Technische Universität München

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The Economics of Corporate Research and Development:

The Role of Specialization, the Market for Knowledge, and Founder Personality

Annette Becker

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Vorsitzende:	Prof. Dr. Nicola Breugst
Prüfer der Dissertation:	1. Prof. Dr. Hanna Hottenrott
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Abstract

Corporate Research and Development (R&D) investments constitute a major source of innovation flows in knowledge-based economies. The decision whether and how much to spend on R&D is therefore one of the most strategic managers and entrepreneurs need to make. A part of firms' strategy is to decide upon the relative size of the Research (R) compared to the Development (D) component in total R&D expenditures, thus scaling relative intensities. The relative focus not only determines the returns to an investment but shifts a firm's position on the market for knowledge where purchasing and vending firms trade their inventive outputs. In established firms, the choice of corporate R&D strategy typically follows factual rules of relative returns gained from the specialization in an innovative activity, and is often path-dependent. In contrast, firms in an early stage of their life cycle lack past experience, and R&D decisions are consequently much more person-centered and strongly imprinted by the personality signature of the individual decision maker. This thesis theoretically and empirically typecasts corporate R&D decisions according to firm size, specialization strategy, and founder personality.

First, I explore the relationship between firm size and corporate R&D activities, while explicitly differentiating between the R versus the D component of R&D. I demonstrate that firms display different research intensities according to their firm size, conforming to the law of relative returns: While larger firms do indeed invest higher absolute amounts in both, R and D activities, the relative research focus is much stronger in smaller firms. In line with their comparative advantage in operations that do not require or allow scaling, the relative focus of smaller firms is on research rather than on product or process development. Larger firms, on the other hand, find it relatively more profitable to invest more in D compared to R. My results show that the strategy choice is consistent with the estimated lower returns to R in larger firms. This finding suggests the existence of a profit-maximizing labor division strategy in R and D between firms of different sizes.

Second, I examine how markets for knowledge coordinate firms' demand and supply for external know-how and technology. Firms act as buyers and sellers by exchanging inventive outputs through the channels of collaboration, licensing, or contract research which allows them to complement own capabilities, and pool knowledge across firms. Using the market for coordination and trade of knowledge assets allows firms to specialize in innovative activities. I empirically analyze whether firms specialized in R or D engage more actively in the knowledge and technology transfer. I find that firms heterogeneously select channels to source external R&D inputs: Whereas firms with high research intensities are more likely to collaborate in R&D or to license technologies, those with low or high research intensities more frequently commission contract R&D. The results stress that firms choosing an innovative strategy depend on a functioning market for knowledge in order to gain from the specialization outlined in the previous exploration.

Third, I investigate R&D decisions in entrepreneurial firms and contrast them to investments in tangible assets. Challenging the view that discretionary behavior is independent of the decision maker's personality, I hypothesize that investment decisions, in particular for R&D, are sensitive to the personality profile of the entrepreneur. The findings identify higher risk tolerance and openness to experience to affect the decision to embark on an R&D project positively, while these personality traits matter less for tangible investments. Similarities between R&D and tangible investments exist for agreeableness and neuroticism, since high levels in both reduce the likelihood that a founder pursues a growth strategy. The evidence obtained from this analysis contributes to the literature that lies at the intersection between trait psychology and entrepreneurial discretion as well as investment decisions under uncertainty by illustrating entrepreneurial R&D behavior to be prevailed by subjective perceptions of returns to an investment.

Overall, this dissertation advances the comprehension that R&D decisions do not form in isolation, but originate as a function of organizational and even individual context. In profound analyses, this thesis visualizes the interplay of corporate R&D with firm characteristics, strategic specialization, as well as entrepreneurial personality. The insight that R&D behavior features a salient link to firm and founder characteristics is valuable for informing policy makers. Regulations designed to target economic mechanisms and reaching firms and entrepreneurs according to their specific attributes can render industrial policy instruments more effective in supporting private sector knowledge production, promoting technology transfer, and paving the way for an innovation-oriented economy.

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1 | Introduction

1.1 Motivation

Continuous innovation over the past centuries led to substantial increases in living standards. Innovation and its outcomes not only transformed lives and societies, but also contributed to rising competitiveness, technological progress and productivity growth. Corporate Research and Development (R&D) has been shown to constitute an essential driver of innovation at the firm level, and hence to foster sustainable economic growth (Romer, 1990; Aghion and Howitt, 1992; Acemoglu, 1997). Investments in R&D involve not only the generation of new knowledge, but also the implementation and recombination of existing knowledge in order to create technological discoveries which result in new and enhanced processes, products, and services (Griliches, 1980; Griliches and Mairesse, 1984; Hall and Mairesse, 1995). It is thus a key interest of economies to offer good conditions for R&D and sustain idea-based growth (Weitzman, 1998). Understanding the drivers and impediments of corporate R&D, therefore, is of fundamental importance for both managers as well as policy makers.

The ultimate goal of corporate R&D activities is the creation of new knowledge. This sets R&D apart from other types of investment (Nelson and Winter, 1985; Acemoglu, 1997). In recent years, investment in knowledge-based capital has grown more rapidly than investment in physical capital in many OECD countries (OECD, 2017). This underlines that intangible assets are indispensable in knowledge economies which rely heavily on knowledge-based capital and intellectual capabilities (Powell and Snellman, 2004; OECD, 2017). Business spending on R&D amounted to 71% of total R&D expenditures in OECD countries in 2019 (OECD, 2021). Germany, for instance, experienced another record high and constant upsurge of corporate R&D of 2.2% of gross domestic product, worth €75 billion in 2019 (Stifterverband, 2021). This stresses the high relevance of corporate R&D in our economy. Yet, R&D as a pivotal type of strategic investment has properties that cause challenges for managers who make corporate R&D

decisions. Generally, firms invest in order to realize returns from the investment. Unlike other forms of investment in tangible assets, like property, equipment, and plants, R&D investment is typically associated with a high degree of uncertainty. For instance, firms may end up in a 'blind alley' (Teece, 1998), leading to costly failure and loss potential. Furthermore, since knowledge constitutes a public good, i.e. it is non-excludable and non-rival by nature, there are substantial positive externalities related to investments in R&D. That is, the investment does not only provide benefits to the company that bears risk and cost, but also for others who are able to absorb the knowledge that is being created (Nelson, 1959; Nelson and Winter, 1985).

Knowledge spillovers can occur through a variety of channels such as suppliers, customers, and worker mobility. The economic relevance of such knowledge spillovers may vary across industries – depending on the effectiveness of intellectual property rights – and by type of R&D activity. In seminal articles, both Nelson (1959) and Griliches (1987) describe the externalities generated by R&D activities in the form of knowledge spillovers which result from the often imperfect appropriability of the returns to innovation. Richard R. Nelson was also one of the first to emphasize that especially for basic research projects, the newly created knowledge, at least in part, spills over to third parties. Likewise, Arrow (1962) stressed that the social returns to basic research are typically larger than the private returns. Recent estimates of the social returns to R&D demonstrate that they outrun multiples of the expenditures (Jones and Summers, 2020). Moreover, the resulting innovations provide welfare-enhancing benefits to consumers, such as life expectancy and product quality, which do not directly translate into private returns to the investing firm (Benmelech et al., 2021). Incentives of private sector firms for investing in research may, therefore, be lower than socially desirable. The tension between social and business interests gives emphasis to incentives and rewards for corporate R&D activities, and, in particular, for private sector research. In addition, Jones (2009) emphasizes that knowledge in accumulation creates a knowledge burden through the growing complexity of new technologies, thereby making new discoveries increasingly costly and difficult to obtain. To mount the knowledge burden, both intellectual efforts as well as access to existing knowledge appear to be indispensable (Mokyr, 2005). It is this knowledge burden that has been discussed to be at the root of the recent productivity growth slowdown (OECD, 2016), the rising concentration of R&D activities with fewer firms engaged overall (Rammer and Schubert, 2018), and a withdrawal of large firms from basic research as reflected in scientific publications (Arora et al., 2017; Arora et al., 2018; Bloom et al., 2020).

In light of these developments, it seems crucial to study corporate R&D from novel perspectives, thereby extending our understanding beyond what is currently known about the drivers and impediments to innovation. In this pursuit, this dissertation analyzes the role of specialization in activities along the R&D process, and investigates how specialized R or D activities contribute to firm-level productivity (Chapter 2). Additionally, it examines how markets for knowledge facilitate specialization (Chapter 3). Importantly, this thesis presents research covering firms of all sizes, ranging from newly founded ventures to established, smaller and larger organizations. My research further illustrates how R&D decisions are a function of founders' personality traits and that the decision making process for R&D is in fact quite distinct from investments in tangible assets (Chapter 4).

My overarching motivation to undertake research on the economics of corporate R&D originates from the basic need to understand the economic mechanisms behind innovation activities in firms. Profound knowledge on the behavior and strategies of firms in R&D activities gives a starting point to policy makers as well as managers for evidence-based decision making. The studies carried out for this dissertation further allow to explore organizational heterogeneity which prior work often neglected. The results obtained from these studies contribute to our understanding of corporate R&D in the economy, while capturing the contributions to the innovation system by firms of different sizes and at different stages of maturity. The findings provide novel insights for managers as well as policy makers on how to stimulate innovation which will be discussed in detail in Chapter 5.

1.2 Literature Context and Background

This thesis strongly builds on prior work by scholars in economics and management research. Most prominently, it draws from work by Richard R. Nelson, Zvi Griliches and Edward Mansfield who have provided groundbreaking work in the field of innovation economics. Mansfield (1995) represents a seminal paper on the contribution of corporate R&D to firm-level productivity and, in particular, of basic research. This dissertation also augments more recent work by Czarnitzki et al. (2011), (2014) and Hottenrott et al. (2017) by investigating the returns to R and D and its contribution to firm-level productivity while taking into account the organizational differences between small, entrepreneurial firms, and larger corporations.

My research on the markets for knowledge draws on studies on knowledge differentiation for commercial purposes (Guilhon, 2001a, 2010), and connects them with seminal work by Gans et al. (2002) and Gans and Stern (2003) on technology licensing, highlighting the role of intellectual property rights. It also feeds on work by Arora et al. (2001) and Arora and Gambardella (2010b) which focuses on markets for technology, licensing and technology transfer, and complements it with insights from research on collaborative R&D (Hottenrott and Lopes-Bento, 2012, 2016; Czarnitzki and Hottenrott, 2017).

By investigating the link between firms' focus on research activities and how this relates to engagement into markets for knowledge via licensing and collaboration, my dissertation extends the understanding of knowledge networks and co-production of innovations. Integrating the market for technology to a compound market for knowledge enables the comprehension of the preconditions that give rise to a functioning knowledge exchange of patented technologies as well as unprotected intangible assets. The insight that the market for knowledge is a fundamental feature in knowledge-based economies is paramount for understanding those preconditions that best facilitate successful R&D and hence innovation.

The analysis of founder R&D decisions draws from the literature on entrepreneurial decision making (Rauch and Frese, 2007; Caliendo et al., 2009; Caliendo et al., 2020), and previous research that found the success of emergent firms to substantially depend on the entrepreneurs that founded them (Shane and Stuart, 2002; Dencker and Gruber, 2015). Studying how the personality of a founder affects R&D (as compared to tangible investments) demonstrates that personality imprints its signature on the way in which founders think, decide and act in their role as entrepreneurial decision makers. Thereby, the reach of personality traits stretches far into strategic decision making, such as R&D. My research advances earlier work on the importance of individual characteristics in entrepreneurial discretion (Costa and McCrae, 1997; Smith et al., 2018). In this regard, my thesis adds notable new aspects to prior insights, such as by Stewart and Roth (2001) and Brandstätter (2011) who find that firm-level innovation decisions operate at the founder level by stressing the role of trait psychology as a key determinant of R&D strategies.

Moreover, studying the role of founder personality for both R&D and tangible investments is central for understanding the personality-performance link documented in the entrepreneurial psychometry literature. In addition, as both types of investment are crucial for the up-scaling of new firms, my research shows that it is relevant to distinguish the decision to invest (extensive margin) from the amount of the investments conditional on the investment decision (intensive margin). The insight that personality matters particularly at the extensive margin provides important implications for innovation and entrepreneurship policy, since the success of policy measures in encouraging R&D activities may be affected by personality attributes. In light of declining founding rates and the scarcity of innovative high-growth ventures in Europe and beyond (Decker et al., 2016; Expertenkommission Forschung und Innovation, 2021), understanding the link between investor personality, R&D decisions and growth strategies closes an critical gap in literature. Taking the insights gained in this dissertation into account in the design of policy instruments bears the opportunity for creating more effective policy measures in the future.

1.3 Findings and Contribution

The research presented in this thesis demonstrates that firm heterogeneity in R&D activities can be traced back to firm or entrepreneurial characteristics. To uncover the exact mechanisms at work, I exploit the outcome variation of R&D decisions which manifests at different stages: Whether to engage in R&D investments during firm formation, and conditionally, how much to spend on R&D (Chapter 4), as well as composing the total spendings relative to each other, hence scaling the intensity of R compared to D (Chapter 2) which defines how actively a firm participates in technology transfer on the market for knowledge (Chapter 3). Novel to the entrepreneurial and investor personality literature is the finding in Chapter 4 that the investment decision, investment volume and entrepreneurial personality profile differ by investment type. While a specific personality profile would drive the founder to invest in tangible assets, it might lower the likelihood to spend on R&D, or diminish the R&D expenditure amount.

Unlike the absolute amount of R&D spending which is limited by firm size, Chapter 2 depicts that the firm can strategically decide on its ratio of R to D. Larger firms enjoy an absolute advantage in both, R and D operations, whereas smaller firms are comparatively advantaged when choosing to specialize in R. The decreasing relative returns to a higher research intensity are visualized by the marginal effects on total factor productivity, which shrink and even turn negative with growing firm size. This returns-guided labor division in R and D between firms of different sizes is of interest with respect to productivity contributions in the overall economy, particularly in light of the recently documented withdrawal of firms from R. It further highlights the role of specialization for technology transfer and raises the question in Chapter 3 whether firms specialized, either in R or D, are more actively participating in the market for knowledge. Since specialized firms cannot accommodate in-house provision of the component not specialized in but are in need for it out of complementarity, they can seek for external sources by trading inventive outputs on the market for knowledge. Identifying innovative specialization of firms through the level of their research intensity indeed predicts differences between firms exhibiting mean and extreme value research intensity: Specialized firms are more likely to engage in R&D collaboration, to license technology, and to commission contract R&D, and thus exchange knowledge.

1.3.1 Research Aim and Overview

The aim of this dissertation is to advance the literature on R&D decisions at the intersection of entrepreneurial investment behavior, knowledge production and R&D productivity, as well as innovative specialization and technology transfer. In general, it contributes to understanding how firms' R&D decision form and how R&D strategies translate into outcomes. In detail, it extends the understanding of how R&D spending decisions and conditional investment volumes depend on founders' subjective assessment, as well as how firm characteristics link to an innovative specialization strategy, and in aggregation, shape the dynamics on the market for knowledge. Empirical analyses based on firm-level data draw evidence for the ideas presented in theoretical frameworks and in doing so, synthesize theoretical modelling with empirical work. An evidence-informed comprehension of R&D decisions in firms can elevate industrial policies designed to support the knowledge production within the private sector, to promote knowledge transmission and technology transfer between firms, and to pave the way for an economy that is oriented towards corporate agents enabling innovation.

Chapters 2 to 4 entail the three main studies that I conduct as part of my dissertation. They are all built on unique firm-level data. A commonality of the first two studies is that they are based on a data set of firms located in Belgium: This sample originates from the a) Flemish part of the Belgian OECD R&D survey, b) the Thomson/Reuters Belfirst database, and c) the European Patent Office's (EPO) PATSTAT database. Due to its richness in detail and quality, I employ the detailed firm-level survey data in both Chapter 2 and 3. Chapter 4 is based on data from the ZEW/IAB start-up panel which provides likewise dedicated information at the firm level including a broad set of founder characteristics. In the following, I briefly review the chapters that portray different stages of decision formation and outcomes in corporate R&D.

1.3.2 Division of Labor in R&D? Firm Size and Specialization in Corporate Research

Chapter 2 explores the relationship between firm size and corporate R and D expenditures. Facing a recent decline in corporate R indicated by article publications (Arora et al., 2017; Arora et al., 2018; Bloom et al., 2020) necessitates to separately view the components of R&D.

Baumol (2002) establishes the notion of a 'David-Goliath symbiosis' in which firms split the innovative labor according to their work power, with small firms providing heterodox ideas, and large firms progressing these discoveries into commercial products. This tacit labor division in R and D follows the economic rules of absolute and comparative advantages. The advantage size materializes in relative returns to an activity, for example when extracting total factor productivity (TFP) of conducting R compared to D. This chapter combines theoretical with empirical work. First, Section 2.3 introduces the theoretical context and derives an investment decision model for choosing R and D and explicitly integrates a firm size parameter.

Next, the empirical part of this chapter models a firm's research intensity as a function of corporate characteristics. For this goal, I use research expenditures divided by total R&D expenditures, the R-share (research share), which informs about the relative focus of a firm when choosing to invest in R and D. Firm size predicts a decreasing R-share, with firms of median and mean size (37 and 196 employees, respectively) having an almost twice as high R-share as firms at the 95^{th} percentile (691 employees). Third, I approximate the logic of relative returns by estimating firms' total factor productivity and the R-share's impact on it (average marginal effects). Again, I look at the entire range of firm size distribution to see that the marginal effect of R-share on TFP varies: While for smaller firms the productivity contribution is positive, it is continuously falling and even turns negative for larger firms.

For the execution of the estimation strategy, I compose a firm-level panel of almost 15,000 firm-year observations, amounting to around 4,400 unique firms located in Belgium, across 17 manufacturing and knowledge-intensive service sectors with information on internal R and D expenditures, contract R&D spending, patent stock, firm characteristics, and accounting variables on firm liquidity and debt. Three steps are implemented. First, when estimating the R-share, I primarily rely on the fractional response method by Wooldridge (2019). To account for unobserved firm-specific effects, within-sample means of all covariates are added to construct a Mundlak-Chamberlain device (Mundlak, 1978; Chamberlain, 1982). The results are robust to general least square (GLS) and Tobit specifications with random effects (RE). Second, for the productivity analysis, I enter major factor inputs (capital, labor, net R&D expenditures) and adopt the method of Ackerberg et al. (2015), which is cross-validated by the method of Levinsohn and Petrin (2003). Third, I insert the productivity estimates into the final stage where I regress TFP on firm characteristics. By interacting the R-share with firm size, I strictly control for firm size-induced dispersion of research intensity across firms.

The main finding from this examination is that firms display variability within conducting R, and these differences conform to firm size. This pattern is not only visible when predicting the R-share but also manifests in the relative returns, measured in the marginal effects of R-share on TFP. Smaller firms receive a productivity premium for investing relatively more in R, whereas it is less profitable or even unproductive for larger firms. The results confirm the hypothesis that firms follow the rationale of comparative advantages, which leads to a labor division in R and D between firms of different sizes. Since this natural alignment is productivity-efficient on the economy level, it is advisable for policy makers to design measures strengthening firms' comparative advantages. Particular importance pertains to smaller firms' research contributions when returns to public funding of industrial R&D programs are pursued, e.g. targeted R&D funds like direct grants instead of R&D tax credits being more effective when supporting research in small firms. This study also highlights the important role of small, research-intensive firms in innovation systems for augmenting corporate R&D. Chapter 2 speaks to the growing scholastic documentation on research neglect which reports the shift of chiefly large firms retracting from corporate research, and within that withdrawal, ascribes retained knowledge production to small firms, apart from institutional players like universities, while maximizing productivity.

1.3.3 Specialization in Corporate Research and the Market for Knowledge

Chapter 3 follows the line of argument from Chapter 2, advancing the phenomenon of firms' decision to specialize in R or D towards an innovation strategy which utilizes markets for knowledge. Specialization as a starting point for the emergence of submarkets has long been described for tangible assets and services (Alchian, 1984; Pavitt, 1984; Arora and Gambardella, 2010b). Less established is the view that intangible and information assets spare market capacities to specialize in, since their public good nature is susceptible to knowledge leakage, litigation, as well as misappropriation, and such imperfections impede a formalized market from evolving (Guilhon, 2001a; Gans et al., 2002; Becker et al., 2020). Gans and Stern (2003) and Gans et al. (2008) depart from intellectual property rights (IPR) and attribute them, thanks to their legal enforceability, to not only yield an immediate effect but to also unfold a wider 'non-expropriation reputation' which surrounds the holder and signals competitors as well as cooperators a downsized disclosure risk. Overcoming the prior protection hurdle adds non-patentable goods to the existent trade of patentable commodities, like physical prototypes, and thus extends the market for technology to a compound market for knowledge. Lemley and Feldman (2016) ascribe the 'peripheral disclosure' of information beyond reading a patent to be necessary for absorbing knowledge, since patents do not transfer things like know-how and complementary assets. Firms choose their orientation towards R or D in tandem with their activity commitment as participants in the market for knowledge, guided by the returns obtained correspondent to their comparative advantages. The market for knowledge thereby supplies complementary R&D inputs. In this chapter, I outline a stylized model of the interdependence between strategy choice and engagement in knowledge and technology transfer (Figure 3.1) which builds the foundation for the hypotheses development.

We can observe firms participating in the market for knowledge through multiple channels. This motivates the hypothesis that engagement in the market for knowledge is determined by a firm's specialization strategy. Engagement is observed as a binary status to participate in or the amount invested in a specific market channel. Empirically, the examination proceeds in three steps: First, I investigate whether the R-share predicts a more active participation in any of the four engagement modes at the mean value of R-share. Then I look at firms specialized in R or D, located at both ends of the R-share distribution (high or low R-share) and test whether the prediction from before holds, since a non-monotonic relationship could modify direction, magnitude and statistical significance of the impact at other values of the R-share. Lastly, the coefficient of the interacted R and D expenditures informs us about any substitution or complementarity at work between doing R and D with regard to a specific sourcing channel. I study the association between research spending over the range of absolute development expenditures to see whether the engagement activity (likelihood, monetary units) in the market for knowledge changes as both types of investment increase. For this objective, I calculate the average marginal effects of R investments on each engagement mode over the spread of D spendings.

The empirical investigation draws from a dedicated subset of the OECD R&D survey data which I merge with other data sources similar to the ones presented in Section 1.3.2, allowing a detailed examination of the response variables which comprise the modes of engagement in the market for knowledge: The activity status of collaboration, licensing inward and outward (licensing in, licensing out), and commissioning contract R&D (as spending amount). Retrieving the main effects requires to account for a set of essential confounding variables including firm characteristics, like employee number, firm age, patent stock (for accumulated intangible assets), and a firm's financial situation. For cohesively mapping out the transfer channels which are mutually non-exhaustive, I estimate a simultaneous recursive 4-equation multivariate probit model. This method accounts for the simultaneity of the four modes and calculates probabilities conditional on the status of the other dependent variables. The method is executed with a conditional mixed process (CMP) estimator which is sufficiently flexible to take the different variable types (binary and continuous) into account. The key predictors of interest are the R-share and the research and development expenditures. In the process of specialization, it is fundamental to understand whether conducting R and D are substitutes or complements in terms of choosing a specific knowledge and technology sourcing channel.

The major insight from these explorations is that R&D strategy choice and market participation are interdependent. Yet, there is considerable heterogeneity with regards to the individual transfer channels. Specialization in fact predicts engagement activity: Collaboration likelihood grows in conjunction with a higher R-share, implying that firms that are more research-oriented are more likely to collaborate in their R&D activities. A more nuanced picture arises for licensing out and contract research: They are more likely only at relatively low and very high levels of R-share, suggesting that firms rather sell licenses or commission contract research when they are specialized in either R or D. Substitution effects are at work for collaboration and both licensing types: Spending more on R and D in parallel crowds out participation activity. Reversely, contract research rises when more is dedicated to both, R and D. The results are consistent with earlier work documenting in-house and extramural R&D to complement each other (Arora and Gambardella, 1990; Cassiman and Veugelers, 2006; Ceccagnoli et al., 2010; Grimpe and Kaiser, 2010), and corroborates evidence that firm-level specialization in intangible asset provision depends on a functioning market exchange (Gans et al., 2008; Arora and Gambardella, 2010b, 2010a). Signals on the market condition are also transmitted by the surrounding IPR system which only shields non-patentable intangible assets from misappropriation when formally enforcable. This is a precondition to the exchange of all intangible goods, prompting regulators to sensibly design and modify the protection of patentable commodities since there are secondary effects attached. By discussing the implications from these findings in detail, Chapter 3 speaks to the developing scholarly field concerned with individual firms' specialization in the supply of intangible goods, and how this stimulates corporate knowledge production and technology transfer across firms.

1.3.4 Founder Personality and R&D Decisions in Entrepreneurial Firms

Chapter 4 revolves around R&D decisions during the infancy of a firm's life cycle. It is entrepreneurs that make these decisions and act upon them (Lumpkin and Dess, 1996; Frese, 2009).

Moreover, there is a tension between short-run and long-run investments in emerging firms, and in light of resource constraints, founders need to balance their investment strategy against the expected benefits a lot more carefully than non-owner managers in larger firms (Baysinger and Hoskisson, 1989; Czarnitzki and Hottenrott, 2011b; Hottenrott et al., 2018).

R&D is a paramount facilitator of innovation performance in order for entrepreneurial firms to thrive to maturity (Caliendo and Kritikos, 2008; Rauch et al., 2009), and in that pursuit they depend on early-stage investments. Hence, young firms need to invest in tangible assets which consist of physical capital like buildings, equipment, and plants, and in intangible goods, e.g. goodwill and knowledge-based capital, such as patents and non-patentable knowledge assets (see Section 1.3.3) which are typically generated through persistent R&D efforts. Both investment types direct firm performance (Cassar and Friedman, 2009; Gambetti and Giusberti, 2019), and previous evidence on CEO characteristics (Barker and Mueller, 2002), or the entrepreneur's attitude to tolerate the inherently risky nature of R&D (Caggese, 2012) suggest that founder personality is tied to firms' spending behavior on R&D, but also to tangible investments. Departing from the link between personal attributes and entrepreneurial accomplishments consistent with prior work (Zhao et al., 2010; Jong et al., 2013), this chapter responds to the question whether entrepreneurial firms' investment decisions and investment volumes are a reflection of founders' personality traits, and how specific psychometric profiles lead to different discretion outcomes in R&D and tangible investments. The research in Chapter 4 synthesizes a theoretical framework and empirical analyses, while adopting a founder-level utility-based modelling approach which complements the firm-level profit maximization model derived in Chapter 2 (2.3) for the exploration of R and D investment choices (see Section 1.3.2).

I hypothesize that investment in entrepreneurial firms is driven by founder personality and that this is particularly true for R&D expenditures. In the examination, I focus on six baseline personality traits (risk tolerance, openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism), and study how these channel discretion behavior in intangible and tangible investments. The model takes into account parameters affecting founder utility derived from the financial gains of investment returns and integrates, for instance, the ability to tolerate risk and the individual's reaction to a higher variance of returns, i.e. a risky project. By impacting the perceived volatility of the expected returns, it predicts personality dimensions to affect investment decisions. To cross-check these theoretically formulated predictions, I empirically investigate entrepreneurial decisions at two stages: The decision whether to engage in an investment at all (extensive margin), and conditionally on the affirmative investment decision, how much to invest (intensive margin). In line with the theoretical model, each stage in this empirical estimation is modelled to be a function of firm and founder characteristics as well as the psychometric attributes.

The data used for this analysis are part of the German start-up panel created by the IAB (Institute for Work and Occupation Research) and ZEW (Center for European Economic Research) of which I extract the subset of independent ventures. Besides the annual reports on firms' founders and business activities, two survey waves supply questions on founders' entrepreneurial orientation and personality traits. The final sample contains more than 5,300 firm-year-observations which correspond to over 4,700 unique ventures across 11 sectors covering trade, other services and high-tech manufacturing, and across all sixteen German federal states. The variables employed belong to four categories. The response variables for R&D expenditures and tangible investments are a binary decision indicator (extensive margin), and the investment amount (intensive margin) for each. The key explanatory variables on entrepreneurial personality, 'RO-CEAN' in short, are retrieved from the survey items and their predictive values from principal component factor analyses, and assign scores to each of the six traits. To absorb founder characteristics, control variables on the personal, academic and industrial background are included in the estimation. Firm characteristics capture work force, firm maturity, physical capital, legal form, founding background, and the competitive environment (sector and region).

The estimation strategy is implemented in four steps. First, I examine the decision indicator (extensive margin) for each, R&D and tangible investments, and how they relate to psychometric variables, founder and firm characteristics in a simple discrete choice model. Second, I transfer this procedure to the investment volume (intensive margin) in ordinary least square (OLS) models. Third, to see how the R&D intensity compared to R&D expenditures reacts, the spending per employee is predicted for the same set of variables in an OLS estimation. Fourth, adding to the previous independent regressions, I estimate the intensive contingent on the extensive margin in Heckman selection models that account for the sample selectivity. To identify the second stage, I first choose – as common in Heckman corrected models – exclusion restrictions (ER) guided by the related literature and economic reasoning (university degree, tangible asset stock, and firm age). To test the sensitivity of the results to the variable composition of the ER, I make us of a novel machine learning approach to detect valid ER (Farbmacher, 2021) which results from a Least Absolute Shrinkage and Selection Operator (LASSO) estimation. LASSO is characterized by discarding variables with little contribution by means of a penalty term. This approach allows a data-driven identification of ER that is not subject to researchers' judgement.

Consistent with the original hypothesis, this study offers evidence that founder personality mediates investment decisions, with specific personality traits governing discretionary behavior for both investment types, R&D expenditures and tangible assets. Both investment types respond differently to personality profiles, and even yield heterogeneity within an investment type when comparing the extensive to the intensive margin. Entrepreneurial psychometry most prominently imposes its signature at the extensive margin of R&D decisions. The evidence is less pronounced for tangible investments, for which founder discretion is responsive to some traits at both margins. I test the sensitivity of these results at the extensive and intensive margin to alternative variable measurements, model compositions, and estimation methods to validate whether the results remain robust to alternative specifications. Multiple analyses in fact reproduce the result that risk tolerance dominates founder decision in R&D both at the extensive and intensive margin, with a positive influence the more risk-inclined a founder is. Therefore, the ability to tolerate the presence of risk, and to cognitively override the threat of failure and loss, proves to be a precondition to conduct R&D, withstand a safe-but-small returns mentality, and instead pursue a growth strategy. Openness to experience positively affects R&D decision at the extensive margin, requiring the entrepreneur to settle without hesitation into new environments, overthink conventions and enjoy unfamiliar stimuli in order to affirm R&D, and to embark on knowledge creation.

Chapter 4 speaks to the literature on personality as a driver of entrepreneurial decision making. In the exploration of different investment types, the findings support the overarching hypothesis that subjective assessments direct founder discretion. These results inform entrepreneurship policy as well as innovation policy more generally. Policies targeted at the extensive margin of R&D decisions could promote a stronger variety of founder investments in knowledge production, instead of a strict selection of high-in-volume but low-in-number R&D investments by entrepreneurs. There are further implications regarding entrepreneurship education. The exposition of decisions and firm performance to personality-channelled perception could be alleviated the more informed the decision makers are. For instance, Camuffo et al. (2020) consult scientific heuristics which assist entrepreneurs in sharpening their return recognition and return size estimation, and consequently enlarge actual return retrieval to projects. Uncertainty will naturally always rule entrepreneurial discretion when founders need to judge the returns from risky activities. Yet, equipping them with tools for risk evaluation could absorb the negative impact of some of the personality dimensions on investment decisions, especially for R&D activities. Krueger and Sussan (2017) and Caliendo et al. (2020) furthermore illustrate strategic and critical thinking to be malleable and learnable to some extent, and repeated engagement in new business ventures on the individual level to be determined by personality jointly with human capital, of which the latter can be upskilled through training. Thus, my insights complement recent research that indicates that entrepreneurial training enables to adjust decision making towards investment returns.

1.4 Outline of the Thesis

Each of the following Chapters 2 to 4 is self-contained, with a separate introduction allowing it to be read independently from the rest of the thesis. Chapter 5 concludes my investigations in a summary of the main insights, discusses the compound results and reaches policy implications for industrial, innovation and entrepreneurship regulators. By reflecting the wider context of my findings, I point out underresearched aspects suitable for follow-on studies. The last chapter, the Appendix, aggregates the appendices of Chapters 2 to 4 and corresponds to the order of the individual chapters. It provides supplementary analyses and results from robustness tests either in the form of figures or tables. The bibliography for all the three essays closes the dissertation.

2 | Division of Labor in R&D? Firm Size and Specialization in Corporate Research

2.1 Introduction

Investments in corporate R&D stimulate innovation enabling economic development, with R&D intensity being a central driver of productivity growth (Griliches, 1987; Romer, 1990; Doraszelski and Jaumandreu, 2013). Policy makers and economists are therefore interested in firms' incentives to invest in R&D in order to design regulations and conditions that promote such activities. However, recent studies document a decline in corporate research measured by the number of scientific articles published by companies (Arora et al., 2017; Arora et al., 2018; Bloom et al., 2020). This may be cause for concern since basic research activities, in particular, have been shown to drive firm-level productivity (Griliches, 1980; Mansfield, 1980; Czarnitzki and Thorwarth, 2012). At the same time, research-intensive and science-based industries such as artificial intelligence, biotechnology, nanotechnology, and renewable energy emerged. This trend is also reflected in data from the Organisation for Economic Co-operation and Development (OECD), reporting the growth of research expenditures relative to development expenditures over the past 30 years. While development expenditures have doubled from 1985 to 2015, research expenditures have almost tripled in real terms (see Appendix Figure A.1.1).

These two trends may seem paradoxical at first sight. However, earlier studies on corporate research tended to focus on large firms, thereby overlooking the contribution of small firms to overall research activities. Traditionally, it has been argued that larger firms possess an absolute advantage over smaller firms in terms of R&D due to economies of scale and scope, market reach, and access to financial resources (Schumpeter, 1942; Teece, 2010; Czarnitzki and Hottenrott, 2011a). On these grounds, it is of essential to stress that while R&D is often seen as

Author contributions: This chapter is joint work with Hanna Hottenrott and Anwesha Mukherjee.

one activity, it consists of two distinct components: research and development (OECD, 2015). As demonstrated in recent research, both activities respond to different drivers, pursue different goals and result in different outcomes (Czarnitzki et al., 2009; Czarnitzki et al., 2011; Barge-Gil and López, 2015; Hottenrott et al., 2017). Research typically involves analyzing fundamental principles and phenomena, and it often aims at generating new ideas and testing hypotheses without a specific application in mind (Martinez-Senra et al., 2015). Development operations encompass the application of knowledge, usually start from an existing 'proof of concept' and aim at improving specific products, processes or services (OECD, 2015). Hence, when cost-spreading and complementary assets are important, larger firms have higher incentives and better preconditions for conducting both, research as well as product or process development activities (Cohen and Klepper, 1996a; Rothaermel and Hill, 2005). Moreover, firm size comes along with advantages in appropriating the returns to R&D because larger firms may possess greater abilities to find commercial applications for research outcomes and may benefit from internalizing spillovers between multiple products or R&D projects (Henderson and Cockburn, 1996; Belenzon and Patacconi, 2014). On the other hand, prior research documents innovation advantages for small firms in emerging, research-intensive sectors (Acs and Audretsch, 1987) which indicates that they might be comparatively advantaged in research-intensive activities.

Drawing from the concept of comparative advantages, Baumol (2002) refers to a 'David-Goliath symbiosis' in which smaller firms provide more breakthrough discoveries and heterodox ideas, whereas larger firms create value from developing those innovations further and thereby contributing to their usefulness. In this symbiosis, 'Markets for Ideas' (Gans et al., 2002; Gans and Stern, 2003) and 'Markets for Technology' (Arora et al., 2001; Arora and Gambardella, 2010b) enable smaller firms to sell research outcomes to other (larger) companies rather than developing the final goods themselves.

Thus, the related but yet distinct properties of R versus D suggest that firms may have comparative advantages in one or the other activity, with firm size being a factor determining the relative returns to each activity. While the absolute advantage of larger firms may result in higher expenditures for R <u>and</u> D than in smaller firms, smaller firms may have a higher research share in their total R&D. Larger firms, contrarily, may gain more per unit of investment if they devote it to D instead of R. If the returns to product development positively depend on a firm's size measured in its existing customer base (or simply sales), larger firms' relative returns to D may outweigh those to R, resulting in lower research intensities of larger firms.

Building on these considerations, this study addresses on the question whether the incentives to invest in R versus D depend on firm size and whether the returns to each activity vary with firm size. A comparative advantage of larger corporations in development could explain their decreasing engagement in research, resulting in a division of labor in R&D between smaller and larger firms. This contribution to the analysis of corporate R&D is to theoretically illustrate firms' research and development spending decisions in an R&D investment model and to show analytically firms' relative engagement in R versus D activities, with each activity contributing differently to productivity. The model accounts for the relative returns to R and D as well as for the interdependence of both activities.

The model predicts higher R&D investments of larger firms but demonstrates that development becomes relatively more (and research relatively less) profitable the larger the firm is, resulting in lower optimal research intensities (R-share of R&D) in larger firms. We test this proposition using firm-level data of R&D-active firms which range from very small firms to large corporations observed during the period 2000-2015. Unlike previous research, our examination does not need to rely on scientific publications as a proxy of research intensity. The detailed data allow us to distinguish between firms' research and development expenditures, and to account for other firm-level characteristics driving R&D decisions. Results from panel model estimations show that the relative focus on research declines with firm size. Additionally, the results reveal that specialization is explained by the returns to each activity regarding total factor productivity (TFP) with the returns to R declining (and the returns to D rising) with firm size. In other words, focusing on product and process development pays a greater productivity premium to larger firms compared to research. These results yield implications for the discussion on the role of corporate research in knowledge-based economies, and the design of policy measures for stimulating private sector R&D.

2.2 Corporate Research and Development

R&D comprises two related but yet distinct activities: research and product & process development (OECD, 2015). While these activities are typically considered jointly, each responds to different drivers and pursues different goals. Consequently, it seems important to distinguish between the R and D component of R&D when investigating firms' innovation efforts (Czarnitzki et al., 2009; Czarnitzki et al., 2011; Barge-Gil and López, 2015). Research is concerned with exploring underlying principles and phenomena, fueled by curiosity (Martinez-Senra et al., 2015). It aims at generating and pioneering revolutionary ideas and concepts, formulates and tests hypotheses, theories or laws, and ultimately broadens the knowledge base (OECD, 2015). In this context, it is important to stress that research is often carried out without a specific application or use in mind. The lack of a predefined goal has an upside as well as a drawback. As a positive aspect, conducting research without targeting a specific application or use supports the application of possible findings to a spectrum of different fields, which the researcher potentially did not take into account (Levy, 2011). However, the lack of a clear target also raises the risk of generating a commercially viable outcome (Rosenberg, 1989; Pavitt, 1991).

Firms also undertake research ventures for building absorptive capacity in order to make better use of external knowledge (Cohen and Levinthal, 1989, 1990; Gambardella, 1992). Research may also serve in enhancing firm reputation, helping to attract customers and investors, as well as pleasing regulators (Hicks, 1995; Belenzon and Patacconi, 2014). In addition, firms may have incentives to invest in (basic) research which can be published in scientific journals in order to signal high-skilled scientists and inventors their science-promoting work conditions (Audretsch and Stephan, 1996; Stern, 2004). In contrast, development activities encompass the application of established knowledge, e.g. gained through basic and applied research (OECD, 2015). It directly aims at improving existing products or at creating new products and services based on the knowledge derived from research. The linear innovation model (Rosenberg, 1989) as well as the chain-linked model (Kline and Rosenberg, 2009) acknowledge that R and D are interdependent activities with both contributing to innovation outcomes (Griliches, 1985; David et al., 1992; Fleming and Sorenson, 2004).

While this argues in favor of any firm to perform at least some R and some D, there are higher-ranking aspects affecting the role of research in smaller versus larger firms. Prior work has largely focused on the question whether smaller or larger firms are more likely to produce innovative output rather than differentiating between the returns to research versus development spending, and how these returns depend on firm size (Henderson, 1990; Henderson and Cockburn, 1996; Macher and Boerner, 2006; Arora et al., 2009).

An exception is the study by Belenzon and Patacconi (2014). They investigate to which extent large and small firms differ in their ability to benefit from different types of research. They distinguish between basic and applied research with the outputs of basic research being scientific publications versus applied research resulting in patents. They find that large firms profit more from publishing, whereas smaller firms appear to benefit more from patenting. However, they also propose that publications seem to complement large firms' marketing and sales efforts which is less relevant for smaller firms due to their smaller customer base or market share. While not including development activities into their analysis and by using (output) proxies for research rather than expenditures, this study hints at varying returns to research activities depending on firm size. The higher returns to patenting for smaller firms may reflect the important role of research in these firms and hints at an underlying mechanism similar to the one suggested by Baumol (2002). The same reasoning also suggests that engaging in the activity for which a firm can exploit a higher relative return increases the overall returns to innovation efforts. For these reasons, studying firms' relative engagement in R and D seems crucial for understanding the division of labor by firms of different sizes in the innovation process.

2.2.1 Firm Size and Heterogeneity of R&D

In line with the preceding arguments, when studying incentives for R&D as well as the returns to such activities, it is indispensable to take the relative returns to one or the other individual component – R and D – into account. Equal importance pertains to the consideration of firms in their competitive environment, as their incentives to invest in one or the other activity is also contingent on the corresponding investments of other firms in the market. Smaller firms may then possess a comparative advantage in doing research relative to product development, since the latter is often capital-intensive and requires substantial investments for which smaller firms may not be able to reap the benefits of economies of scale (Arrow, 1993; Baumol, 2002). These properties may result in a relatively stronger orientation of larger firms towards development, despite holding an absolute advantage in both. Whereas smaller firms may be overall more constrained in their ability to invest in R&D due to its riskiness and due to fewer assets that can serve as collateral for debt (Czarnitzki and Hottenrott, 2011a, 2011b), they could still obtain higher relative returns to research than to development. Baumol (2002) argues that the routinization of innovation processes in larger firms is particularly beneficial for improvements of existing inventions rather than for creating heterodox breakthrough innovation. The routinized R&D processes in larger firms are hence more aptfor development rather than for green-field research activities. Thus, it is the *relative* return of development that is higher for larger firms and lower for smaller ones.

Making a similar point in a study on publicly traded US-based firms during the 1970-1989 period, Dhawan (2001) argues that the higher efficiency of smaller firms results from their leaner organizational structure which allows them to exploit opportunities in new markets. Being less entrenched in existing technology, smaller firms can engage in more fundamental R&D, although this is achieved at the cost of increasing these firms' riskiness. Larger firms, on the contrary, may consequently outsource or spin-off research activities to other (smaller) firms or entities. By the organizational separation of knowledge creation from product development, firms free capacities to specialize in the activity which is relatively most profitable to them, which Arora et al. (2001) coined 'division of innovative labor'. This organizational detachment can also occur within the same enterprise group, leading to the vertical disintegration of R and D, with research activities being delegated to smaller entities (Williamson, 1971; Monteverde, 1995).

In some industries, such as biotechnology, a division of labor in R and D has long been present (Danzon et al., 2005; Arora et al., 2009). Small research-intensive firms carry out much of the work related to exploring new active substances needed for drug development. Developing novel drugs is nevertheless extremely resource-intensive. Clinical trials are costly and may eventually fail, requiring even higher investments. While drug-related research is likewise costly and risky, the relative returns for smaller firms when focusing on this activity (and leaving drug development to larger pharmaceutical firms) may be relatively higher compared to development.

Larger firms with the necessary infrastructure may find it more profitable to focus on development benefiting from routinization and economies of scale in production and sales. The drug development process is an example of a very pronounced labor division in R and D, where the transmission of research through collaboration and the market for technology appears to be well-functioning. However, these patterns are not exclusive to this industry as similar observations can be made in software development and (digital) product commercialization (Lee and Berente, 2012).

In the context of innovative output performance rather than return to investments in terms of productivity, previous studies already gave evidence supportive of comparative innovation advantages for small firms in research-intensive industries (Acs and Audretsch, 1987; Henderson, 1990; Henderson and Cockburn, 1996; Macher and Boerner, 2006; Arora et al., 2009; Belenzon and Patacconi, 2014). Moreover, firm asymmetry in size has been linked to patent output, with smaller firms being more productive per US dollar spent (Cohen and Klepper, 1996b) which may be explained by research rather than development activities contributing to higher patenting numbers (Czarnitzki et al., 2009).

With respect to specialization, earlier documentations typically analyzed the relationship between firm size and product or process innovation, observing that larger firms find it relatively more profitable to invest in process improvements rather than in new products (Cohen and Klepper, 1996a, 1996b; Yin and Zuscovitch, 1998; Plehn-Dujowich, 2009), or with regard to the innovation degree bearing evidence that larger firms innovate more incrementally compared to smaller firms (Corsino et al., 2011).

Previous research does not yet provide an analysis of specialization in R or D, and the theoretical arguments may not be directly adoptable from the product versus process innovation framework. If research and development activities differ in determination, scaling and effects, the relative intensity of both (the respective expenditure component over total R&D expenditures) can be seen as a function of firm properties of which many vary with firm size (Barge-Gil and López, 2015).

The remainder of this paper is arranged as follows: Section 2.3 presents the theoretical framework which incorporates both research and development explicitly as strategic firm decisions. Section 2.4.1 proceeds with the data description, explains the estimation strategy and discusses the results. Section 2.5 concludes with a summary of the main insights, suggested follow-on studies, and policy implications.

2.3 An R and D Investment Model

2.3.1 Model Set Up

Assume the production function for firm i is of the standard form

$$q_i = \omega_i K_i^{\alpha_i} L_i^{\beta_i} R_i^{\gamma_i} D_i^{\delta_i} \tag{2.3.1}$$

where q_i denotes the output of firm i, K_i represents the firm's assets, L_i is the number of employees in non-R&D tasks, R_i is the research expenditure, D_i is the development expenditure, and ω_i denotes the Total Factor Productivity (TFP). The parameters α_i, β_i, γ_i, δ_i are the output elasticities of capital, non-R&D labor, research expenditure, and development expenditure, respectively. Marginal products of research and development expenditures are $\gamma_i q_i/R_i$ and $\delta_i q_i/D_i$, respectively.

Suppose, the profit of firm i from the product market is given by

$$\pi_i = p(q_i)q_i - c_i(q_i)$$

where $p = a - bq_i$ denotes the inverse market demand and $c_i(q_i) = c_{i0} + c_{i1}q_i + c_{i2}q_i^2$ is the firm's quadratic cost function[2].

The profit accruing exclusively from the existing product market is rewritten as

$$\begin{aligned}\pi_i &= (a - bq_i - c_{i1} - c_{i2}q_i)q_i - c_{i0} = (a - c_{i1})q_i - (b + c_{i2})q_i^2 - c_{i0} \\ &= (A_i - B_i q_i)q_i - c_{i0}\,, \quad \text{where} \quad A_i = a - c_{i1}, B_i = b + c_{i2}. \end{aligned} \tag{2.3.2}$$

Put simply, A_i and B_i are the coefficients of the linear and quadratic components in the profit function. Furthermore, in line with the assumption of increasing but diminishing returns to R&D expenditure from the literature on product and process innovation (Cohen and Klepper, 1996b; Yin and Zuscovitch, 1998; Fritsch and Meschede, 2001; Plehn-Dujowich, 2009), we assume that $A_i = f(D_i)$ with $f'(D_i) > 0$ and $f''(D_i) < 0$. That is, the per-unit price-cost margin itself can be increased by investing more in development. Development may, for instance, improve product quality or reduce cost of production, both resulting in a higher price-cost margin (Dorfman and Steiner, 1954; Grabowski, 1970). We define quality improvement in the sense of "any alteration in quality which shifts the demand curve to the right over the relevant range" (Dorfman and Steiner, 1954, p.831). This definition is based on Grabowski (1970, p.218) who notes "...firms in oligopolistic market structures prefer to compete by demand-shifting strategies like new product development, advertising, and the like, rather than trying to influence demand directly by price". Alternatively and equivalently, one could assume that B_i is a decreasing function of development expenditure. In graphical terms, this would imply a flattening of the demand curve with higher development activity, enabling the firm to charge a higher price for every unit sold, or the costs becoming less convex. Assuming either A_i or B_i to be a function of D_i serve similar purposes with regards to the scope of this model. We proceed with the first one for the sake of analytical simplicity and further assume that $f(D_i) = D_i^{\theta_D}$, where $\theta_D \in (0, 1)$ is the elasticity of the price-cost margin with respect to the development expenditure, and $f'(D_i) > 0$, $f''(D_i) < 0$.

Additionally, we assume that research activity undertaken by the firm can potentially open up a new product market, for instance by winning a patent race and licensing the technology, or through selling in the product market directly. That is, carrying out research has a benefit on two levels. On one hand, it enhances firm's output level as is apparent from the production function in Equation (2.3.1). On the other hand, research activities can contribute to a firm's revenue independently of the firm's existing production activities. Such additional gains provide incentives to increase research expenditures. Using a simple functional construct similar to the

[2]A quadratic cost function is assumed for the sake of higher generalizabiliy but is not necessary for the model.

innovation production function in Cassiman et al. (2002), or Plehn-Dujowich (2009), we define the additional net gains from research as $f(R_i) = \mu_i R_i^{\theta_R}$, where $\theta_R \in (0, 1)$ is the elasticity of the additional net gains with respect to research expenditure. These additional gains are also increasing at a diminishing rate.

Considering that research can be uncertain with regard to success, the above function can alternatively be interpreted as the expected net return from a Bernoulli process. If success in research is a binomially distributed random variable, $\tilde{\mu}$ is the estimated average probability of success in a single project, and $R_i^{\theta_R}$ is the number of projects that can be carried out from R_i, the amount of research expenditure, then expected success from research will be given by $\tilde{\mu} R_i^{\theta_R}$. If net gains upon success in research are denoted by M_i, then $\mu_i R_i^{\theta_R}$, where $\mu_i = \tilde{\mu} M_i$ will represent the expected net gains from research alongside the gains from the product market.

It is important to note that unlike Cohen and Klepper (1996b), Fritsch and Meschede (2001), and Plehn-Dujowich (2009), we do not simply subtract the expenditures on research and development from the firm's revenue. As development expenditure is assumed to be tied to production, the cost of development is entirely accounted for through $c_i(q_i)$. The cost of research can have components which depend on the level of output and components which are independent of the output level. The former is included in $c_i(q_i)$. To take the latter into account, $\mu_i R_i^{\theta_R}$ is defined as the expected *net* gains from research upon success.

The firm's expected profit from both R and D activities can then be written as

$$\pi_i^e = (D_i^{\theta_D} - B_i q_i) q_i + \mu_i R_i^{\theta_R} - c_{i0}. \tag{2.3.3}$$

Firm i's profit thereby depends on both R_i and D_i and the firm maximizes this expected profit by deciding on research and development expenditures. We assume θ_D and θ_R to be similar across firms within an industry.

2.3.2 Analysis of R and D Choices

To focus on the relationship between firm size and firm's emphasis on research vis-à-vis development activity, we assume that firms choose their research and development expenditures while holding the other factor inputs constant. Costs for any additional employee employed in research and development tasks and investments in R&D-related equipment are captured through the R&D expenditures. Adjustments in non-R&D labor and non-R&D capital inputs may eventually be needed in the production technology. However, those are not assumed to be instantaneous changes and, therefore, ignored in our static analysis. We are interested in firms' decision regarding research and development expenditures at a given point in time. The non-R&D labor and non-R&D capital stock at that particular point in time are treated as parameters indicating the firm size. This approach helps in distinctly focusing on the contribution of R&D activities to the firm's profit maximization, independently of other factor choices.

Maximizing the expected profit function with respect to R_i and D_i require

$$\frac{\partial \pi_i^e}{\partial R_i} = D_i^{\theta_D} \frac{\gamma_i q_i}{R_i} - 2B_i \frac{\gamma_i q_i^2}{R_i} + \mu_i \theta_R R_i^{\theta_R - 1} \tag{2.3.4}$$

$$\text{and} \quad \frac{\partial \pi_i^e}{\partial D_i} = (\theta_D + \delta_i) D_i^{\theta_D - 1} q_i - 2B_i \frac{\delta_i q_i^2}{D_i}. \tag{2.3.5}$$

The first order conditions for profit maximization are obtained by setting these first derivatives equal to zero. Setting (2.3.4) equal to zero, we obtain

$$\mu_i \theta_R R_i^{\theta_R} = \gamma_i q_i (2B_i q_i - D_i^{\theta_D}). \tag{2.3.6}$$

Setting (2.3.5) equal to zero, we obtain

$$q_i = \frac{\delta_i + \theta_D}{2B_i \delta_i} D_i^{\theta_D}. \tag{2.3.7}$$

Plugging the expression for q_i from Equation (2.3.7) into Equation (2.3.6) and simplifying, we obtain

$$R_i^{\theta_R} = g_i D_i^{2\theta_D}\ , \quad \text{where} \quad g_i = \frac{\gamma_i \theta_D (\delta_i + \theta_D)}{2B_i \mu_i \delta_i^2 \theta_R}. \tag{2.3.8}$$

Further, plugging in the production function from Equation (2.3.1) into Equation (2.3.7), we can write

$$D_i = h_i^{\frac{1}{\theta_D - \delta_i}} R_i^{\frac{\gamma_i}{\theta_D - \delta_i}}\ , \quad \text{where} \quad h_i = \left(\frac{2B_i \delta_i \omega_i}{\delta_i + \theta_D} K_i^{\alpha_i} L_i^{\beta_i} \right). \tag{2.3.9}$$

Note that both g_i and h_i are arbitrary parametric constructs used for the exclusive purpose of representational simplification. Incorporating Equation (2.3.9) into Equation (2.3.8) and simplifying we get the following:

$$R_i = g_i^{\frac{\delta_i - \theta_D}{\theta_R(\delta_i - \theta_D) + 2\gamma_i \theta_D}} h_i^{\frac{-2\theta_D}{\theta_R(\delta_i - \theta_D) + 2\gamma_i \theta_D}}. \tag{2.3.10}$$

The second order conditions for profit maximization requires $\delta_i - \theta_D > 0$. Note that, a lower μ_i implies a higher g_i and therefore a higher R_i. That is, ceteris paribus, a firm with lower expected returns from research has to spend relatively more in research to maintain the competitive edge.

Inserting the profit-maximizing value of R_i, the profit-maximizing value of D_i is immediately determined from Equation (2.3.9).

The total R&D expenditure is given by

$$R_i + D_i = R_i + h_i^{\frac{1}{\theta_D - \delta_i}} R_i^{\frac{\gamma_i}{\theta_D - \delta_i}} = R_i \left(1 + h_i^{\frac{-1}{\delta_i - \theta_D}} R_i^{\frac{-\gamma_i - (\delta_i - \theta_D)}{(\delta_i - \theta_i)}} \right). \tag{2.3.11}$$

Consequently, the R-share of firm i's total R&D expenditures can be expressed as

$$\begin{aligned} \frac{R_i}{R_i + D_i} &= \frac{1}{1 + h_i^{\frac{-1}{\delta_i - \theta_D}} R_i^{\frac{-\gamma_i - (\delta_i - \theta_D)}{(\delta_i - \theta_D)}}} \\ &= \frac{1}{1 + g_i^{\frac{-\gamma_i - (\delta_i - \theta_D)}{\theta_R(\delta_i - \theta_D) + 2\gamma_i \theta_D}} h_i^{\frac{(2\theta_D - \theta_R)}{\theta_R(\delta_i - \theta_D) + 2\gamma_i \theta_D}}}. \end{aligned} \tag{2.3.12}$$

Based on the above deductions, we can claim the following:

Proposition 1: *If output elasticities of research and development (γ_i and δ_i) are sufficiently comparable across firms, then for $2\theta_D > \theta_R$, a profit-maximizing firm with a higher L_i (or higher K_i) will incur a lower R-share compared to another firm with lower L_i (or, lower K_i).*

Proof: Ceteris paribus, a higher L_i or K_i, or both, implies a higher value of h_i. The profit-maximizing $R_i/(R_i+D_i)$ is lower for a higher value of h_i when $2\theta_D > \theta_R$. Given θ_D and θ_R both lie in the $(0, 1)$ interval, this implies that, with other parameter values sufficiently comparable across firms, when the elasticity of the price-cost margin with respect to development expenditure (as captured by θ_D) is larger or at least not too small in comparison with the elasticity of expected additional gains from research expenditure (as captured by θ_R), the optimal R-share is associated inversely with the firm size as measured by its number of non-R&D employees L_i, or accumulated fixed assets K_i. $\square$

2.3.3 Intuition

To elaborate further on the mechanism behind the above proposition, we reformulate Equations (2.3.4) and (2.3.5) as below.

$$\begin{aligned} & \frac{\partial \pi_i^e}{\partial R_i} = D_i^{\theta_D} \frac{\gamma_i q_i}{R_i} - 2B_i \frac{\gamma_i q_i^2}{R_i} + \mu_i \theta_R R_i^{\theta_R - 1} \\ \implies \quad & \frac{\partial \pi_i^e}{\partial R_i} / \frac{\partial q_i}{\partial R_i} = D_i^{\theta_D} - 2B_i q_i + \frac{\theta_R}{\gamma_i} \frac{\mu_i R_i^{\theta_R}}{q_i} \ , \text{ since } \quad \frac{\partial q_i}{\partial R_i} = \frac{\gamma_i q_i}{R_i} \end{aligned} \tag{2.3.13}$$

$$\text{and} \quad \frac{\partial \pi_i^e}{\partial D_i} = (\theta_D + \delta_i) D_i^{\theta_D - 1} q_i - 2B_i \frac{\delta_i q_i^2}{D_i}$$

$$\implies \quad \frac{\partial \pi_i^e}{\partial D_i} \Big/ \frac{\partial q_i}{\partial D_i} = \frac{\theta_D + \delta_i}{\delta_i} D_i^{\theta_D} - 2B_i q_i \ , \ \text{since} \quad \frac{\partial q_i}{\partial D_i} = \frac{\gamma_i q_i}{D_i} \tag{2.3.14}$$

The left hand side of Equation (2.3.13) is the marginal gain in profit from research over the marginal gain in output from research. Similarly the left hand side of Equation (2.3.14) is the marginal profit from development over the marginal output from development. In our model, both research and development directly contribute to production. But they also have additional contributions toward the firm's revenue; research might open up additional sources of revenue, such as patents, and development increases the per-unit price-cost margin. The higher the ratio of the marginal gain in profit to marginal gain in output resulting from a unit increase in some input factor, the higher is this factor's exclusive contribution (i.e., contribution over and above the increase in output) in the firm's revenue.

By construction, both the measures decrease as q_i increases, but Equation (2.3.13) falls faster. That is, the ratio of marginal profit to marginal output from research falls faster for a firm with a higher q_i. This is because the additional gains from R_i are independent of the firm's ex-ante output level and therefore the bigger firm does not have any additional advantage there. More specifically, comparing the right hand sides of Equations (2.3.13) and (2.3.14), we see that the ratio of marginal profit to marginal output from development is higher than the ratio of marginal profit to marginal output from research when

$$\frac{\theta_D + \delta_i}{\delta_i} D_i^{\theta_D} > D_i^{\theta_D} + \frac{\theta_R}{\gamma_i} \frac{\mu_i R_i^{\theta_R}}{q_i}$$

$$q_i > \frac{(\theta_R/\gamma_i)\mu_i R_i^{\theta_R}}{(\theta_D/\delta_i) D_i^{\theta_D}}. \tag{2.3.15}$$

In other words, the marginal gain in profit over output from development is higher than the same from research when the ex-ante output is above a certain threshold determined by the ex-ante R&D expenditures and the model parameters. Increasing the development expenditure is profitable as long as this threshold condition holds. We can further observe from this equation that even if the ex-ante R&D ratios are similar for larger and smaller firms, and the output elasticities of research and development are also comparable, a higher μ_i would raise this threshold output. So, when expected additional gains from success in research is higher, smaller firms are more likely to find development less profitable compared to the larger ones.

In the following empirical analysis, we measure firm size by the number of employees (L_i), resulting in the hypothesis that the R-share declines with L_i. Finally, it should be noted that a relatively higher R-share among smaller firms can happen because of multiple reasons, including different sizes of the non-R&D activities (as reflected in L_i or K_i), or asymmetric additional returns from research activity (as captured by μ_i). Proposition 1 shows that, ceteris paribus, the R-share varies with firm size. Alternatively, focusing on g_i in Equation (2.3.12), one can see that g_i decreases in μ_i, which in turn implies that the R-share falls. So, ceteris paribus, a firm with a higher μ_i spends relatively less in research. Given that the larger firms may often have a higher average success rate (i.e., higher $\tilde{\mu_i}$), or a higher scope of appropriating the fruits of research activity (i.e., higher M_i) thanks to their reach and reputation, a higher μ_i may as well induce a lower R-share.

2.4 Data and Empirical Strategy

2.4.1 Data Description

The empirical study is based on data from three main sources: a) the Flemish part of the Belgian OECD R&D survey, b) the Thomson/Reuters Belfirst database, and c) the European Patent Office's (EPO) PATSTAT database. The OECD R&D survey is harmonized across OECD countries and follows the guidelines in the Frascati Manual. It is conducted biannually and each wave collects information for the year covered in order to compose the OECD Main Science and Technology Indicators. The collected data is based on the permanent inventory of all R&D-active companies[3] in Flanders and hence covers a large proportion[4] of all R&D activity in the region. A firm is considered R&D-active in the following if it spent at least some money on R&D in at least one year during the sample period.

Information on R&D expenditures and on shares devoted to research and development as well as the number of R&D employees are taken from the OECD survey. To capture a firm's financial situation and in order estimate firm-level productivity, the survey data is complemented with accounting and balance sheet data from the Thomson/Reuters Belfirst database. It comprises financial information even for small, non-listed firms, since in Belgium all limited liability firms (except for financial institutions, insurance companies, exchange brokers and hospitals) had been

[3]Firms are considered to be part of the R&D-active firm population (about 12,000 for each wave) stemming from information based on previous surveys, accounting reports as well as based on government information about the application for R&D grants and tax credits. The response rate varies by year at around 75% across all firms and up to 98% for the top-200 R&D firms. For details, see https://www.vlaamsindicatorenboek.be/2.2.1/methodologie. Further information on each wave is documented here: https://www.vlaamsindicatorenboek.be/vorige-edities.

[4]According to the documentation, it is estimated that the included firms are responsible for around 90% of all R&D spending in the region.

legally required to file annual accounts with the National Bank during our period of analysis. We furthermore construct the patent application stock of each company based on information in the PATSTAT data.[5]

Table 2.1: Sample details

	Observations	Firms	Share (%)
SME (<250 employees)	12,447	3,948	84.28
Large firms (≥250 employees)	2,322	425	15.72
All	14,769	4,373	100.00
Sectors	14 manufacturing sectors, 3 service sectors		

The sample covers the years from 2000 to 2015 and includes firms in the manufacturing and knowledge-intensive service sectors. Table 2.1 illustrates that the final data set consists of 14,769 observations from 4,373 unique firms in 17 different sectors. The majority of firms in the sample can be classified as SME following the definition of the European Commission (2015) which applies an employment threshold of 250 employees.

Figure 2.1: Distribution of firm size

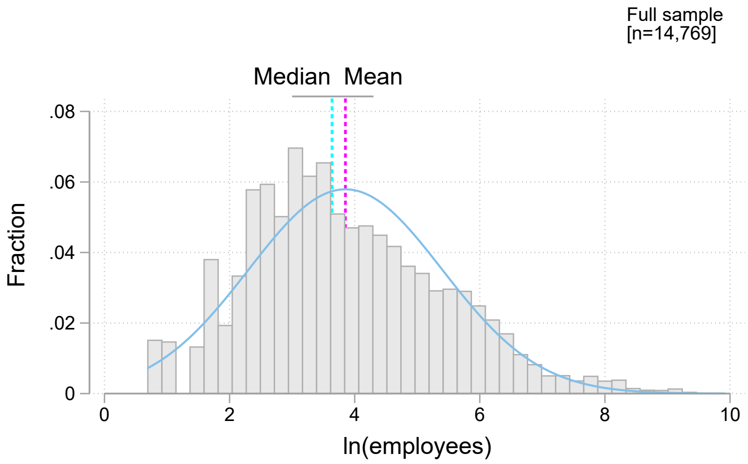


Figure 2.1 depicts the sample distribution in terms of firm size based on the logged number of employees.[6] Key descriptive statistics for the full sample are presented in Table 2.2. Research and development expenditures as well as all monetary variables are indicated in thousands of Euros. The data confirm that compared to external R&D, internal R&D plays a more important

[5]We match invention patent applicants based on names and addresses and account for patent families in order to avoid double counting of patents filed at several patent offices worldwide. The patent data is available as a time series for each firm, since we retrieve all patents of a firm dating back to its first application included in the data base.

[6]The sample distribution over sectors and size classes can be found in Appendix Table A.1.1. Figure A.1.2 delineates the distribution of the logged number of employees for the subsample of R- or D-active firm-year observations.

Table 2.2: Descriptive statistics of control variables

	Mean	P50	Sd	Min	Max
Internal R&D[1]	1,887.77	0	17,626.75	0	858,104
External R&D[1]	695.10	0	14,823.20	0	695,000
Research[1]	829.75	0	6,838.47	0	390,866
Development[1]	1,057.73	0	13,000.10	0	686,483
# total employees	195.81	37	678.01	1	20,132
# R&D employees	11.94	0	65.98	0	1,662
Age	27.28	23	18.74	1	144
Fixed assets[1]	42,755.44	1,073	364,157.88	0	14,374,981
Working capital[1]	9,431.60	1,237	47,947.05	-289,570	1,795,746
Long-term debt[1]	11,542.39	10	145,766.71	0	6,771,719
Short-term debt[1]	13,451.38	429	104,824.01	0	5,129,187
Patent stock	3.33	0	37.33	0	1,342
Enterprise group dummy	0.66	1	0.47	0	1
Observations			14,769 *(full sample)*		

[1] Measured in €1,000

role in firms' innovation investments. It is also visible that the average research expenditure is lower than the average development expenditure. Firms in the sample are on average 27 years old and 66 percent of the firms belong to an enterprise group.

Table 2.3: Descriptive statistics of share variables

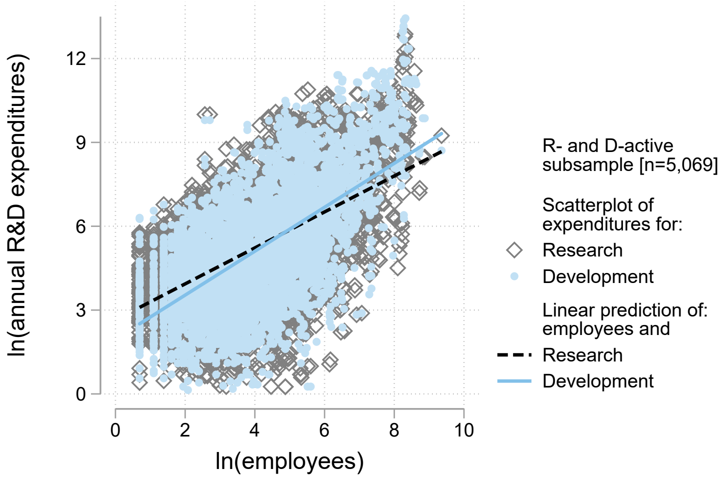
	Count	Mean	P50	Sd	Min	Max
Full sample						
R-share	14,769	0.28	0.00	0.38	0	1
D-share	14,769	0.22	0.00	0.33	0	1
R- or D-active subsample						
R-share	7,373	0.56	0.60	0.35	0	1
D-share	7,373	0.44	0.40	0.35	0	1

Table 2.3 shows the average R-share and D-share[7] in the full sample as well as in the subsample of firm-year observations with positive R&D expenditures. The overall average R-share is 28% whereas the average value is 56% when we only consider firm-year observations in which there were positive R&D expenditures (referred to as R- or D-active subsample in the following). All 17 industries show positive average R and D expenditures. There are differences in the amount as well as the shares between sectors with the chemical and, in particular, the pharmaceutical industry, showing the highest expenditures. High average R-shares ($\geq$40%) can be observed in the latter, but also in the sector including computers, electronics and optical products. See Table A.1.2 for details.

Figure 2.2 shows within-sample correlations between R as well as D expenditures and firm size. For both R and D, there is a strong positive correlation with firm size, supporting the idea that larger firms can afford to spend more. The slope of the linear prediction line is steeper for D

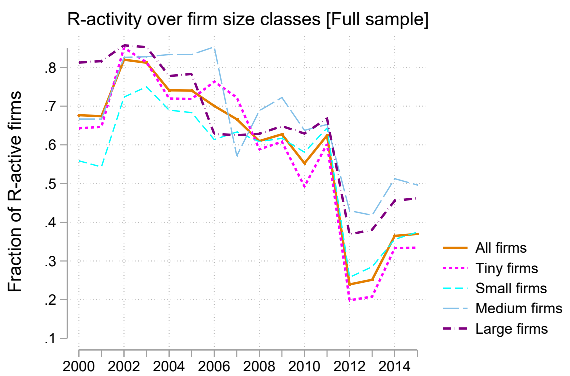
[7] The R-share is calculated as the share in total R&D expenditures devoted to research activities. The D-share is the remaining share in the total.

Figure 2.2: Correlation between firm size and R and D expenditures

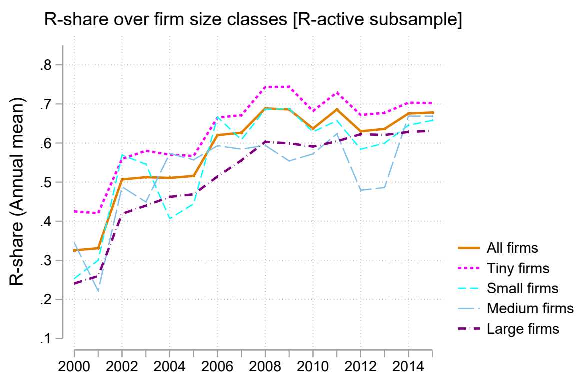


than for R. Departing from this evident relationship, it is therefore interesting to consider relative amounts, i.e. the research share in R&D.

Figure 2.3: Development of the extensive and intensive margin for R-activity



(a) Extensive margin



(b) Intensive margin

Figure 2.3 illustrates the evolution over time of (a) the R-activity of all firms (fraction of observations with a positive R-share, i.e. the extensive margin), and (b) the size of the R-share in the R-active subsample (intensive margin). For a more fine-grained understanding of the attribution of effects to differently sized firms, we distinguish four size classes: tiny firms (< 50 employees), small firms (≥ 50 employees and < 150 employees), medium firms (≥ 150 employees and < 250 employees), and large firms (≥ 250 employees). As can be seen in the left panel, the R-active fraction of observations experienced a sharp decline in 2012. Due to the spending horizon of R&D budgets which stretches over longer cycles, this may be accountable to the delayed aftermath of the global financial and the Euro crisis with firms quitting R or D activities altogether. The right panel visualizes that the R-share of the R-active subsample over all four firm size classes grew over time. However, this growth was particularly strong in tiny and small firms.[8]

Thus, unlike studies that proxy research activity with scientific publications, we cannot confirm that the average research focus – within the R-active subsample – is declining. Rather, we observe that the fraction of research-performing firms is considerably lower at the end of our sample period. This suggests a rise in the concentration of research activities in fewer firms across the economy considered here over time. This is compatible with conclusions from a study for the German economy by Rammer and Schubert (2018) which highlights that the concentration of innovation spending in a smaller number of firms has increased over time, to the context of research activities. Figure A.1.4 shows the corresponding information for D-activity, depicting that the average D-share among D-active firms diminished over time, reflecting the opposite evolution for the R-share. Yet, also for development the proportion of D-active firms has fallen, pointing to an growing concentration of R and D activities in fewer firms.

2.4.2 Analysis of Research Intensity

To investigate the relationship between firm size and the share of R&D expenditures devoted to research when controlling for other firm characteristics, the variable research share (R-share) is used as the dependent variable. Besides firm size measured by the logged[9] number of employees [ln(employees)] as the main variable of interest, we control for the firm's age [ln(age)] in order to not confound size effects with the firm's maturity[10]. Moreover, we account for the level of internal and external R&D expenditures [ln(internal R&D+1), ln(external R&D+1)], and enterprise group association (dummy indicating whether the firm is a single company or associated to a group). A firm's financial situation is likely to affect research efforts and hence we control for liquidity and debt (working capital, long-term debt and short-term debt). We further include the patent application stock as a measure of the firm's knowledge stock (Patent_stock). We follow the standard approach based on Griliches and Mairesse (1984) and compute the stock of each firm and year as a perpetual inventory of past and present patent applications with a constant depreciation rate (δ) of 15 percent:

[8] Appendix Figure A.1.5 accounts for firm characteristics and time trends by including a firm size-year-interaction of the observation period. The rising trend of the predicted R-share over time is still especially strong for tiny and small firms. This is in line with Figure 2.3(b) where firms with fewer than 150 employees as well took the lead in high R-shares.

[9] We applied the natural logarithm. All logged variables with non-negative values were transformed by adding 1 before taking the log. Otherwise, observations with a value of 0 would have been dropped.

[10] It should be noted that age and size are not perfectly correlated in our data. There is a considerable fraction of young and large firms as well as old and small firms. See Figure A.1.3 for the distribution of firm age over size classes.

$$\text{Patent\_stock}_{i,t} = (1-\delta)\,\text{Patent\_stock}_{i,t-1} + \text{Patent\_applications}_{i,t}\,.$$

Sector fixed effects enter as a set of industry dummies, and year dummies capture business cycle effects that are common for all firms and industries.

2.4.2.1 Estimation of the R-Share in R&D

We estimate Ordinary Least Squares models with firm-fixed effects (OLS FE), Generalized Least Squares models with random effects (GLS RE), as well as models for limited dependent variables. The Tobit model accounts for the censoring of the R-share at zero and one, as well as random effects. The fractional response (FR) model directly takes into account that the dependent variable is non-continuous, i.e. a share with limits at zero and one (Papke and Wooldridge, 1996). The log-likelihood function to be maximized in the FR model is

$$\ln L = \sum_{j=1}^{N} w_j y_j \ln\left\{G\left(\boldsymbol{x}_j'\boldsymbol{\beta}\right)\right\} + w_j\left(1-y_j\right)\ln\left\{1-G\left(\boldsymbol{x}_j'\boldsymbol{\beta}\right)\right\}$$

with the functional form for $G(\boldsymbol{x}_j'\beta)$ corresponding to a logit function $\exp\Big(\boldsymbol{x}_j'\Big)/1+\exp\Big(\boldsymbol{x}_j'\Big)$. To additionally capture unobserved firm-specific effects in the FR model, we follow a Mundlak-Chamberlain (FR MC) approach (Mundlak, 1978; Chamberlain, 1982) which relaxes the assumption that covariates must be independent of unobserved heterogeneity (correlated random effects model), and augment the specification by the within-sample means of all covariates (Wooldridge, 2019).

The results from these estimations are shown in Table 2.4. The random effects models (columns 2 and 3) suggest that the R-share indeed declines with the first order term of the variable ln(employees), holding other firm parameters – including the level of R&D expenditures – constant.

That is, larger firms are less research-intensive than smaller ones. The second order term is likewise negative and statistically significant, indicating that the association is negative over the entire firm size distribution in the sample. This negative relationship is similarly pronounced in the fractional response models for both specifications, without (column 4) and with Mundlak-Chamberlain within-sample means (column 5).[11] The fixed effects model (column 1) is less precisely estimated, suggesting that the models capture between-firm variation rather than within-firm variation. Note that there is in fact little within-firm variation in both firm size as well as

[11] The test of joint significance of the within-sample means (MC variables) is highly significant ($\chi^2(8) = 111.49$***).

Table 2.4: Estimations of R-share

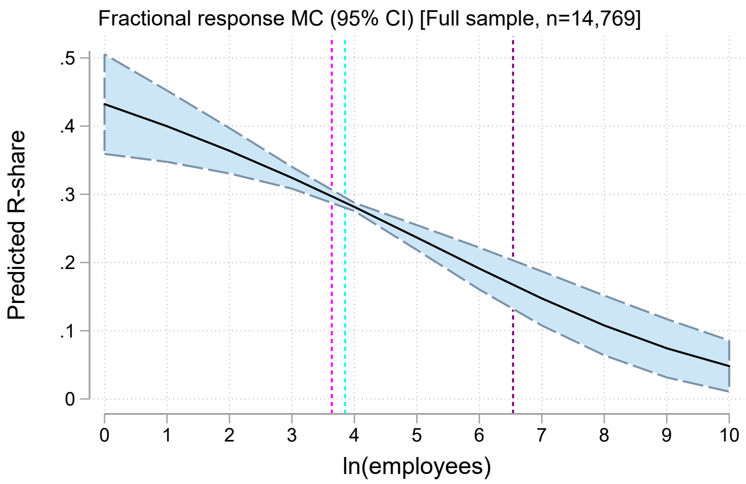
	(1) OLS FE	(2) GLS RE	(3) Tobit RE	(4) FR	(5) FR MC
ln(employees)	0.002	-0.022**	-0.073***	-0.204***	-0.247***
	(0.029)	(0.011)	(0.020)	(0.052)	(0.093)
ln(employees) × ln(employees)	-0.005	-0.001	-0.006**	-0.023***	-0.016**
	(0.003)	(0.001)	(0.002)	(0.006)	(0.006)
ln(age)	0.047	0.013	0.039	0.554***	0.459**
	(0.142)	(0.036)	(0.060)	(0.172)	(0.219)
ln(age) × ln(age)	-0.017	-0.003	-0.004	-0.090***	-0.076***
	(0.036)	(0.006)	(0.010)	(0.028)	(0.029)
ln(internal R&D)	0.096***	0.093***	0.218***	0.596***	0.703***
	(0.003)	(0.002)	(0.003)	(0.008)	(0.018)
ln(external R&D)	0.000	-0.007***	-0.007***	-0.072***	0.002
	(0.003)	(0.002)	(0.002)	(0.009)	(0.014)
Patent stock	-0.000	-0.001***	-0.001***	-0.004***	-0.001
	(0.000)	(0.000)	(0.000)	(0.001)	(0.002)
Working capital ratio⋆	0.000*	-0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Long-term debt ratio⋆	0.000***	0.000*	-0.000	-0.000	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Short-term debt ratio⋆	-0.000	0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Enterprise group dummy	-0.000	-0.016**	-0.034***	-0.236***	-0.222***
	(0.014)	(0.007)	(0.012)	(0.043)	(0.043)
MC ln(employees)					-0.000
					(0.081)
MC ln(age)					-0.003
					(0.188)
MC ln(internal R&D)					-0.111***
					(0.019)
MC ln(external R&D)					-0.115***
					(0.018)
MC patent stock					-0.002
					(0.002)
MC working capital ratio⋆					-0.000
					(0.000)
MC long-term debt ratio⋆					-0.001***
					(0.000)
MC short-term debt ratio⋆					0.000
					(0.000)
Sector FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Pseudo R^2				0.341	0.345
R^2 *within*	0.323				
R^2 *between*	0.604	0.631			
Wald $\chi^2(42)$		5,558.57	6,569.94	8,912.99	8,956.78
F (42, 4372)	28.980				
Observations	14,769 *(full sample)*				

Standard errors in parentheses (clustered at sector level): Note that we apply time-variant sector affiliations in the sector fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.
⋆ Ratio uses fixed assets in the denominator
All values are rounded; 0.000 indicates values of < 0.001.

the research intensity so that we should interpret these findings in terms of between-firm effects.

Since the properties of fractional response model match the nature of the dependent variable

Figure 2.4: Adjusted predictions of R-share over firm size



The vertical dashed lines indicate the sample mean, the median and the 95^{th} percentile.

best, the FR MC method serves as the basis for the visualization of the main effect in Figure 2.4. Figure 2.4 illustrates the main results graphically by displaying the predicted R-share (adjusted predictions) at different values of ln(employees).

2.4.3 Analysis of Productivity

In order to analyze the link between firms' R-share and productivity, we estimate the firms' total factor productivity (TFP) based on a production function approach. The production function is specified as in Equation (2.4.1). Output is measured as the natural logarithm of the firms' annual value added [q]. Note that we do not use accounting profits as a measure for profitability due to their sensitivity to reporting, depreciation and losses carried forward, for instance, which make annual values incomparable over time and between firms. Instead, we estimate TFP using the same set of input factors used to produce a certain value added. One should, however, keep in mind that the added value (i.e. mark-up) that a firm creates also depends on its market power (De Loecker and Warzynski, 2012) which we do not explicitly account for in the following, assuming that the competitive environment is captured by the sector fixed effects.

Capital input is measured by the natural logarithm of firms stock of fixed assets [k], and labor input by the logged number of employees in non-R&D jobs [l] in a given year. As an augmentation to the classical production function, we add R&D activity to the production function which has been shown to explain productivity differences between firms (Doraszelski and Jaumandreu, 2013). More precisely, we differentiate between logged research and development expenditures [research = r, development = d]. Because a large proportion of R&D expenditures is typically labor costs, the use of non-R&D employees as the labor variable allows us to measure R&D input without double counting of R&D expenditures that reflect wages of R&D employees. A central challenge in the estimation of production functions is the correlation between unobservable productivity shocks and input levels (Griliches and Mairesse, 1998), i.e. productivity beliefs which influence the firm's input decisions. The approach by Ackerberg et al. (2015) [ACF] – which we adopt in the following – addresses the potential collinearity problem in earlier productivity estimators like the one by Olley and Pakes (1996) [OP], or Levinsohn and Petrin (2003) [LP] by proposing a functional dependence correction. In the ACF method, firms are no longer assumed not to adjust their labor input immediately when subject to productivity shocks. The input demand function is then conditional on the choice of both labor and capital inputs. Whereas the OP framework uses investment as a proxy for productivity in the control function, LP and ACF use intermediate inputs (materials) instead because investment decisions tend to be implemented in blocks which violates the monotonicity assumption underlying the framework. Not only are intermediate inputs less costly to adjust, they are also more responsive to the entire productivity term and provide a simple link between theory and the estimation strategy because intermediate inputs are not typically state variables. By taking the natural logarithm of the Cobb-Douglas function in Equation (2.4.1), the factor inputs relate in an additive manner. The error term in Equation (2.4.1) has two components: the transmitted productivity component ω_{it}, and u_{it}. The component u_{it} is an unobservable error term that is uncorrelated with input choices, whereas ω_{it} is observable or predictable by firms when making input decisions. Furthermore, β_0 is the mean efficiency level across firms and over time:

$$q_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \gamma r_{it} + \delta d_{it} + \omega_{it} + u_{it}. \tag{2.4.1}$$

Since ω_{it} as a prior productivity belief gives rise to endogeneity (factor choices will depend on it, resulting in a correlation between inputs and ω_{it}), the control function based on intermediate inputs $m_{it} = f(\omega_{i,t}, k_{it}, l_{it}, rd_{it})$ is introduced as a first stage estimation. Inverting this function for $\omega_{i,t}$ and substituting into the production function yields

$$q_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \gamma r_{it} + \delta d_{it} + f^{-1}(m_{it}, k_{it}, l_{it}, r_{it}, d_{it}) + u_{it}. \tag{2.4.2}$$

This provides an estimate of the composite term $\widehat{\Phi}_{it}$ which can be expressed as $\Phi_{it}(m_{it}, k_{it}, l_{it}, r_{it}, d_{it})$ so that a measure for total factor productivity (TFP) can be derived from

$$\widehat{\omega}_{it} = \widehat{\Phi}_{it} - \beta_k k_{it} - \beta_l l_{it} - \gamma r_{it} - \delta d_{it}. \tag{2.4.3}$$

The empirical strategy used here consists of two sequential steps. In the first, we estimate productivity equations on major factor inputs (*K, L, R&D*) which are instrumented as suggested by Ackerberg et al. (2015)[12]. This stage predominantly serves to obtain $\widehat{\omega}_{it}$ while netting out the unobserved part of the error term, u_{it}.

In a second step, we estimate the effect of variation in the R-share on the estimated TFP. We further interact the R-share with firm size to test the hypothesis that the return to research varies with firm size. Because we expect the research orientation to have a delayed impact on TFP, we apply a two-year lag for the R-share. Firm size is measured in contemporaneous values to capture output effects at the firms' current size. Since past productivity has been shown to be a reliable predictor of future productivity (Doraszelski and Jaumandreu, 2013), we also add lags of TFP to the model[13]. In addition, we control for firm characteristics to account for remaining observed firm-level heterogeneity. Unobserved firm heterogeneity is captured by the fixed or random effects. The equation to be estimated can be described as:

$$\widehat{\omega}_{it} = f(R\text{-}share_{it-2}, ln(empl)_{it}, R\text{-}share_{it-2} \times ln(empl)_{it}, controls) \qquad (2.4.4)$$

2.4.3.1 Estimation of TFP and its Relation to the R-share

Figure 2.5: Kernel density of TFP by firm size class

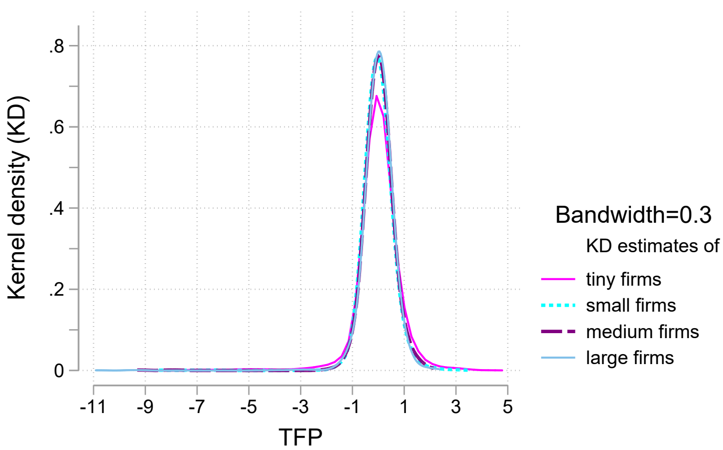


Figure 2.5 depicts the estimated TFP for the four firm size classes and visualizes that there is no strong relationship between firm size and TFP, except for very small firms with less than 50 employees.[14] Appendix Table A.1.3 displays the results from the sector-wise productivity

[12] As a robustness check, we apply the LP estimation method and compare the resulting TFP distribution.

[13] Note that we apply the same lag structure as for the R-share by adding a two-year lag and to capture TFP prior to the included R-share by adding a three-year lag.

[14] A pairwise correlation coefficient of 0.0172, however, significant at the 1% level, indicates that larger firms are more productive when not controlling for further firm characteristics.

estimations in detail.[15]

Table 2.5: Panel estimations of TFP on R-share

	OLS FE	GLS RE	GLS RE	GLS RE	GLS RE	GMM
R-share$_{t-2}$	0.082	0.206***	0.199***	0.283***	0.224***	4.118***
	(0.063)	(0.062)	(0.062)	(0.097)	(0.062)	(1.144)
ln(employees)	-0.352**	-0.034**	-0.024*	-0.012	-0.034**	0.085
	(0.165)	(0.015)	(0.013)	(0.008)	(0.014)	(0.319)
R-share$_{t-2}$ × ln(employees)	-0.018	-0.038***	-0.035***	-0.043***	-0.041***	-0.802***
	(0.014)	(0.013)	(0.014)	(0.016)	(0.013)	(0.268)
ln(age)	-0.163	0.371*	0.195	0.189	0.361*	-22.718**
	(0.592)	(0.192)	(0.134)	(0.151)	(0.196)	(11.425)
ln(age) × ln(age)	0.094	-0.047*	-0.023	-0.024	-0.047*	3.544**
	(0.124)	(0.026)	(0.019)	(0.019)	(0.027)	(1.717)
ln(external R&D)	0.011	0.012	0.010	0.011*	0.011	0.023
	(0.013)	(0.010)	(0.008)	(0.006)	(0.009)	(0.111)
Patent stock	-0.000	-0.000	-0.000	0.000	-0.000	0.005
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.004)
Working capital ratio*	-0.000	0.000	0.000	0.000***	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Long-term debt ratio*	0.000***	0.000***	0.000***	0.000**	0.000***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Short-term debt ratio*	-0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)
Enterprise group dummy	-0.063	0.055	0.044	0.041	0.056	-0.309
	(0.050)	(0.047)	(0.039)	(0.025)	(0.041)	(0.345)
TFP ACF$_{t-2}$			0.242***	0.206***		0.102
			(0.025)	(0.064)		(0.077)
TFP ACF$_{t-3}$				0.106*		-0.005
				(0.061)		(0.073)
Sector FE	Yes	Yes	Yes	Yes	No	No
Year FE	Yes	Yes	Yes	Yes	No	No
Observations	4,847	4,847	4,840	3,379	4,847	3,379

Cluster-robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.
Note that we apply time-variant sector affiliations in the sector fixed effects.
* Ratio uses fixed assets in the denominator
All values are rounded; 0.000 indicates values of < 0.001.

Note the average productivity in our sample is relatively low. This may be due to several factors: First, we have a high fraction of small firms in the data and these are all comparatively R&D-intensive firms which likely excludes firms that are producing at a large scale (and low cost). Besides this, our sample period covers the financial and economic crisis 2008/2009. Another reason may be the relatively high degree of foreign ownership in Belgium leading to profit shifting within company groups which we account for in the regressions by including a group indicator. The resulting productivity distribution is very similar when we replicate the TFP estimation using the LP method. Figure A.1.6 compares the TFP distributions based on both methods.

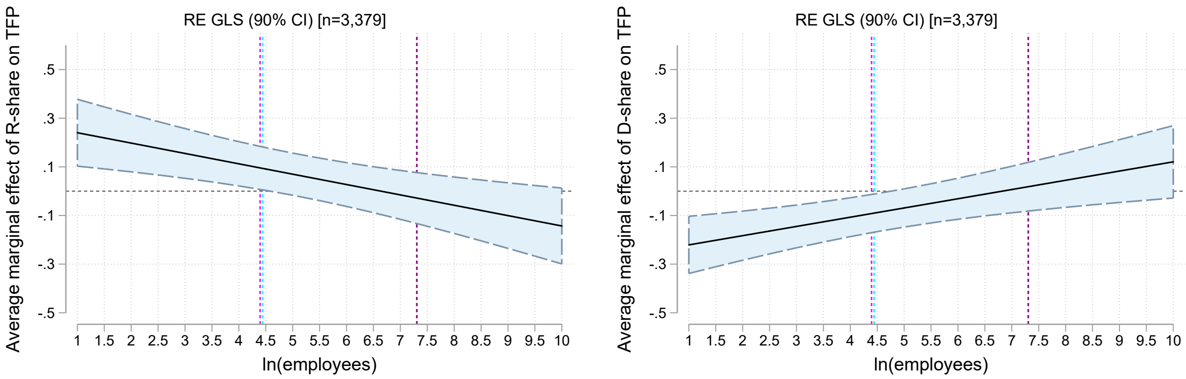
Table 2.5 presents the results from the linear estimation of Equation (2.4.4). The R-share

[15]Separate estimations by sector are standard in the productivity literature and can, for instance, be found in Hottenrott et al. (2016).

significantly contributes to TFP in the random effects specifications. Consistent with prior research, the direction of the effect is such that a higher research share results, on average, in higher productivity (Czarnitzki and Thorwarth, 2012). Considering the interaction term between R-share and ln(employees), we see however that the incremental research premium declines significantly with firm size.[16] Past productivity plays an important role in explaining current productivity even still with a thee-period lag.

Rather than interpreting the results only at the mean of the variables, we look at the average marginal effects of R-share at different values of firm size. Figure 2.6 illustrates that the returns to increasing the R-share are positive but declining up to the mean firm size in the sample (left panel). Beyond the mean, the returns to increasing the research intensity are negative on average, but the marginal effect is not statistically different from zero, indicating no significant harm to productivity. This suggests that for medium-sized and larger firms, an additional percentage point devoted to research (rather than to development) is no longer beneficial for productivity.

Figure 2.6: Marginal effects of R- and D-share on TFP over firm size



(a) R-share on TFP **(b)** D-share on TFP

The vertical dashed lines indicate the subsample mean, the median and the 95$^{\text{th}}$ percentile.

The opposite holds true for D-share (Figure 2.5(b)).[17] Increasing the D-share yields higher returns for larger firms. Both results are in line with the proposition that larger firms find it more profitable than small firms to devote relatively more resources to development activities (and vice versa).

[16] Note that we employ a two year lag between R-share and TFP which leads to a drop in observations to 4,847.
[17] The underlying regression results are presented in Table A.1.4.

2.5 Conclusion and Discussion

This investigation analyzed the link between firm size, research orientation and productivity. While earlier studies discussed the comparative advantages of small versus large firms with regard to product or process innovation, the role of investments in research compared development as drivers of productivity-enhancing innovations remained little explored. Our results confirm the idea that a firm's optimal research focus, i.e. the share of the R&D budget devoted to R, declines with firm size. While larger firms spend more on both R and D in absolute terms, we find that the optimal R-share falls continuously with firm size. Our analysis based on total factor productivity estimations moreover strengthens previous findings that research is a key driver of productivity. However, they further show that the incremental research premium from increasing the research share in R&D by one unit is higher for smaller firms.

The results therefore suggest that a division of labor between smaller and larger firms with larger firms focusing on development may indeed be efficient in terms of expected aggregate productivity gains. This finding supports Baumol's (2002) idea of a 'David-Goliath symbiosis' in which small and large firms contribute at different stages of the innovation process. The study thereby extends prior work that focused solely on research activities (Belenzon and Patacconi, 2014), or shed light on specialization in terms of innovative outputs rather than the returns on investment (Acs and Audretsch, 1987; Henderson, 1990; Henderson and Cockburn, 1996; Macher and Boerner, 2006; Arora et al., 2009).

It remains, however, to be examined in future research how much these results are affected by activities not accounted for in the analysis, like outsourcing of R or D in the form of collaborations or licensing. The possibility to conduct collaborative R&D, i.e. in cooperation with other firms like suppliers and joint R&D with universities, may be a factor that explains the declining returns to carrying out research in-house for larger firms. Furthermore, the possibilities of licensing-in or licensing-out technology have not been explicitly accounted for in our analysis but may affect the modelling of the returns to research for both smaller and larger firms. In this context, we may overlook the role played by opportunities for external knowledge sourcing and therefore over- or underestimate the benefits of labor division. Finally, the results may be context-specific in the sense that they originate from an industry landscape with a high proportion of (very) small firms and a substantial fraction of firms that are part of enterprise groups cannot be generalized to other economies.

The results yield implications for innovation policy. Facilitating labor division may be crucial for maximizing overall productivity gains from private sector R&D operations. The analysis also highlights the important role of small, research-intensive firms in innovation systems for augmenting corporate R&D. Policy instruments may be best designed to strengthen firms' comparative advantages. R&D support programs, for instance through direct grants, may be more effective targeted at research in small firms rather than in larger ones, thereby increasing the returns to public funding of industrial R&D. In light of discussions on the decline in productivity growth in developed economies, this study aims to offer a starting point for a debate and for further research on division of labor in R&D between firms and between firm and public research organizations or universities. A further goal is to draw attention to the role of firm size heterogeneity in the analysis of economy-wide productivity development.

3 | Specialization in Corporate Research and the Market for Knowledge

3.1 Introduction

Technology transfer through collaboration and licensing has been proven to be valuable because it pools firms' complementary capabilities (Mowery et al., 1996), facilitates the internalization of knowledge spillovers (Kamien et al., 1992; Cassiman et al., 2002) and provides incentives for internal R&D for the formation of absorptive capacities needed to benefit from the external knowledge (Kamien and Zang, 2000; Leahy and Neary, 2007).

Knowledge circulation and technology transfer may also facilitate specialization in R&D, since 'markets for ideas' (Gans et al., 2002; Gans and Stern, 2003) and 'markets for technology' (Arora et al., 2001; Arora and Gambardella, 2010b) enable firms to trade research outcomes. For new entrepreneurial firms, for instance, markets for technology can make a focused business model more feasible. Larger and more established firms, on the other hand, may find it more profitable to buy or contract in basic technology that helps them to develop and commercialize their product portfolio. Recent research indeed suggests that smaller firms find it more profitable to specialize in the 'R' component of R&D because of their comparative advantage in research as compared to product development (Becker et al., 2020). While smaller firms often have a smaller market share, larger firms can derive benefits from their market reach and product portfolio, rendering development and commercialization activities relatively more profitable. This gives them a comparative advantage in focusing their resources on product and process development (Mitchell, 1989; Arrow, 1993; Nerkar and Roberts, 2004). An example is the joint activity of the large German engineering company Bosch and the much smaller British company Ceres Power

Author contributions: This chapter is joint work with Hanna Hottenrott.

– a fuel cell technology and engineering company[2] – in the development of fuel-cells with mass manufacturing of multiple applications on Bosch's side, and Ceres contributing its technology via licensing agreements.[3]

While the organizational forms of collaborative R&D and other models of knowledge transfer, such as licensing and contract R&D as well as their benefits for productivity and innovation performance, have been subject to extensive investigation in the economics as well as in the strategic management literature (see e.g. Hagedoorn et al. (2000), Caloghirou et al. (2003) or Hottenrott and Lopes-Bento (2016) for surveys of this literature), rather little attention has been paid to the role of such activities for facilitating specialization in corporate research (or development).

This study therefore focuses on the question whether firms that specialize in research (R) or product/process development (D) are more active in the market for knowledge through collaboration, licensing or external contract R&D than firms with a balanced R and D strategy. Building on a conceptual framework of firms adopting a returns-maximizing innovative strategy, a higher likelihood of an active engagement in the market for knowledge by more specialized firms reflects the complementarity and interdependence between internal R&D provision and technology sourcing. The contribution of this study is to provide first insights into firms' engagement in four vital technology transfer channels, and how they relate to the firms' level of specialization in R or D. We analyze a large sample of firms active in knowledge-intensive industries, and distinguish between four modes of engagement: Collaboration, acquisition of licenses (licensing in), selling of licenses (licensing out), and the commission of contract R&D to external providers. Results from simultaneous equation models that account for the co-occurrence and common drivers of these activities show that in fact a higher share of research expenditures in firms' total R&D (R-share) increases the likelihood of firms engaging in collaborative R&D with other organizations. We also find that firms with higher R-shares are more likely to license in or out technology, and observe a pronounced U-shaped relationship between the R-share and the annual amount spent on R&D contracting, with firms with no internal research or a high R-share spending most.

The remainder of this paper is organized as follows: Section 3.2 outlines the motivation for this research as well as the conceptual framework of our analysis. Subsequently, Section 3.3 describes the data, the econometric model specifications, and the results. Section 3.4 concludes with a

[2]Ceres was founded in 2001 and has a headcount of 191 employees. Bosch was founded in 1886 and has – as of December 2019 – 403,000 employees world-wide.
[3]https://www.bosch-presse.de/pressportal/de/en/press-release-206400.html

summary of the key findings and their compatibility with the existing literature, derives policy implications and gives suggestions to future research.

3.2 Specialization and Incentives for Knowledge Exchange

Multiple motivations drive firms to specialize in the provision of products or services targeted at specific customers or sectors. In general, specialization allows a division of labor in certain tasks and often implies organizational separation. Separate production brings forward specialists who benefit from learning over time and their specialized knowledge enables more efficient processes (Alchian, 1984). Also along the supply chain, firms can vertically diversify and serve as, for instance, specialized suppliers selling to purchasers from other sectors (Pavitt, 1984), or as upstream suppliers vending to firms further downstream in so-called vertical markets (Arora and Gambardella, 2010b).

While these considerations regarding the production of tangible goods or services are well established in the economic literature, the increasing importance of intangible assets draws attention to specialization in the production of knowledge. Few studies so far document an rising specialization in knowledge creation which has the potential to fuel corporate innovative labor division (Becker et al., 2020), where 'specialized firms produce and sell knowledge to other firms which accumulate them [knowledge assets] to build new competences' (Guilhon, 2010, p. 166). A growing number of studies moreover shows that external knowledge sourcing (externally contracted R&D and technology licensing) and collaboration have become increasingly wide-spread, suggesting major benefits for firms from engaging in such activities (Cassiman and Veugelers, 2006; Abramovsky et al., 2009; Arora and Gambardella, 2010b; Grimpe and Kaiser, 2010; Añón Higón et al., 2018). We know, however, still relatively little about the role of gains from specializing as a driver of such activities.

As illustrated by the Bosch-Ceres example, smaller firms often act as specialized suppliers who lack own downstream infrastructure for production and marketing but – by their expertise through own technological advances – are capable of assessing the value of external technology that they can provide for others (Grimpe et al., 2019). Rocha (1999) finds that technologically specialized, often smaller firms cannot internally access some knowledge-intensive assets on grounds of skills shortage or underdeveloped product diversification. This deficiency makes them likely to engage in cooperations with partners who can provide these assets. Similarly, Hagedoorn and Schakenraad (1994, p. 306) argue that 'one partner, usually a large company, contracts another company, frequently a small specialized R&D firm, to perform particular research projects'. In this vein, Gans et al. (2002) contrast smaller research-oriented firms with larger more established firms, and Hall and Ziedonis (2001) depict small firms as vendors of intellectual property, and, in particular, patents as factors of income making specialization in patent production profitable to them. An empirical examination of patent flows and firm size by Figueroa and Serrano (2019) observes that for small firms, internal relatedness of prior and subsequent sold patents is negatively associated with patent sales. Unlike large firms, small firms vend patents that do not show close technological relationships, and this dissimilarity to previous inventions seems to be the reason for offering them as a commodity. This finding hints to a link between specialization and engagement in the market for knowledge.

Recent research also suggests that there is a division of labor along the knowledge production process with smaller firms finding it more profitable to engage in (basic) research, while larger firms derive larger productivity gains from product or process development (Becker et al., 2020). The dependency of this innovative labor division on firms' external knowledge sourcing has, however, not been addressed in earlier research. For both smaller and larger firms who specialize in research or development, engagement in technology transfer or exchange is a crucial precondition for being able to reap the gains from specializations.

Thus, for specialization in (basic) research or product development to be profitable and a sustainable strategy, markets for technology are crucial (Arora et al., 2001; Arora and Gambardella, 2010b). They facilitate the trading of knowledge goods and hence determine the returns of specialization. While the market for technology is often defined relatively narrowly referring to the trade of technology via licenses (Arora et al., 2001; Arora and Gambardella, 2010b), in the context of this study, we will understand this market more broadly, i.e. including other contracts that specify the exchange of knowledge, ideas or research outcomes which are neither transmitted easily nor commodified as explicit blueprints (Nelson and Winter, 1985; Guilhon, 2001b).[4] In the following, we refer to it as the 'market for knowledge'.

3.2.1 The Market for Knowledge

The quality and reliability of the exchange between supply and demand of knowledge depends on a functioning market mechanism: 'Markets allow knowledge producers to sell the knowledge

[4]Frequently used synonyms for the trade of intellectual assets are the market for innovation, know-how and knowledge (Teece, 1998; Arora et al., 2001; Hall and Ziedonis, 2001; Gans and Stern, 2003; Gans et al., 2008; Arora and Gambardella, 2010b; Gans and Stern, 2010; Guilhon, 2010; Agrawal et al., 2015).

itself instead of developing complementary assets in, for example, distribution, manufacturing, or servicing for the purpose of commercializing that knowledge on the product market.' (Grimpe et al., 2019, p. 8). When we think about specialization in research or development, we therefore need to consider that trading knowledge requires some formalization of it in order to make it a tradeable good. Typical models of achieving this are licensing (in or out) of patented technology, collaboration agreements (formal or informal), as well as contracts that specify R&D services to be pursued by external organizations, sometimes also referred to as 'R&D procurement'[5].

When comparing the market for know-how with the market for pollution rights and the market for arts, Teece (1998) shows that these markets possess overlapping properties. Among these are the existence of selection and transfer costs, externalities, uncertainty, information asymmetry, difficulty in estimating production costs and asset quality, and adverse selection. These properties result in market imperfections.

Arora and Gambardella (2010a) point out the public good nature of knowledge through its spillovers, which provide involuntary knowledge transfer, and thereby impact incentives for knowledge production as well as voluntary or intended transactions. A formal exchange of knowledge goods through an inter-firm division of innovative labor via licenses, collaboration or contract R&D does not only transform spillovers into a pecuniarily compensated form of externality but also demonstrates that knowledge transmission can be market-mediated. However, unlike the circulation of tangible goods on formal markets[6], the use of ideas is not rival as well as their exchange is neither completely reproducible nor easily standardizable (Gans and Stern, 2010). Therefore, ideas exchange requires organizational mechanisms (Teece, 1998; Guilhon, 2010; Teece, 2010).

Patents and other formal forms of intellectual property rights (IPR) therefore play an important role in markets for knowledge. They are sometimes even an essential precondition for trading inventive outputs. On these grounds, Gans et al. (2002) stress that the effectiveness of an IPR regime also affects how well the ideas exchange or technology trade works. The more enforceable the IPR, the less threatening the risks of idea disclosure from and expropriation potential to both cooperators and competitors. Collaborations or negotiations over the sale of an idea inevitably involves a disclosure risk. This can erode the bargaining position, for instance of the young or small firm, and reduce the larger firm's willingness to pay. The IPR regime thus impacts absolute expected returns of innovation as well as relative returns to technology sourcing or trade (Gans

[5] https://www.pharmaceuticalprocessingworld.com/the-new-role-of-rd-procurement-in-pharma

[6] A clear distinction of the interplay between the market for technology and the market for products is illustrated in Aoki and Schiff (2008).

and Stern, 2003). Formal protection may also help collaboration as it secures IP, and hence reduces the expropriation risk associated with collaboration in key firm functions such as R&D. The more secure formal property rights, the lower the risk of knowledge leakage, litigation and misappropriation, and the higher the incentives to participate in the market for ideas (Gans et al., 2008). Formal IPR are therefore not only a necessary condition for licensing, but also are valuable for collaborative R&D and contract R&D as they facilitate assigning clear property rights.

However, Hall et al. (2014) point out the differences between formal and informal intellectual property and highlight that it is a fraction of innovative companies that only relies on formal IPR like patents to protect their inventions. Informal protection, e.g. non-disclosure agreements, trade secrets, and a 'nonexpropriation reputation' of knowledge-purchasing firms (Gans et al., 2002), play an important role for non-patentable goods vulnerable to expropriation in inter-organizational transfer transactions. Thus, the market for knowledge can be seen as an extension of technology markets that rely solely on licensing.

3.2.2 Knowledge Sourcing as an Innovation Strategy

The emphasis on knowledge production, as well as the emergence of and trade on the market for knowledge is essential for understanding firm specialization and exchange. Knowledge acquisition is based on specialized and differentiated knowledge[7], whereas transdisciplinary knowledge[8] makes knowledge comprehensible to various agents (Postrel, 2002; Guilhon, 2010). By separating these knowledge types, Gambardella et al. (2001) contrast corporate knowledge exploration against knowledge exploitation. They suggest that for the single firm, however, it is not necessary to exclusively specialize in knowledge exploration and production, as applies to e.g. research laboratories. By strategically choosing relative specialization, firms operate as both, knowledge and industrial producers, being active on the market for knowledge as well as the market for products, respectively (Guilhon, 2010).

3.2.2.1 The Cost-Benefits Trade-Off

Inter-firm transmission of ideas can take multiple modes of which some vary in the prerequisites and degrees of formality (Arqué-Castells and Spulber, 2018). Studies differentiate in the sourcing of knowledge between three strategies: Make, buy or ally (Rocha, 1999; Audretsch and Belitski, 2020). 'Make' defines the vertically integrated in-house provision of knowledge and technology,

[7]Guilhon (2001a) terms it 'instrumental knowledge' which can be further used as an input factor.
[8]Guilhon (2001a) terms it 'interpretative knowledge'.

whereas 'buy' demarcates extra-mural sourcing or even imitation by reversely engineering products. 'Ally' refers to an inter-firm relationship with sometimes recurrent interaction. To 'ally' implies partnerships as in R&D collaborations or cooperation and joint R&D (Hagedoorn, 1993). A common example for 'buy', external sourcing or outsourcing, is licensing in which implies that knowledge is incoming from the purchaser's perspective. This is the opposite of licensing out, that is when knowledge is outgoing from the vendor's perspective (Mariti and Smiley, 1983). Both 'buy' and 'ally' strategies are 'boundary-spanning knowledge linkages' (Love et al., 2014) and can be summarized under the terms knowledge and technology transfer.

The engagement in knowledge transfer hence affects the extent to which firms engage in 'Make'-type activities, and a labor-divided knowledge transfer between firms brings cost benefits to vendors and recipients. Vendors bear expenses for the installation of research-specific equipment, etc. (Bartel et al., 2014) but avoid duplicate investments in commercialization, e.g. manufacturing expertise, distribution channels or brand names (Teece, 1986; Gans et al., 2002). Recipients participate in the latest technologies without costs sunk in imitative research programs necessary for 'catching-up' (Gans and Stern, 2003), and can avoid the fixed costs incurred to the vending firm (Bartel et al., 2014). Bartel et al. (2014) further stress that outsourcing requires some fixed costs and fixed transaction costs in search for compatible suppliers which makes large firms more likely to engage in one-directional technology transfer on the purchasing side. This cost view on extra-firm sourcing complements groundwork on transaction costs (Coase, 1937; Williamson, 1971; Teece, 1980; Pisano, 1990), with firm size pre-allocating the roles of knowledge producers and recipients.

Outsourcing (in the sense of external R&D) and collaboration may however serve differing functions: A clear advantage of sourcing R or D externally is cost economizing (Hagedoorn, 1993; Adams, 2005), while joint R&D can substantiate technological complementarity (Mariti and Smiley, 1983; Hagedoorn and Schakenraad, 1994), gives access to dissimilar competencies in more specialized firms (Rocha, 1999), overcomes financial constraints (Czarnitzki and Hottenrott, 2017) and pools risks (Abramovsky et al., 2009).

3.2.2.2 R and D Strategy Choice

Complementary assets are at the forefront of inter-firm resource pooling; they come into play when the value of an asset is a function of its use in conjunction with other assets, which might be a consequence of evolving in parallel during co-specialization of firms (Pitelis and Teece, 2010). At the extreme end, complete co-specialization, complementary assets are more valuable in combined deployment, with value convergence towards zero in isolation, and a high value in joint use (Pitelis and Teece, 2010). It is known from the standard analysis of production that economies of scope cause this cost efficiency: When activities can share inputs at no additional cost, the costs of conducting two or more activities jointly are lower than if they are conducted separately (Henderson and Cockburn, 1996). Firms can reuse the knowledge asset gained through knowledge production as a productive input to other related programs, at little or no additional cost to the firm. This 'idea complementarity' reverses for downstream users, since ideas' interdependence necessitates them to access multiple ideas in combination to extract value from a single idea (Gans and Stern, 2010).

Comparisons of firms with pure and mixed innovation strategies, i.e. combining internal, market-mediated and joint knowledge provision, can bring forward whether and which firms are specialized, and how much they depend on inter-firm versus intra-firm knowledge production (Guilhon, 2010). In the theoretical literature, drawing from transaction costs economics and property rights, make-or-buy innovation decisions replace each other interchangeably with a net effect of zero (Coase, 1937; Arrow, 1962). From a resource-based view of the firm, internal knowledge production improves external acquisition by maintaining a certain level of absorptive capacity and overcoming the 'Not-Invented-Here' syndrome (Veugelers and Cassiman, 1999). According to Rocha (1999), firms that are more specialized are in need to access necessary complementary and dissimilar assets which strengthens the relation between the specialization of firms and the propensity to cooperate. Taking firm size into account, Baumol (2002) considers the outcome of technology transfer between smaller and larger firms to be characterized by a 'superadditive complementarity' and argues that growth is enhanced by vertically disintegrated labor division. The body of literature on technology transfer indeed shows that there are substantial benefits to external knowledge sourcing. In a study of Belgian firms across different sectors, externally conducted R&D stimulates intramural investments when measuring innovative performance (Cassiman and Veugelers, 2006), thus confirming a complementarity effect. Laursen and Salter (2006) analyze data of firms in the U.K. and find that internal R&D is replaced by external knowledge sourcing, hence confirming a substitution effect. Using firm-level data in the German manufacturing sector, Schmiedeberg (2008) examines internal R&D, R&D contracting and R&D cooperation with the result that there are significant complementarities between intramural R&D and R&D cooperation. Own innovation activities are hence not crowded out but reinforced by an ally.

Other papers find that R&D is more effective in the presence of both internal R&D and formal R&D collaboration (Grimpe and Kaiser, 2010). It can be the level of in-house R&D investment that determines whether external R&D is complementary to internal R&D (high) or a substitute for it (low) (Hagedoorn and Wang, 2012), and buyer's characteristics that moderate R&D effectiveness, such as absorptive capacity, economies of scale and licensing experience (Ceccagnoli et al., 2014). Further studies investigate the complementarity between internal R&D activities and innovative input from different sources. In a panel analysis of Spanish firms, García-Vega and Vicente-Chirivella (2020) find university technology transfer to improve corporate innovativeness by boosted innovative output, measured in patents, product and process novelties. Audretsch and Belitski (2020) examine a British time-series data set on the firm-level and review firms' innovation strategies (make, buy, ally). They demonstrate that 'buy'-type firms have lower internal R&D spendings in the presence of high regional or industry knowledge spillovers. While this effect presents a substitution of own R&D investments with spillover transmission, the context of productivity estimation has shown that intramural R&D and spillovers work complementary and increase labor productivity. In this line, Añón Higón et al. (2018) test a Spanish manufacturing panel for complementarity of internal versus external R&D as innovation strategies. They find firm size to be the determinant in high-tech sectors: While for large firms, internal crowds in external R&D, for small firms internal and external R&D efforts substitute each other.

These insights suggest that the option to source technology externally through R&D contracting, collaboration or licensing, affects firms' internal R&D orientation. In other words, firms focusing on development (rather than research) internally, may do so if they can source research externally and vice versa. When comparing internal R&D investments and several modes of engagement in the market for knowledge, we have to take into account that internal R and D decisions as well as collaboration, licensing and contracting activities are not independent from each other. The following analysis is consequently interested in how corporate technology transfer is related to firms' specialization in a certain type of own knowledge production. Understanding such firm-specific behavior can be informative for understanding patterns in R&D spending across firms, and for assessing the role of functioning markets for technology and ideas in knowledge-based economies.

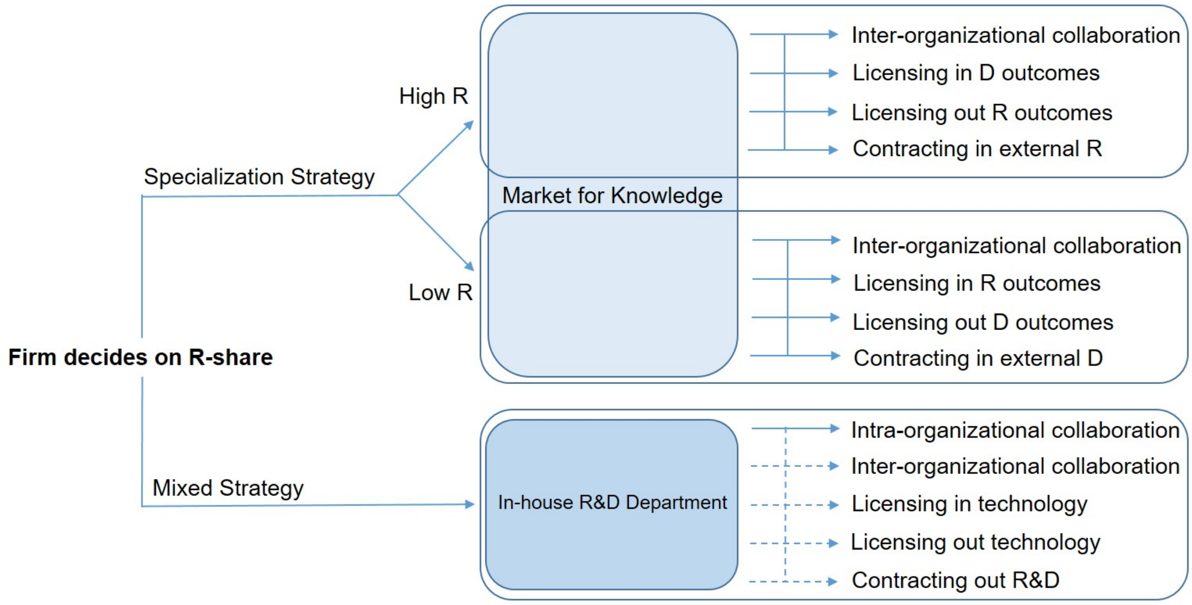
3.2.3 Specialization in R and D

Previous studies typically analyzed R&D in its compound form. However, characteristics usually attributed to R&D in general, such as intangibility and outcome uncertainty, are in fact more applicable for the 'R' component of R&D than to 'D' (OECD, 2015). Provided that opportunities for knowledge and technology transfer exist, it may not be required for each single firm to be engaged in both R and D, and if they do, they may still focus relatively more (or less) on one activity. Research comprises the analyses of fundamental principles and phenomena (Martinez-Senra et al., 2015). While it aims at generating and pioneering novel concepts and tests hypotheses, theories or laws, it usually does so without a specific commercial application in mind (OECD, 2015). Development activities deal with the application of already established knowledge and typically aim at improving existing products. Both are therefore separate but highly related activities. Rosenberg (1989), Kline and Rosenberg (2009), and Hottenrott et al. (2017) acknowledge that R and D are interdependent activities, with both contributing to innovation outcomes (Griliches, 1985; David et al., 1992; Fleming and Sorenson, 2004).

From this perspective, it seems crucial to distinguish between the R and D component of R&D when analyzing firms' innovation efforts and their engagement in technology and knowledge transfer (Czarnitzki et al., 2009; Czarnitzki et al., 2011; Barge-Gil and López, 2015; Becker et al., 2020).

Figure 3.1 presents the conceptual framework for the following analysis. It outlines our assumption that firms decide on their R and D investments such that they select a strategy expressing a certain level research intensity (R-share). In doing so, they choose from a a High R or Low R strategy (specialization in R or D, respectively), or a mixed strategy in which they conduct a certain amount of both. This strategic choice affects the options available to them both internally (lower panel), and externally in the market for knowledge (upper panel). When picking a specialization strategy, the potential for internal collaboration in the firm's own R&D department is limited and channels of external knowledge sourcing grow in relevance to firms. Within their strategy choice, firms consider the costs and benefits of engaging in a specialized versus mixed strategy. In line with theoretical arguments in Hottenrott and Lopes-Bento (2016), we propose that engagement in knowledge sourcing comes with transaction costs, disclosure costs and costs stemming from contract monitoring. These costs are higher when engaging with external partners compared to pursing R and D in-house through separate departments. However, as argued above, firms carrying out R&D in a self-sustained manner are less likely to reap benefits from specialization. Thus, firms are assumed to trade off costs against benefits when choosing their strategy in the research orientation stage, and conditionally on a specialized strategy, in the market for knowledge stage.

Figure 3.1: Conceptual framework: Research strategy and knowledge sourcing



Based on the discussion above, we derive the following four hypotheses on the relationship between in-house R versus D focus and engagement in technology transfer activities:

Hypothesis 1: *Firms that specialize in research, i.e. have a higher R-share in total R&D, are more likely to collaborate with other organizations.*

Hypothesis 2: *Firms that specialize in research, i.e. have a high R-share in total R&D, are more likely to purchase technology via the market for technology through licensing in.*

Hypothesis 3: *Firms that specialize in research or development, i.e. have either a low or a relatively high R-share in total R&D, are more likely to sell technology via the market for technology through licensing out.*

Hypothesis 4: *Firms that specialize in research or development, i.e. have either a very low or a relatively high R-share in total R&D, spend more on external R&D.*

3.3 Data and Estimation Strategy

3.3.1 Data Description

The empirical study relies on data from three sources: 1) the Flemish part of the Belgian OECD R&D survey, 2) the Thomson/Reuters Belfirst database, and 3) the European Patent Office's (EPO) PATSTAT database. The OECD R&D survey is conducted biannually across OECD countries and collects yearly information in order to compose the OECD Main Science and Technology Indicators. The data in use for this paper stem from the permanent inventory of all R&D-active firms[9] in Flanders and captures a major portion of R&D activity[10] in the region.

The OECD survey also delivers information on technology transfer activities. In particular, firms were asked to indicate whether they bought or sold licences during the reference period, engaged on collaborative R&D or had contracted out R&D tasks to external parties. Moreover, the survey collects annual values for internal R&D expenditures and the expenditure shares devoted to basic and applied research, and (experimental) development. We augment the survey data with firms' financial statements to gather information on liquidity and the debt situation. For this purpose, accounting and balance sheet data from the Thomson/Reuters Belfirst database were extracted and merged based on the VAT identifier information. This data also contains information on the incorporation date, the sectors of activity, and the ownership structure of firms included in the survey. The data set entails information on all size classes, even on small, non-listed companies, since all Belgian limited liability firms (except for financial institutions, insurance companies, exchange brokers and hospitals) had been legally required to file annual accounts with the National Bank during the period under consideration. Lastly, the EPO's PATSTAT database is used to calculate each firm's patent stock[11].

Table 3.1 provides an overview of the full sample consisting of 14,769 firm-year observations from 4,373 unique firms. The data set has a panel structure for a time series of 16 years (2000-2015) and was sampled over 17 different sectors, predominantly manufacturing and knowledge-intensive service industries (see Appendix, Table A.2.1). The table shows the technology transfer (TT) variables by engagement modes: Collaboration[12], licensing, and contracted R&D which will be referred to as external R&D. The subsamples of the TT variables are available for an overlapping time period: While information on collaboration and external R&D is available for the entire time series of 16 years, the licensing status is captured by the survey for ten years (2004-2013).

[9] Firms are considered to be R&D-active (population of approx. 12,000 firms per wave) based on previous surveys, accounting reports and government information about the application for R&D grants and tax credits. The response rate varies by year around 75% across all firms and up to 98% for the top 200 R&D firms. Details are available at https://www.vlaamsindicatorenboek.be/2.2.1/methodologie. Information on each wave is documented at: https://www.vlaamsindicatorenboek.be/vorige-edities.

[10] The documentation estimates that included firms cause approximately 90% of all regional R&D expenditures.

[11] Invention patent applicants based on names and addresses are matched. To prevent redundant counting of patents filed at several patent offices around the globe, we further account for patent families. The complete patent stock of each firm dating back to its first application has been retrieved, such that the format of the patent data is a time series for each company.

[12] We conduct a confirmatory principle component factor analysis on the six different collaboration types captured by the survey (Collaboration with competitors, with customers or suppliers, with universities and research organizations or with consultants. Table A.2.2 presents the factor analysis results (Eigenvalues and factor loadings) which confirm that there is a high correlation between the different types, so that they essentially map into a single factor. The Cronbach's alpha, i.e. scale reliability coefficient, is 0.8562, suggesting a high internal consistency.

Table 3.1: Sample details

	Observations	Firms	Share (full sample)
Full sample	14,769	4,373	100.00%
Information on collaboration (2000-2015)			
Collaboration subsample	11,242	3,213	76.17%
Collaboration-active subsample	2,228	730	15.09 %
Information on licensing (2004-2013)			
Licensing subsample	6,191	1,830	41.94 %
Licensing-active subsample	681	275	4.61 %
Information on contract research (2000-2015)			
External R&D subsample	14,769	4,373	100.00%
External R&D-active subsample	3,114	988	21.09%
Information on technology transfer			
TT subsample: Collaboration or licensing	11,360	3,231	76.97 %
TT subsample: Collaboration and licensing	6,073	1,785	41.15 %
TT-active subsample: Collaboration or licensing or external R&D	4,063	1,239	27.51 %
TT-active subsample: Collaboration and licensing and external R&D	231	87	1.56 %

In the final sample, 14,769 observations have information on external R&D, 11,242 observations provide information on the activity status of collaboration, and 6,191 observations on licensing (licensing in and licensing out of technology). In these subsamples, 20% of observations (2,228 out of 11,242) are actively engaged in collaboration, about 11% of observations engage in licensing (681 of 6,191), and about 21% (3,114 observations out of 14,769) commission external R&D.

Table 3.2: Matrix of interdependent observations in TT subsamples

Collaboration	**Licensing**					
	0		**1**		**Total**	
0	4,918	89.26%	324	57.55%	5,242	86.32%
1	592	10.74%	239	42.45%	831	13.68%
Total	5,510	100.00%	563	100.00%	6,073	100.00%
Collaboration	**External R&D (activity status)**					
	0		**1**		**Total**	
0	7,683	92.10%	1,331	45.90%	9,014	80.18%
1	659	7.90%	1,569	54.10%	2,228	19.82%
Total	8,342	100.00%	2,900	100.00%	11,242	100.00%
Licensing	**External R&D (activity status)**					
	0		**1**		**Total**	
0	4,045	93.14%	1,465	79.27%	5,510	89.00%
1	298	6.86%	383	20.73%	681	11.00%
Total	4,343	100.00%	1,848	100.00%	6,191	100.00%

Aggregating the collaboration and licensing subsample observations to firms, there are 3,213 unique firms involved in collaboration, and 1,830 unique firms in licensing, which provides status information on 76.17% and 41.94% of the sample, respectively. Joint status indications on collaboration, licensing and external R&D have been collected for 4,063 observations (1,239 unique firms). The matrix in Table 3.2 breaks down observations in the subsamples of collaboration, licensing and external R&D, and their activity status which is dichotomously measured. An activity status of 1 describes active engagement, 0 implies that the observation was inactive in a specific form of technology transfer. It becomes visible that there is a high share of firms active in licensing in parallel engages in collaborative R&D (42.45%). More than half of the observations conducting collaborative R&D also contract in external R&D (54.10%). For those firms engaged in licensing, the link to external R&D is less pronounced, although still around 21% of licensing-active observations also have external R&D contracts. These patterns illustrate that firms often operate at multiple engagement modes of TT and underline the importance to analyze them in a joint framework which accounts for the interdependence between specialization strategy and transfer channel.

Table 3.3: Descriptive statistics of main variables by sample

	Collaboration subsample		**Licensing subsample**		**Full sample**	
	Mean	Sd	Mean	Sd	Mean	Sd
Collaboration	0.20	0.40	*	*	*	*
Licensing in	*	*	0.07	0.26	*	*
Licensing out	*	*	0.06	0.24	*	*
External R&D (activity status)	0.26	0.44	0.30	0.46	0.21	0.41
External R&D (expenditures)[1]	900.45	16,983.22	1,005.72	19,898.14	695.10	14,823.20
R-share	0.34	0.39	0.40	0.39	0.28	0.38
Research expenditures[1]	1,038.72	7,789.72	1,161.86	8,463.96	829.75	6,838.47
Development expenditures[1]	1,322.00	14,775.35	1,231.51	12,513.81	1,057.73	13,000.10
Patent stock	4.31	42.73	4.81	41.97	3.33	37.33
# total employees	222.62	727.24	230.38	712.71	195.81	678.01
Age	28.42	19.36	28.43	19.67	27.28	18.74
Enterprise group dummy	0.65	0.48	0.65	0.48	0.66	0.47
Fixed assets[1]	54,169.14	415,846.17	58,590.95	458,320.40	42,755.44	364,157.88
Working capital[1]	11,072.87	52,681.58	12,099.48	57,900.25	9,431.60	47,947.05
Long-term debt[1]	13,022.59	160,529.12	6,210.16	132,811.57	11,542.39	145,766.71
Short-term debt[1]	14,253.96	116,705.27	7,542.47	108,254.34	13,451.38	104,824.01
Observations	11,242		6,191		14,769	

[1] Measured in € 1,000
* There are no values for the respective sample since the TT activity status is not available for all observations.

Table 3.3 presents descriptive statistics of the main variables for the collaboration subsample, the licensing subsample, and the full sample. We differentiate licensing by whether licenses are bought or sold by a firm (licensing in: focal firm is licensee; licensing out: focal firm is licensor). Since the primary metric[13] of the four TT variables, collaboration, licensing in, licensing out, and external R&D, is the binary activity status (1 - active, otherwise 0), their mean value is a fraction within the interval between 0 an 1. Licensing in is slightly more common than licensing out. The fraction of observations with external R&D is slightly higher in the licensing subsample

[13] Except for external R&D which is available as both, dichotomous and intensity (expenditures).

than in the collaboration subsample which may simply be due to sample composition and a response bias in the direction of firms with a more open innovation strategy. In the licensing subsample, we also observe higher expenditures for external and internal R&D (summing up the separate spendings for research and development), higher patent stocks as well as a higher share of research in R&D expenditures.

We account for this by controlling for firm characteristics in the following analyses. These characteristics are firm size (measured by the total number of employees), firm age, whether the firm belongs to an enterprise group, the value of fixed assets as a measure of tangible assets, and its patent stock as a measure of intangible assets. We follow Griliches and Mairesse (1984) in the calculation of the patent stock. A firm's patent stock experiences a constant rate of obsolescence, δ, of 15 percent per year such that: $\text{Patent\_stock}_{i,t} = (1-\delta)\,\text{Patent\_stock}_{i,t-1} + \text{Patent\_applications}_{i,t}$. Controlling for the firms' patent stock is crucial since – as argued above – it is major determinant of the engagement in knowledge and technology transfer activities. In addition, we control for the value of working capital, long-term debt and short-term debt as measures for firms' financial situation. The average firm size amounts to 200 employees, indicating that a large share of firms in our sample are Small- and Medium-sized Enterprises (SME)[14] (European Commission, 2015). The average firm age is around 28 years.[15]

The key variables of interest are the measures that capture a firm's orientation towards research versus development. The R-share is calculated as the share of total R&D expenditures devoted to research activities. The mean R-share for the full sample is 0.28, whereas the mean is 0.34 and 0.39 when we consider the TT subsamples of collaboration and licensing. This bears observational evidence that the relative capacities devoted to knowledge production, the R-share, are higher when the TT status is known. We deconstruct firms' internal R&D spendings into research and development expenditures in order to derive absolute investments of a firm in addition to the relative R-share. Research and development expenditures[16], as well as all monetary variables are displayed in €1,000. The average research expenditure is lower than the average development expenditure in all samples. These numbers also confirm that the total amount of internal R&D is overall larger than the amount spent on external R&D. Yet, it is almost as much as what firms spend on in-house research in our sample.

[14]The European Commission sets an upper limit of 250 employees for micro, small and medium-sized enterprises.
[15]Note that firm size and age are not perfectly correlated in our sample. The majority of firms in the dataset, SME, stretches over all age classes.
[16]They are derived as the R-share and D-share multiplied by total internal R&D expenditures.

We observe at least some activity in each TT engagement mode and industry, with collaboration and external R&D being more common than licensing across all sectors. Collaboration is most common in 'other manufacturing'[17] (39.44% of firms in the subsample), Computers Electronics (35.22%) and the chemical industry (33.83%). Licensing in is most common the Pharmaceutical Industry (22.99%), Computers Electronics (35.22%), but also in Education, Health and Public services (13.16%). Licensing out is also relatively frequent in Education, Health and Public services (18.42%) as well as in 'other manufacturing' (16.33%). The proportion of observations that are active in external R&D is comparatively high in all sectors except Building & Construction (only 8.81%), and overall highest in manufacturing sectors. Table A.2.1 reviews the distribution of the TT activity over the 17 sectors in detail.

In the following, we measure a firm's specialization into R or D by the R-share, while controlling for the level of investment in both research and development. We account for both since higher spendings on research do not necessarily translate into a higher R-share. If development expenditures are higher than those for research, the R-share will still be smaller than the D-share, at any level of R and D spending.

3.3.2 Method

As outlined above, firms can (and do) choose multiple modes of engagement in the market for knowledge. The decision for each of the alternatives might be influenced by common unobservable factors, such as firm-specific characteristics, or even the individual preferences of managers. While estimating a single probit equation for each engagement mode provides consistent estimates, the simultaneous estimation that takes into account the full covariance structure, is generally more efficient as it reflects that different choice variables are not independent from each other. We therefore estimate a 4-equation multivariate probit model that can be written as a simultaneous system of equations

$$
\begin{aligned}
y_m^* &= \boldsymbol{x}_m \beta_m + \varepsilon_m, \quad m = 1, \ldots, 4. \qquad (3.3.1)\\
y_m &= I(y_m^* > 0), \quad m = 1, \ldots, 4.\\
\epsilon &= (\varepsilon_1, \ldots, \varepsilon_4)' \sim N(0, \Sigma)
\end{aligned}
$$

where m represents the decision space of engaging in collaboration, licensing in or licensing out of technology, or to pay for external R&D via contract research. The variance-covariance matrix

[17] Includes manufacturing sectors except Paper, Chemicals, Pharmaceuticals, various Materials, Machine and Equipment manufacturing, Computers, Electronics, Optical products as well as Transport Manufacturing.

Σ has values of 1 on the diagonal due to normalization and correlations $\rho_{jk} = \rho_{kj}$ as off-diagonal elements. The log-likelihood function is then given by

$$lnL(\beta_1, \ldots, \beta_4, \Sigma; y \mid \boldsymbol{x}) = \sum_{i=1}^{N} ln\Phi_4 \left(\left(q_{i1}\boldsymbol{x}_{i1}\beta_1, \ldots, q_{i5}\boldsymbol{x}_{i4}\beta_4 \right); \boldsymbol{\Omega} \right) \tag{3.3.2}$$

where $q_{im} = 2y_{im} - 1$. The matrix $\boldsymbol{\Omega}$ has values of 1 on the diagonal, and $\omega_{jk} = \omega_{kj} = q_{ij}q_{ik}\rho_{jk}$ for $j \neq k$ and $j, k = 1, \ldots, 4$ as off-diagonal elements. Φ_4 denotes the joint normal distribution of order 4. The expression for lnL thus involves a 4-dimensional integral that does not have a closed form. It can be evaluated numerically through simulation. We employ the Maximum Simulated Likelihood Method (MSL) using the GHK simulator formulated by Geweke (1989), Keane (1994), and Hajivassiliou and McFadden (1998), for a detailed description of simulation methods, we also refer to Train (2009). The MSL estimator is consistent if the number of draws R rises with N. It is also efficient if R rises faster than $\sqrt{N}$. Furthermore, the simulation bias is negligible when the ratio of the number of draws to $\sqrt{N}$ is sufficiently large (Hajivassiliou and Ruud, 1994). We set the number of draws to $2\sqrt{N}$. The simulation method requires to draw random variables from an upper-truncated normal distribution. We employ draws based on Halton sequences as they are more effective for simulated MSL estimation than pseudo-random draws (Train, 2009).

We estimate the model's parameters using a conditional mixed process (CMP). The mixed process allows different kinds of dependent variables and corresponding estimation processes within one model. Thus, while multiple equations are estimated simultaneously, each equation can vary by observation, conditional (C) on the data.[18] For the binary indicators (collaboration and licensing), we employ a probit specification, and for contract research, measured in monetary units, we employ an uncensored specification designed for continuous outcome variables. The key predictors of interest are the R-share and the amount of research and development expenditures.

A series of variables have been log-transformed, with the purpose to smooth data skewness, to linearize the relationship to outlying data points, and hence stabilize the variance. We applied the natural logarithm to research and development expenditures, external R&D, the patent stock, employees, and firm age[19]. Since we make use of two different equation types and associated functions in the CMP, probit and linear regression, the transformation renders the explanatory

[18]This leads to different observation numbers summed up below each equation in Tables 3.4 and A.2.4.

[19]For variables with non-negative values, we constructed the transformation by adding 1 and then taking the log. Otherwise, the value would not be defined for observations with a value of 0.

variables robust to distributional problems and outlier distortion. The financial variables, working capital, long- and short-term debt, are presented as ratios which puts them into the context of each firm's physical capital, like premises, equipment and plants, and have been divided by fixed assets.

3.3.3 Estimation Results

Table 3.4 shows the results from the simultaneous equation model. The ρ values indicated at the bottom of the table inform about the error term correlation of the four equations and, exhibiting statistical significance for all, imply that the equations should be estimated as a system rather than separately. Model 1 shows that a firm's R-share predicts the likelihood to engage in collaboration, licensing in, licensing out, as well as the amount spent on contract R&D. For collaboration, we find that a higher R-share is associated with a higher probability for the entire range of R-share values. While firms with zero R-share have an average predicted collaboration likelihood of about 10%, firms with an R-share of 50% or higher have an about twice as large probability to collaborate. Figure 3.2(a) illustrates these differences graphically.

We further see interesting differences between firms with regard to licensing activities. The probability to buy licenses increases only at relatively high values of R-share, while the probability to sell licenses is highest at very low and very high shares of research (see Figures Figure 3.2(b) and (c)). Intriguingly, licensing out and the commission of contract R&D follow a similar pattern, as both grow for firms that either invest very little in research, or are specialized in research, i.e. have a high R-share. Contract research is governed by a very pronounced U-shaped relationship, with firms spending about half of their R&D budget on research have a zero predicted amount of external R&D. This suggests that these firms perform knowledge creation mainly in-house, whereas firms with lower or higher R-shares relative to them complement own internal R&D with external expertise (see Figure 3.2(d)).

Model 2 shows an alternative modelling approach in which we test the hypothesis that firms that are specialized in research or development, measured by their absolute expenditures, are more likely to engage in the market for technology. The results confirm this idea for collaboration and licensing, for which the interaction term [ln(research) $\times$ ln(development)] is negative and statistically significant, in addition to the R-share patterns discussed above. The only exception is contract R&D. Here, the interaction effect is positive and statistically significant, indicating that firms that spend more on both, R and D, also contract in more R&D in absolute terms.

Table 3.4: Estimation results – Simultaneous equations model

	Model 1 (without interaction)				**Model 2 (with interaction)**			
	Collaboration	Licensing in	Licensing out	ln(ext. R&D)	Collaboration	Licensing in	Licensing out	ln(ext. R&D)
R-share	1.002**	-0.524	-1.918**	-5.050***	1.124***	-0.471	-1.771**	-5.011***
	(0.408)	(0.625)	(0.789)	(0.749)	(0.404)	(0.620)	(0.743)	(0.721)
R-share × R-share	-0.043	1.107**	1.993***	4.168***	-0.461	0.924*	1.605**	4.534***
	(0.386)	(0.565)	(0.727)	(0.721)	(0.388)	(0.555)	(0.676)	(0.749)
ln(research)	0.074***	0.053*	0.142***	0.375***	0.168***	0.098***	0.243***	0.287***
	(0.024)	(0.030)	(0.037)	(0.032)	(0.019)	(0.032)	(0.052)	(0.031)
ln(development)	0.188***	0.137***	0.117***	0.154***	0.242***	0.168***	0.199***	0.125***
	(0.020)	(0.019)	(0.026)	(0.032)	(0.029)	(0.026)	(0.026)	(0.034)
ln(research) × ln(development)					-0.017***	-0.008*	-0.019***	0.015***
					(0.003)	(0.004)	(0.005)	(0.006)
ln(patent stock)	0.141***	0.205***	0.233***	0.434***	0.162***	0.216***	0.252***	0.398***
	(0.039)	(0.061)	(0.064)	(0.075)	(0.038)	(0.055)	(0.062)	(0.078)
ln(employees)	-0.182**	-0.009	-0.194**	-0.182	-0.244**	-0.047	-0.287***	-0.154
	(0.089)	(0.133)	(0.093)	(0.147)	(0.101)	(0.143)	(0.101)	(0.139)
ln(employees) × ln(employees)	0.018*	-0.006	0.004	0.024	0.025**	-0.001	0.015	0.020
	(0.010)	(0.016)	(0.011)	(0.019)	(0.011)	(0.018)	(0.011)	(0.018)
ln(age)	-0.092	-0.270	0.387	-0.559*	-0.063	-0.255	0.410	-0.559*
	(0.294)	(0.532)	(0.503)	(0.313)	(0.297)	(0.537)	(0.515)	(0.318)
ln(age) × ln(age)	0.010	0.026	-0.061	0.078*	0.009	0.026	-0.060	0.076
	(0.047)	(0.086)	(0.083)	(0.046)	(0.048)	(0.086)	(0.086)	(0.047)
Working capital ratio*	-0.000	-0.006***	0.000***	-0.000***	-0.000	-0.006***	0.000***	-0.000***
	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)
Long-term debt ratio*	0.000	-0.000	0.001**	0.000	0.000*	-0.000	0.001*	0.000
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
Short-term debt ratio*	-0.000*	-0.004	-0.001***	0.000***	-0.000*	-0.004	-0.001**	0.000***
	(0.000)	(0.004)	(0.000)	(0.000)	(0.000)	(0.004)	(0.000)	(0.000)
Enterprise group dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\rho^{\dagger}$ 12/23/34	0.227***	0.476***	0.048*		0.226***	0.475***	0.053*	
$\rho^{\dagger}$ 13/24/14	0.258***	0.094***	0.386***		0.262***	0.097***	0.384***	
Observations	11,242	6,191	6,191	14,769	11,242	6,191	6,191	14,769

Estimates are coefficients

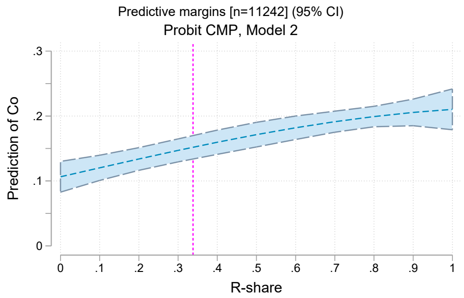
Standard errors in parentheses (clustered at firm level)

* Ratio uses fixed assets in the denominator

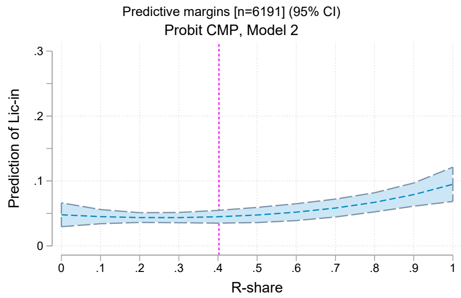
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

† ρ displays the error term correlation between two equations (numbers indicate equation 1-4), e.g. 24 – Lic-in & ln(external R&D)

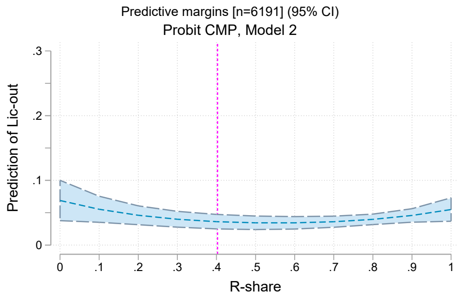
Figure 3.2: Predictive margins of TT variables over R-share



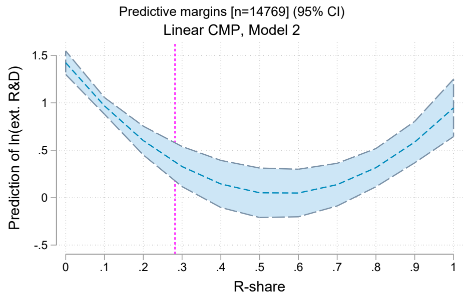
(a) Collaboration



(b) Licensing in



(c) Licensing out



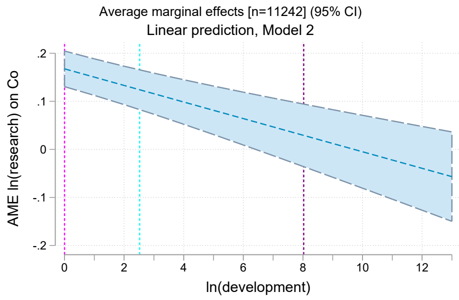
(d) External R&D (expenditures)

The vertical dashed line in each subfigure indicates the subsample mean.

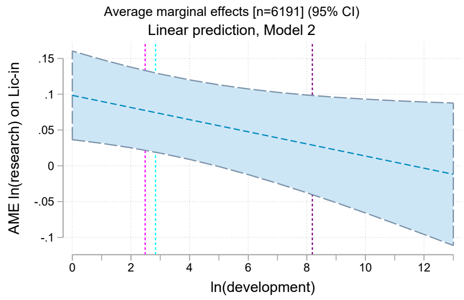
Figure 3.3 visualizes the average marginal effects of research expenditures on TT variables at different levels of development expenditures.[20] The negative slope of the curves in Figure 3.3(a), (b) and (c) show that increasing research investments has a smaller marginal impact on the collaboration and licensing likelihood in firms that also invest more in development. Thus, firms that do little development are more likely to collaborate when they increase their research spending compared to firms that do a lot of development themselves. This pattern is even more pronounced for licensing out. For licensing in, the confidence bands are much wider although the general pattern is similar. In contrast to that, Figure 3.3(d) shows that an additional unit more spent on research increases the amount spent on external R&D, while the firm also invests higher volumes in development. This finding is consistent with earlier research showing that internal and external R&D are complements, and investments in one of them increases the returns to the other activity. This result also mirrors the earlier finding that both very low and very high R-shares are associated with higher external R&D expenditures, but that a higher R-share (up

[20] For easier comparison, the linear prediction based on the estimation in Table 3.4 has been computed for all four TT variables. Subfigures 3.3 (a) to (c) depict a decreasingly positive effect of research expenditures on collaboration and licensing, which eventually turns into a negative effect from an individual threshold on (The threshold of development expenditures approximates €600,000 for collaboration, €150,000 for licensing in, and €10,000,000 for licensing out.). Conversely, the AME rises for external R&D measured in expenditures.

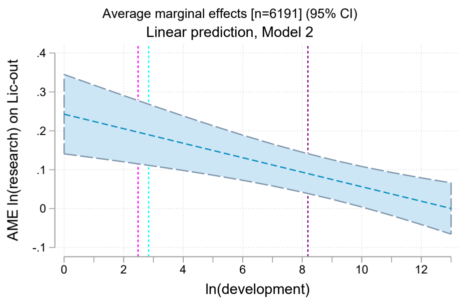
Figure 3.3: Average marginal effects of research on TT variables over development



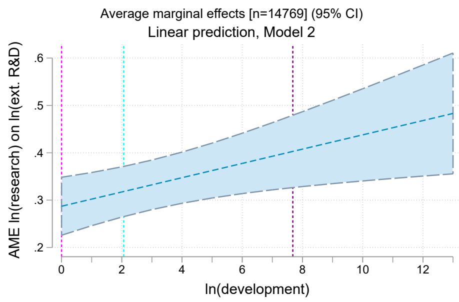
(a) Collaboration



(b) Licensing in



(c) Licensing out



(d) External R&D (expenditures)

The vertical dashed lines in each subfigure indicate the subsample median, mean and 95$^{\text{th}}$ percentile.

to about 50%) comes with almost no external R&D budget, while only from an R-share >0.5 on, firms spend again more on external R&D.

To check whether specialization has been double accounted for, we test the sensitivity of Table 3.4 results to the omission of the R-share variables from the model. The outcome of this exercise shows that the direction, magnitude and significance of the interaction term estimates remain unchanged, even when we exclude the R-share (see Table A.2.4 for details).

When looking at the control variables, we see that the patent stock signals a strong positive effect throughout all equations. As expected, the intellectual assets should notably matter when testing the four TT channels. From the firm characteristics, number of employees, and firm age do neither exhibit a persistent nor unidirectional effect. It should be further noted that firm size affects the likelihood to collaborate significantly and negatively for the simple term, and positively for the squared term in all models. That could hint to a co-specialization dependent on firm size, and research versus development focus. Only the collaboration equation displays an increasing likelihood when the R-share grows in tandem. Firm size could moderate this relationship such that the argument of smaller research-specialized firms might hold true.

3.4 Conclusion and Discussion

Investment in R&D is an integral policy concern as a lack of it may result in a slowdown in productivity growth, and consequently have detrimental effects on technological progress and economic development. Incentives for R&D have been shown to depend on the returns to research or development activities (Becker et al., 2020). The question how firms make use of the market for knowledge to complement their own R&D efforts is therefore a critical one.

The idea that markets for technology facilitate firms' specialization in R or D, and hence increase the returns to investments has, however, been little explored so far. Our results suggest that collaborative R&D, licensing and contract research are ways that allow firms to focus on research versus development. Collaborative R&D may not only help firms to absorb knowledge spillovers from their partners, but also facilitate organizational learning and allow higher degrees of efficiency in the R&D process, thereby reduce risk and provide effective insurance against technological and market uncertainty (Blind et al., 2017). Furthermore, it may transmit a positive signal to potential investors and creditors about the quality and the expected success of the project (Hottenrott and Lopes-Bento, 2015, 2016; Czarnitzki and Hottenrott, 2017). Licensing and external contract R&D may likewise facilitate firms to focus on their core competencies, while sourcing complementary know-how elsewhere.

Building on a conceptual framework in which firms decide on their research strategy, and thus their relative focus in corporate research relative to development, we show that strategy choice and engagement in knowledge and technology transfer are interdependent. In particular, we find that higher R-shares in total R&D are associated with a significantly higher likelihood of firms to engage in R&D collaborations. Higher R-shares also come with higher likelihoods of licensing in and out, although licensing out is also relatively more frequently observed in firms that specialize in D rather than R. The results further document that specialization either in R or D comes along with higher spending on external R&D, that is contracting in of research and development activities conducted by external providers. We further document substitution effect for research and development investments as higher simultaneous investments in both lower the likelihood to collaborate or license technology. For R&D contracting, on the other hand, we find that spending on both types are complements, since firms investing more in internal R&D overall are also buying more external R&D. Our results confirm prior research stressing the complementarity of internal and external R&D (Arora and Gambardella, 1990; Cassiman and Veugelers, 2006; Ceccagnoli et al., 2010; Grimpe and Kaiser, 2010; Añón Higón et al., 2018), as well as the importance of the market for technology for firms' specialization strategy (Gans et al., 2008; Arora and Gambardella, 2010b, 2010a).

The results yield implications for innovation policy as they illustrate the dependence on well-functioning IPR systems that are a precondition for formal exchanges, like technology licensing, and beyond support protection of IP in R&D collaborations. Modifying IPR can lead to weaker rights or lower the hurdle for misappropriation of non-patentable intangible assets. Particularly collaborative R&D could benefit from competition law that provides exemptions to this transfer channel. Moreover, the findings supply empirical evidence that the gains from specialization may fundamentally depend on firms being able to engage in cross-firm technology transfer to cope with increasing technological complexity and the resulting knowledge-burden (Jones, 2009).

Despite all efforts, this study is not without some limitations. First, we did not explore the licensing and collaboration contracts in more detail. There may be considerable heterogeneity in both the scale and scope of the agreements included in our data. Second, we did not differentiate between contract or collaboration partners the extent to which firms collaborate repeatedly with the same partners, and the complexity of the collaboration portfolio, although it has been shown in previous work to matter for the effects of technology sourcing on innovation outcomes (Hottenrott et al., 2016). We therefore suggest further research on the role of specialization in technology sourcing strategy and ultimately innovation performance.

4 | Founder Personality and R&D Decisions in Entrepreneurial Firms

4.1 Introduction

Entrepreneurial firms contribute to radical innovation and new technology diffusion which are both drivers of economic growth (Wennekers and Thurik, 1999; Van Praag and Versloot, 2007; Haltiwanger et al., 2013). Yet, the success of new firms depends substantially on the entrepreneurs that found them (Shane and Stuart, 2002; Dencker and Gruber, 2015), and the ways in which they think, decide and act. Previous research suggests that such behavioural patterns are strongly determined by their personality (Costa and McCrae, 1997; Smith et al., 2018).

Differences in personality surface in professional choices, for example when comparing entrepreneurs to managers. The attraction[2] to an entrepreneurial career opposed to a contractual employment does not only reveal talents and motives of the individual, but these occupational groups also provide insights into dimensions of personality such as openness or risk tolerance (Stewart and Roth, 2001; Brandstätter, 2011). In addition, personality influences decisions within professions and roles (Kerr et al., 2017). Most actions in small, entrepreneurial firms are initialized by the founder (Rauch and Frese, 2000). Founders' personality affects their behavior including the search for and processing of information and hence their informed decision making (Winter et al., 1998). Founder personality traits have indeed been empirically linked to business creation as well as to the success of start-ups through their impact on entrepreneurial behavior (Zhao et al., 2010; Brandstätter, 2011; Jong et al., 2013; Rosenbusch et al., 2013). For instance, founders that are more proactive, open, and readily take risks, are more likely to search for,

Author contributions: This chapter is joint work with Hanna Hottenrott and Anwesha Mukherjee.

[2]Based on the 'Attraction-Selection-Attrition' Model of Schneider (1987) which evolved at the intersection between vocational psychology and organizational theory.

detect and exploit new opportunities that can drive their firm's growth (Covin and Slevin, 1991; Rauch and Frese, 2007). Founders who are more performance-oriented or competitive are also more inclined to seek external finance (Vaznyte and Andries, 2019).

Most parts of entrepreneurial discretion, including planning, goal setting and strategy, are driven by preferences, expectations and often subjective assessments of choice options. Founder personality likely shapes these factors and therefore likely explains the link between the personal attributes and entrepreneurial accomplishments of founders (Caliendo and Kritikos, 2008; Rauch et al., 2009).[3] Based on the insight from prior work that founder personality can predict start-up performance (Frese, 2009; Brandstätter, 2011), we therefore suggest that this observation can be traced back to founder personality's impact on early-stage Research & Development (R&D) and investment decisions. Both types of investment have been shown to be important for scaling of the business and longer-run firm performance, and previous research examined the individual-level drivers of investment activity (Cassar and Friedman, 2009). The role of personality as a key determinant is less well understood. Barker and Mueller (2002) observe CEO characteristics and how they relate to R&D spending and find that younger, R&D-experienced CEOs and those with higher financial stakes in the firm invest more. This implies that even in larger firms, R&D decisions are affected by individual attributes of the decision makers. This is further supported by the finding by Caggese (2012) who investigates the role of uncertainty for risky R&D investments and concludes that R&D engagement is determined by entrepreneurial risk tolerance.

While previous research argued that investments in R&D are fundamentally different from tangible investments (Czarnitzki and Hottenrott, 2011b), we know little about whether and how the effects of personality on R&D investments diverge from those on other investments. R&D decisions are typically characterized by a higher degree of uncertainty compared to investments in tangible assets, and the assessment of the expected returns could consequently depend more on the personality of the individual decision maker. In synthesis with the personality performance link documented in earlier work, studying the role of founder personality for R&D and investments contributes to a better understanding of the performance drivers in young, innovative companies. Since both investment types are fundamental to the up-scaling of newly founded firms, it appears furthermore important to delineate the decision to invest (extensive margin) from the amount of the investments conditional on the investment decision (intensive margin). Following these ideas, our analysis differentiates between the decision whether to engage in R&D

[3]In the Giessen-Amsterdam Model of small business owners, success depends on personality, human capital, goals, strategies and environment (Rauch and Frese, 2000).

activities, and the decision on how much to invest, from the stance that personality already matters at the extensive margin.

To capture founder personality, we make use of the established constructs from the five-factor model of personality (Big 5) which organizes personality traits into five basic dimensions (Costa and McCrae, 1997; George and Zhou, 2001; Zhao and Seibert, 2006; Rauch and Frese, 2007). These personality traits reflect distinct dimensions of human personality: Openness to experience (O) captures how pronounced imaginative, curious, and accepting of novel and unorthodox ideas, perspectives and experiences an individual is, as opposed to preferring convention and familiarity. Conscientiousness (C) illustrates the manifestation of the properties diligent, task-directed, achievement-oriented and rule-obedient, while extraversion (E) reflects the extent to which someone is assertive, active and impulsive. The fourth dimension – agreeableness (A) – reflects benevolence towards others as well as how conflict-eschewing and anxious of negative consequences a person is. Finally, neuroticism (N) scores higher in individuals that display little self-confidence, are indecisive and cannot easily adapt to new circumstances.

Besides these baseline personality traits, we include a measure of entrepreneurial risk tolerance in line with the literature on entrepreneurial decision making (Rauch and Frese, 2007; Caliendo et al., 2009; Caliendo et al., 2020). Prior empirical work portrays the role of risk tolerances for entry into and exit from self-employment (Caliendo et al., 2009; Caliendo et al., 2014) and for firm survival (Caliendo et al., 2010; Sharma and Tarp, 2018). As the meta-analysis of Kerr et al. (2017) illustrates, the work on entrepreneurial personality is frequently synthesized with the willingness to take risk.

We hypothesize that founders' risk tolerance additionally to baseline personality impacts R&D decisions at the extensive and intensive margin, and that individual preferences and traits matter more for R&D investments than for investments in tangible assets. We build these arguments derived from a simple decision making model under uncertainty which visualizes that personality matters more when there is more room for subjective judgement, i.e. when residual uncertainty is higher. Our empirical analysis of more than 5,200 founders in over 4,700 new firms founded between 2007 and 2017 in Germany demonstrates that personality indeed fuels decisions for R&D operations as well as investments in tangible assets. Nevertheless, after controlling for other founder characteristics and firm attributes, we find that risk tolerance and openness to experience explain R&D activities, while risk tolerance is less influential for taking up investments in tangible assets. Higher levels of agreeableness and neuroticism render both types of scaling, i.e. the decision to engage in R&D and tangible investments, less likely. Conscientiousness, on the other hand, negatively affects R&D engagement, and reversely yields a positive association to the amount invested into tangible assets. This likewise reflects the uncertainty inherent to R&D activities which is less utility-enhancing for highly conscientious founders who are generally not opposed to pursuing a growth strategy as reflected in their willingness to invest in tangible assets.

These results have implications for entrepreneurs as well as entrepreneurship research and policy. Since personality traits show a high degree of stability across time as well as context (Costa and McCrae, 1997; Roccas et al., 2002; Cobb-Clark and Schurer, 2011), and affect firm behavior, founder personality has a lasting impact on the performance of new firms in the long-run. This study adds to our understanding of the large variation in start-up survival rates and the previously documented link to founder attributes. Within entrepreneurial firms, our results could guide founders when deciding about team composition such as to counterbalance an overly aligned decision making. Founders who knowingly choose certain entrepreneurial personalities as co-founders could reinforce, offset or reverse behavioral dynamics. Also, explicitly defining one investment type apart from the other and their sensitivity to psychometric manifestations makes different role requirements for stimulating R&D visible. The success of policies designed to incentivize R&D activities may chiefly depend on which founders they reach. Moreover, knowing the decision process is twofold between entering an investment at all, and conditionally scaling the invested amount, this information is useful for the timing and extent of support for start-ups. Observing the strong tie between psychometry and entrepreneurial discretion allows a micro-based view at the intersection between individual behavior and investment decisions at the firm level. With an analysis of start-ups, we contribute to research on high-growth strategies of newly founded businesses which allow a better understanding of their role as drivers of innovation and employment growth. Our findings also point out routes for further research on founder personality, its role for the nature of R&D, and the types of innovation that entrepreneurs pursue.

The remainder of this paper is structured as follows: Section 4.2.1 provides the theoretical framework which models personality attributes on two stages of the investment decision. Section 4.2.2 posits the corresponding hypotheses, Section 4.3.1 presents the data description and the empirical strategy. Section 4.4 discusses the results and adds robustness checks in Section 4.4.2. Section 4.5 concludes with a test of the hypotheses, showcases policy implications and points out avenues for further research.

4.2 Personality and Entrepreneurial Investment Decisions

Investment decisions are among the most important decisions of entrepreneurs and managers.[4] While traditionally economic research assumed rational decision making which should not depend on the decision maker's personality, this view has been challenged in more recent research that suggests that personality dimensions do indeed play a decisive role for investment decisions (McCrae and Costa, 2004). Gambetti and Giusberti (2019) review research on personality, financial behavior and investment decision and conclude that there is strong evidence of the investors' personality influencing investment decision making: Rizvi and Fatima (2015) study how the investor's Big 5 traits correlate with investment patterns in the stock market, and Chen et al. (2019) find investors' personality to shape short-term and long-term trading performance. Considering firm-level investments, spending money on research and development (R&D) is one of the most fundamental decisions made by top managers. On these grounds, a stream of research has examined the determinants of corporate R&D spending. These studies, however, generally focused on the role of firm or ownership characteristics rather than the characteristics of the decision makers themselves (Scherer, 1984; Graves, 1988; Baysinger et al., 1991; Hansen and Hill, 1991; Czarnitzki and Hottenrott, 2011a, 2011b; Wang, 2014; Becker et al., 2020).

A notable exception is Barker and Mueller (2002) who document for a sample of publicly traded firms that CEO characteristics explain a significant proportion of the sample variance in firm R&D spending, even when they control for corporate strategy, ownership structure, and other firm-level attributes. While this is insightful, the study focus only on easily observable attributes such as CEO's age, wealth invested in the firm, career experience and education, but baseline personality traits are still unaccounted for. Importantly, recent research by Piovesan and Willadsen (2021) suggests that baseline personality dimensions and risk preference are not correlated, but that risk preferences and personality traits are complementary measures of individual heterogeneity of behavior. This highlights the need to investigate both the set of Big 5 personality traits as well as the taste for risk. This is further stressed in a lab experiment where participants make hypothetical R&D decisions (Carson et al., 2020). The results from this experiment show that more risk tolerant individuals are more likely to fund the highly risky breakthrough projects. Participants with average risk preference stick to low-risk projects even though their

[4]Studies empirically distinguish between entrepreneurs and non-entrepreneurs since entrepreneurs combine the functions of founders, owners and managers which does not apply vice versa (Rauch and Frese, 2000; Zhao and Seibert, 2006; Caliendo and Kritikos, 2008).

experimental design specifically incentivized the choice of the high-risk projects.

In addition, insights on small, entrepreneurial firms in which the CEO or other members of the top management team are highly influential, are still scarce. Entrepreneurial decisions often entail decision making under high pressure and great uncertainty. While a larger number of studies have examined task performance under pressure, Byrne et al. (2015) were first to look specifically at the role of personality for decision making under pressure. They find that both more pronounced neuroticism and agreeableness negatively affect decision making quality under both situational and time pressure. The negative effect of neuroticism on decision making is likely explained by distraction theory which suggests that higher (lower) emotional stability enhances (deteriorates) information integration under high pressure (Markman et al., 2006).

Another important factor in R&D decision is the evaluation of the prospective returns which determines the decision to invest. Once an entrepreneur decides to engage in R&D activities, the amount of R&D expenditure is often determined by project characteristics. Yet, Hirsh et al. (2008) report that higher emotional stability predict lower discounting rates among individuals with high cognitive ability. Lower discounting rates mean higher present value of future returns, which should understandably encourage R&D activities both at the extensive as well as the intensive margin. Moreover, Ostaszewski (1996) show that both extraversion and neuroticism correlate with higher temporal discounting rates which suggests that both these traits might be negatively associated with R&D at both the external and internal margins. Investigating the role of founder personality for strategic decisions, such as investments in R&D, appears particularly crucial given the importance of such early stage strategies for new venture performance and eventually survival (Stam and Wennberg, 2009; Braymen et al., 2011). Furthermore, R&D as investment in knowledge and the resulting innovations create externalities that benefit the economy and society beyond the individual firm (Cohen and Klepper, 1992).

4.2.1 A Two Stage Model on Investment Decisions

In the following we present as a simple theoretical investment decision framework. Firms' investment and R&D decisions are not uni-dimensional, but depend both on firm characteristics as well as the personal attributes of the decision maker. Considerations of multiple factors related to the inherent risk of and uncertainty about future returns and individual firm factors can affect a firm's decision to engage in a certain type of investment and the extent of such engagement. Therefore, we consider different investment types, that is R&D investments and tangible investment options as well as the fact that those decisions involve both the extensive as well as the intensive margin.

We assume a two stage decision mechanism for taking up an investment opportunity in an entrepreneurial venture. R&D and investments in tangible assets are considered as the two types of entrepreneurial investment options which differ in their properties. In reality, R&D and tangible investments are not mutually exclusive, most likely, even not independent of each other. For our purpose, however, we consider a unified framework for both types of undertakings and draw the distinctions with regard to certain parameters and marginal effects. $\boldsymbol{B}= \{O, C, E, A, N\}$ is the vector of the Big 5 personality traits, the elements of which enter the decision making in different fashions.

At the first stage, the entrepreneur decides whether to engage in an investment (in tangible assets, denoted hereafter as T, or in $R\&D$) at all. The second stage, where the entrepreneur decides the amount of investment, arises conditional upon the decision at the first stage. We consider the first stage as an entry decision.

$$e_i = \mathbf{1}(\text{expected net utility from the entrepreneurial investment } i > 0)$$

i denotes the type of the investment, $i \in \{R\&D, T\}$. The investment is taken up only if $e_i = 1$ and is not taken up when $e_i = 0$. The total utility from taking up the investment is realized upon the decision on the investment amount in the second stage.

$$U_i = e_i[\phi_i(O)^{1/r} + U(y_i)] \ ,$$

$$\text{where} \quad U(y_i) = -exp(-ry_i)$$

$$y_i = \begin{cases} \alpha_i E + (\theta_{\mathbf{i}} \zeta')x_i + \upsilon_y(C, N) + \epsilon_y & \text{if} \quad x_i > 0 \\ 0 \quad \text{if} \quad x_i = 0 \end{cases}$$

y_i is the financial return from the investment and x_i indicate the units of money invested. r is the coefficient for the constant absolute risk aversion. A lower value of r indicates a higher risk tolerance.

The first term inside the square bracket in the expression for U_i formalizes the non-material utility of taking up an investment which is due to the openness trait. Individuals with higher openness tend to be interested widely and draw utility from unusual thought processes (McCrae and John, 1992). They are more likely to be independent thinkers, to value intellectual challenges

(Jong et al., 2013), show intellectual curiosity (Zhao and Seibert, 2006), and are amenable to variety and novelty (George and Zhou, 2001). Without loss of generality, one may assume that $\phi(O)$ is higher for R&D investments than regular investments in tangible assets. Moreover, the $1/r$ in the exponent indicates that a risk tolerant entrepreneur is likely to achieve higher fruits from openness than a risk-averse entrepreneur.

ζ is the vector of other characteristics (e.g., education, firm size, age, and so on) of the entrepreneur which determines the effectiveness of per unit of investment. The variable E is the measurement of extraversion; E is stylized as an profitability-enhancing parameter which builds up the base return from the investment. This is because extraversion is positively related to assertiveness which involves being sociable, talkative, and maintaining social networks with investors, suppliers, and customers (Caliendo et al., 2016). This may relate extraversion to optimistic expectations for the future (Winter et al., 1998), as reflected in the finding that it is associated with the correlation between the intentions of setting up a business with firm performance (Caliendo et al., 2016).

The stochastic part of the return has two components: ϵ_i, the random error on unit return, is distributed with mean zero and variance $\sigma^2_{\epsilon i}$; on the other hand, $\upsilon_i(C,N)$ is the perceived volatility in the returns which is a function of C and N and is distributed with mean zero and variance $\sigma^2_{\upsilon i}(C,N)$. The joint variance is therefore $\sigma^2_i(C,N) = \sigma^2_{\upsilon i}(C,N) + \sigma^2_{\epsilon i} + 2\rho_{\epsilon\upsilon}\sigma_{\upsilon i}(C,N)\sigma_{\epsilon i}$. One unit of money invested has mean $\alpha_i E + \theta_{\mathbf{i}}\zeta')$ and variance σ^2_i. Given that the entrepreneur invests x_i units of money in i, we can say that $y_i \sim (\alpha_i E + (\theta_{\mathbf{i}}\zeta')x_i, x_i^2\sigma_i^2)$. The optimal x_i at the internal margin is determined by maximizing the expected utility $\overline{U(y_i)} = \alpha_i E + (\theta_{\mathbf{i}}\zeta')x_i - \frac{r x_i^2 \sigma_i^2}{2}$. Accordingly, the optimal investment is given by $x_i^* = \frac{\theta_{\mathbf{i}}\zeta'}{r\sigma_i^2(C,N)}$.

The main distinctions we draw between R&D and tangible investments are with respect to the volatility of the returns, in particular, both the perceived and the true components. As delineated above, the perceived volatility is a function of conscientiousness and neuroticism. However, we assume that $\partial\sigma^2_{\upsilon R\&D}/\partial C > 0$ but $\partial\sigma^2_{\upsilon T}/\partial C < 0$ whereas $\partial\sigma^2_{\upsilon i}/\partial N < 0$ for both $i \in \{R\&D, I\}$. The assumption regarding conscientiousness follows from a conscientious individual's preference for certainty. Low conscientiousness facilitates crossing the cognitive barriers of need for control, deliberation and conformity (Nicholson et al., 2005) which are inversely related to the very nature of R&D projects. For tangible assets, on the other hand, we can argue that the direction is reversed so that we expect a positive link between conscientiousness and perceived volatility of tangible investment returns at the intensive margin. Consequently, the more conscientious an entrepreneur, the higher their $\sigma^2_{\upsilon R\&D}$ implying a lower $x_{R\&D}$ and the lower their $\sigma^2_{\upsilon T}$, implying a higher x_T. The more neurotic an entrepreneur, the higher their perceived volatility, resulting in a higher joint variance and therefore lower amount invested. Second, we assume that R&D expenditures are also truly riskier in comparison to tangible investments, i.e., $\sigma^2_{\epsilon R\&D} > \sigma^2_{\epsilon T}$. These assumptions together mean that the joint variance for an R&D investment is higher than the joint variance for a tangible investment undertaking and more so for a conscientious entrepreneur. Therefore, given comparability in terms of other characteristics ζ, the same amount of R&D investment calls for a higher risk tolerance, i.e., a lower r.

Proposition 1: *At the intensive margin,*

(i) Higher risk tolerance increases the amount invested.

(ii) R&D investment calls for higher risk tolerance in comparison to a similar tangible investment.

(iii) A more conscientious entrepreneur undertakes more tangible investments and less R&D investment.

(iv) A more neurotic entrepreneur undertakes a lower amount of investment regardless of the type of investment.

Next, we come to the first stage or the entry stage where the entrepreneur decides whether to take up the investment at all. The entry decision can be rewritten as

$$\begin{aligned} e_i &= \mathbf{1}(\phi_i(O)^{1/r} + \overline{U(y_i)} - \eta(A) > 0) \\ &= \mathbf{1}(\phi_i(O)^{1/r} + \alpha_i E + (\theta_{\mathbf{i}}\zeta')x_i - \frac{r x_i^2 \sigma_i^2}{2} - \eta(A) > 0). \end{aligned}$$

This model is adapted from the entry decision model of Hvide and Panos (2014). The expression inside the parentheses simply indicates a higher expected return from the investment than a potential outside alternative with expected value $\eta(A)$ which increases in A, i.e., $\eta_A(A) > 0$. The rationale behind this assumption is that higher scores in agreeableness reduce competitive thinking and may hence relate to a lower willingness to invest in any type of competitiveness-enhancing activities, R&D spending or tangible assets. Incorporating the optimal solution from the second stage, the above can be written as

$$e_i = \mathbf{1}\left(\phi_i(O)^{1/r} + \alpha_i E + \frac{(\theta_{\mathbf{i}}\zeta')^2}{2r\sigma_i^2(C,N)} > \eta(A)\right).$$

We can claim that:

Proposition 2: *At the extensive margin* *(i)* *A higher level of openness or a higher level of extraversion, or both, is more likely to make an entrepreneur undertake the investment.*

(ii) *A higher level of risk tolerance is more likely to make an entrepreneur undertake the investment.*

(iii) *An entrepreneur with a higher level of conscientiousness is more likely to take up a tangible investment but less likely to take up an R&D investment.*

(iv) *An entrepreneur with a higher level of neuroticism or a higher level of agreeableness, or both, is less likely to undertake any sort of investment with a stochastic return.*

In the following subsection, we put down our hypotheses based on the above propositions and additional support from existing literature.

4.2.2 Hypotheses

Based on the previous considerations, we hypothesize that risk tolerance and personality traits have heterogeneous effects on R&D spending and tangible investment decisions. Specifically, the effects differ not only between these two investment types but also between the decision to invest (extensive margin), and the decision on the investment volume conditional on the decision to invest (intensive margin). This yields six main hypotheses.

Our first hypothesis relates to the entrepreneurial risk tolerance. Risk tolerance reflects the taste of an individual to take actions judged to be risky (Simon et al., 2000). Since investments in newly founded firms are indisputably risky (Hvide and Panos, 2014), in particular when considering R&D projects, risk tolerance is likely a key driver of the decision to invest (Sataloff et al., 2005). The body of literature addressing the role of risk taking for firm performance, survival and failure rates of entrepreneurs highlights its importance: Knight (1921) argues that more risk tolerant individuals are more likely to start up a firm but perform worse, and Caliendo et al. (2010) suggest an inverse U-shaped relation between risk affinity and entrepreneurial survival. Contrarily, Rauch and Frese (2007) conclude that risk preference affects entrepreneurial success only to a low degree, and this trait does not necessarily raise success probability. Risk-loving entrepreneurs may therefore target high variance projects since the lowest and the highest possible return increases with the riskiness of investments (Caliendo et al., 2010; Hvide and Panos, 2014). Likewise, Carson et al. (2020) observe participants in an R&D decision experiment, on average, to select investments with greater variance when they score high in risk preference.

Synthesizing the theoretical and empirical literature, we hypothesize that an entrepreneur is more likely to invest in R&D (Proposition 2.ii) and also to invest higher amounts (intensive margin) with a growing risk tolerance (Proposition 1.i and 1.ii). In the case of tangible investment, however, risk tolerance should play a subordinate role in the updating of the project as a result of better predictable returns (Proposition 1.ii). Given that our data include entrepreneurs who have already taken up some form of investment, we are unlikely to observe individuals with a risk tolerance which is too low for qualifying for the decision at the extensive margin. Thus, although a higher variance would impose a stronger stimulus to a risk tolerant entrepreneur in both cases, we expect risk tolerance to have a positive effect on tangible investments mainly at the intensive margin (Hypothesis 1b).

Hypothesis 1a: *Higher risk tolerance increases R&D expenditures at both margins.*
Hypothesis 1b: *Higher risk tolerance increases tangible investments mainly at the intensive margin.*

The idea of a controllable fraction in risk is described by Caliendo et al. (2009) who suggest that two individuals who share the identical risk attitude but diverge in their skill set or working experience would expose the less trained person more to 'bad risk'. This indicates that risk preferences may be important, but are certainly not the only determinant in decision making. The subsequent hypotheses concern the Big 5 dimensions of baseline personality of the entrepreneurs.

Our second main hypothesis relates to openness to experience as a personality trait. Particularly, the trait descriptions on wide interest and variety amenability align the investor findings of Baker et al. (2019) that relate openness to experience to grow along with the tendency to mentally account, and focus on the individual returns to a segmented portfolio separately. Thus, we hypothesize that openness to experience positively affects R&D expenditures at the extensive margin (Proposition 2.i), but could be less relevant (or even reduce the amount invested) at the intensive margin (Hypothesis 2a). This duality is based on the idea that openness relates to creating variety by engaging in an R&D project (extensive margin), but when weighing opportunities to deploy budget against each other, a higher spending volume (intensive margin) would come at the cost of fewer projects invested in, implying that the entrepreneur may restrict the amount invested in a single project. We hence expect openness to experience to impact R&D investments positively, though predominantly at the extensive margin. It may overall be less relevant for investment into tangible assets because they are typically less related to curiosity and a taste for change (George and Zhou, 2001; Jong et al., 2013). Though the openness trait is compatible with tolerance for all ideas, it conflicts with security and preserving the status quo

(Roccas et al., 2002). In firms, the decision to invest into tangible assets itself (extensive margin) brings about little change, since it cannot set aside convention and traditional structures (Jong et al., 2013). Nevertheless, the readiness to spend higher investment volumes (intensive margin) could still have a positive impact on achieving significant change in the firm (Zhao and Seibert, 2006).

Hypothesis 2a: *Higher openness to experience increases R&D expenditures at the extensive margin.*

Hypothesis 2b: *The effect of higher openness to experience on tangible investments is ambiguous.*

Conscientious individuals have been shown to display impulse control (George and Zhou, 2001), inhibition (Roccas et al., 2002), as well as favoring conforming, rule-obeying, and task-directed behavior (Bernardino and Santos, 2016). These properties propose conscientiousness to be negatively associated with the decision to embark on R&D at the extensive margin (Proposition 2.iii), and to invest lower amounts at the intensive margin, too (Proposition 1.iii). Tangible investments, on the other hand, constitute almost a necessity for firms to sustain and grow their operations. A conscientious individual can be more certain about achieving higher control on the volatility of the returns which in turn may stimulate them to undertake tangible investments (Proposition 2.iii and 1.iii). More conscientious founders may hence give priority to tangible investments in accordance with their business plan, reducing the uncertainty of future returns as well as the overall failure risk.

Hypothesis 3a: *Higher conscientiousness reduces R&D expenditures at both margins.*

Hypothesis 3b: *Higher conscientiousness increases tangible investments at both margins.*

With regard to the trait of extraversion, we expect more extraverted individuals to search for excitement, novelty, challenge, and achievement (Roccas et al., 2002), leading to the suggestion that extraversion increases the likelihood to take up R&D projects (Proposition 2.i). Yet, again the prediction is less clear at the intensive margin. These attributes may not necessarily promote higher amounts in total spent on research projects, or could ambivalently point to the opposite direction. Social skills, assertiveness and determination may translate into a effectiveness of investment into tangible assets as well as a stronger confidence resulting in larger investment amounts.

Hypothesis 4a: *Higher extraversion increases the likelihood to invest in R&D at the extensive* *margin.*

Hypothesis 4b: *Higher extraversion increases tangible investments at both margins.*

The trait of agreeable is more controversial. More agreeable individuals care for the welfare of close others (Roccas et al., 2002), and show decrements in decision making performance under social and time pressure (Byrne et al., 2015). Low scores in agreeableness may express self-centeredness and hard-bargaining and have been shown to promote entrepreneurial survival (Caliendo et al., 2014). Therefore, we hypothesize that there is a negative relationship at the extensive margin for both investment types (Proposition 2.iv). At the intensive margin, the prediction are less clear, but likely works in the direction of higher levels of agreeableness to be associated with lower investment volumes.

Hypothesis 5a: *Higher agreeableness reduces the likelihood to invest in R&D at the extensive margin.*

Hypothesis 5b: *Higher agreeableness reduces the likelihood to invest in tangible assets at the extensive margin.*

Similarly for neuroticism, we expect higher scores in this trait to reduce investment propensity for any type of investment. Higher neuroticism is related to more pronounced anxiety about potential negative consequences (Nicholson et al., 2005), while less neurotic individuals show higher self-confidence and resilience in stressful situations (Zhao and Seibert, 2006). Highly uncertain investment decisions should be related to stronger emotional distress in individuals with high levels of neuroticism (Jong et al., 2013), and thus reduce their willingness to take up such investments. We therefore hypothesize that neuroticism has a negative influence on both investment types at the extensive margin (Proposition 2.iv) and also at the intensive margin (Proposition 1.iv). The fact that neurotic distress prevents successful integration of diverse ideas and that neurotic individuals tend to be indecisive (Jong et al., 2013) is an unsurmountable contradiction to an entrepreneurial mentality generally, and for R&D decisions specifically.

Hypothesis 6a: *Higher neuroticism reduces R&D expenditures at both margins.*

Hypothesis 6b: *Higher neuroticism reduces tangible investments at both margins.*

4.3 Data and Empirical Strategy

4.3.1 Data

The data used for the empirical analysis is part of the IAB/ZEW start-up panel. The survey-based panel has been established in 2008 by the Center for European Economic Research (ZEW), the KfW Bankengruppe, and Creditreform in order to collect representative data on entrepreneurial firms in Germany. On an annual basis, the survey is conducted via computer assisted telephone interviews (CATI) and covers detailed information of the the firms' founders and business activities. The survey is sampled across various sectors and regions as it is based on stratified random sampling. See Fryges et al. (2009) for a more detailed description of the data set.

Our focus is on independent ventures, that is we eliminate firms that are de-mergers (spin-offs), franchises or subsidiaries of other firms. We make use of the 2018 and 2019 waves of the survey that contain elaborate questions on founders' entrepreneurial orientation and personality traits. The reference years for the survey questions are 2017 and 2018, respectively. After erasing observations with missing information, the full sample encompasses 5,252 firm-year observations corresponding to 4,732 ventures founded during the period from 2011 to 2017. Appendix Table A.3.1 lists the number of firms per founding cohort of the full sample and the annual pattern of investment-related variables. Table A.3.2 displays the distribution of firms across sectors and Table A.3.3 shows the geographical distribution across German federal states.

Dependent Variables: R&D activity, Investments and R&D Intensity

R&D activity is measured in terms of the annual amount spent on R&D (R&D expenditures). If the value is above zero, the firm's status is R&D-active and the indicator R&D (binary) takes on the value 1 (otherwise 0). We benchmark R&D spendings – which incorporates investment in knowledge and mostly takes the shape of wages for R&D employees – with investments into tangible goods. For this purpose, we make use of the annual investment amount into tangible assets which are unrelated to R&D (Investments (binary), Investments (expenditures). The relative focus of a firm on R&D is captured by its R&D intensity which is the ratio of R&D expenditures over the total number of employees. Tables A.3.1 and A.3.2 present descriptive statistics of R&D expenditures and investments by survey wave and by sector. We distinguish eleven different sectors from trade and other services to high-tech manufacturing. As expected does the share of R&D-active firms amongst all start-ups differ as well as the amounts spent on R&D differ by sector.

Key Explanatory Variables: Personality Traits

The key information about founders' personality traits were collected in the 2017-2018 waves of the survey. They are measured based on an established and standardized 15-item scale testing the manifestation of the so-called 'Big 5' personality traits. The five-factor approach is the best-known model of personality traits (McCrae and John, 1992) and synthesizes the baseline personality of an individual (Goldberg and Saucier, 1998; Hurtz and Donovan, 2000). The five traits consist of openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism, and are commonly abbreviated as 'OCEAN' (McAdams, 1992; Lumpkin and Dess, 1996; Lumpkin et al., 2009; Covin and Wales, 2012).

Since risk tolerance is an important dimension in the entrepreneurial context, we complement the baseline personality traits with a risk tolerance metric from the entrepreneurial orientation literature (Lumpkin and Dess, 1996; Anderson et al., 2015; Covin and Wales, 2019; Wales et al., 2020).[5] Entrepreneurial risk tolerance stretches on a scale from positive to negative risk valuation and records how much risk taking is acceptable to the entrepreneur. In this context, it labels the propensity to accept the risks inherent in an opportunity, not the preference to risk as in sensation-, stimulation or thrill-seeking per se (Ostaszewski, 1996; Nicholson et al., 2005).[6] The specificity of entrepreneurial risk taking is important because it deviates from generic risk tolerance of an individual which is already reflected by the compound baseline personality traits. Table A.3.4 shows the survey questions (items) in more detail.

We perform two separate principal component factor analyses: One on the two items measuring risk tolerance and one on the 15 items for the baseline personality traits. Table A.3.5 illustrates the results of the first factor analysis and confirms that both items map into the latent factor 'risk tolerance'. Table A.3.6 visualizes that each of the 15 items on personality traits correlates – as expected – strongly with one of the five underlying factors.

Figure 4.1(a) depicts quantitatively how the personality profile measured in predicted factor scores (PFS) differs between R&D-active and -inactive firms.[7] The profile differences between R&D-active and -inactive entrepreneur personalities are remarkable.[8]. In particular, risk toler-

[5] As a simplification, we acronymize risk tolerance and the OCEAN variabels to 'ROCEAN'.

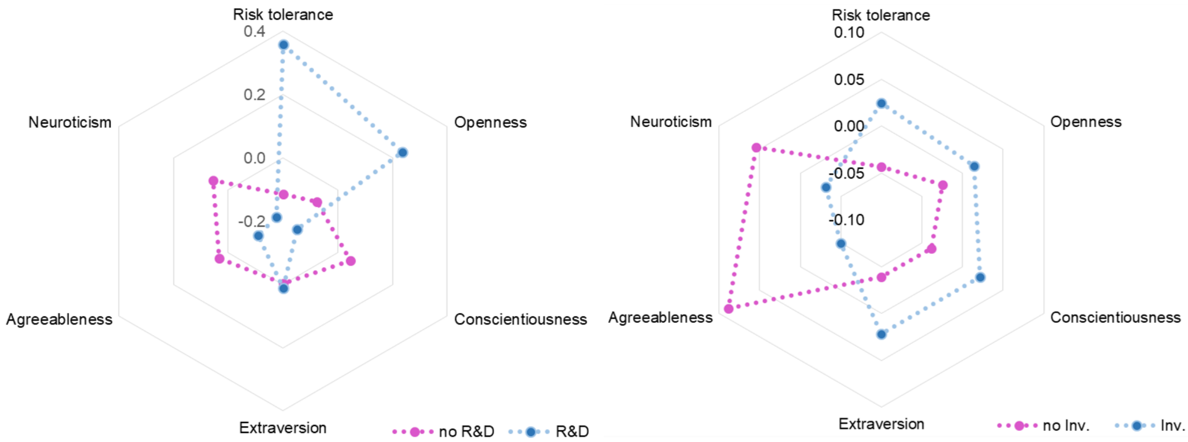
[6] Krueger and Sussan (2017) use the related concepts of ambiguity tolerance and venturesomeness which measures the propensity to take intelligent risks for a more precise description.

[7] PFS is our prime metric of the ROCEAN variables. We further construct two alternative versions of the variables for robustness checks: A binary format which takes the value of one (i.e. trait is present) if the item value of each item belonging to a factor is larger than 3, and the average of the item scores (AIS) from Table A.3.4.

[8] The trivariate distributions in Appendix Figures A.3.1 to A.3.5 provide a detailed graphical impression. For five

ance and openness are substantially more prominent in founders deciding pro R&D compared to those that do not conduct any R&D in their firm. Besides that, conscientiousness, agreeableness and neuroticism are traits that are less pronounced in R&D-inactive founders. Only the degree of extraversion is about the same level in both groups. When comparing personality profiles of investing to non-investing founders in Figure 4.1(b), we see also intriguing divergences. Here, the differences between groups in terms of risk tolerance and openness are less dominant. Yet, we also see that agreeableness and neuroticism are manifest to a greater extent in the non-investing group, while higher levels of conscientiousness and extraversion substantiate in the investing group.

Figure 4.1: Webcharts of personality profiles by investment type



(a) R&D decision **(b)** Tangible investment decision

Control variables

In the following analysis, we control for commonly understood drivers of corporate R&D decisions which can be categorized into founder and firm characteristics. At the founder level, 'Industry experience' is an elementary factor for assessing the returns to R&D and investments more generally. Whether the entrepreneur is a re-starter, i.e. has founded a firm before the current one (Serial entrepreneur), complementarily informs about entrepreneurial experience beyond the specific industry. Furthermore, characteristics of the decision maker as a person include the entrepreneur's age (Age), gender (Female), and scientific biography with an indicator variable for individuals who have a university degree (Academic).

At the firm level, we control for the start-up's maturity with an indicator for firm age (Cohort FE), the value of its physical capital (Tangible assets), and firm size (Employees). The firm's legal

pairs of ROCEAN variables, the heatmaps indicate how the average R&D expenditures vary by a color gradient.

form (Limited company) is of interest in the context of risk taking behavior, since limited liability may allow for a higher risk readiness than personal liability. On top, the founders' motives for becoming an entrepreneur may be noteworthy for the analysis of R&D and investments. We distinguish between founders who were opportunity driven and those who founded out of necessity (Opportunity driven), for instance to escape unemployment. We consider a founder to be opportunity driven if she/he states to have pursued a specific business idea, saw an opportunity to increase her/his income, or pursued the opportunity to work more independently. Since team dynamics can impact decision making, we also control for whether other founders were involved in the process (Team). Finally, the industry of business activity (Sector FE) and the firm's location within Germany (Federal state FE), as well as life cycle stage (Survey wave FE) are included as fixed effects.

We log-transformed a number of variables to reduce distributional skewness, to linearize the relationship to outlying data points and hence stabilize variance. We applied the natural logarithm to R&D and investments (ln(R&D), ln(investments)), tangible assets (ln(tangible assets)), and firm size (ln(employees))[9].

4.3.2 Descriptive Statistics

Table 4.1 summarizes the main variables used in the estimations. The dependent variables describe whether founders decided to invest in R&D or in (non-R&D-related) tangible assets (binary indicators): Whereas more than half of entrepreneurs opted for general investments with a mean of 64%, it is only roughly a quarter (24%) who decide to invest in R&D. Conforming with this difference, the average value of €33,451 investments is higher than average R&D expenditures with €22,806. Also the maximum values diverge strikingly: The largest amount for R&D is €5 million, while investments at most amount to double as much with €10 million. The average annual amount of R&D expenditures spent per employee is €5,200.

Concerning the characteristics at the founder level, the average founder has 17 years of industry experience and is 45 years old. About half of the entrepreneurs have completed a university (or college) degree (49.3%), 41% have founded a company before, and 17% of founding teams comprise at least one women. At the firm level, the average firm is around 3.5 years old, employs around four employees (measured in full time equivalents), and owns tangible assets worth approximately €11,000. On average, half of the firms are legally registered as limited companies

[9]For variables with non-negative values, we constructed the transformation by adding 1 and then taking the log. Otherwise, the value would not be defined for observations with a value of 0.

Table 4.1: Descriptive statistics of main variables

	Mean	**Sd**	**Min**	**Max**
Dependent variables				
R&D (binary)	0.241	0.428	0	1
R&D (expenditures)[1]	22,806	123,812	0	5,000,000
Tangible investments (binary)	0.640	0.480	0	1
Tangible investments (volume)[1]	33,451	266,113	0	10,000,000
R&D per employee[2]	5,200	29,043	0	1,200,000
Entrepreneurial and personality traits (ROCEAN)				
Risk tolerance	-0.000	1	-1.539	1.862
Openness	0.000	1	-4.413	2.207
Conscientiousness	0.000	1	-6.016	1.696
Extraversion	0.000	1	-4.351	1.936
Agreeableness	-0.000	1	-4.612	2.147
Neuroticism	-0.000	1	-2.408	3.548
Founder characteristics				
Female	0.167	0.373	0	1
Founder age	45.158	11.237	18	99
University degree	0.493	0.500	0	1
Industry experience	17.266	10.552	1	58
Serial entrepreneur	0.409	0.492	0	1
Firm characteristics				
Employees (full time equivalents)	4.091	6.894	0	177.5
Tangible assets[1]	10,953	46,086	0	1,700,000
Limited company	0.536	0.499	0	1
Opportunity driven	0.848	0.359	0	1
Team founder	0.210	0.408	0	1
Cohort	3.431	1.755	1	7
East Germany	0.135	0.342	0	1
Observations (*Unique firms*)		5,252 (*4,732*)		

[1] Measured in €
[2] Some observations were omitted when calculating this ratio since the denominator was zero.

and the vast majority was founded out of opportunity motives (84.8%) and by a solo founder (79%). Most of the founding activity takes place in Western Germany as only 21% of firms are located in the five federal states in Eastern Germany. Cross-correlations between the variables are presented in Tables A.3.7-A.3.9. There are significant pairwise correlations between personality traits and control variables, but none of them is higher than 0.2.

4.3.3 Method

In accordance with the literature, we assume that risk tolerance and personality traits remain constant over time (Costa and McCrae, 1997; Cobb-Clark and Schurer, 2011; Roccas et al., 2002), and that they are exogenous to R&D (and investment) decisions, i.e. there is no reverse causality. We model the founder's R&D (and investment) decisions as a function of personality as well as factors determining the need and opportunities for R&D (and investment), such as founder and firm characteristics. We abstract from other firms' R&D decision, presuming that the competitive environment is captured by the sector and region FE, the maturity by the cohort FE, and the business cycle by the survey wave FE.

In the empirical analysis, we proceed in four steps. We start with estimating separate models for the extensive and intensive margin, i.e. the decision to invest (extensive margin) and the decision on on the investment amount (intensive margin). Next, we model the relative R&D intensity (relative to the size of the work force) to account for the adjustment of expenditures to firm growth in terms of employment. Finally, we model the the decision to invest and the decision on the amount spent jointly in two-stage selection models for both R&D and tangible investments.

In the first step, we estimate probit models for the decision to conduct R&D in the form of

$$\Pr(R\&D = 1 \mid X) = \Phi(\boldsymbol{X}^T \beta) \tag{4.3.1}$$

where Pr denotes the probability, and Φ is the Cumulative Distribution Function (CDF) of the standard normal distribution. The parameters β are estimated via maximum likelihood estimation. The vector $\boldsymbol{X}$ contains both the key explanatory variables (ROCEAN) as well as controls (founder and firm characteristics). We build nested models in which we start with only the ROCEAN variables, and subsequently add founder and firm characteristics. To benchmark the R&D decision to investments in tangible assets, we estimate corresponding models for non-R&D-related investments.

Second and third, for the logged amount of R&D expenditures and R&D intensity (R&D expenditures per employee), ordinary least squares (OLS) models are estimated in the shape of

$$\text{R\&D variable} = \boldsymbol{X}^T \beta + \epsilon \tag{4.3.2}$$

where ϵ captures unobserved random variables (errors) that absorb factors affecting the R&D variables other than the regressors in $\boldsymbol{X}$. Again, we estimate corresponding models for the logged amount invested in tangible, non-R&D-related assets. Additionally, models are estimated for R&D intensity using OLS and stepwise adding the set of founder and firm controls.

Fourth, we estimate Heckman selection models that account for the fact that the outcome variables (R&D and tangible investments) are censored at zero and that quantities are not observed for firms that do not invest. Expressed differently, the amount of R&D expenditures is by definition unobserved for firms that indicate not to conduct R&D. Hence, we model this sample selection explicitly with the selection equation representing the decision to engage in R&D on the first stage, and the second stage equation reproduces how much to invest conditional on the decision to invest. The model can be written such that there is a selection equation

$$\text{R\&D} = \boldsymbol{Z}^T\gamma + \epsilon_1 \tag{4.3.3}$$

and an outcome equation with

$$\ln(\text{R\&D expenditures}) = \boldsymbol{X}^T\beta + \epsilon_2 \tag{4.3.4}$$

with $\epsilon_1 \sim N(0;\sigma)$ as well as $\epsilon_2 \sim N(0;1)$ and $corr(\epsilon_1, \epsilon_1) = \rho$. If $\rho \neq 0$, standard regression techniques may yield biased results and the Heckman selection model should provide consistent, asymptotically efficient estimates for all the parameters in such models as explained in the following.

In a two steps procedure, probit estimates from the selection model are obtained in the first stage (extensive margin). In the second stage (intensive margin), the probit estimates are inserted as initial values for the βs of the outcome equation and serve to construct λ, the selection hazard parameter. In a post-estimative test, λ's significance informs about the sample selectivity, i.e. if significant confirms that a non-random sample selection from the selection to the outcome model is at work (indicated in all Tables 4.4, A.3.12 to A.3.16) which functions as a validation of choosing this estimation method. The two-step procedure augments the second stage OLS regression and ensures consistent estimates. However, including the λ as the so-called Heckman correction causes collinearity between the correction term and the regressors (Bushway et al., 2007) and can lead to mis- and particularly underestimated standard errors. To compare estimate precision, asymptotic variance is approximated via bootstrap resampling and generates corrected standard errors in Section 4.4.2, Robustness Checks.

The identification of the second stage requires at least one ER to be included in the first stage that predicts the decision to engage in R&D but is penalized for the amount, conditional on the decision to invest. In our model, we select the information on an academic degree, since founders with a higher education background may be more inclined to engage in R&D or pursue a more scientific approach to decision making that also affects the propensity to invest more generally (Camuffo et al., 2020). As a second ER, we employ the value of the stock tangible assets (logged). Tangible assets may determine production capacity and hence the need to invest as well, since they affect the expected returns to R&D and often represent complementary assets (Rothaermel and Hill, 2005; Ceccagnoli et al., 2010). As a third ER, we add the firm's development stage, measured in years since founding. In line with the selection model for R&D, the model for the logged amount invested in tangible, non-R&D-related assets is estimated accordingly. In a robustness check described more detail in Section 4.4.2, we test the sensitivity of the results to the choice of these ER using a machine learning, i.e. LASSO, approach for selection of ER (Farbmacher, 2021). This approach will also allow to test whether the same set of ER applies to R&D as well as investments in tangible assets.

4.4 Empirical Analysis

4.4.1 Estimation Results

We first discuss the results for the likelihood to engage in R&D (extensive margin) and the amount spent on R&D (intensive margin), before we turn to tangible investments as the outcome variable (Table 4.2), and the relative importance of R&D over firm size (Table 4.3). The results at the extensive margin depict that the decision to invest in R&D is significantly determined by founder personality (see Models 1-3 in Table 4.2). Founders with a high levels of risk tolerance and openness are more likely to invest, and those with strong manifestations of conscientiousness, agreeableness and neuroticism are less likely to. These results are robust to the inclusion of other founder and firm characteristics (Models 2 and 3). The same pattern emerges when looking at expenditures, the intensive margin (see Models 4-6 in Table 4.2). For the more general decision to invest, we identify different patterns. Here, risk tolerance does not matter at the extensive margin. Yet, before controlling for firm characteristics at the intensive margin, higher risk tolerance is associated with larger investment amounts. Moreover, just as for R&D, the trait openness yields a higher likelihood to invest and also with larger amounts, whereas agreeableness and neuroticism display a negative effect at the extensive and intensive margin (see Models 7-9 in Table 4.2). For the control variables, the expected signs are observable: Academic founders invest more in both, R&D and general investments. The intesive margin pattern looks different for serial entrepreneurs: They spend more on R&D but less on physical investments. Teams with female founders reduce the amount invested in terms of both. Interestingly, the limited liability status correlates positively with R&D, but negatively with tangible investments, and industry experience drives investments, but not R&D, ceteris paribus. The analysis for R&D intensity confirms the prior results that more risk-loving and more open founders invest more R&D per employee. Again, this is robust to the inclusion of controls. Founders with higher degrees of neuroticism invest less in R&D per employee (see Models 1-3 in Table 4.3).

Table 4.2: Separate estimations – Models: R&D and tangible investment decision (ROCEAN as PFS)

	Models: R&D decision						**Models: Tangible investment decision**					
	Extensive margin (R&D (binary))			**Intensive margin** (ln(R&D))			**Extensive margin** (Investments (binary))			**Intensive margin** (ln(Investments))		
	1	2	3	4	5	6	7	8	9	10	11	12
Risk tolerance	0.228***	0.176***	0.138***	0.801***	0.601***	0.423***	0.020	0.028	0.011	0.175**	0.200***	0.105
	(0.021)	(0.022)	(0.024)	(0.065)	(0.064)	(0.059)	(0.019)	(0.019)	(0.020)	(0.069)	(0.070)	(0.067)
Openness	0.242***	0.242***	0.256***	0.656***	0.613***	0.521***	0.030	0.038*	0.045**	0.089	0.113	0.144**
	(0.023)	(0.024)	(0.026)	(0.064)	(0.062)	(0.057)	(0.020)	(0.020)	(0.021)	(0.074)	(0.073)	(0.071)
Conscientiousness	-0.126***	-0.075***	-0.053**	-0.387***	-0.213***	-0.138**	0.055***	0.047**	0.031	0.236***	0.204***	0.133*
	(0.021)	(0.022)	(0.024)	(0.066)	(0.064)	(0.058)	(0.019)	(0.020)	(0.020)	(0.072)	(0.072)	(0.069)
Extraversion	-0.080***	-0.060***	-0.024	-0.217***	-0.146**	-0.047	0.008	0.002	-0.007	0.071	0.058	0.004
	(0.022)	(0.022)	(0.024)	(0.066)	(0.064)	(0.058)	(0.020)	(0.020)	(0.020)	(0.072)	(0.071)	(0.068)
Agreeableness	-0.073***	-0.064***	-0.067***	-0.232***	-0.198***	-0.172***	-0.105***	-0.092***	-0.080***	-0.429***	-0.378***	-0.302***
	(0.021)	(0.022)	(0.024)	(0.067)	(0.066)	(0.059)	(0.019)	(0.020)	(0.020)	(0.069)	(0.069)	(0.067)
Neuroticism	-0.129***	-0.092***	-0.078***	-0.390***	-0.256***	-0.187***	-0.045**	-0.041**	-0.054***	-0.193***	-0.176**	-0.216***
	(0.021)	(0.022)	(0.024)	(0.062)	(0.061)	(0.056)	(0.019)	(0.019)	(0.020)	(0.069)	(0.069)	(0.067)
Female		-0.270***	-0.191***		-0.772***	-0.487***		-0.221***	-0.194***		-0.856***	-0.727***
		(0.060)	(0.066)		(0.151)	(0.140)		(0.049)	(0.052)		(0.183)	(0.180)
Founder age		0.000	-0.003		0.004	0.002		-0.014***	-0.010***		-0.050***	-0.034***
		(0.002)	(0.003)		(0.007)	(0.007)		(0.002)	(0.002)		(0.008)	(0.008)
University degree		0.633***	0.392***		1.894***	1.027***		0.052	0.124***		0.153	0.357**
		(0.046)	(0.054)		(0.130)	(0.133)		(0.039)	(0.045)		(0.143)	(0.151)
Industry experience		0.001	-0.001		0.004	-0.009		0.007***	0.007***		0.033***	0.029***
		(0.002)	(0.003)		(0.007)	(0.007)		(0.002)	(0.002)		(0.008)	(0.008)
Serial entrepreneur		0.240***	0.079		0.782***	0.203		-0.116***	-0.126***		-0.282*	-0.365**
		(0.045)	(0.050)		(0.137)	(0.129)		(0.039)	(0.042)		(0.145)	(0.144)
ln(employees)			0.175***			0.796***			0.298***			1.598***
			(0.036)			(0.102)			(0.034)			(0.116)
ln(tangible assets)			0.009*			0.024*			0.016***			0.052***
			(0.005)			(0.013)			(0.004)			(0.015)
Limited company			0.455***			1.063***			-0.143***			-0.327**
			(0.056)			(0.128)			(0.046)			(0.154)
Opportunity driven			0.100			0.216			-0.018			-0.075
			(0.068)			(0.140)			(0.054)			(0.179)
Team founder			0.075			0.295			-0.005			-0.060
			(0.062)			(0.183)			(0.055)			(0.198)
Cohort FE	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Sector FE	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Federal state FE	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Survey wave FE	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Observations	5,252	5,252	5,252	5,252	5,252	5,252	5,252	5,252	5,252	5,252	5,252	5,252

Estimates are coefficients

Standard errors in parentheses (clustered at firm level)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Corresponding to the previous findings, academic and serial entrepreneurs as well as older ones invest more, female founders less. Beyond, opportunity driven founders spend more on R&D per employee than others. The models presented in Tables 4.2 and 4.3 provide useful first insights into the role of personality for R&D and investment in nascent firms. However, they do not allow to conclude whether personality traits matter more at the extensive or intensive margin, since the amount observed is conditional on investing at all. Exploring this conditionality, we consider the results from the selection models presented in Table 4.4. The significance of the correlation between errors, i.e. ρ[10], of both stages indicates that adding the two stages in a joint model is indeed appropriate for both, R&D and tangible investments.

Table 4.3: Separate estimations – Model: R&D intensity (PFS)

	R&D per employee		
	1	2	3
Risk tolerance	2,404.826***	2,002.448***	1,769.244***
	(391.305)	(368.800)	(379.831)
Openness	1,623.021***	1,471.251***	1,221.528**
	(519.429)	(512.819)	(557.876)
Conscientiousness	-929.925**	-515.527	-514.124
	(418.586)	(451.693)	(478.755)
Extraversion	-339.443	-10.965	364.294
	(332.880)	(385.204)	(397.242)
Agreeableness	-547.801*	-548.869*	-579.362*
	(310.580)	(315.001)	(318.908)
Neuroticism	-935.259***	-612.887**	-445.045
	(288.196)	(305.574)	(295.613)
Female		-2,829.254***	-2,060.631**
		(716.468)	(809.253)
Founder age		171.597**	175.753**
		(71.774)	(73.336)
University degree		2,852.163***	1,896.541**
		(888.299)	(759.920)
Industry experience		7.178	16.607
		(57.115)	(63.318)
Serial entrepreneur		2,579.384***	1,415.816*
		(656.924)	(740.119)
ln(employees)			-1,623.024**
			(798.159)
ln(tangible assets)			-103.949
			(125.080)
Limited company			2,808.807***
			(972.174)
Opportunity driven			2,364.428***
			(741.696)
Team founder			1,353.273
			(1,446.972)
Cohort FE	No	No	Yes
Sector FE	No	No	Yes
Federal state FE	No	No	Yes
Survey wave FE	No	No	Yes
Observations[1]	5,237	5,237	5,237

Estimates are coefficients
Standard errors in parentheses (clustered at firm level)
[1] Some observations from the full sample (n=5,252) were omitted when calculating the dependent variable (ratio) since the denominator was zero.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

[10]For R&D, ρ=-1.004***; for tangible investments, ρ=-0.505***

Table 4.4: Selection estimations – Models: R&D and tangible investment decision (ROCEAN as PFS)

	Models: R&D decision			**Models: Tangible investment decision**		
	Selection estimation (twostep)		Average marginal effects	Selection estimation (twostep)		Average marginal effects
	Intensive margin	Extensive margin (linear)	Extensive margin (prob.)	Intensive margin	Extensive margin (linear)	Extensive margin (prob.)
Risk tolerance	0.129***	0.136***	0.032***	0.097***	0.012	0.004
	(0.046)	(0.023)	(0.005)	(0.024)	(0.020)	(0.007)
Openness	-0.260***	0.257***	0.060***	-0.039	0.047**	0.016**
	(0.065)	(0.025)	(0.006)	(0.025)	(0.021)	(0.007)
Conscientiousness	0.067	-0.059**	-0.014**	0.062**	0.028	0.010
	(0.045)	(0.024)	(0.006)	(0.025)	(0.020)	(0.007)
Extraversion	0.056	-0.023	-0.005	0.066***	-0.009	-0.003
	(0.044)	(0.024)	(0.005)	(0.025)	(0.020)	(0.007)
Agreeableness	0.034	-0.065***	-0.015***	-0.036	-0.082***	-0.028***
	(0.042)	(0.023)	(0.005)	(0.022)	(0.020)	(0.007)
Neuroticism	0.031	-0.078***	-0.018***	-0.034	-0.056***	-0.019***
	(0.047)	(0.024)	(0.006)	(0.024)	(0.020)	(0.007)
Female	-0.125	-0.188***	-0.044***	-0.115*	-0.190***	-0.065***
	(0.141)	(0.065)	(0.015)	(0.066)	(0.052)	(0.018)
Founder age	0.021***	-0.002	-0.001	0.000	-0.010***	-0.003***
	(0.005)	(0.003)	(0.001)	(0.003)	(0.002)	(0.001)
Industry experience	-0.001	-0.001	-0.000	0.009***	0.007***	0.002***
	(0.005)	(0.003)	(0.001)	(0.003)	(0.002)	(0.001)
Serial entrepreneur	-0.008	0.080	0.019*	0.115**	-0.121***	-0.041***
	(0.091)	(0.049)	(0.011)	(0.050)	(0.042)	(0.014)
ln(employees)	0.679***	0.166***	0.039***	0.828***	0.295***	0.101***
	(0.070)	(0.035)	(0.008)	(0.038)	(0.034)	(0.011)
Limited company	0.511***	0.452***	0.105***	0.239***	-0.132***	-0.045***
	(0.150)	(0.056)	(0.013)	(0.054)	(0.046)	(0.016)
Opportunity driven	0.149	0.101	0.024	0.021	-0.015	-0.005
	(0.138)	(0.067)	(0.016)	(0.061)	(0.054)	(0.018)
Team founder	-0.114	0.072	0.017	-0.098	-0.006	-0.002
	(0.110)	(0.061)	(0.014)	(0.064)	(0.055)	(0.019)
University degree		0.350***	0.081***		0.105**	0.036**
		(0.052)	(0.012)		(0.043)	(0.015)
ln(tangible assets)		0.008*	0.002*		0.015***	0.005***
		(0.005)	(0.001)		(0.004)	(0.001)
Cohort FE	No	Yes	Yes	No	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Federal state FE	Yes	Yes	Yes	Yes	Yes	Yes
Survey wave FE	Yes	Yes	Yes	Yes	Yes	Yes
ρ	-1.004***			-0.505***		
λ	-1.247***			-0.593***		
$ln(\sigma)$	0.491***			0.241***		
Observations	1,268	5,252	5,252	3,359	5,252	5,252

Standard errors in parentheses (clustered at firm level)
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

In the results of the two-step estimations, personality matters more in the first stage at the extensive margin with the direction of the effects as described above. In the second stage, the R&D amount is larger for more risk-loving founders, but in fact lower for those with higher degrees of openness. This can possibly be explained by the utility that 'open' people derive from trying unorthodox paths, while valuing a multitude of experiences. They may therefore be more likely to invest, but then invest lower amounts, ceteris paribus. Inspecting this result's robustness checks in Table A.3.10 and A.3.11, the negative association is not robust to model specification, suggesting that there is no persistent negative relationship between openness and the R&D amount.

The picture looks different for tangible investments. Here, risk tolerance does not impact the decision to invest (while openness does), but the amount (while openness does not). Notably, higher degrees of conscientiousness and extraversion explain higher investment amounts in the case of tangible investments, but not for R&D. What is more is that agreeableness and neuroticism matter more at the extensive than the intensive margin. The comparison of the average marginal effects shows that higher levels of openness influence R&D more strongly than investment, although openness matters for both.

The finding that higher degrees of conscientiousness are associated with a lower likelihood to engage in R&D (while being positively associated with the amount of tangible investments) may seem surprising at first. However, conscientiousness involves being someone who enjoys conforming to a protocol and accomplishing tasks. Conscientious people work diligently and strive for goals, hence dislike lack of rules and uncertainty in task completion. Unlike to that, the nature of R&D activities is inherently risky and yields uncertain outcomes.

4.4.2 Robustness Checks

We test the robustness of our results to variations in variable measurement, estimation method and model specification. First, we switch from using the predicted factor scores (PFS) as key explanatory variables to applying variables created by a heuristic approach. As an alternative to the PFS approach, we construct the Big 5 personality traits measures and the risk tolerance measure as average item scores (AIS). These are calculated as the average value of all items belonging to the factor as identified by the factor analysis[11]. The results are displayed in Tables A.3.10 and A.3.11. The insights concerning the role of the personality traits for R&D and

[11]See Table A.3.4: 3 items per personality trait, 2 items for risk tolerance.

investment decisions remain very similar to the ones presented in the Empirical Analysis of Section 4.4.

As a second check, we account for error correlation resulting from the repeated cross-sectional nature of the data set. Furthermore, the standard errors may be susceptible to imprecision because the model variable comes from a earlier estimation (collinearity between the Heckman correction term and the included regressors). Table A.3.12 shows the results from this robustness check. We focus on the Heckman selection model (compare to the results in Table 4.4) for which we now calculated bootstrapped instead of firm-clustered standard errors. This approximates asymptotic variance and allows to estimate standard errors more precisely. The results from these alternative measures conform to the previously reported ones.

As a final robustness test, we estimate Heckman models based on a Least Absolute Shrinkage and Selection Operator (LASSO) approach to select which covariates should be included in the outcome model. LASSO prevents overfitting by the reduction of potential regressors number to the ones reliably affecting the outcome[12]. For this purpose, LASSO imposes a penalty term which is composed of the sum of the absolute (A) coefficients, and weighs this penalty according to the tuning parameter λ that determines the extent of shrinkage (S)[13]. When producing coefficient estimates, the penalty constrains coefficient values towards zero, such that less contributive variables amount to close or equal to zero and are discarded. Model selection (S) is thus performed in conjunction with coefficient estimation.

Following the seminal paper by Farbmacher (2021), the advantage of employing a machine learning LASSO in selection models is that we do not rely on researchers' reasoning regarding the choice of exclusion restrictions (ER) [14]. Instead, we use a data-driven analysis to identify those variables that are technically valid ER. In doing so, two approaches are adoptable. The first is a fully unconstrained approach in which we allow the entirety of main as well as control variables to serve as potential ER (penalized approach[15]).

Alternatively, we can shield some variables from penalization, i.e. variables that should not be penalized and be included in the final post-LASSO Heckman regression. The results from the first version are displayed in Tables A.3.14. Here – for the case of R&D – some of the personality

[12]The so-called sparsity assumption reduces overcomplexity in high-dimensional models.

[13]When λ=0, linear LASSO equals the OLS estimation. The cost of each nonzero β grows in union with the penalty term that covaries with λ. An increasing λ shrinks the magnitude of the estimated coefficients.

[14]An ER is a variable that helps to model the selection process but is excluded from the outcome model.

[15]Since the penalty accrues, the costs for including all coefficients are borne.

traits are selected as ER (conscientiousness, agreeableness and neuroticism) and enter the first stage, but not the second. Moreover, industry experience, the serial entrepreneur information, the log of tangible assets, the team dummy and the founding year (cohort) are excluded from the second stage. The conclusion that can be drawn from the outcome model estimates is still soundly comparable to the results from theory-informed ER: A strong risk tolerance is associated with a higher likelihood to invest in R&D at the extensive margin, and with a greater amount at the intensive margin. Openness predicts the first stage significantly and positively, while it is negative (and only weakly significant) in the second stage. For investments, the set of ER is indeed different. Openness, founder age, the amount of fixed assets, the indicator for opportunity driven, and the team dummy are removed from the second stage. Despite these different ER, the conclusions resemble the previously discussed investment models (see Table 4.4).

Table A.3.15 contains the results from the partially penalized model and Table A.3.16 the ones from the non-penalized model. In the partially penalized model, ROCEAN variables are allowed in the ER, but not any variables that are considered to be fixed at the firm level (FE). The specification is again highly similar to the prior results, except that openness is no longer significant in the second stage. In the non-penalized models, where ROCEAN variables are not allowed to be picked as ER (Table A.3.16), we find once more industry experience, the serial entrepreneur indicator, the log of tangible assets and the team dummy to be ER. The results are again aligned to those before, with the Big 5 identically predicting the extensive margin, and risk tolerance predicting both extensive as well as the intensive margin.

For investments, the ER in the non-penalized case are founder age, the opportunity-driven indication and the log of tangible assets. The results are still very much in line with the previously discussed ones. Openness predicts the decision to invest positively, but not the amount which even is negatively insignificant. In addition, extraversion is a predictor of the amount of investment, but not the decision to invest. Agreeableness and neuroticism predict the outcome variables in both stages negatively.

Overall, these specification tests suggest that the main conclusions are not very sensitive to changes in the measurement of the main variables, the estimation method and the choice of ER.

4.5 Conclusion and Discussion

This study highlights the role of founder personality for decision making in entrepreneurial firms. The analysis focused on investments in intangible assets through R&D activities and compared these to investments in tangible assets. The research builds on and adds to prior work on firm performance (Rauch et al., 2009; Jong et al., 2013; Dencker and Gruber, 2015) and entrepreneurial actions (Lumpkin and Dess, 1996; Frese, 2009; Zhao et al., 2010) pivoting around CEO personality. Making use of detailed data for over 5,200 founders in more than 4,700 firms, we provide evidence that founders' entrepreneurial orientation and personality traits (risk tolerances, openness to experience, conscientiousness, extraversion, agreeableness, neuroticism) determine R&D decisions as well as other investment choices. Interestingly, there are common patterns, but also differences in the role of the distinct attributes on these strategic decisions.

The findings from the empirical analysis conform to the prediction from our simple theoretical model of entrepreneurial investment decision making. We derived hypotheses for each of the six personality dimensions and with regard to both R&D investments and tangible investments. These main hypotheses and insights from Section 4.4 are summarized as follows.

First, we hypothesized that risk tolerance matters for both investment types, but should matter more for R&D expenditures than for tangible investments at the extensive margin.

Hypothesis 1a: *Risk preference matters (+) for R&D expenditures at both margins.*

R ↗ ⇾ R&D ↗ at the extensive margin ✓

R ↗ ⇾ R&D ↗ at the intensive margin ✓

Hypothesis 1b: *Risk preference matters (+) for tangible investments at the intensive margin.*

R ↗ ⇾ Inv. ↗ at the intensive margin ✓

Thus, the results indeed demonstrate that founders who are more risk-loving are more likely to invest into R&D than other founders. For both R&D and investments, the amount spent rises along with the level of risk tolerance of the decision maker.

Second, we proposed that a higher degree of openness to experience should affect both investment types, but at the extensive margin, it should be more relevant for R&D than for tangible investments.

Hypothesis 2a: *Openness matters (+) for R&D expenditures at the extensive margin.*

O ↗ ⇾ R&D ↗ at the extensive margin ✓

O ↗ ⇾ R&D ↗ at the intensive margin ✗ ⇾ *O ↗ ⇾ R&D ↘ at the intensive margin*

Hypothesis 2b: *The effect of openness on tangible investments is ambiguous.*

O ↗ ⇾ Inv. ↗ at the extensive margin

However, we do not find openness to matter consistently over all specifications for R&D at the intensive margin. This suggests that founders may value engaging in new projects that affects the single founder's openness to (new) R&D projects, adding to the variety of the R&D portfolio, but does not result in higher investment volumes. In this regard, risk tolerance and openness are in fact quite different personality dimensions that do not necessarily result in similar behavioral patterns.

Third, we argued that also conscientiousness might impact both types of investment, but in opposite directions. As conscientious founders may value unpredictable outcomes less than those who score lower on that trait, they may be less keen to engage in R&D projects which are inherently uncertain and may not only be characterized by procedural uncertainties, but also involve substantial outcome and market uncertainty. For more predictable, and in that sense attainable, investment, on the other hand, we would expect that higher conscientiousness results in higher investment as this could be expected to reduce the failure risk of the firm overall:

Hypothesis 3a: *Conscientiousness matters (–) for R&D expenditures at both margins.*

C ↗ ⇾ R&D ↘ at the extensive margin ✓

C ↗ ⇾ R&D ↘ at the intensive margin ✗

Hypothesis 3b: *Conscientiousness matters (+) for tangible investments at both margins.*

C ↗ ⇾ Inv. ↗ at the extensive margin ✗

C ↗ ⇾ Inv. ↗ at the intensive margin ✓

Fourth, the expectations regarding the role of extraversion as a trait based on prior research were less clear, but given the potential importance of communication and networking skills also for entrepreneurial expansion strategies, we hypothesized that there could be positive link between extraversion and both types of investment and specifically at the intensive margin for the case of investments in tangible assets:

Hypothesis 4a: *Extraversion matters (+) for R&D expenditures at the extensive margin.*

E ↗ ⇾ R&D ↗ at the extensive margin ✗

Hypothesis 4b: *Extraversion matters (+) for tangible investments at both margins.*

E ↗ ⇾ Inv. ↗ at the extensive margin ✗

E ↗ ⇾ Inv. ↗ at the intensive margin ✓

The key finding with regard to extraversion is that is matters less at the extensive margin for R&D decisions than at the intensive margin for other investments. Thus, in line with our arguments it may relate to short-term scaling goals in reach and in sight, rather than distant long-term investments like R&D.

Fifth and sixth, we proposed that higher degrees of agreeableness and neuroticism should be related to lower investments overall. This affects both the decision to invest as well as the amount spent, but for R&D these traits may, in particular, matter for the likelihood to invest in the first place, since this is the point in time when sunk costs are realized.

Hypothesis 5a: *Agreeableness matters (–) for R&D expenditures at the extensive margin.*

A ↗ ⇾ R&D ↘ at the extensive margin ✓

Hypothesis 5b: *Agreeableness matters (–) for tangible investments at the extensive margin.*

A ↗ ⇾ Inv. ↘ at the extensive margin ✓

Hypothesis 6a: *Neuroticism matters (–) for R&D expenditures at both margins.*

N ↗ ⇾ R&D ↘ at the extensive margin ✓

N ↗ ⇾ R&D ↘ at the intensive margin ✗

Hypothesis 6b: *Neuroticism matters (–) for tangible investments at both margins.*

N ↗ ⇾ Inv. ↘ at the extensive margin ✓

N ↗ ⇾ Inv. ↘ at the intensive margin ✗

The expected negative association between agreeableness as well as neuroticism with entrepreneurial growth strategies are therefore confirmed by our results. The insignificance of neuroticism at the intensive margin is likely due to the fact that successful founders in general display little neuroticism which is also supported by our data. Therefore, although a neurotic individual are likely to perceive higher volatility, the effects at the intensive margin are less likely to be borne out by the data.

It should be noted that all these discussed traits still significantly explain R&D and investment even after accounting for a large set of other drivers. Moreover, it is remarkable that the effects related to these traits exhibit such pronounced patterns, considering that we looked at the investment decision of individuals who have already embarked on founding a firm, and thereby represent a group of people that is in general not hesitant to risk, change or adventure.

Taken together, our results illustrate that these personality attributes affect decisions on R&D at least as much as other investments. This is in line with the idea that the inherent uncertainty related to R&D leaves more room for subjective assessments of returns and profitability.

Particularly, risk tolerance has been shown to mentally compensate failure and loss potential, and openness requires structuring and developing of the enterprise in novel ways (Brandstätter, 2011), and therefore both these traits are strongly associated with R&D decisions. Yet, there are also other psychometric similarities between decisions in R&D and tangible investments, with more agreeable and more neurotic founders being less likely to invest in both. These results are robust to different variable measurements, model specifications and estimation methods. Especially the main results are insensitive to the choice of the exclusion restriction included in the selection models. The strongest discretionary sensitivity to personal properties is observable at the extensive margin, i.e. when entrepreneurs decide whether to invest in R&D. Above all, these findings contribute to the discussion on why some firms engage in R&D and pursue a growth strategy, while others do not.

4.5.1 Implications and Limitations

These insights complement those from the meta-analyses by Brandstätter (2011) and Kerr et al. (2017) that demonstrated that there is a relationship between psychometric attributes and firm performance. Brandstätter (2011) suggests that risk propensity supports business foundation, nonetheless not necessarily business success. Our results may link to the higher innovation likelihood of firms that engage in R&D, but also to the inherent risk profile that such investment bears. That is, while higher risk tolerance enables more R&D activities, it may also lead to a higher variance of returns. Kerr et al. (2017) summarize the trait openness to experience to be related to own originality but also an attraction to changing environments. This aligns with our results conveying that high openness levels produce a stronger R&D investment likelihood. Though only weakly significant and not persistently cross-validated at the intensive margin, the investment amount decision, expresses a negative association between R&D and openness, speaking to the taste for diversifying into many R&D projects instead of a low number but high volume R&D stimuli to the entrepreneur.

In earlier work, such as Lumpkin and Dess (1996), entrepreneurship and firm performance are conceived to evolve from a compound of individual, organizational, or environmental factors. Our study advances this concept by linking individual factors to specific firm strategic investments. The insight that individual personality explains investments even after other firm characteristics and the competitive environment are controlled for is informative for policy makers. It is paramount to know which founder types to reach when drafting entrepreneurial policy in the attempt to address a non-random founder selectivity. Previous research stressed that targeted policy instruments can foster entrepreneurial performance and indicate that entrepreneurial investments are indeed below the social optimum (Hottenrott and Richstein, 2020).

In spite of all efforts, this study is not without limitations. First, we do not analyze the decision to become an entrepreneur, as our data covers founders only. Despite personality traits being non-transient (Roccas et al., 2002), Kerr et al. (2017) raise the issue of endogenously strengthened personality traits after adopting an entrepreneurial role. To avoid confusion of exogenous metrics with endogenous outcomes, using pre- and post-founding information or entrepreneurial training records would make the exposition to interventions and personality's time variance observable. Second, entrepreneurial risk tolerance is shiftable by personal, family's and friends' financial wealth. To prevent distortion by material endowment, a control for absorbing failure bail-out would enrich the data and allow to test how sensitive a self-reported risk construct is to external compensation mechanisms. Third, we explored only selected personality traits which may not represent fundamental aspects in an entrepreneurial context, such as cooperativeness, reciprocity, patience or trust. For this reason, we strongly encourage more extensive research on this topic to investigate other dimensions of personality, especially those that capture inter-human behavior. Moreover, we did not shed light on team composition and how different founders' personalities may complement or nullify each other. Looking at personality in a within team setting might provide additional insights into the role of founder personality on entrepreneurial behavior. Ultimatively, we did not deconstruct the nature of R&D by into its components, although personality may play a different role for (basic) research as compared to development or for R&D activities, with particularly high social returns from, for instance, environmentally beneficial technologies.

5 | Conclusion

5.1 Summary of Main Insights

This dissertation presents the results from extensive research on R&D decisions interacting with firm characteristics (Chapter 2), being an outcome of strategic specialization (Chapter 3), and carrying the handwriting of entrepreneurial personality (Chapter 4). I examine these topics in light of firms' R&D contribution to productivity, the role of R&D focus in technology transfer, and founders' investing style. Understanding that R&D behavior is strongly determined by firm and entrepreneurial characteristics can be picked up by and integrated into policy making. Informed regulators can identify and target economic mechanisms that drive R&D decisions and use them as guidance on how to design industrial policy such that it effectively reaches firms and entrepreneurs, supports knowledge transmission and technology transfer, and creates an innovation-promoting economy.

From the analyses presented in Chapter 2, we learn that there is a central link between firm size, research orientation, and firm-level productivity. I show analytically that firms differ in their relative focus to conduct R, and that these differences comply with firm size: Smaller firms exhibit higher R-shares compared to larger firms, and generate relatively higher returns to research in terms of productivity. This insight is in line with prior work that emphasizes the comparative advantages of small versus large firms with regard to product or process innovation. The findings support the idea that a firm's optimal research focus, i.e. the share of the R&D budget devoted to R, is lower for larger firms than for smaller ones. Moreover, the results depict that research is a key driver of productivity, but that the incremental research premium is higher for smaller firms than for larger corporations. On the other hand, larger firms are absolutely advantaged in doing both, R and D, but since it is more profitable to dedicate financial resources to D, their optimal R focus is lower compared to the one of smaller firms. Taken together, the labor division in R and D by firm size follows the economic gains obtained by absolute and comparative advantages, and is efficient since firms align their R and D strategies with the expected returns from productivity. The findings do not confirm concerns describing an overall decline in corporate research with firms trapped in a position of undersupplying knowledge. Instead, they suggest a shift of research, steadily being conducted in smaller, specialized firms which serve as a input providers to larger firms that are oriented towards product development. This is also reflected in the declining share of research-active firms which points to a rearrangement of overall activities on the economy level.

These results have implications for innovation policy. Policy makers may be well advised to design measures that strengthen firms' comparative advantages. The facilitation of the tacit labor division between firms of different sizes can help to maximize total productivity of corporate R&D activities across firms. Moreover, the results highlight the role of small, research-intensive firms in innovation systems. Innovation policy needs to account for smaller firms' relatively higher research orientation when designing R&D support instruments. In reply to the debate about the slowdown in productivity growth in developed economies (Griliches, 1980; OECD, 2016), this essay offers the insight that any impediments of the labor division in R&D could cause inefficiencies in the realization of productivity premiums from R&D. Finally, this study extends earlier analyses that considered research activities in isolation (Belenzon and Patacconi, 2014), or discussed specialization regarding innovative outputs rather than the returns on investments. (Acs and Audretsch, 1987; Henderson, 1990; Henderson and Cockburn, 1996; Macher and Boerner, 2006; Arora et al., 2009).

Chapter 3 progresses the findings from Chapter 2 on innovative specialization and focuses on the interdependence between strategy choice and the market for knowledge. The question whether and to what extent firms make use of the market for knowledge to source complementary know-how is vital to technology transfer. I present the strategy choice in a stylized framework in Figure 3.1 and argue that labor division in R and D is contingent on a functioning market (Gans et al., 2008; Arora and Gambardella, 2010b) to source complementary R&D inputs. Firms with a strong specialization trade their inventive outputs through the channels of collaboration, licensing, and contract research. In this line of argument, market participation facilitates the provision of those intangible assets which a firm does not produce in-house.

By and large, firms benefit from the market for knowledge as it allows them to realize returns to specialization. As a means to absorb knowledge spillovers from collaboration partners, but also by making organizational learning viable, collaboration increases the returns to specialization.

It furthermore delivers exchanging knowledge including tacit knowledge, bundling resources, increasing cost efficiency, and hence, reduces risk by insuring against technological and market uncertainty. Relying on licensing and contract R&D, firms can focus on their core competencies which stimulates corporate knowledge production and technology transfer across firms, and can be a reaction to the accumulating technological complexity and the resulting knowledge-burden (Jones, 2009). Building on a conceptual framework in which firms decide on their research strategy, and thus their relative focus in corporate research relative to development, the results from a detailed empirical analysis of a large sample of R&D-active firms show that strategic choice and participation in knowledge and technology transfer are interdependent. The empirical results of Chapter 3 depict that collaborative R&D, licensing and contract research to indeed be integral forms of compensating for a highly specialized R&D profile. More precisely, the analysis provides evidence for higher R-shares of total R&D to rise in union with the likelihood of firms engaging in R&D collaborations. More research-oriented firms are also more likely to license technology. Unlike collaboration and licensing, however, contracting research seems to reinforce investing more in internal R&D operations in terms of both R and D, underlining the complementarity of internal and external R&D as documented in earlier work (Arora and Gambardella, 1990; Grimpe and Kaiser, 2010; Añón Higón et al., 2018). The findings from this chapter add to those presented in Chapter 2 by demonstrating that the gains from specialization depend on firms' ability to participate in cross-firm knowledge and technology transfer. Moreover, these insights add to previous research that highlighted the role of collaborative R&D for innovation performance, but has largely neglected the role of technology licensing and external R&D contracts (Hottenrott and Lopes-Bento, 2016; Hottenrott et al., 2016).

The results presented in Chapter 3 have implications for innovation policy as well as for managers. The findings emphasize the salience of well-functioning IPR systems when exchanging knowledge and transferring technology across firms (Gans et al., 2002; Gans and Stern, 2003), and competition law that provides exemptions for R&D collaborations. IPR offer an informal security to participants, particularly in R&D collaborations, and transmit important signals on the functioning of the market for knowledge. In addition, regulators should carefully assess possible side-effects of modifying IPR systems that result in weaker rights or lowers the hurdle for misappropriation of non-patentable intangible assets.

Chapter 4 investigates R&D decisions in new, entrepreneurial firms. Unlike the preceding chapters that operate at the firm level using data from established companies, this chapter is settled at the founder level. In doing so, it compares two types of investments that are important for the scaling of new businesses: R&D expenditures and tangible investments. A theoretical framework that ties personality dimensions to entrepreneurial discretion serves as a basis to study the role of psychometric profiles for decision outcomes. In the empirical analysis, I predict the investment decision (extensive margin) and investment volume (intensive margin) by characteristics of the personality profile, and study how the impact differs according to the investment type. The diverse dimensions of founder personality (Big 5 traits and risk tolerance) are used to identify which attributes imprint R&D decisions, and what sets them apart from decisions on tangible investments. While risk tolerance positively relates to both the extensive and the intensive margin in R&D decisions, openness to experience only raises the likelihood to invest in R&D but not the volume. All and above, entrepreneurial personality mostly matters at the extensive margin of R&D decisions. The findings strengthen the hypothesis that in cases of investments under uncertainty entrepreneurial discretion tends to be guided by subjective assessments of profitability. These insights also illustrate the substantial behavioral differences in firms' pursuit of growth strategy, and speak to the literature on the variation in start-up performance, growth and eventually survival. The results suggest that within emergent firms, founder team composition could counterbalance excessively aligned and asymmetric decision making by choosing entrepreneurial personalities that reinforce, offset or reverse behavioral dynamics.

The findings from this study supply policy makers with novel insights for designing entrepreneurship and innovation policy. Regulators could encourage investments in knowledge production by directing measures to the extensive margins of R&D instead of promoting a strict selection of high-in-volume but low-in-number R&D investments. Policy is also sensitive to reaching specific entrepreneurs in the attempt to address a non-random founder selectivity. Entrepreneurial education could serve as a vehicle to constrain founders' exposition to subjective perception dominating a decision. The more informed a decision maker, the less decisions of long-term firm performance could be purely commanded by personality-constituting attributes of the entrepreneur. Camuffo et al. (2020) recently demonstrated that a scientific approach to entrepreneurial decision making improves discretionary precision by relying on heuristics to accurately estimate the returns to a project, in particular to recognize low or high returns, or to pivot to alternative ideas which are more profitable. Analogously, my results extend related evidence from entrepreneurial pyschometry: Krueger and Sussan (2017) categorize strategic thinking to depend on personal and situational factors of which even non-transient individual attitudes towards thinking strategically remain malleable to some degree, as well as critical thinking and creativity which belong to the learnable skill set. Caliendo et al. (2020) ascribe entrepreneurial persistence to be the reason for constantly renewed active engagement in a new business venture despite counter-forces, and empirically proves that beside personality, human capital is an important determinant. Since human capital can be upskilled, entrepreneurs are trainable to exploit business opportunities and realize potential economic benefits. My research extends scholars' recent line of work on entrepreneurial education and suggests that training founders equips them with tools for informed entrepreneurial decision making.

5.2 Limitations

The insights provided by this dissertation are based on results from observational studies. While the underlying data condense a large set of firms from a variety of sectors and attributed diverse characteristics, there are some limitations that arise from the non-experimental design. First, external validity is presumably high due to the representativeness of the survey samples which allows to generalize beyond the study sample to other contexts. Since firm exposure to the outcome variables was not allocated and not all design features were chosen, there may be some concerns regarding unobservable factors of the sample that affect unobservable factors of the outcome. I address several threats to internal validity, such as accounting for confounding elements and selection bias, by controlling for important factors that could distort the main effects. The selectivity of observations into subsamples is accounted for by the choice of estimation methods and has been cross-checked with alternative estimators and robustness tests. In spite of all econometric techniques aiming at constraining their impact on the conclusions, each study should still be interpreted with the typical caution originating from observational research.

Second, the results are based on analyses of companies located in two European countries – Belgium and Germany – and both of these countries have commonalities which may impose limits on how far they can be replicated for other economies. One of the characteristics is the industry landscape with a high proportion of small- and medium sized enterprises (SME) shaping the innovation system. The findings may also be context-specific, since both countries are relatively unique in their openness to and dependence on international trade (Germany), and foreign direct investment as well as multinational corporations (Belgium). Lastly, the data used in Chapter 4 draw from the only recently introduced questions on entrepreneurial orientation and personality dimensions. Before the person-specific traits' temporal continuity as theorized in trait psychological literature has not been tested over time in longer time-series data, there remains potential to unobserved interventional impacts and transient elements framing entrepreneurial discretion. In this regard, we may underestimate the extent to which entrepreneurial experience affects personality and hence the role of personality for decision making over time.

5.3 Avenues for Future Research

Despite the comprehensive approach adopted in this dissertation, there is still room for additional analyses and thus requires further research on the topics examined. First, my work underlines the need to study privately-owned firms as well as SME, since they are leading agents of economic growth, employment, and productivity. Yet, their strategies and objectives receive less attention in vast parts of economic research than those of large, stock-market listed firms or entrepreneurial ventures. European economies benefit especially from these firms 'in the middle' that secure the majority of jobs as employers, but also feed and sustain the innovation system. I wish my thesis to be an impetus to follow-on studies on the role of such firms, often also referred to as hidden champions.

Particularly, Chapter 2 suggests that R&D activities are becoming more concentrated in the economy. This supports observations made in earlier documentations, for instance Rammer and Schubert (2018). That is, fewer firms engage in any R&D operations at all. The potentially detrimental effects resulting from this development are currently being debated. A source of concern for innovation regulators is the welfare-reducing market power to which a policy reaction at best includes instruments that promote incremental innovations.

One of the central implications of my research is that there is a division of labor in R&D which allows firms to generate productivity gains. However, I also demonstrate that functioning markets for knowledge are a precondition for these benefits to materialize. Policy makers so far pay still relatively little attention to fostering markets for knowledge. I therefore strongly advocate research to take the lead in pointing out the mutual dependence between the returns to intramural R&D and the sourcing of external knowledge. Future studies could evaluate public open-access and resource-pooling initiatives that aim at collecting and publicly diffusing knowledge.

A topical proximity to the market for knowledge also pertains to the breadth and depth of external search for the complementary provision of inventive inputs: Not only could the sourcing channels be typecasted according to the business relationship into suppliers and customers, but also to the non-commercial institutions of higher education like universities and research institutions. Studying in more detail to what extent the outcomes of these exchanges exhibit patterns of variation, for example when predicting expenditure amounts, patent output, and innovation novelty, could paint a more nuanced picture of the corporate innovation landscape.

My work furthermore emphasizes the interaction between firms in knowledge creation activities. Nonetheless, prior research typically focuses on formal forms of exchange and neglects the role played by the exchange types of collaboration and social interaction. Yet, the investigations presented suggest that such activities may dynamically enable sourcing strategies as well as determine the returns from these strategies. I hope that my research inspires explorations of tools' effectiveness that incentivize non-formalized interaction between firms on markets for knowledge. The topic appears to be underresearched with respect to the profitability of jointly produced innovations and to the division of the returns between partnering companies.

Finally, Chapter 4 provides evidence that personality matters more for the decision to engage in R&D in the first place than for the volume invested. My findings identify the prominent role of risk tolerance in both investment decisions, for R&D expenditures and tangible assets. Since the literature recurrently picks up how the perception of volatility and recognition of returns shapes the attitude to take risk and to improve outcome variance in entrepreneurial decisions, follow-on research could include ex-post information on the factual riskiness (success/failure) of an investment in delay to the earlier recorded investor's risk attitude. Likewise, a wider view on measures for cognitive biases fits well to a mental compensation causing risk distortion. Further room can be accommodated for cooperativeness, reciprocity, patience, and trust that capture inter-human behavioral dynamics influencing how readily an individual takes risk. The financial wealth of the investor, family and friends represent a material compensation distorting the aversion to the risk to fail. Controlling for failure bail-out would prevent that private endowment shifts the willingness towards entrepreneurial risk.

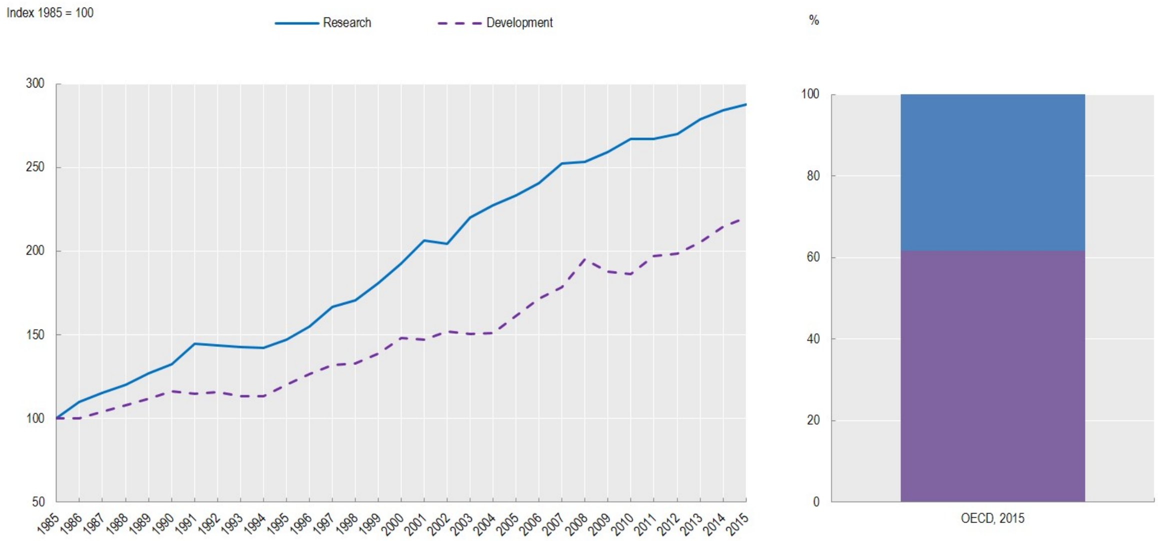
Departing from the insight that the extensive trumps the intensive margin concerning R&D decisions, the design and implementation of regulations could be prioritized to the extensive rather than to the intensive margin. Current R&D support measures, such as R&D tax credits or project funding, are overly oriented towards spending on R&D instead of nudging new engagement of firms in knowledge production, diversifying their product and service portfolio. There is also a need for taking into account the complexity and heterogeneity of founder- and firm-level response to policy instruments, and, in particular, R&D incentives which follow-on studies could address.

All in all, the findings obtained from the research consolidated in this dissertation offer plenty of avenues for future research. The complex interactions and market dynamics of firms, entrepreneurs and their R&D decision require policy makers to grasp the economic mechanisms at work. This thesis is another step paving the way for further elaborations on the economics of corporate research and development. Embedding its insights into the context of innovation-guided knowledge economies points out relevant factors and new questions, leaving room for exploration in future work.

Appendix

A.1 Division of Labor in R&D? Firm Size and Specialization in Corporate Research

Figure A.1.1: Trends in research and development in the OECD Area, 1985-2015



Source: OECD (2017)

Table A.1.1: Distribution of sectors by firm size

#	Sector	SME		Large firms		All firms	
		Count	%	Count	%	Count	%
1	Food,fishery & tobacco	674	5.41	148	6.37	822	5.57
2	Textile	438	3.52	99	4.26	537	3.64
3	Forestry & furniture	266	2.14	13	0.56	279	1.89
4	Paper	261	2.10	78	3.36	339	2.30
5	Chemicals	371	2.98	134	5.77	505	3.42
6	Pharmaceuticals	128	1.03	56	2.41	184	1.25
7	Rubber, plastic & materials	477	3.83	109	4.69	586	3.97
8	Natural resource extraction & waste man.	907	7.29	282	12.14	1,189	8.05
9	Machines & equipment	760	6.11	133	5.73	893	6.05
10	Computer, electronic & optical products	365	2.93	73	3.14	438	2.97
11	Transport manufacturing	381	3.06	149	6.42	530	3.59
12	Building & construction	772	6.20	94	4.05	866	5.86
13	Miscellaneous industry	170	1.37	41	1.77	211	1.43
14	Commerce, storage & transport	2,743	22.04	403	17.36	3,146	21.30
15	Financial & other services	2,282	18.33	325	14.00	2,607	17.65
16	ICT & software	1,286	10.33	136	5.86	1,422	9.63
17	Education, health & public personal service	166	1.33	49	2.11	215	1.46
	Total	12,447	100.00%	2,322	100.00%	14,769	100.00%

Table A.1.2: Descriptive statistics of R&D variables by sector

Sector	Mean	P50	Sd	Min	Max
1					
Research	192.13	0	765.18	0	12,240
Development	148.47	0	587.23	0	6,950
R-share	0.30	0	0.39	0	1
D-share	0.20	0	0.32	0	1
2					
Research	254.95	25	842.14	0	8,956
Development	238.57	15	566.26	0	3,900
R-share	0.33	0	0.36	0	1
D-share	0.30	0	0.35	0	1
3					
Research	56.85	0	164.30	0	1,080
Development	38.42	0	115.88	0	978
R-share	0.22	0	0.34	0	1
D-share	0.15	0	0.28	0	1
4					
Research	148.97	0	453.49	0	4,860
Development	180.46	0	486.30	0	4,400
R-share	0.19	0	0.32	0	1
D-share	0.26	0	0.37	0	1
5					
Research	865.49	38	2,642.51	0	25,064
Development	938.24	35	3,329.95	0	30,569
R-share	0.35	0	0.37	0	1
D-share	0.33	0	0.36	0	1
6					
Research	12,419.48	28	50,990.12	0	390,866
Development	23,796.43	15	102,553.92	0	686,483
R-share	0.40	0	0.41	0	1
D-share	0.35	0	0.39	0	1
7					
Research	344.96	3	1,111.24	0	10,450
Development	487.19	0	1,983.87	0	19,000
R-share	0.30	0	0.36	0	1
D-share	0.27	0	0.34	0	1
8					
Research	749.86	0	4,300.76	0	65,268
Development	958.92	0	5,922.70	0	142,200
R-share	0.27	0	0.36	0	1
D-share	0.25	0	0.34	0	1
9					
Research	1,277.96	40	4,865.00	0	50,050
Development	1,726.34	24	6,992.49	0	88,336
R-share	0.38	0	0.37	0	1
D-share	0.34	0	0.36	0	1
Observations	5,334				

Sector	Mean	P50	Sd	Min	Max
10					
Research	1,688.08	181	3,922.12	0	29,972
Development	2,736.22	42	12,175.06	0	104,936
R-share	0.46	0	0.39	0	1
D-share	0.32	0	0.35	0	1
11					
Research	1,377.14	36	5,455.25	0	72,000
Development	1,289.82	15	4,149.85	0	47,879
R-share	0.35	0	0.39	0	1
D-share	0.37	0	0.40	0	1
12					
Research	154.35	0	1,160.93	0	25,000
Development	60.22	0	327.24	0	3,750
R-share	0.12	0	0.29	0	1
D-share	0.07	0	0.20	0	1
13					
Research	4,125.20	108	11,551.64	0	104,030
Development	6,859.20	70	28,027.67	0	232,133
R-share	0.44	1	0.37	0	1
D-share	0.36	0	0.35	0	1
14					
Research	221.84	0	1,745.10	0	45,907
Development	283.68	0	2,480.89	0	54,000
R-share	0.17	0	0.32	0	1
D-share	0.14	0	0.29	0	1
15					
Research	1,035.14	0	4,917.37	0	97,705
Development	1,049.82	0	6,190.53	0	90,000
R-share	0.31	0	0.39	0	1
D-share	0.20	0	0.32	0	1
16					
Research	580.41	18	2,471.36	0	34,100
Development	289.79	0	2,609.63	0	90,877
R-share	0.38	0	0.42	0	1
D-share	0.21	0	0.33	0	1
17					
Research	1,120.51	0	3,872.06	0	31,724
Development	265.38	0	906.85	0	5,627
R-share	0.28	0	0.40	0	1
D-share	0.17	0	0.32	0	1
Observations	9,435				

Figure A.1.2: Distribution of firm size in the subsample of R- or D-active firm-year observations

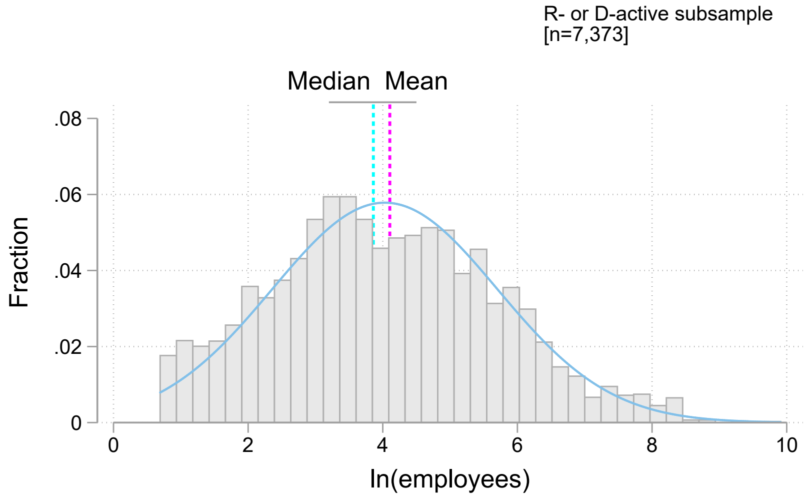


Figure A.1.3: Distribution of firm age in different firm size classes

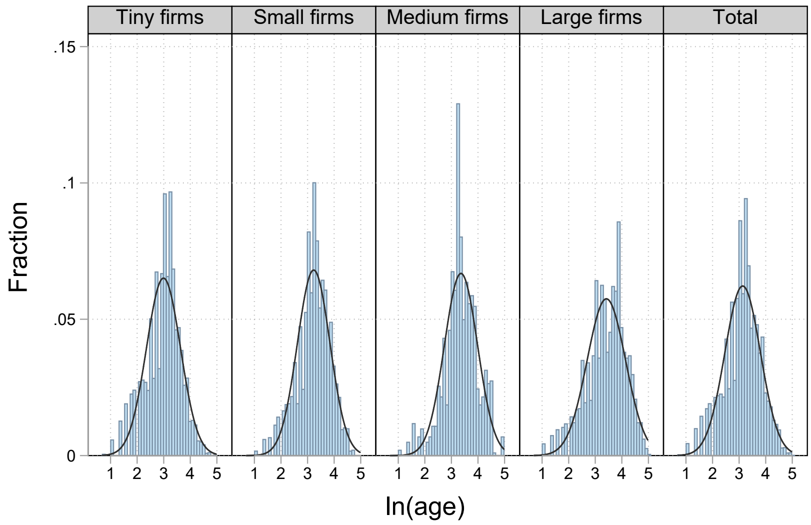
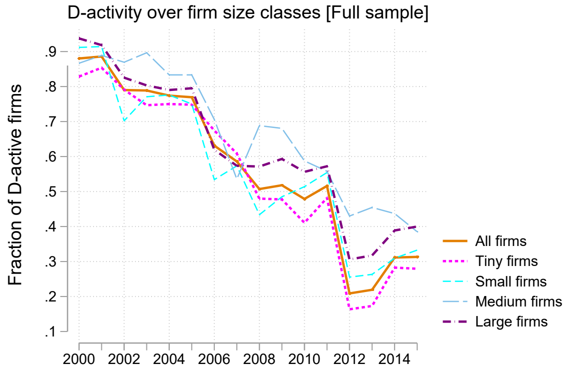
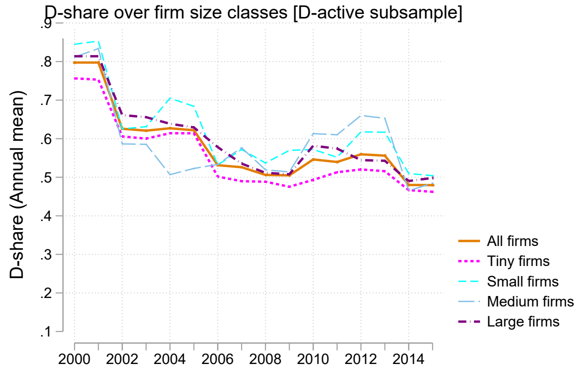


Figure A.1.4: Development of the extensive and intensive margin for D-activity



(a) Extensive margin



(b) Intensive margin

Figure A.1.5: Interaction of firm size classes with years

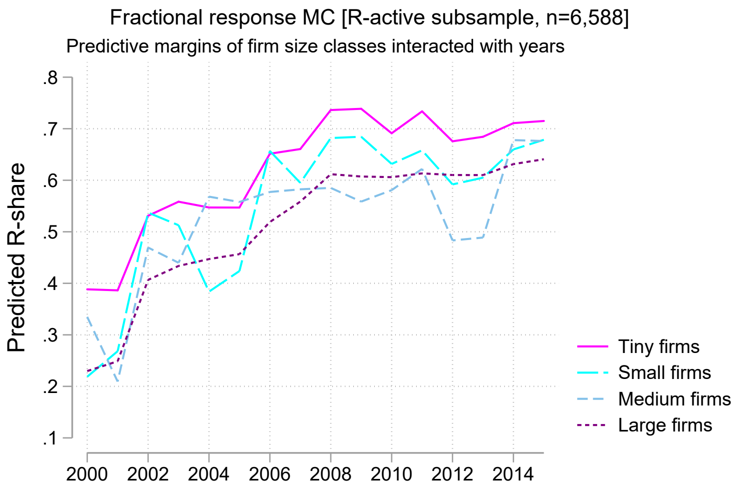


Table A.1.3: Production function estimations by sector

	1	2	3	4	5	6	7	8	9
ln(non-R&D employees)	0.648***	0.786***	0.738***	1.042***	0.863***	1.122***	0.904***	0.863***	0.721***
	(0.019)	(0.060)	(0.027)	(0.020)	(0.041)	(0.051)	(0.012)	(0.064)	(0.010)
ln(research expenditures)	0.056***	0.106***	-0.065**	-0.029	-0.017	0.056	0.048*	0.012	0.080***
	(0.012)	(0.025)	(0.026)	(0.037)	(0.051)	(0.039)	(0.027)	(0.040)	(0.018)
ln(development expenditures)	0.034	0.030	-0.015	-0.039	-0.039	0.069	0.012	-0.004	0.022*
	(0.025)	(0.026)	(0.022)	(0.037)	(0.029)	(0.123)	(0.027)	(0.042)	(0.011)
ln(fixed assets)	0.199***	0.114	0.123***	0.083***	0.262***	-0.037	0.165***	0.203***	0.180***
	(0.040)	(0.075)	(0.019)	(0.028)	(0.032)	(0.042)	(0.053)	(0.040)	(0.037)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	819	535	279	338	503	183	575	1,171	888

	10	11	12	13	14	15	16	17
ln(non-R&D employees)	0.447***	0.736***	0.884***	0.517***	0.900***	0.793***	0.878***	1.024***
	(0.029)	(0.018)	(0.017)	(0.045)	(0.010)	(0.049)	(0.027)	(0.047)
ln(research expenditures)	0.140***	0.018	0.001	0.190***	0.044***	0.129**	0.075***	0.003
	(0.019)	(0.014)	(0.016)	(0.039)	(0.014)	(0.061)	(0.022)	(0.112)
ln(development expenditures)	0.090***	-0.018	0.074***	0.020	0.014	0.050**	0.015	0.022
	(0.018)	(0.027)	(0.009)	(0.034)	(0.011)	(0.023)	(0.015)	(0.082)
ln(fixed assets)	0.183***	0.203***	0.189***	0.327***	0.123***	0.192***	0.113***	0.126*
	(0.031)	(0.023)	(0.046)	(0.046)	(0.015)	(0.021)	(0.021)	(0.075)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	436	529	861	211	3,105	2,542	1,410	208

Standard errors in parentheses (bootstrapped)

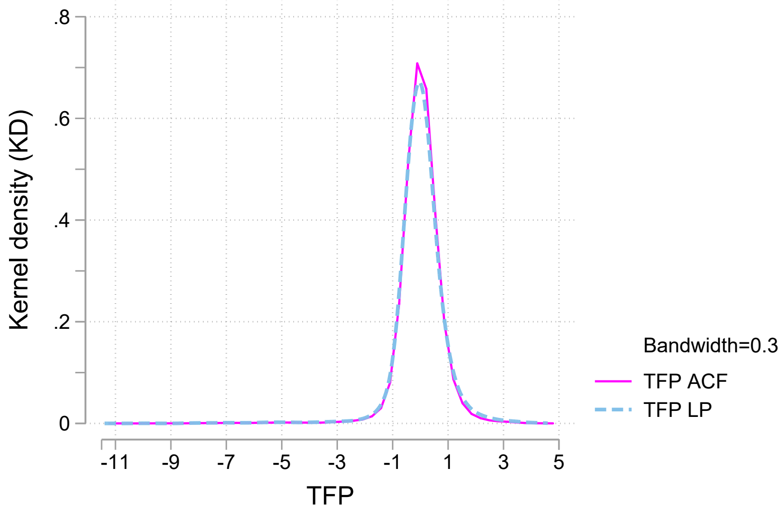
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table A.1.4: Panel estimations of TFP on D-share

	OLS FE	GLS RE	GLS RE	GLS RE	GLS RE	GMM
D-share $_{t-2}$	-0.264*	-0.146	-0.165*	-0.259***	-0.138	-3.944***
	(0.136)	(0.100)	(0.088)	(0.083)	(0.101)	(0.867)
ln(employees)	-0.378**	-0.055***	-0.046***	-0.042***	-0.056***	-0.426*
	(0.161)	(0.016)	(0.012)	(0.007)	(0.015)	(0.219)
D-share $_{t-2}$ $\times$ ln(employees)	0.053*	0.027	0.031	0.038***	0.024	0.616***
	(0.029)	(0.025)	(0.023)	(0.014)	(0.026)	(0.161)
ln(age)	-0.120	0.349*	0.176	0.172	0.334*	-16.623*
	(0.576)	(0.184)	(0.133)	(0.144)	(0.187)	(9.548)
ln(age) $\times$ ln(age)	0.081	-0.045*	-0.020	-0.022	-0.044*	2.559*
	(0.123)	(0.025)	(0.019)	(0.019)	(0.026)	(1.415)
ln(external R&D)	0.010	0.011	0.010	0.013*	0.011	0.013
	(0.013)	(0.010)	(0.009)	(0.007)	(0.010)	(0.095)
Patent stock	-0.000	-0.000	-0.000	0.000	-0.000	0.005**
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.002)
Working capital ratio*	-0.000	0.000	0.000	0.000***	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Long-term debt ratio*	0.000***	0.000***	0.000***	0.000*	0.000***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Short-term debt ratio*	-0.000*	0.000	0.000	0.000	0.000	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Enterprise group dummy	-0.063	0.055	0.044	0.041	0.056	-0.255
	(0.052)	(0.047)	(0.039)	(0.026)	(0.041)	(0.303)
TFP ACF$_{t-2}$			0.242***	0.206***		0.081
			(0.025)	(0.063)		(0.077)
TFP ACF$_{t-3}$				0.106*		-0.026
				(0.060)		(0.061)
Sector FE	Yes	Yes	Yes	Yes	No	No
Year FE	Yes	Yes	Yes	Yes	No	No
Observations	4,847	4,847	4,840	3,379	4,847	3,379

Cluster-robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.
Note that we apply time-variant sector affiliations in the sector fixed effects.
* Ratio uses fixed assets in the denominator
All values are rounded; 0.000 indicates values of < 0.001.

Figure A.1.6: Kernel density of TFP by estimation method



A.2 Specialization in Corporate Research and the Market for Knowledge

Table A.2.1: Distribution of sectors – Row percentages over TT-active subsamples

#	Sector	Collab. active	Lic.-in active	Lic.-out active	External R&D active	Full sample Count	Full sample %
1	Food, fishery & tobacco	17.24%	5.26%	2.01%	21.17%	822	5.57
2	Textile	22.92%	8.48%	2.47%	28.12%	537	3.64
3	Forestry & furniture	9.80%	8.33%	7.50%	15.05%	279	1.89
4	aper	14.71%	5.00%	8.13%	24.48%	339	2.30
5	Chemicals	33.83%	5.77%	1.54%	29.90%	505	3.42
6	Pharmaceuticals	22.99%	10.08%	4.65%	27.17%	184	1.25
7	Rubber, plastic & materials	21.74%	3.04%	2.70%	25.26%	586	3.97
8	Natural resource extraction & waste management	21.08%	4.16%	5.89%	25.32%	1,189	8.05
9	Machines & equipment	23.26%	7.62%	5.81%	35.05%	893	6.05
10	Computer, electronic & optical products	35.22%	10.14%	6.64%	39.27%	438	2.97
11	Transport manufacturing	26.37%	4.11%	3.08%	36.79%	530	3.59
12	Building & construction	8.31%	1.11%	2.22%	6.81%	866	5.86
13	Other manufacturing	39.44%	15.31%	16.33%	47.87%	211	1.43
14	Commerce, storage & transport	11.46%	5.72%	3.89%	12.68%	3,146	21.30
15	Financial & other services	21.88%	9.93%	10.23%	19.18%	2,607	17.65
16	ICT & software	16.35%	9.95%	11.08%	15.96%	1,422	9.63
17	Education, health & public services	23.36%	13.16%	18.42%	22.33%	215	1.46
	Total	19.82%	7.16%	6.23%	21.08%	14,769	100.00

Table A.2.2: Factor analysis of collaboration partners

	Eigenvalues
Factor1	2.964
Factor2	0.076
Factor3	-0.020
Factor4	-0.081
Factor5	-0.132
Factor6	-0.151

	Factor loadings	
Item	Factor1	Factor2
Customer collaboration	0.788	-0.134
Supplier collaboration	0.780	-0.140
Firm collaboration	0.625	0.134
Consultant collaboration	0.675	0.055
Research collaboration	0.582	0.130
University collaboration	0.741	0.026

The method applied is principal component factor analysis (principal component analysis) and assumes variance to be fully explained by common variance shared among items. Principal factor analysis (exploratory factor analysis) assumes the variance to be explained by common variance plus uniqueness (specific factor variance and error variance).

Table A.2.3: Cross-correlations of main variables

	1	2	3	4	5	6	7	8	9	10
Collaboration	1									
Licensing in	0.232***	1								
Licensing out	0.230***	0.341***	1							
ln(external R&D)	0.600***	0.262***	0.248***	1						
R-share	0.172***	0.0993***	0.0850***	0.192***	1					
ln(research)	0.379***	0.241***	0.248***	0.463***	0.731***	1				
ln(development)	0.341***	0.231***	0.228***	0.433***	0.0408***	0.570***	1			
ln(patent stock)	0.336***	0.284***	0.314***	0.424***	0.0900***	0.421***	0.420***	1		
ln(employees)	0.197***	0.102***	0.112***	0.255***	-0.0413***	0.281***	0.328***	0.338***	1	
ln(age)	0.0332***	0.000217	0.00774	0.0347***	-0.0960***	-0.00396	0.0604***	0.0902***	0.351***	1

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Pairwise correlations, i.e. no listwise deletion of missing observations. For each correlation pair, the smaller corresponding subsample from Table 3.1 applies.

Table A.2.4: Estimation results – Simultaneous equations model (modified model composition)

	Model 3 (with interaction, without R-share)			
	Collaboration	Licensing in	Licensing out	ln(ext. R&D)
ln(research)	0.269***	0.154***	0.217***	0.167***
	(0.014)	(0.023)	(0.035)	(0.011)
ln(development)	0.223***	0.133***	0.191***	0.064**
	(0.020)	(0.021)	(0.029)	(0.031)
ln(research) × ln(development)	-0.021***	-0.012**	-0.021***	0.015***
	(0.004)	(0.005)	(0.005)	(0.005)
ln(patent stock)	0.146***	0.225***	0.274***	0.495***
	(0.038)	(0.053)	(0.063)	(0.087)
ln(employees)	-0.282***	-0.058	-0.271**	-0.106
	(0.096)	(0.148)	(0.111)	(0.170)
ln(employees) × ln(employees)	0.026**	0.000	0.017	0.020
	(0.011)	(0.018)	(0.011)	(0.021)
ln(age)	-0.011	-0.219	0.326	-0.600*
	(0.296)	(0.526)	(0.503)	(0.330)
ln(age) × ln(age)	0.002	0.021	-0.047	0.083*
	(0.048)	(0.085)	(0.085)	(0.049)
Working capital ratio⋆	-0.000	-0.006***	0.000***	-0.000***
	(0.000)	(0.002)	(0.000)	(0.000)
Long-term debt ratio⋆	0.000	-0.001	0.001	0.000
	(0.000)	(0.001)	(0.001)	(0.000)
Short-term debt ratio⋆	-0.000*	-0.004	-0.001***	0.000***
	(0.000)	(0.003)	(0.000)	(0.000)
Enterprise group dummy	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
ρ 12/23/34		0.229***	0.477***	0.064*
ρ 13/24/14		0.273***	0.099***	0.373***
Observations	11,242	6,191	6,191	14,769

Estimates are coefficients

Standard errors in parentheses (clustered at firm level)

⋆ Ratio uses fixed assets in the denominator

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

A.3 Founder Personality and R&D Decisions in Entrepreneurial Firms

Table A.3.1: Year distribution and annual pattern of firm characteristics

Year	Full sample		Employees	Firm age	R&D (exp.)	Tang. inv. (vol.)	Tangible assets
	Count	Share	Mean				
2017	3,654	69.57%	3	3	17,684	34,000	11,385
2018	1,598	30.43%	6	4	34,517	32,195	9,966
Total	5,252	100.00%	4	3	22,806	33,451	10,953

Table A.3.2: Sector distribution and sectoral pattern of R&D and investment variables

#	Sector	Full sample		R&D (bi.)	R&D (exp.)	R&D/empl.	Inv. (bi.)	Inv. (vol.)
		Count	Share	Mean				
1	Cutting edge tech	287	5.46%	0.484	70,193	14,126	0.641	31,125
2	High tech manu	274	5.22%	0.609	77,673	13,200	0.639	75,692
3	Tech services	989	18.83%	0.313	23,705	5,470	0.665	28,619
4	Software	479	9.12%	0.532	61,060	11,906	0.595	13,063
5	Low tech manu	504	9.60%	0.254	0.645	5,834	0.645	59,970
6	Knowledge-int. services	511	9.73%	0.160	9,759	2,331	0.611	12,067
7	Oth. company services	417	7.94%	0.065	12,390	5,928	0.614	36,897
8	Creative services	393	7.48%	0.148	7,203	1,856	0.631	31,341
9	Other services	351	6.68%	0.054	1,056	505	0.613	46,607
10	Construction	549	10.45%	0.067	1,710	989	0.760	37,446
11	Trade	498	9.48%	0.092	7,001	997	0.570	20,961
	Total	5,252	100.00%	0.241	22,806	5,200	0.640	33,451

Table A.3.3: Distribution of German federal states

Federal state	Full sample		East Germany	
	Count	Share	Count	Share
Schleswig-Holstein	166	3.16%	Dummy=0	
Hamburg	172	3.27%		
Niedersachsen	471	8.97%		
Bremen	48	0.91%		
Nordrhein-Westfalen	1,269	24.16%		
Hessen	406	7.73%		
Rheinland-Pfalz	246	4.68%		
Baden-Würtemberg	629	11.98%		
Bayern	844	16.07%		
Saarland	43	0.82%		
Berlin	247	4.70%		
Brandburg	118	2.25%	Dummy=1	
Mecklenburg-Vorpommern	83	1.58%		
Sachsen	255	4.86%		
Sachsen-Anhalt	103	1.96%		
Thüringen	152	2.89%		
Total	5,252	100.00%	711	13.54%

Table A.3.4: Questions on entrepreneurial orientation and personality dimensions from the start-up panel survey (IAB/ZEW survey waves 2018 and 2019)

No.	Question	Item	Factor
	Entrepreneurial orientation[1]		
1	In order to achieve corporate goals even in uncertain situations, my company proceeds...	$risk_1$	risk tolerannce
a)	...rather cautiously, in a wait and see approach, in order to avoid wrong decisions.		
b)	...rather bravely and aggressively so as not to miss any business opportunities.		
2	My company has a strong inclination for projects with...	$risk_2$	
a)	...low risk and thus normal but secure returns.		
b)	...high risk and thus opportunities for very high returns.		
	Personality traits (OCEAN)[2]		
3	I am someone who is original and who brings up new ideas.	$open_1$	Open-ness
4	I am someone who values artistic experiences.	$open_2$	
5	I am someone who has vivid fantasies and a good imagination.	$open_3$	
6	I am someone who works thoroughly.	$consc_1$	Conscien-tiousness
7	I am someone who is rather lazy.	$consc_2^*$	
8	I am someone who gets things done effectively and efficiently.	$consc_3$	
9	I am someone who is communicative and talkative.	$extra_1$	Extra-version
10	I am someone who can get out and be sociable.	$extra_2$	
11	I am someone who is reserved.	$extra_3^*$	
12	I am someone who is at times a little rude to others.	$agree_1^*$	Agreeable-ness
13	I am someone who can forgive.	$agree_2$	
14	I am someone who is considerate and kind to others.	$agree_3$	
15	I am someone who worries often.	$neuro_1$	Neuro-ticism
16	I am someone who gets nervous easily.	$neuro_2$	
17	I am someone who is relaxed and can handle stress well.	$neuro_3^*$	

Answer options were self-ratings on a Likert scale from 1 to 5 with:
[1] 1: completely a), 2: rather a), 3: undecided, 4: rather b), 5: completely b)
[2] 1: does not apply to me at all, and 5: fully applies to me
* These items have been reversely rescaled to align scale direction.

Table A.3.5: Factor analysis of risk tolerance (Entrepreneurial orientation)

	Eigenvalues
Factor1	1.387
Factor2	0.613

Factor loadings	
Item	Factor1
$risk_1$	0.622
$risk_2$	0.622

The method applied is principal component factor analysis (principal component analysis) and assumes variance to be fully explained by common variance shared among items. Principal factor analysis (exploratory factor analysis) assumes the variance to be explained by common variance plus uniqueness (specific factor variance and error variance).

Table A.3.6: Factor analysis of OCEAN (Personality traits)

	Eigenvalues
Factor1	2.803
Factor2	1.653
Factor3	1.635
Factor4	1.396
Factor5	1.121
Factor6	0.885
Factor7	0.815
Factor8	0.719
Factor9	0.673
Factor10	0.636
Factor11	0.592
Factor12	0.553
Factor13	0.542
Factor14	0.504
Factor15	0.472

	Factor loadings				
Item	Factor1	Factor2	Factor3	Factor4	Factor5
$open_1$	0.059	**0.740**	0.081	-0.119	-0.108
$open_2$	-0.162	**0.717**	-0.171	0.134	0.074
$open_3$	0.052	**0.796**	-0.019	-0.101	-0.029
$consc_1$	-0.091	-0.054	**0.820**	0.052	0.077
$consc_2$	0.054	-0.164	**0.661**	-0.026	-0.037
$consc_3$	-0.004	0.062	**0.784**	-0.112	-0.068
$extra_1$	**0.768**	0.071	0.025	0.162	0.064
$extra_2$	**0.792**	0.023	-0.006	0.136	0.094
$extra_3$	**0.745**	-0.126	-0.089	-0.236	-0.125
$agree_1$	-0.029	-0.155	-0.077	**0.784**	-0.159
$agree_2$	0.170	0.118	-0.063	**0.499**	-0.030
$agree_3$	0.112	0.049	0.093	**0.740**	0.068
$neuro_1$	0.007	0.026	0.131	0.035	**0.750**
$neuro_2$	0.012	-0.003	-0.061	-0.018	**0.778**
$neuro_3$	0.064	-0.151	-0.101	-0.230	**0.652**

Table A.3.7: Cross-correlations of ROCEAN & dependent variables

		1	2	3	4	5	6	7	8	9	10	11
1	Risk tolerance	1.000										
2	Openness	0.130***	1.000									
3	Conscientiousness	-0.067***	0.217***	1.000								
4	Extraversion	0.115***	0.300***	0.228***	1.000							
5	Agreeableness	-0.119***	0.204***	0.257***	0.012	1.000						
6	Neuroticism	-0.184***	0.025	-0.044**	-0.155***	0.013	1.000					
7	R&D (binary)	0.203***	0.133***	-0.084***	0.007	-0.062***	-0.099***	1.000				
8	ln(R&D exp.)	0.222***	0.125***	-0.088***	0.009	-0.067***	-0.106***	0.983***	1.000			
9	Tang. inv. (binary)	0.032*	0.019	0.029*	0.029*	-0.067***	-0.041**	0.060***	0.061***	1.000		
10	ln(Tang. inv.)	0.056***	0.019	0.033*	0.042**	-0.079***	-0.053***	0.081***	0.089***	0.971***	1.000	
11	R&D per employee	0.099***	0.052***	-0.032*	0.012	-0.026	-0.043**	0.317***	0.379***	-0.004	0.017	1.000

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.3.8: Cross-correlations of ROCEAN & founder characteristics

		1	2	3	4	5	6	7	8	9	10	11
1	Risk tolerance	1.000										
2	Openness	0.130***	1.000									
3	Conscientiousness	-0.067***	0.217***	1.000								
4	Extraversion	0.115***	0.300***	0.228***	1.000							
5	Agreeableness	-0.119***	0.204***	0.257***	0.012	1.000						
6	Neuroticism	-0.184***	0.025	-0.044**	-0.155***	0.013	1.000					
7	Female	-0.031*	0.038**	0.047***	0.040**	0.086***	0.076***	1.000				
8	Founder age	-0.008	-0.005	-0.040**	-0.099***	0.056***	-0.003	0.050***	1.000			
9	University degree	0.182***	-0.014	-0.154***	-0.045**	-0.058***	-0.113***	0.048***	0.209***	1.000		
10	Industry experience	-0.077***	-0.024	0.027*	-0.073***	0.031*	0.018	-0.068***	0.569***	-0.023	1.000	
11	Serial entrepreneur	0.156***	0.064***	-0.096***	0.016	-0.053***	-0.060***	-0.043**	0.270***	0.167***	0.108***	1.000

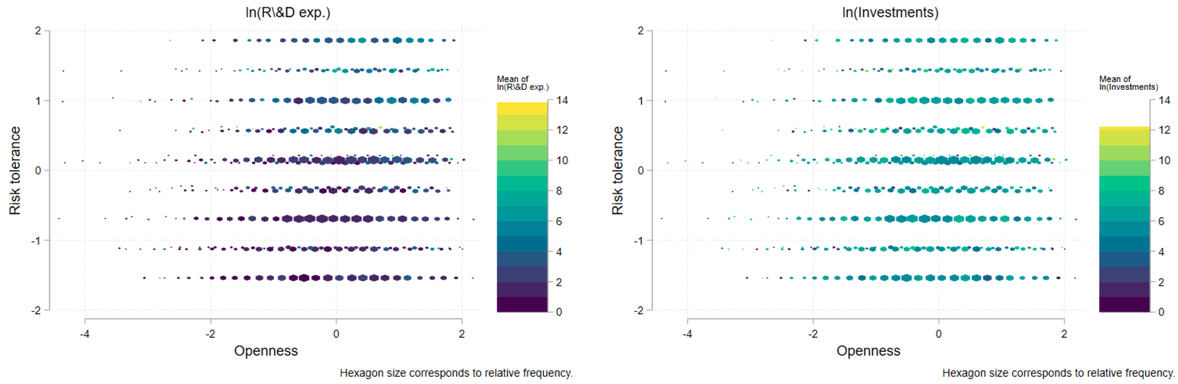
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.3.9: Cross-correlations of ROCEAN & firm characteristics

		1	2	3	4	5	6	7	8	9	10	11
1	Risk tolerance	1.000										
2	Openness	0.130***	1.000									
3	Conscientiousness	-0.067***	0.217***	1.000								
4	Extraversion	0.115***	0.300***	0.228***	1.000							
5	Agreeableness	-0.119***	0.204***	0.257***	0.012	1.000						
6	Neuroticism	-0.184***	0.025	-0.044**	-0.155***	0.013	1.000					
7	ln(employees)	0.109***	-0.013	-0.037**	0.048***	-0.055***	-0.025	1.000				
8	ln(tangible assets)	0.011	0.034*	-0.024	-0.009	-0.035*	0.043**	-0.099***	1.000			
9	Limited company	0.191***	0.008	-0.119***	-0.030*	-0.073***	-0.127***	0.281***	-0.113***	1.000		
10	Opportunity driven	0.070***	0.037**	0.002	0.048***	0.010	-0.058***	0.032*	-0.003	0.063***	1.000	
11	Team founder	0.081***	0.002	-0.078***	-0.031*	0.012	-0.023	0.309***	-0.013	0.278***	0.053***	1.000

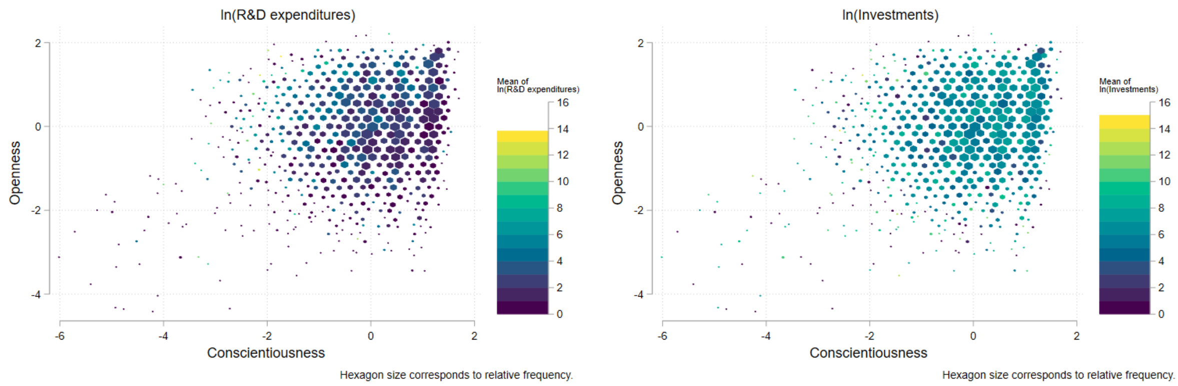
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure A.3.1: Heatmaps of risk tolerance & openness



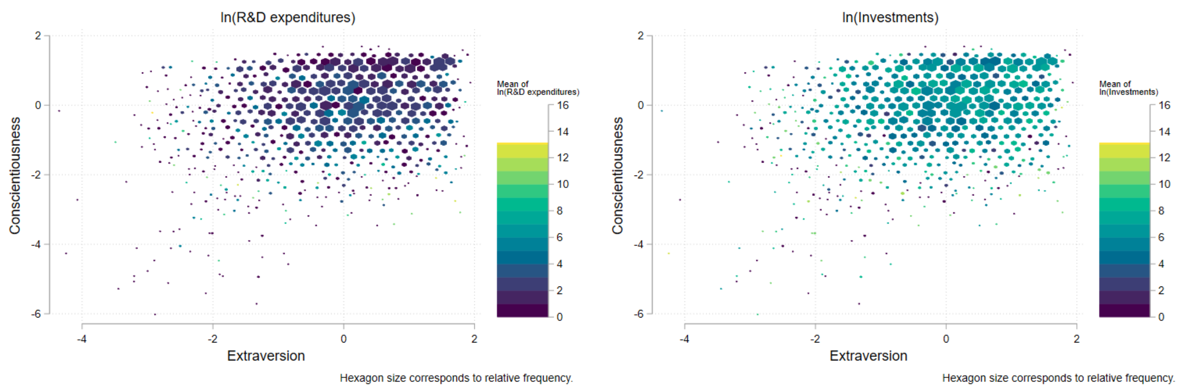
(a) R&D decision **(b)** Tangible investment decision

Figure A.3.2: Heatmaps of openness & conscientiousness



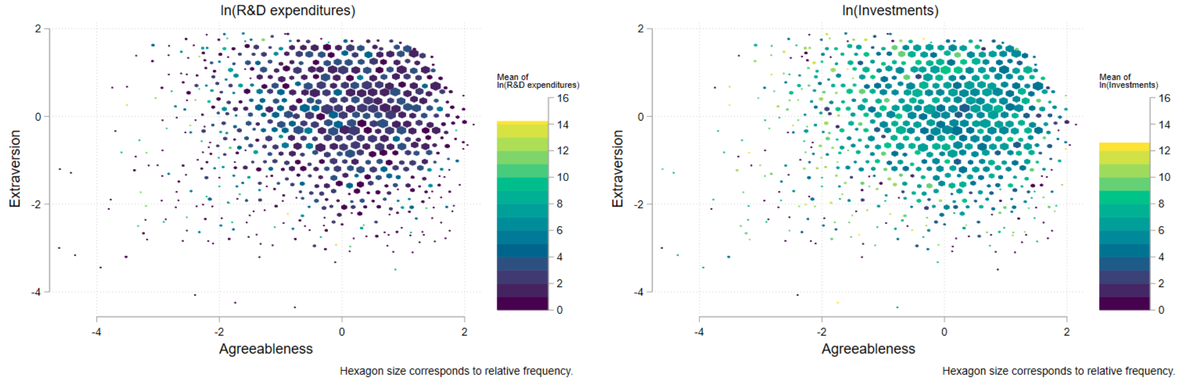
(a) R&D decision **(b)** Tangible investment decision

Figure A.3.3: Heatmaps of conscientiousness & extraversion



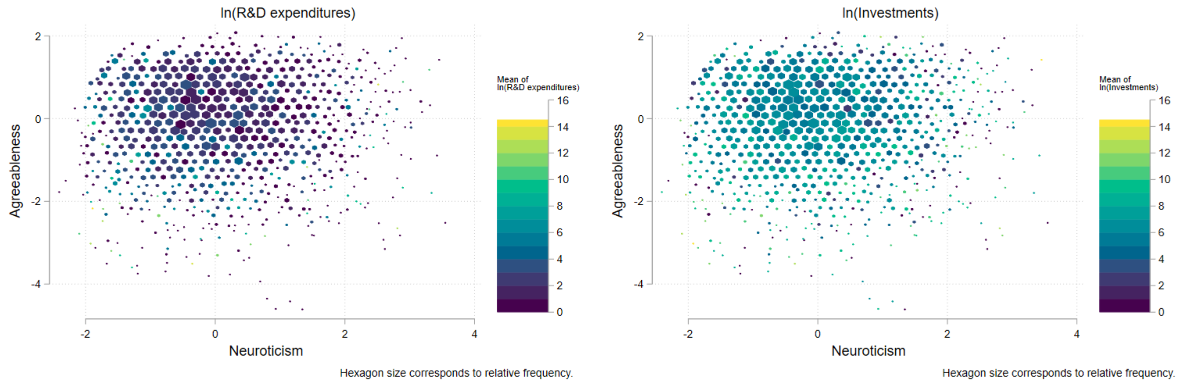
(a) R&D decision **(b)** Tangible investment decision

Figure A.3.4: Heatmaps of extraversion & agreeableness



(a) R&D decision **(b)** Tangible investment decision

Figure A.3.5: Heatmaps of agreeableness & neurocitism



(a) R&D decision **(b)** Tangible investment decision

Table A.3.10: Separate estimations – Models: R&D and tangible investment decision (ROCEAN as AIS)

	Models: R&D decision						Models: Tangible investment decision					
	R&D (binary) - Probit			ln(R&D) - OLS			Investments (binary) - Probit			ln(Investments) - OLS		
	1	2	3	4	5	6	7	8	9	10	11	12
Risk tolerance (AIS)	0.204***	0.157***	0.123***	0.714***	0.534***	0.374***	0.024	0.029*	0.014	0.179***	0.194***	0.108*
	(0.018)	(0.018)	(0.020)	(0.055)	(0.054)	(0.050)	(0.016)	(0.016)	(0.017)	(0.058)	(0.059)	(0.057)
Openness (AIS)	0.277***	0.285***	0.319***	0.731***	0.706***	0.624***	0.028	0.042*	0.050*	0.070	0.115	0.159*
	(0.029)	(0.030)	(0.033)	(0.081)	(0.078)	(0.072)	(0.025)	(0.025)	(0.026)	(0.092)	(0.091)	(0.089)
Conscientiousness (AIS)	-0.171***	-0.091***	-0.055	-0.537***	-0.271***	-0.165*	0.082***	0.076**	0.054*	0.358***	0.330***	0.228**
	(0.031)	(0.033)	(0.037)	(0.100)	(0.098)	(0.088)	(0.029)	(0.030)	(0.031)	(0.109)	(0.109)	(0.105)
Extraversion (AIS)	-0.094***	-0.067**	-0.013	-0.261***	-0.164**	-0.021	0.025	0.016	0.001	0.145	0.121	0.047
	(0.028)	(0.029)	(0.031)	(0.086)	(0.083)	(0.075)	(0.025)	(0.026)	(0.027)	(0.093)	(0.093)	(0.089)
Agreeableness (AIS)	-0.066**	-0.051	-0.073**	-0.193**	-0.142	-0.163*	-0.130***	-0.114***	-0.097***	-0.533***	-0.465***	-0.374***
	(0.031)	(0.032)	(0.036)	(0.098)	(0.095)	(0.087)	(0.029)	(0.029)	(0.030)	(0.103)	(0.102)	(0.098)
Neuroticism (AIS)	-0.144***	-0.095***	-0.084***	-0.428***	-0.255***	-0.189***	-0.052**	-0.047*	-0.064**	-0.222**	-0.195**	-0.258***
	(0.028)	(0.029)	(0.032)	(0.081)	(0.079)	(0.073)	(0.024)	(0.025)	(0.026)	(0.090)	(0.090)	(0.087)
Female		-0.288***	-0.210***		-0.829***	-0.531***		-0.230***	-0.202***		-0.895***	-0.755***
		(0.060)	(0.066)		(0.151)	(0.140)		(0.049)	(0.052)		(0.183)	(0.180)
Founder age		-0.000	-0.003		0.002	0.000		-0.015***	-0.011***		-0.051***	-0.036***
		(0.002)	(0.003)		(0.007)	(0.007)		(0.002)	(0.002)		(0.008)	(0.008)
University degree		0.639***	0.394***		1.920***	1.036***		0.057	0.127***		0.172	0.367**
		(0.045)	(0.054)		(0.130)	(0.133)		(0.039)	(0.045)		(0.143)	(0.152)
Industry experience		0.001	-0.001		0.004	-0.009		0.007***	0.007***		0.033***	0.028***
		(0.002)	(0.003)		(0.007)	(0.007)		(0.002)	(0.002)		(0.008)	(0.008)
Serial entrepreneur		0.250***	0.085*		0.813***	0.220*		-0.110***	-0.121***		-0.257*	-0.348**
		(0.044)	(0.050)		(0.137)	(0.129)		(0.039)	(0.042)		(0.145)	(0.144)
ln(employees)			0.181***			0.808***			0.300***			1.608***
			(0.035)			(0.102)			(0.034)			(0.116)
ln(tangible assets)			0.009*			0.024*			0.016***			0.052***
			(0.005)			(0.013)			(0.004)			(0.015)
Limited company			0.467***			1.091***			-0.137***			-0.304**
			(0.056)			(0.128)			(0.046)			(0.154)
Opportunity driven			0.103			0.220			-0.017			-0.074
			(0.068)			(0.140)			(0.054)			(0.179)
Team founder			0.076			0.297			-0.006			-0.062
			(0.062)			(0.184)			(0.055)			(0.198)
Cohort FE	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Sector FE	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Federal state FE	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Survey wave FE	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Observations	5,252	5,252	5,252	5,252	5,252	5,252	5,252	5,252	5,252	5,252	5,252	5,252

Estimates are coefficients
Standard errors in parentheses (clustered at firm level)
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table A.3.11: Estimation results – Model: R&D intensity (ROCEAN as AIS)

	Model: R&D per employee - OLS		
	1	2	3
Risk tolerance (AIS)	2,095.817***	1,739.889***	1,536.278***
	(338.219)	(313.387)	(319.909)
Openness (AIS)	1,633.361**	1,500.387**	1,199.552*
	(672.348)	(664.238)	(706.628)
Conscientiousness (AIS)	-1,462.986**	-849.384	-847.216
	(635.317)	(690.238)	(740.842)
Extraversion (AIS)	-358.619	93.134	581.226
	(454.152)	(522.440)	(524.998)
Agreeableness (AIS)	-596.961	-550.179	-664.428
	(519.868)	(529.925)	(559.247)
Neuroticism (AIS)	-1,151.857***	-731.410*	-548.512
	(359.604)	(390.264)	(390.738)
Female		-2,908.224***	-2,109.334***
		(708.561)	(799.954)
Founder age		168.092**	172.491**
		(71.827)	(73.309)
University degree		2,869.581***	1,890.845**
		(913.875)	(775.234)
Industry experience		7.101	16.183
		(57.183)	(63.415)
Serial entrepreneur		2,656.841***	1,473.883**
		(659.650)	(741.652)
ln(employees)			-1,583.737**
			(793.881)
ln(tangible assets)			-103.197
			(124.460)
Limited company			2,862.561***
			(983.654)
Opportunity driven			2,396.431***
			(751.442)
Team founder			1,343.477
			(1,440.234)
Cohort FE	No	No	Yes
Sector FE	No	No	Yes
Federal state FE	No	No	Yes
Survey wave FE	No	No	Yes
Observations[1]	5,237	5,237	5,237

Estimates are coefficients
Standard errors in parentheses (clustered at firm level)
[1] Some observations from the full sample (n=5,252) were omitted when calculating the dependent variable (ratio) since the denominator was zero.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table A.3.12: Selection estimations – Models: R&D and tangible investment decision (ROCEAN as PFS, bootstrapped SE)

	Models: R&D decision			**Models: Tangible investment decision**		
	Selection estimation (twostep)		Average marginal effects	Selection estimation (twostep)		Average marginal effects
	Intensive margin	Extensive margin (linear)	Extensive margin (prob.)	Intensive margin	Extensive margin (linear)	Extensive margin (prob.)
Risk tolerance	0.219***	0.138***	0.032***	0.091***	0.011	0.004
	(0.036)	(0.022)	(0.005)	(0.026)	(0.018)	(0.006)
Openness	-0.101**	0.256***	0.059***	-0.045*	0.045**	0.015**
	(0.049)	(0.025)	(0.006)	(0.025)	(0.022)	(0.007)
Conscientiousness	0.031	-0.053**	-0.012**	0.056**	0.031	0.011
	(0.038)	(0.026)	(0.006)	(0.026)	(0.020)	(0.007)
Extraversion	0.030	-0.024	-0.005	0.068**	-0.007	-0.003
	(0.039)	(0.027)	(0.006)	(0.029)	(0.022)	(0.008)
Agreeableness	-0.012	-0.067**	-0.015**	-0.022	-0.080***	-0.027***
	(0.042)	(0.026)	(0.006)	(0.024)	(0.020)	(0.007)
Neuroticism	-0.022	-0.078***	-0.018***	-0.026	-0.054***	-0.019***
	(0.037)	(0.029)	(0.006)	(0.025)	(0.019)	(0.006)
Female	-0.240*	-0.191***	-0.044***	-0.079	-0.194***	-0.067***
	(0.137)	(0.070)	(0.016)	(0.065)	(0.052)	(0.018)
Founder age	0.021***	-0.003	-0.001	0.002	-0.010***	-0.004***
	(0.005)	(0.002)	(0.001)	(0.003)	(0.002)	(0.001)
Industry experience	-0.003	-0.001	-0.000	0.008**	0.007***	0.002***
	(0.005)	(0.003)	(0.001)	(0.004)	(0.002)	(0.001)
Serial entrepreneur	0.043	0.079	0.018	0.130**	-0.126***	-0.043***
	(0.098)	(0.052)	(0.012)	(0.057)	(0.043)	(0.015)
ln(employees)	0.792***	0.175***	0.040***	0.796***	0.298***	0.102***
	(0.081)	(0.035)	(0.008)	(0.039)	(0.034)	(0.011)
Limited company	0.872***	0.455***	0.105***	0.252***	-0.143***	-0.049***
	(0.155)	(0.057)	(0.013)	(0.052)	(0.050)	(0.017)
Opportunity driven	0.217*	0.100	0.023	0.019	-0.018	-0.006
	(0.124)	(0.067)	(0.015)	(0.052)	(0.049)	(0.017)
Team founder	-0.008	0.075	0.017	-0.089	-0.005	-0.002
	(0.099)	(0.061)	(0.014)	(0.072)	(0.050)	(0.017)
University degree		0.392***	0.090***		0.124***	0.043***
		(0.045)	(0.010)		(0.046)	(0.016)
ln(tangible assets)		0.009**	0.002**		0.016***	0.005***
		(0.005)	(0.001)		(0.004)	(0.001)
Cohort FE	No	Yes	Yes	No	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Federal state FE	Yes	Yes	Yes	Yes	Yes	Yes
Survey wave FE	Yes	Yes	Yes	Yes	Yes	Yes
λ	-0.285***			-0.933***		
Observations	1,268	5,252	5,252	3,359	5,252	5,252

Standard errors in parentheses (bootstrapped)
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table A.3.13: Selection estimations – Models: R&D and tangible investment decision (ROCEAN as AIS)

	Models: R&D decision			**Models: Tangible investment decision**		
	Selection estimation (twostep)		Average marginal effects	Selection estimation (twostep)		Average marginal effects
	Intensive margin	Extensive margin (linear)	Extensive margin (prob.)	Intensive margin	Extensive margin (linear)	Extensive margin (prob.)
Risk tolerance (AIS)	0.111***	0.122***	0.028***	0.085***	0.015	0.005
	(0.040)	(0.020)	(0.005)	(0.020)	(0.017)	(0.006)
Openness (AIS)	-0.347***	0.318***	0.074***	-0.048	0.053**	0.018**
	(0.082)	(0.032)	(0.007)	(0.031)	(0.026)	(0.009)
Conscientiousness (AIS)	0.073	-0.065*	-0.015*	0.093**	0.051*	0.017*
	(0.067)	(0.036)	(0.008)	(0.037)	(0.031)	(0.011)
Extraversion (AIS)	0.051	-0.012	-0.003	0.096***	-0.001	-0.000
	(0.057)	(0.031)	(0.007)	(0.032)	(0.027)	(0.009)
Agreeableness (AIS)	0.081	-0.071**	-0.016**	-0.047	-0.102***	-0.035***
	(0.064)	(0.035)	(0.008)	(0.034)	(0.030)	(0.010)
Neuroticism (AIS)	0.056	-0.085***	-0.020***	-0.036	-0.068***	-0.023***
	(0.061)	(0.031)	(0.007)	(0.031)	(0.026)	(0.009)
Female	-0.115	-0.207***	-0.048***	-0.118*	-0.198***	-0.068***
	(0.141)	(0.065)	(0.015)	(0.067)	(0.052)	(0.018)
Founder age	0.021***	-0.003	-0.001	0.000	-0.010***	-0.003***
	(0.005)	(0.003)	(0.001)	(0.003)	(0.002)	(0.001)
Industry experience	-0.001	-0.001	-0.000	0.009***	0.006***	0.002***
	(0.005)	(0.003)	(0.001)	(0.003)	(0.002)	(0.001)
Serial entrepreneur	-0.004	0.086*	0.020*	0.116**	-0.117***	-0.040***
	(0.091)	(0.049)	(0.011)	(0.051)	(0.042)	(0.014)
ln(employees)	0.677***	0.173***	0.040***	0.829***	0.297***	0.102***
	(0.069)	(0.035)	(0.008)	(0.038)	(0.034)	(0.011)
Limited company	0.500***	0.463***	0.108***	0.243***	-0.125***	-0.043***
	(0.152)	(0.056)	(0.013)	(0.054)	(0.046)	(0.016)
Opportunity driven	0.148	0.104	0.024	0.022	-0.014	-0.005
	(0.137)	(0.067)	(0.016)	(0.061)	(0.054)	(0.018)
Team founder	-0.122	0.073	0.017	-0.099	-0.006	-0.002
	(0.110)	(0.061)	(0.014)	(0.064)	(0.055)	(0.019)
University degree		0.354***	0.082***		0.107**	0.037**
		(0.052)	(0.012)		(0.043)	(0.015)
ln(tangible assets)		0.007	0.002		0.015***	0.005***
		(0.005)	(0.001)		(0.004)	(0.001)
Cohort FE	No	Yes	Yes	No	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Federal state FE	Yes	Yes	Yes	Yes	Yes	Yes
Survey FE	Yes	Yes	Yes	Yes	Yes	Yes
ρ	-1.003***			-0.506***		
λ	-1.247***			-0.595***		
$ln(\sigma)$	0.492***			0.242***		
Observations	1,268	5,252	5,252	3,359	5,252	5,252

Standard errors in parentheses (clustered at firm level)
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table A.3.14: Selection estimations – Models: R&D and tangible investment decision
Method: Heckman LASSO, penalized (FE and ROCEAN allowed as exclusion restrictions)

	Models: R&D decision			**Models: Tangible investment decision**		
	Selection estimation (twostep)		Average marginal effects	Selection estimation (twostep)		Average marginal effects
	Intensive margin	Extensive margin (linear)	Extensive margin (prob.)	Intensive margin	Extensive margin (linear)	Extensive margin (prob.)
Risk tolerance	0.228***	0.138***	0.032***	0.096***	0.011	0.004
	(0.042)	(0.023)	(0.005)	(0.023)	(0.020)	(0.007)
Openness	-0.083*	0.256***	0.059***		0.045**	0.015**
	(0.047)	(0.026)	(0.006)		(0.020)	(0.007)
Female	-0.282**	-0.191***	-0.044***	-0.165**	-0.194***	-0.067***
	(0.115)	(0.065)	(0.015)	(0.068)	(0.051)	(0.017)
Founder age	0.019***	-0.003	-0.001		-0.010***	-0.004***
	(0.003)	(0.003)	(0.001)		(0.002)	(0.001)
University degree	0.107	0.392***	0.090***	-0.059	0.124***	0.043***
	(0.101)	(0.051)	(0.012)	(0.050)	(0.044)	(0.015)
ln(employees)	0.786***	0.175***	0.040***	0.910***	0.298***	0.102***
	(0.055)	(0.035)	(0.008)	(0.049)	(0.031)	(0.011)
Limited company	0.889***	0.455***	0.105***	0.201***	-0.143***	-0.049***
	(0.120)	(0.054)	(0.012)	(0.055)	(0.045)	(0.015)
Opportunity driven	0.236**	0.100	0.023		-0.018	-0.006
	(0.119)	(0.066)	(0.015)		(0.052)	(0.018)
Conscientiousness		-0.053**	-0.012**	0.058**	0.031	0.011
		(0.024)	(0.006)	(0.023)	(0.020)	(0.007)
Extraversion		-0.024	-0.005	0.057***	-0.007	-0.003
		(0.024)	(0.006)	(0.022)	(0.020)	(0.007)
Agreeableness		-0.067***	-0.015***	-0.059**	-0.080***	-0.027***
		(0.023)	(0.005)	(0.024)	(0.020)	(0.007)
Neuroticism		-0.078***	-0.018***	-0.051**	-0.054***	-0.019***
		(0.023)	(0.005)	(0.023)	(0.019)	(0.007)
Industry experience		-0.001	-0.000	0.010***	0.007***	0.002***
		(0.003)	(0.001)	(0.002)	(0.002)	(0.001)
Serial entrepreneur		0.079	0.018	0.076	-0.126***	-0.043***
		(0.048)	(0.011)	(0.050)	(0.041)	(0.014)
ln(tangible assets)		0.009*	0.002*		0.016***	0.005***
		(0.005)	(0.001)		(0.004)	(0.001)
Team founder		0.075	0.017	-0.063	-0.005	-0.002
		(0.061)	(0.014)	(0.061)	(0.054)	(0.019)
Cohort FE	No	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Federal state FE	Yes	Yes	Yes	Yes	Yes	Yes
Survey wave FE	No	Yes	Yes	No	Yes	Yes
λ	-0.284***			-0.875***		
Observations	1,268	5,252	5,252	3,359	5,252	5,252

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table A.3.15: Selection estimations – Models: R&D and tangible investment decision
Method: Heckman LASSO, partially penalized (ROCEAN allowed in exclusion restrictions)

	Models: R&D decision			**Models: Tangible investment decision**		
	Selection estimation (twostep)		Average marginal effects	Selection estimation (twostep)		Average marginal effects
	Intensive margin	Extensive margin (linear)	Extensive margin (prob.)	Intensive margin	Extensive margin (linear)	Extensive margin (prob.)
Risk tolerance	0.275^{***}	0.148^{***}	0.034^{***}	0.103^{***}	0.012	0.004
	(0.060)	(0.025)	(0.006)	(0.024)	(0.021)	(0.007)
Openness	-0.047	0.256^{***}	0.059^{***}		0.044^{**}	0.015^{**}
	(0.069)	(0.026)	(0.006)		(0.020)	(0.007)
Female	-0.276^{**}	-0.190^{***}	-0.044^{***}	-0.164^{**}	-0.194^{***}	-0.067^{***}
	(0.124)	(0.065)	(0.015)	(0.072)	(0.051)	(0.017)
Founder age	0.019^{***}	-0.003	-0.001		-0.010^{***}	-0.004^{***}
	(0.004)	(0.003)	(0.001)		(0.002)	(0.001)
University degree	0.169	0.391^{***}	0.090^{***}	-0.052	0.124^{***}	0.043^{***}
	(0.140)	(0.051)	(0.012)	(0.051)	(0.044)	(0.015)
ln(employees)	0.844^{***}	0.175^{***}	0.040^{***}	0.923^{***}	0.298^{***}	0.102^{***}
	(0.068)	(0.035)	(0.008)	(0.057)	(0.031)	(0.011)
Limited company	0.961^{***}	0.454^{***}	0.104^{***}	0.192^{***}	-0.143^{***}	-0.049^{***}
	(0.168)	(0.054)	(0.012)	(0.058)	(0.045)	(0.015)
Opportunity driven	0.256^{**}	0.100	0.023		-0.018	-0.006
	(0.123)	(0.066)	(0.015)		(0.052)	(0.018)
Conscientiousness		-0.054^{**}	-0.012^{**}	0.059^{**}	0.030	0.010
		(0.024)	(0.006)	(0.024)	(0.020)	(0.007)
Extraversion		-0.023	-0.005	0.057^{***}	-0.007	-0.002
		(0.024)	(0.006)	(0.022)	(0.020)	(0.007)
Agreeableness		-0.066^{***}	-0.015^{***}	-0.062^{**}	-0.079^{***}	-0.027^{***}
		(0.023)	(0.005)	(0.025)	(0.020)	(0.007)
Neuroticism		-0.079^{***}	-0.018^{***}	-0.054^{**}	-0.055^{***}	-0.019^{***}
		(0.023)	(0.005)	(0.023)	(0.019)	(0.007)
Industry experience		-0.001	-0.000	0.010^{***}	0.007^{***}	0.002^{***}
		(0.003)	(0.001)	(0.002)	(0.002)	(0.001)
Serial entrepreneur		0.078	0.018	0.069	-0.126^{***}	-0.043^{***}
		(0.048)	(0.011)	(0.052)	(0.041)	(0.014)
ln(tangible assets)		0.009^{*}	0.002^{*}		0.016^{***}	0.005^{***}
		(0.005)	(0.001)		(0.004)	(0.001)
Team founder		0.074	0.017	-0.071	-0.006	-0.002
		(0.061)	(0.014)	(0.065)	(0.054)	(0.019)
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Federal state FE	Yes	Yes	Yes	Yes	Yes	Yes
Survey wave FE	Yes	Yes	Yes	Yes	Yes	Yes
λ	0.006^{***}			-0.111^{***}		
Observations	1,268	5,252	5,252	3,359	5,252	5,252

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table A.3.16: Selection estimations – Models: R&D and tangible investment decision
Method: Heckman LASSO, non-penalized (ROCEAN and FE not allowed as exclusion restrictions)

	Models: R&D decision			**Models: Tangible investment decision**		
	Selection estimation (twostep)		Average marginal effects	Selection estimation (twostep)		Average marginal effects
	Intensive margin	Extensive margin (linear)	Extensive margin (prob.)	Intensive margin	Extensive margin (linear)	Extensive margin (prob.)
Risk tolerance	0.281***	0.138***	0.032***	0.099***	0.011	0.004
	(0.065)	(0.023)	(0.005)	(0.023)	(0.020)	(0.007)
Openness	0.014	0.256***	0.059***	-0.026	0.045**	0.015**
	(0.103)	(0.026)	(0.006)	(0.025)	(0.020)	(0.007)
Conscientiousness	0.004	-0.053**	-0.012**	0.061**	0.031	0.011
	(0.046)	(0.024)	(0.006)	(0.024)	(0.020)	(0.007)
Extraversion	0.021	-0.024	-0.005	0.064***	-0.007	-0.003
	(0.043)	(0.024)	(0.006)	(0.023)	(0.020)	(0.007)
Agreeableness	-0.042	-0.067***	-0.015***	-0.054**	-0.080***	-0.027***
	(0.045)	(0.023)	(0.005)	(0.026)	(0.020)	(0.007)
Neuroticism	-0.058	-0.078***	-0.018***	-0.047**	-0.054***	-0.019***
	(0.048)	(0.023)	(0.005)	(0.024)	(0.019)	(0.007)
Female	-0.315**	-0.191***	-0.044***	-0.150**	-0.194***	-0.067***
	(0.131)	(0.065)	(0.015)	(0.074)	(0.051)	(0.017)
Founder age	0.019***	-0.003	-0.001		-0.010***	-0.004***
	(0.004)	(0.003)	(0.001)		(0.002)	(0.001)
University degree	0.280	0.392***	0.090***	-0.056	0.124***	0.043***
	(0.175)	(0.051)	(0.012)	(0.051)	(0.044)	(0.015)
ln(employees)	0.879***	0.175***	0.040***	0.906***	0.298***	0.102***
	(0.082)	(0.035)	(0.008)	(0.059)	(0.031)	(0.011)
Limited company	1.084***	0.455***	0.105***	0.203***	-0.143***	-0.049***
	(0.214)	(0.054)	(0.012)	(0.059)	(0.045)	(0.015)
Opportunity driven	0.278**	0.100	0.023		-0.018	-0.006
	(0.127)	(0.066)	(0.015)		(0.052)	(0.018)
Industry experience		-0.001	-0.000	0.010***	0.007***	0.002***
		(0.003)	(0.001)	(0.002)	(0.002)	(0.001)
Serial entrepreneur		0.079	0.018	0.081	-0.126***	-0.043***
		(0.048)	(0.011)	(0.053)	(0.041)	(0.014)
ln(tangible assets)		0.009*	0.002*		0.016***	0.005***
		(0.005)	(0.001)		(0.004)	(0.001)
Team founder		0.075	0.017	-0.071	-0.005	-0.002
		(0.061)	(0.014)	(0.065)	(0.054)	(0.019)
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Federal state FE	Yes	Yes	Yes	Yes	Yes	Yes
Survey wave FE	Yes	Yes	Yes	Yes	Yes	Yes
λ	0.382***			-0.214***		
Observations	1,268	5,252	5,252	3,359	5,252	5,252

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

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