al., 2007) is applied. Following Thomä (2017) and others (Runst & Thomä, 2022; Bischoff et al., 2023), we use a factor analysis followed by a clustering procedure to identify and generate different innovation modes among young, innovation-active firms. 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).[3]

be R&D innovators or STI-oriented firms can also be non-R&D innovators (although both with a lower probability), and hypotheses H1-H5 can therefore be tested in a more detailed and differentiated way from an innovation mode perspective (see section 3.2).

[3] This analysis can only refer to 2014 because information on a number of internal and external sources of innovation is only available for this survey wave.

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.

As mentioned above, the information used to identify these four innovation mode groups is only available for 2014. Therefore, we have to assume a certain persistence of the innovation modes *DUI*, *DUI plus*, *STI* and *STI plus* in order to extend the modes assigned to the young firms in our sample to the immediate years before and after 2014, which results in a panel period from 2010 to 2017 for the regression analysis on innovation modes.[4] Comparing this categorization of young firms' innovation modes with that of the YIC categorization by R&D activity confirms the link between these two alternative ways of classifying young, innovating firms (see Table 2). As expected, the share of non-R&D innovators is considerably higher in the DUI and DUI-plus groups than in the STI and STI-plus groups, where R&D innovators clearly dominate. However, the proportion of R&D innovators in the DUI-oriented groups is still greater than zero. That said, DUI innovators are more likely to be non-R&D innovators, as anticipated. The added value of the innovation mode perspective on YICs becomes apparent at this point, as the simpler categorization of R&D and non-R&D innovator groups is further differentiated in a more nuanced manner. For example, Table 2 shows that there is a considerable share of young firms that combine their DUI mode competencies with the use of in-house R&D, which indicates complementarities between different innovation modes that cannot be explored by using only the YIC categorization by R&D activity.[5]

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[4] For the sake of completeness, the *R&D non-innovator* and *non-innovating company* groups of the first categorization are added to the innovation mode categorization in the regression analysis.

[5] At the same time, the relatively high proportion of R&D innovators in the DUI and DUI plus groups is probably also related

Table 2. Comparison of the two YIC Categorizations used in the Analysis, in percent

Categorization of YICs by R&D activity and innovation output	**Categorization of YICs by innovation mode (assumed persistence on the basis of the 2014 information)**					
	Non-innovating company	R&D non-innovator	DUI plus	STI	DUI	STI plus
Non-innovating company	90.5	4.6	2.5	2.0	6.2	3.4
R&D non-innovator	1.2	78.2	2.7	3.9	1.4	3.1
R&D innovator	1.4	17.2	65.8	80.9	44.6	77.2
Non-R&D innovator	6.9	0.0	29.1	13.2	47.8	16.3
Sum	100.0	100.0	100.0	100.0	100.0	100.0

Note: For example, in the DUI plus group, 2.5% are non-innovating companies, 2.7% are R&D non-innovators, 65.8% are R&D innovators and 29.1% are non-R&D innovators. In the case of the categorization of YICs by innovation mode, the 'non-innovating' and 'R&D non-innovating' groups are formed according to the categorization of YICs by R&D activity and innovation output for the year 2014 and then extended for the other years, as is also the case for the four innovation mode groups.

3.3. Quantile and panel regression analysis

Using quantile regression, we focus on (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-innovating firms in the reference group in each case. The quantile regression estimates the effect of each innovator type conditional on the quantile of the dependent performance variable (see Koenker & Hallock, 2001; Parente & Santos Silva, 2016). 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. Table 3 shows the descriptive statistics for all variables.

Linear panel regressions are used for the binary dependent variables exit, profit and loss. Exit is equal to 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 firms, even after they have left the survey, and thus sample attrition does not bias our results on exit. The overall exit rate is quite low. After five years, about 75 percent of all companies remain in the sample.[6] Profit and loss are additional binary performance indicators that are equal to one if the firm has a positive or negative profit. In panel regressions where the R&D-based categorization is the main explanatory variables of interest, we use company fixed effects.[7] In specifications containing the four innovation modes, we use random effects since our primary explanatory variables are time invariant.

However, we do not fully exploit our information on exit years in the panel regression setting. While we still have the information on the exit year for firms leaving the sample, all other explanatory variables are missing. Thus, the panel regression cannot analyze cases where the exit date is outside the time period during which firms respond to the annual survey. In order to fully exploit the exit year information that is available beyond the sample period, we therefore also run survival regressions (Jenkins, 1995), in particular the Cox proportional hazards model with heteroskedasticity robust standard errors, for which we report hazard ratios (see also Cleves et al., 2010).

$$h_i(t) = h_{0i}(t)\exp\,(x_{1t} + \cdots + x_{kt})$$

The model estimates the hazard of firm i at time period t, i.e. the risk of failure, which amounts to exiting the market. It is dependent on the baseline hazard ho and the explanatory variables. Again, the explanatory variables of interest are the two YIC categorizations presented above. The same set of control variables is used (see Table 3). Time is discrete, so we expect that ties exist, i.e. firms will exit the market at the same time. Since we do not know which firm left before the other, we have to decide which method to use to determine the risk pool, i.e. the firms still active in the market. We apply the Efron method because it is more exact than the frequently used default (i.e. the Breslow method).

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to the fact that R&D active firms are over-represented in our data set (see section 3.1).

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

[7] We also repeat the analysis using a random effects panel regression but refrain from reporting the coefficients. The two sets of results are quite similar and lead to the same overall conclusions.

Table 3. Descriptive statistics

		Mean	Std. dev.
Exit	Companies exiting the market each year (1/0)	0.025	0.156
Profit	Profit in the reference year (1/0)	0.786	0.410
Loss	Loss in the reference year (1/0)	0.162	0.369
Revenue growth	Change in sales generated compared to previous year (in %)	86.994	238.163
Workforce growth	Change in number of active persons compared to previous year (in %)	31.872	118.047
Non-innovating company	Non-R&D non-innovator (1/0)	0.310	0.463
R&D non-innovator	R&D performing firm without innovation output (1/0)	0.047	0.211
R&D innovator	R&D innovating firm (1/0)	0.336	0.473
Non-R&D innovator	Non-R&D innovating firm (1/0)	0.306	0.461
Non-innovating company	Non-R&D non-innovator (1/0)	0.467	0.498
R&D non-innovator	R&D performing firm without innovation output (1/0)	0.067	0.250
DUI plus	Firm with DUI-plus innovation mode (1/0)	0.206	0.404
STI	Firm with STI innovation mode (1/0)	0.090	0.286
DUI	Firm with DUI innovation mode (1/0)	0.098	0.297
STI plus	Firm with STI-plus innovation mode (1/0)	0.073	0.259
Active persons	Persons active in the reference year, including owners (number)	6.881	11.650
Investment per person	Volume of investment per person in the reference year (in thousand euro)	5,145.851	44,902.240
Export orientation	Export activity in the reference year (1/0)	0.238	0.426
High-tech manufacturing	WZ93 (NACE Rev. 1.1): 23.30, 24.20, 24.41, 24.42, 29.60, 30.02, 32.10, 32.20, 32.30, 33.10, 33.20, 33.30, 35.30	0.071	0.257
Advanced manufacturing	WZ93 (NACE Rev. 1.1): 24.13-4, 24.16-7, 24.51, 24.61, 24.63-4, 24.66, 25.11, 25.13, 26.15, 29.11-4, 29.24, 29.31-2, 29.41-3, 29.52-6, 30.01, 31.10, 31.20, 31.40, 31.50, 31.61-2, 33.40, 34.10, 34.30, 35.20	0.060	0.237
Technology intensive services	WZ93 (NACE Rev. 1.1): 64.3, 72 (without 72.2), 73.1, 74.2, 74.3	0.234	0.423
Software	WZ93 (NACE Rev. 1.1): 72.2	0.083	0.275
Low-tech manufacturing	WZ93 (NACE Rev. 1.1): 15–37 (without High-tech/advanced manufacturing)	0.116	0.320
Knowledge-intensive services	WZ93 (NACE Rev. 1.1): 73.2, 74.11-4, 74.4	0.089	0.284
Other business-related services	WZ93 (NACE Rev. 1.1): 60.3, 61, 62, 63.1-2, 63.4, 64.1, 71.1-3, 74.5-8 (without 74.87.7), 90	0.065	0.247
Consumer-related services	WZ93 (NACE Rev. 1.1): 55, 60.1-2, 63.3, 65, 66, 67, 70, 71.4, 80.4, 92, 93	0.072	0.258
Construction	WZ93 (NACE Rev. 1.1): 45	0.086	0.280
Trade	WZ93 (NACE Rev. 1.1): 50–52 (without 51.1)	0.096	0.295
Others	Other industries or no clear assignment possible	0.029	0.168

3.4. Matching specifications

The aim of our regression analysis is to identify differences in economic performance between different types of YICs. However, such results cannot be interpreted as strictly causal if treatment assignment is not random, e.g., firms may self-select into certain YIC categories based on their sectoral or company characteristics. Following Parrilli et al. (2020), we therefore use matching estimators to mitigate endogeneity concerns. Based on observable characteristics, one must first estimate the probability of treatment (propensity score) vis-à-vis the reference group (non-innovating companies) before estimating the outcome regression on an adjusted sample in the second stage.

While matching estimators are commonly used in the case of binary treatment variables, Imbens (2000), Lechner (2001), Imbens & Wooldridge (2009), Cattaneo (2010) and Cattaneo et al. (2013) extend the application to multivalued treatments.[8] Since we have more than one treatment group (e.g. non-R&D and R&D innovators), propensity scores are estimated in the first stage using a multinomial logit model. These scores represent the probability of observing outcome k relative to the reference group K (non-innovating companies). Following Parrilli et al. (2020), we employ firm size, export orientation, and industry as predictors.

$$log\left(\frac{P(Y=k|X)}{P(Y=K|X)}\right)= \beta_{k0}+\beta_{k1}X_1+\beta_{k2}X_2+\cdots+\beta_{kp}X_p$$

After calculating the propensity scores, there are a number of possible adjustment methods, such as nearest neighbor, 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) of the outcome regression. The outcome regressions follow our linear panel regression design described above (see section 3.3), where the dependent variables are given by exit, profit and loss, respectively. The IPWRA adjustment combines the inverse probability weighting (which adjusts for differences in covariates) with the regression adjustment (which further controls for covariates), providing doubly robust estimates. As long as one of the models (propensity score or outcome regression) is misspecified, the estimator can still be consistent, provided the other model is correctly specified.

In the case of linear panel regressions, we implement these IPWRA estimators using `teffects` in Stata. In contrast, 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, pp.70-72).

Next, the overlap (or common) assumption of matching requires that no group has a non-zero probability of being treated and being in the control group. We test this assumption by plotting the predicted probability distribution for each group. In addition, we test whether the matching procedure achieves its aim of balancing the covariates, i.e. reducing covariate differences between the untreated and treated groups, by displaying covariate means by group before and after the weights are applied.

Finally, we conduct tests of the appropriateness of the matching approach. First, we report the propensity score distributions for each innovator type based on the YIC categorization by R&D activity (Figure A2). There is considerable overlap in the propensity score distributions across all groups, with no discernible ranges where one or more groups are highly concentrated. Moreover, there is no tendency towards extreme values near 0 or 1. Secondly, we compare the variable means by YIC group before and after applying the IPWRA-weights (see Table A5 in the appendix). It can be observed that the values differ more before weighting and become more balanced afterward. Overall, we conclude that the propensity scores are suitable for the matching analysis.

4. Results

4.1. Quantile regression analysis of revenue and workforce growth

The quantile regression results for the YIC categorization by R&D and innovation output are shown in Figure 1. There is a clear contrast between the different types of YICs in terms of revenue growth. At the lower quantiles (1st to 3rd), the revenue growth of R&D innovators is similar to that of non-innovating companies, while non-R&D innovators show higher performance. At the middle quantiles (4th to 6th), R&D and non-R&D innovators behave similarly, both showing higher growth rates than non-innovating companies, with differences of 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 innovating counterparts, which in turn outperform young non-innovators. The maximum effect sizes at the top end are quite different, 45 (R&D innovators) and 5.5 (non-R&D innovators) percentage points respectively. Figure 1 also shows the results for the group of R&D non-innovators. They underperform compared to non-innovating companies at the 1st to 4th quantiles, then match their performance, and finally outperform them by around 20 percentage points at the 9th quantile. This performance profile signifies the typical high-risk exposure of young R&D innovators. If their innovation efforts fail, the impact on revenue growth is clearly negative.

This contrast between the different types of YICs is much less pronounced when it comes to workforce performance (see Figure 1). For quantiles 3rd to 7th, their respective growth rates do not differ from those of non-innovating companies. Only at the upper end of the conditional change in the distribution of workforce growth

[8] See also Rios-Avila (2020) and references to 'effects multivalued' in Stata.

does the effect size for innovation-active firms reach around 5 percentage points. Thus, both R&D innovators and non-R&D innovators (as well as R&D non-innovators) experience positive growth effects on the number of persons active in the firm compared to non-innovating companies, but there is little difference between them. To sum up, we find evidence for hypotheses H1 and H2 and H3 regarding revenue growth. In terms of workforce growth, there is evidence for H1 and H3, but not for H2, as all innovator types display similar growth patterns vis-à-vis the reference group.

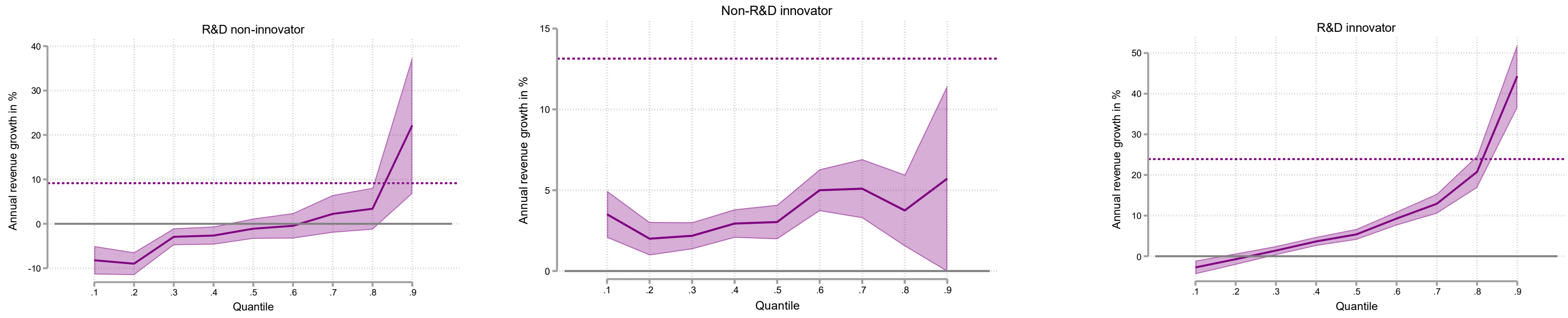
The quantile regressions by mode of innovation (DUI plus, STI, DUI and STI plus) in Figure 2 and Figure 3 give a picture that is consistent with Figure 1, but more detailed because it goes beyond a simple categorization based only on the R&D status of a young innovating firm. On the one hand, the results show that the different types of DUI and STI modes map onto the results of the non-R&D and R&D innovator types, respectively. However, they also show that an R&D-based categorization of YICs masks some underlying heterogeneities. Compared to the reference group of non-innovating companies, 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 the middle quantiles (5th and 6th; see Figure 2). In contrast, DUI plus firms have statistically significant and positive revenue growth 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 in terms of revenue growth. They show growth premia of about 28 (STI) and 60 (STI plus) percentage points respectively at the 9th quantile. Thus, the more outward-looking STI plus type outperforms the more inward-looking pure STI type in terms of revenue growth at the highest quantiles. Again, the R&D non-innovator type underperforms compared to the reference group at lower levels, but performs similarly at higher levels (see Figure 2).

Overall, Figure 2 provides further evidence in favor of H1 and H2 in terms of revenue growth performance. However, the finer YIC differentiation by innovation mode shows, that the mixed and outward-looking DUI plus group achieves a relatively high revenue performance, while the basic DUI group performs only slightly better than the reference group. Hypothesis H3, is therefore only confirmed for the DUI plus group. Thus, DUI and DUI-plus represent distinct categories, separate from both non-innovators and STI-oriented young firms regarding revenue growth. Moreover, in line with hypothesis H6, this confirms a recurring finding in the innovation mode literature, 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).

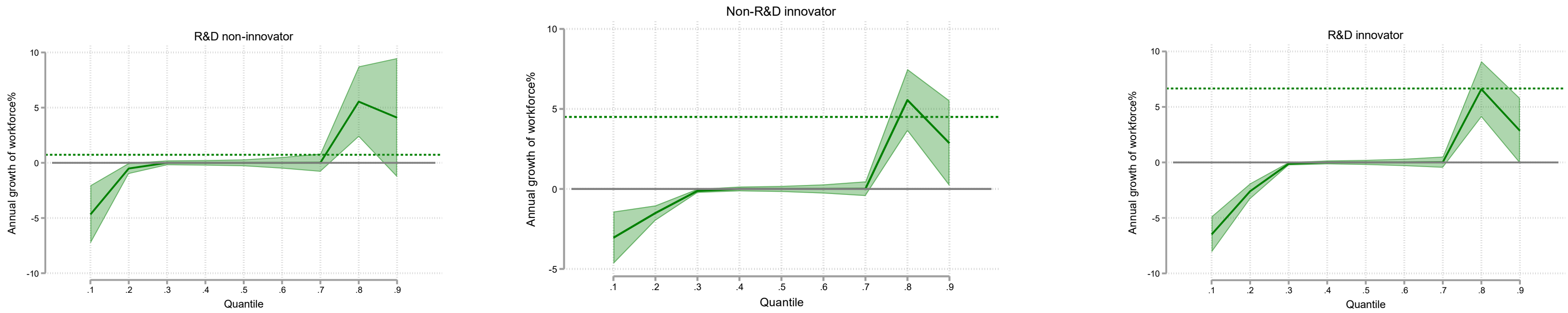
Figure 3 then shows the results of the quantile regression for the dependent variable workforce growth across innovation modes. All innovation modes show some similarity when compared to non-innovating companies. There are some negative deviations in the case of DUI plus and STI at the 1st and 2nd quantile. There is a positive premium for all YIC types from the 6th to the 9th quantile. However, in contrast to the results for revenue growth, the effect size is highest for basic DUI firms, with a growth premium of up to 32 percentage points (at the 9th quantile). Thus, it appears that the labor intensity of basic DUI firms outweighs, or at least partly offsets the stronger revenue growth of STI-oriented firms through an increase in employment. R&D non-innovators do not differ from the reference group. In case of workforce growth, our results thus support H1, H2 and H3, but are not consistent with H6, as the basic DUI group achieves the highest workforce growth rates.

Figure 1. Revenue and workforce growth, quantile regressions (YICs by R&D activity and innovation output)

Revenue growth

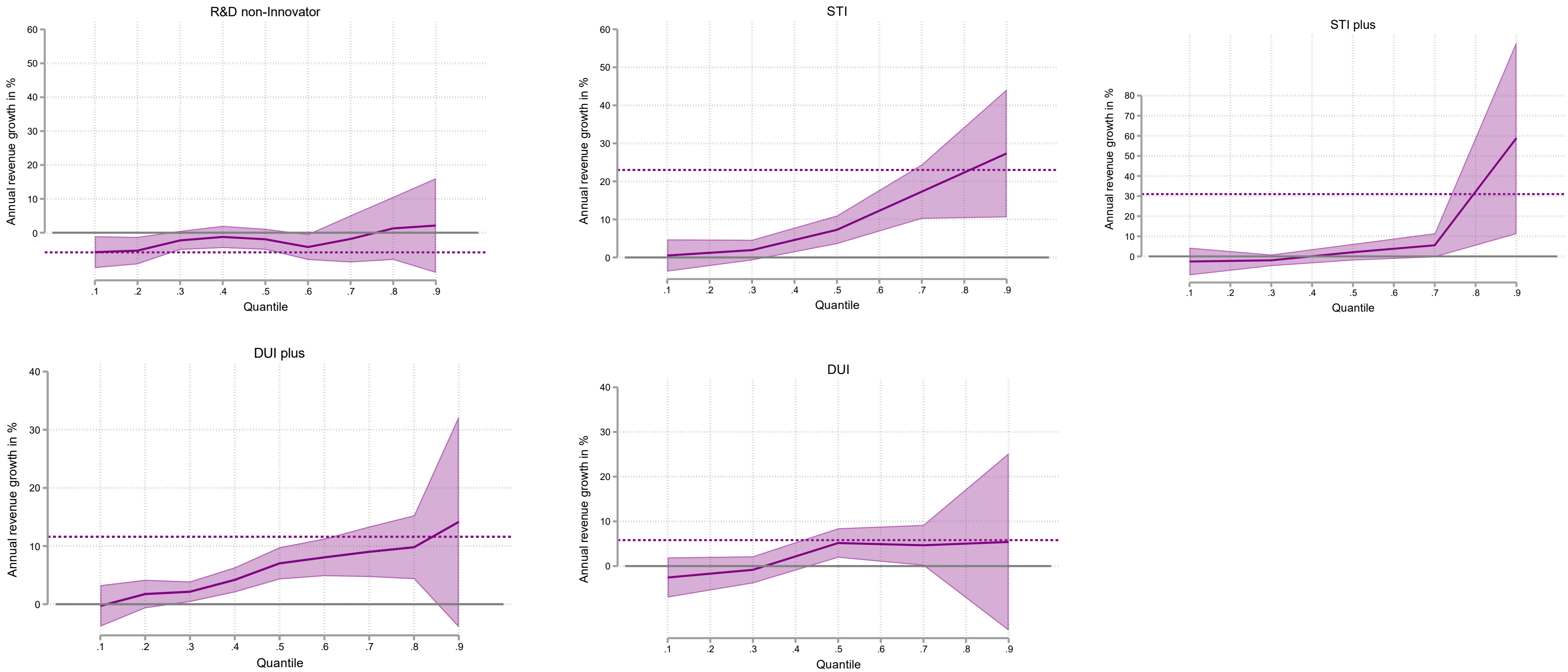


Workforce growth



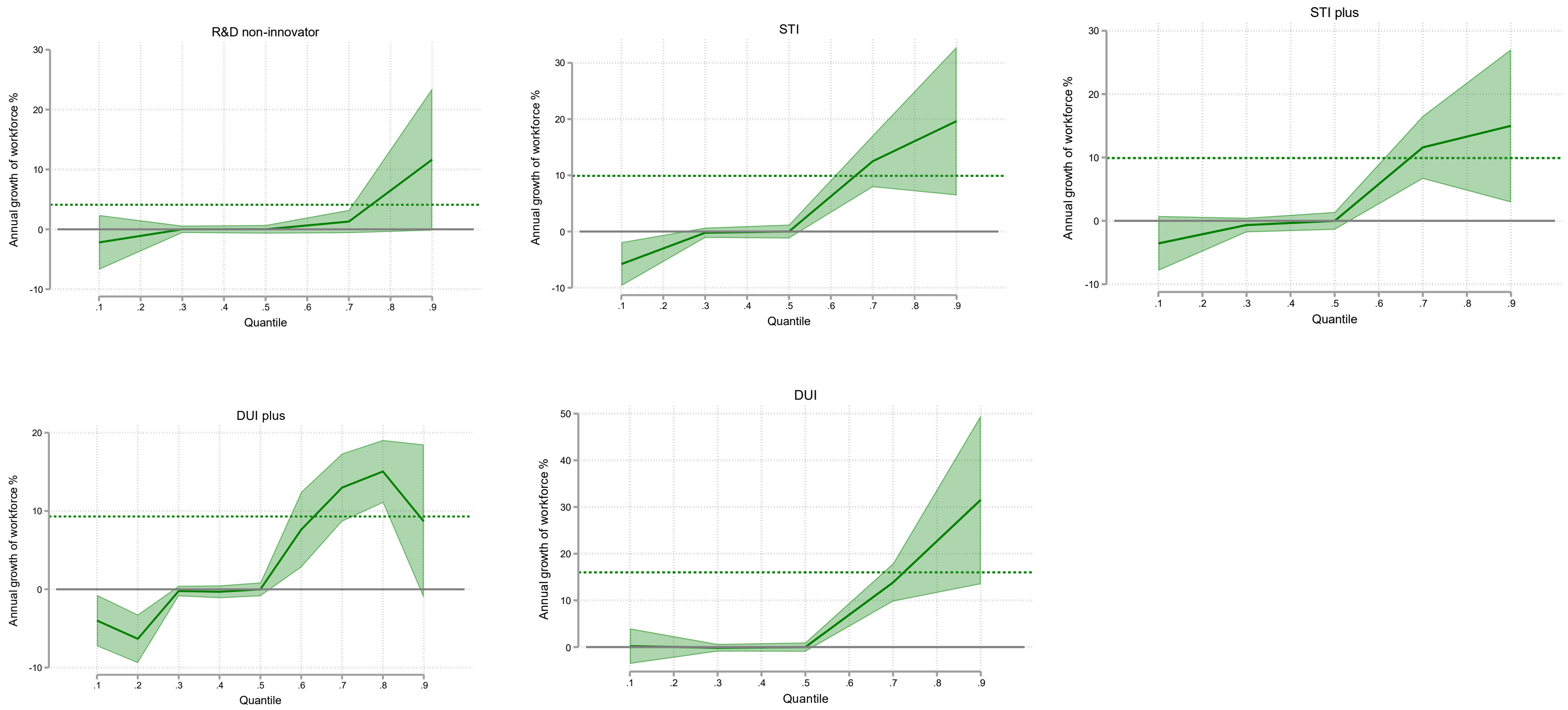
Notes: The values corresponding to each quantile are shown in Tables 4 and 5. The shaded areas correspond to the 90% confidence interval and the horizontal dashed line represents the OLS coefficient.

Figure 2. Revenue growth, quantile regressions (innovation modes)



Notes: The four innovation modes are the result of a cluster analysis (see Table A3) and the values corresponding to each quantile are shown in Tables 4 and 5. The reference group (i.e. non-innovating companies) and the additional group of R&D non-innovators are defined according to the YIC categorization by R&D and innovation output (see Sections 2 and 3). The shaded areas correspond to the 90% confidence interval and the horizontal dashed line represents the OLS coefficient.

Figure 3. Workforce growth, quantile regressions (innovation modes)



Notes: The four innovation modes are the result of a cluster analysis (see Table A3) and the values corresponding to each quantile are shown in Tables 4 and 5. The reference group (i.e. non-innovating companies) and the additional group of R&D non-innovators are defined according to the YIC categorization by R&D and innovation output (see Sections 2 and 3). The shaded areas correspond to the 90% confidence interval and the horizontal dashed line represents the OLS coefficient.

4.2. A different risk-reward trade-off?

In this section we analyze whether R&D performers among the YICs, with their superior revenue growth performance, also face a higher existential risk – in the form of lower survival rates– or experience lower initial profitability due to higher costs than non-R&D innovating firms (see hypotheses H4 and H5). The results of a linear panel regression with fixed-effects are presented in Table 4. The results suggest a significantly lower exit rate for non-R&D innovators by about 1.1 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 (see specification 2). While both, R&D innovators and R&D non-innovators display positive deviations from the reference groups (i.e. hazard ratios above 1), there are no differences in the group of non-R&D innovators, supporting H4. We therefore conclude that the overall exit risk is lower for young non-R&D innovators than for R&D innovators. Focusing on profits and losses in specifications 3 and 4 of Table 4, we find that non-R&D innovators are more likely to generate profits (and less likely to incur losses) compared to the reference group of non-innovating companies. In contrast, both R&D innovators and R&D non-innovators are indistinguishable from the reference group. These results support H5, which posits that young non-R&D innovators experience higher profits and lower losses than young R&D innovators in the early years after start-up.

Table 4. Regression result (exit, profit, and loss, YICs by R&D and innovation output)

	(1) Exit	**(2)** Exit	**(3)** Profit	**(4)** Loss
Ref. Non-innovating companies				
R&D non-innovators	0.001	1.18***	-0.012	0.013
Non-R&D innovators	-0.011***	1.02	0.029***	-0.020**
R&D innovators	-0.005	1.10***	-0.001	0.003
Active persons	-0.000	1.00***	0.000	-0.000
Investment per person	-0.000	0.99	-0.000**	0.000***
Export orientation	-0.006*	0.80***	0.057***	-0.044***
Ref. High-tech manufacturing				
Technology intensive services	0.021	1.22***	0.000	-0.069
Software	0.014	1.08*	0.039	-0.082
Low-tech manufacturing	0.026	1.16***	0.043	-0.092
Knowledge-intensive services	0.025	1.07	0.037	-0.087*
Other business-related services	0.007	1.20***	0.077	-0.090
Consumer-related services	-0.003	1.30***	-0.023	-0.034
Construction	0.003	1.37***	0.012	-0.007
Trade	-0.001	1.07	0.093	-0.112**
Others	0.008	1.43***	0.043	-0.056
Advanced manufacturing	0.010	1.11	0.125*	-0.169***
Specification	*Linear Panel*	*Cox Survival*	*Linear Panel*	*Linear Panel*
Observations	48,088	52,328	51,051	51,051

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.0$; Specifications 1, 3 and 4 show the results of linear panel regressions with fixed effects. Random effects models have also been run and give similar results. Specification 2 refers to a Cox survival model with hazard ratios. In the latter, hazard ratios of less (more) than one indicates a negative (positive) effect on firm exits. Year and year-after-start-up fixed effects are included. Standard errors are clustered at the firm level.

In a next step, we perform the same analysis using the four innovation modes (Table 5). Columns 1 and 2 present regression results for the dependent variable exit, with panel regressions in column 1 and Cox survival regressions in column 2. In column 1, three of the four innovation modes have a statistically significant negative effect on the probability of exit, while only R&D non-innovators have a positive effect. The negative association between innovation modes and the probability of exit persists in column 2. However, only the hazard ratio of the basic DUI dummy variable remains statistically significant in specification 2. The corresponding coefficient indicates that the probability of exit is 50% of the corresponding risk in the reference group of non-innovating companies. The effect size can thus be described as large. Overall, there is evidence in favor of hypothesis H4, i.e., that young non-R&D innovating firms are more likely to survive. The results again point to some underlying heterogeneity in terms of the innovation mode. While there is some evidence of higher survival in all innovation modes except the STI plus group, this is only consistently observed for the basic DUI mode. In this respect, hypothesis H6 is not supported.

In line with this, the coefficients in columns 3 and 4 show that members of the basic DUI group are initially relatively more profitable than firms in the other innovation modes, although their profit/loss performance is not significantly above the reference group. The DUI plus group deviates negatively by 8.6 percentage points in terms of profit from non-innovating companies, while the two STI groups show an even larger negative deviation (14.6 and 16 percentage points). Thus, we observe a clear initial profitability gradient, which is highest in non-innovating companies and basic DUI firms, and decreases as we move from DUI plus to STI plus, and finally to the STI mode with the highest risk in terms of profits and losses. This again confirms hypotheses 4 and 5 and contradicts hypothesis H6, whereby the innovation mode perspective allows some differentiation with regard to the different types of non-R&D innovators among YICs.

Table 5. Regression result (exit, profit, and loss, YICs by innovation mode)

	(1)	(2)	(3)	(4)
	Exit	Exit	Profit	Loss
Ref. Non-innovating companies				
R&D non-innovators	0.019**	1.532**	-0.181***	0.147***
DUI plus	-0.007*	0.925	-0.086***	0.092***
STI	-0.011**	0.801	-0.160***	0.159***
DUI	-0.011**	0.502**	-0.018	0.027
STI plus	-0.007	0.739	-0.146***	0.132***
Active persons	-0.000	0.000	0.001**	-0.001
Investment per person	-0.000	-0.000**	-0.000***	0.000**
Export orientation	-0.010***	-0.288	0.055***	-0.041***
Ref. High-tech manufacturing	0.000	0.000	0.000	0.000
Advanced manufacturing	-0.000	0.740**	-0.004	-0.007
Technology intensive services	-0.002	0.375	0.134***	-0.109***
Software	-0.013*	0.298	0.051	-0.038
Low-tech manufacturing	0.001	0.599*	0.097***	-0.095***
Knowledge-intensive services	-0.001	0.553	0.166***	-0.132***
Other business-related services	0.006	0.803**	0.116***	-0.117***
Consumer-related services	0.002	0.978**	0.063	-0.093**
Construction	-0.003	0.583*	0.179***	-0.145***
Trade	0.002		0.123***	-0.113***
Others	0.452		0.417*	-0.386
Specification	*Linear Panel*	*Cox Survival*	*Linear Panel*	*Linear Panel*
Observations	9,041	1,634	8,847	8,847

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 the matching estimator of the weighted quantile regressions for the dependent variable 'revenue growth' are presented in Table 6. Matching yields very similar but not identical results compared with the non-matching quantile regressions. Similar to our baseline results in Figure 1, we see that R&D innovators clearly outperform non-innovating companies in terms of revenue growth, especially at higher quantiles by up to 77 percentage points (column 3). This pronounced asymmetry of the growth premiums supports H1. In line with Figure 1 (and hypothesis H3), non-R&D innovators also display higher revenue growth than the reference group. We observe positive and statistically significant deviations starting at the 4th quantile and rising to about 18 and 47 percentage points at the 8th and 9th quantiles, respectively (column 2). The matching estimator coefficients thus show an overall stronger performance of non-R&D innovators than in our baseline results, providing more support for hypothesis H3.

The matching results again confirm, that different types of YICs also differ at the lower end of the growth distribution. The growth performance of R&D active firms is worse than that of the reference group of non-innovating companies, while the negative growth deviation is less pronounced for non-R&D innovators. As expected, we observe a distinct pattern for R&D non-innovators, who again show a strong negative deviation from non-innovating companies at the 1st and 2nd quantiles (in line with H2), with little to no deviation thereafter. A positive growth premium for this group is only observed at the 9th quantile (although it is not statistically significant).

Table 6. Quantile Regression results (IPWRA, dep. var. revenue growth, by R&D activity and innovation outp.)

Quantile	Value	(1) R&D non-innovators	p-value	(2) Non-R&D innovators	p-value	(3) R&D innovators	p-value
10	-0.25	-12.09	0.00	-1.07	0.55	-9.50	0.00
20	-0.05	-10.32	0.02	-4.87	0.00	-7.85	0.00
30	0	-1.66	0.62	-1.02	0.61	-1.61	0.46
40	0.14	-0.49	0.86	2.88	0.02	4.33	0.00
50	0.25	0.79	0.81	3.69	0.09	9.95	0.00
60	0.47	-1.77	0.71	1.12	0.64	10.30	0.00
70	0.75	-0.40	0.97	7.91	0.19	20.34	0.00
80	1.33	6.59	0.66	18.29	0.06	29.71	0.01
90	3	53.66	0.16	47.00	0.01	77.27	0.00

Notes: The columns (1), (2) and (3) display the coefficients along the conditional distribution, separately for each group of YICs. We use bootstrapped standard errors and run 100 iterations.

Table 7. Quantile Regression results (IPWRA, dep. var. workforce growth, by R&D activity and innovation outp.)

Quantile	Value	(1) R&D non-innovators	p-value	(2) Non-R&D innovators	p-value	(3) R&D innovators	p-value
10	-0.33	-0.30	0.90	-1.43	0.56	-8.70	0.00
20	-0.08	-0.70	0.82	-12.89	0.00	-15.10	0.00
30	0	0.08	0.82	-0.44	0.06	-0.73	0.00
40	0	0.26	0.42	0.00	0.99	-0.12	0.51
50	0	0.45	0.20	0.44	0.04	0.48	0.01
60	0	-0.40	0.92	-1.11	0.65	-0.16	0.94
70	0.29	8.73	0.03	7.55	0.00	7.41	0.01
80	0.5	20.91	0.13	19.95	0.00	18.20	0.00
90	1	26.53	0.08	12.48	0.01	10.36	0.01

Notes: The columns (1), (2) and (3) display the coefficients along the conditional distribution, separately for each group of YICs. We use bootstrapped standard errors and run 100 iterations.

Table 7 shows that, as in case of the baseline results presented above, R&D innovators and non-R&D innovators behave rather similarly in terms of workforce growth. The former group has a growth premium of up to 18 percentage points and the latter up to 20 percentage points above non-innovators at the 8th and 9th quantiles. They also behave rather similarly at the lower end of the growth distribution, with negative growth differentials at the 1st and 2nd quantiles. The workforce growth pattern for R&D non-innovators is also similar to that in Figure 1, as the negative growth deviations at the lower end of the distribution are similar but slightly less pronounced. Positive deviations at the upper end are also similar, except for the 9th quantile.

The panel regression analysis for the dependent variables exit, loss and profit (in Tables 4 and 5) is confirmed and complemented by the matching estimations, the results of which are presented in Table 8. The coefficient on non-R&D innovators is negative and significant in column 1, suggesting a 0.6 percentage point reduction in exits compared to the reference group. We also apply weights to the Cox survival regression, for which the hazard ratios are displayed in column 2. As before, R&D innovators and R&D non-innovators have a higher exit risk compared to the reference group, while non-R&D innovators do not differ. Overall, the IPWRA results on the dependent variable exit confirm the higher survival rate of non-R&D innovators compared to R&D innovators (i.e., in line with hypothesis H4).

Looking at columns 3 and 4 of Table 8, we again find that non-R&D innovators have higher initial profits and lower losses than R&D innovators (which supports hypothesis H5). Correspondingly, R&D innovators have higher losses than the reference group. In line with hypothesis H2, R&D non-innovators have the lowest probability of profits compared to the reference group of non-innovating companies.

Table 8. Exit, profit and loss regressions (IPWRA, by R&D activity and innovation output)

	(1) Exit	p-value	(2) Exit	p-value	(3) Profit	p-value	(4) Loss	p-value
R&D non-innovators	0.000	0.984	1.188	0.036	-0.146	0.000	0.118	0
Non-R&D Innovators	-0.006	0.022	1.052	0.350	-0.008	0.180	0.015	0.007
R&D Innovators	-0.001	0.719	1.139	0.038	-0.125	0.000	0.117	0
Specification	*Linear Panel*		*Cox Survival*		*Linear Panel*		*Linear Panel*	
N	38,529		11,378		41,816		41,816	

5. Discussion and conclusion

While young innovative companies (YICs) are often defined as small, young, and highly R&D-intensive, this paper employs an expanded YIC categorization and, on this basis, uses panel data from Germany to examine the growth trajectories of different types of YICs. By distinguishing non-R&D innovators and R&D innovators from R&D non-innovators and non-innovating companies, and further refining this fourfold categorization of YICs by identifying different firm-level innovation modes, we offer a deeper understanding of the relationship between innovation and growth in young, small firms. Our findings add to previous analyses that have focused on the traditional R&D vs. non-innovator dichotomy, overlooking non-R&D innovators with their typical emphasis on the 'Learning by Doing, Using, and Interacting' (DUI) mode of innovation.

While the results confirm the superior performance of R&D innovators and young firms engaged in a related mode of innovation (i.e., the 'Science-Technology-Innovation' – STI – mode) at the upper end of the conditional growth distribution, our findings suggest that young non-R&D innovators also experience growth and improved performance (albeit at lower levels) relative to non-innovating companies. This is particularly true for YICs, which rely on an advanced DUI mode version, in which firms are open to external sources of learning, such as suppliers or customers. Our results also suggest that R&D innovators outperform non-R&D innovators only in terms of revenue growth, while overall, there is little difference between them in workforce growth. For the DUI basic group, the situation is even reversed: likely due to their high labor intensity, workforce growth is particularly strong in these firms, surpassing that of STI-oriented YICs. This finding suggests that the widely accepted idea in the innovation mode literature – that firms combining different learning and innovation modes are more economically successful than those with simpler approaches – may not always hold true, especially for young firms with their unique characteristics and business conditions.

Instead, we argue that whether or not young firms employ R&D in their innovation efforts can be usefully be understood as a choice for a particular risk-reward combination. The corresponding analysis shows that while YICs with a non-R&D orientation may have a positive, albeit inferior, growth performance compared to young R&D-oriented firms at the higher end of the performance distribution, they also face a lower risk of failure, bear lower costs, and are therefore initially more profitable after entering the market. For example, firms in the basic DUI group have the lowest likelihood of R&D, yet they report that they innovate. We show that while their growth premium over non-innovating companies is barely visible in terms of revenue performance, they nevertheless benefit from an increased survival and a higher initial profitability. In contrast, the firms classified as DUI plus are more likely to have in-house R&D processes. They display a clear revenue growth premium, retain moderate survivability (i.e. comparable to non-innovating companies), and slightly worse short-term profitability. Finally, the STI and STI plus groups display the highest share of in-house R&D, the highest exit and loss risk, and the lowest initial profitability. However, these firms also experience the strongest revenue growth – which distinguishes them from the group of R&D non-innovators, which carry out R&D but have not yet managed to actually bring an innovation to the market.

For policy makers, our results highlight the previously underestimated growth potential of non- or less R&D-oriented YICs and their role in generating economic dynamism, albeit at a lower level than that of young R&D innovators. As firms belonging to these types of YICs are more numerous in the economy than R&D-intensive high performers, it can also be assumed that their moderate growth performance will nevertheless have a positive effect on growth and job creation, especially at the regional level (Hervás-Oliver et al., 2021). This raises the question of whether the expanded categorization of YICs derived in this paper has been duly taken into account in innovation policy, which has traditionally focused on R&D-intensive types of YICs to achieve economic growth and development (Schneider & Veugelers, 2010; Czarnitzki & Delanote, 2013; Mas-Tur & Simón Moya, 2015; Giraudo et al., 2019; Colombelli et al., 2020). In order to provide further insights for policy makers who aim to address these different types of YICs with their specific ways of innovating and growing, future research could, for example, address the question of whether successful non-R&D-oriented innovators can eventually evolve into firms with more advanced R&D capabilities, thus serving as seedbeds for future high-growth firms. Moreover, one can speculate whether the presence of non-R&D innovators potentially contributes to a richer and more diverse innovation ecosystem (especially at the regional level). For example, incremental DUI mode innovators and the skills and knowledge they possess may be a valuable complementary resource to be combined with the capabilities of R&D-intensive firms through interaction or collaboration. By combining their different learning and knowledge assets within an innovation system, the coexistence of different types of YICs within a given system may provide a fertile basis for stimulating higher-level innovation and growth.[9] However, these questions cannot be answered with the available data and therefore represent suggestions for future research.

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[9] Indeed, previous studies have found positive complementarities between different sources of R&D and non-R&D sources of learning and innovation in terms of economic performance (Apanasovich, 2016; Parrilli et al., 2016 and Santos et al., 2022). It is therefore plausible to hypothesise that such a positive effect extends to a situation where such capabilities are not only integrated within a single firm, but exist in two different but cooperating firms, for example, within a region, where different forms of knowledge and learning are brought together through joint projects or other forms of interaction.

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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)

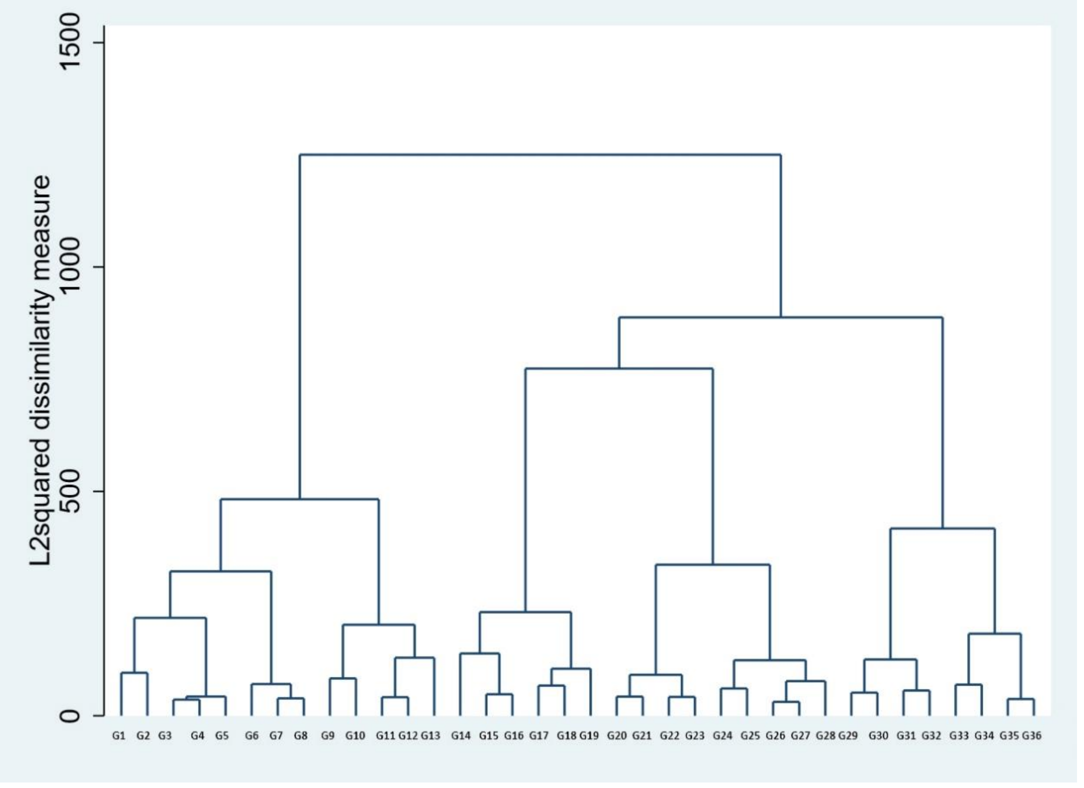
Table A2. Factor Analysis, drivers of learning and innovation (Principal Component Analysis, varimax rotated factor loadings)

	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**				**Chi²**
		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.

Table A4. Comparison of the two forms of YIC categorization used in the analysis (years 2010 to 2017), in percent

Categorization of YICs by R&D activity and innovation output	**Categorization of YICs by innovation mode (Assumed persistence on the basis of the 2014 information)**					
	Non-innovating company	R&D non-innovator	DUI plus	STI	DUI	STI plus
Non-innovating company	90.5	4.6	2.5	2.0	6.2	3.4
R&D non-innovator	1.2	78.2	2.7	3.9	1.4	3.1
R&D innovator	1.4	17.2	65.8	80.9	44.6	77.2
Non-R&D innovator	6.9	0.0	29.1	13.2	47.8	16.3
Sum	100.0	100.0	100.0	100.0	100.0	100.0

Note: For example, in the DUI plus group, 2.5% are non-innovating companies, 2.7% are R&D non-innovators, 65.8% are R&D innovators and 29.1% are non-R&D innovators.

Figure A2. Propensity scores by YIC group

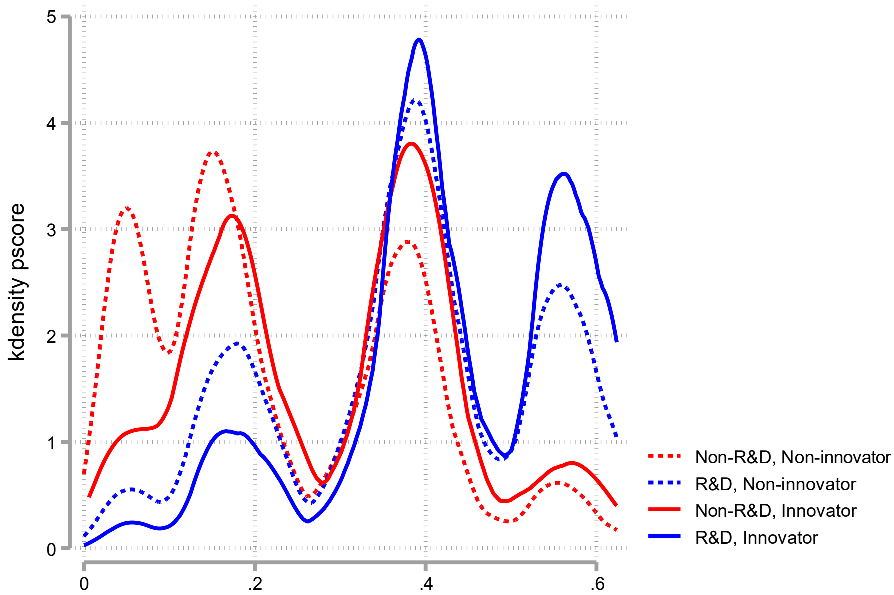


Table A5. Comparison of Variable Means: Unweighted vs. IPWRA-Weighted Results

	1	**2**	**3**	**4**	**1**	**2**	**3**	**4**
	Non-R&D, Non-innovator	*R&D, Non-innovator*	*Non-R&D, Innovator*	*R&D, Innovator*	*Non-R&D, Non-innovator*	*R&D, Non-innovator*	*Non-R&D, Innovator*	*R&D, Innovator*
Exit	0.028	0.030	0.025	0.027	0.028	0.032	0.026	0.029
Workforce (number of active persons)	4.930	5.231	7.886	8.069	5.471	4.369	5.195	6.026
Investment per person	6725.5	5202.9	4690.6	6835.1	6689.1	5375.5	4811.1	7797.1
Export orientation	0.091	0.205	0.160	0.413	0.124	0.095	0.081	0.196
High-tech manufacturing	0.035	0.104	0.083	0.113	0.050	0.060	0.041	0.059
Advanced manufacturing	0.021	0.081	0.029	0.131	0.030	0.043	0.009	0.060
Technology intensive services	0.196	0.290	0.190	0.244	0.222	0.317	0.165	0.287
Software	0.028	0.165	0.043	0.168	0.042	0.074	0.015	0.076
Low-tech manufacturing	0.108	0.124	0.114	0.120	0.119	0.145	0.103	0.137
Knowledge-intensive services	0.087	0.054	0.096	0.077	0.095	0.065	0.090	0.105
Other business-related services	0.090	0.029	0.075	0.032	0.079	0.047	0.096	0.062
Consumer-related services	0.093	0.053	0.108	0.044	0.094	0.072	0.115	0.070
Construction	0.155	0.040	0.102	0.022	0.111	0.078	0.156	0.052
Trade	0.136	0.039	0.118	0.038	0.115	0.063	0.153	0.069
Others	0.052	0.022	0.042	0.012	0.043	0.036	0.057	0.023