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Content

Abstract

We investigate whether appointing a middle management level affects startups' innovation performance. Additional hierarchical levels are often suspected to restrict innovative activities. However, founders' capacities for information processing and resource allocation are usually strongly limited while, at the same time, R&D decisions are among the most consequential choices of startups. We argue that middle management is positively related to introducing product innovations because it improves the success rates from recombining existing knowledge as well as managing R&D personnel. In addition, we suggest that the effectiveness of these mechanisms depends on the riskiness of a startup's business opportunity. Based on a sample of German high-tech startups, we find support for our conjectures.

Zusammenfassung

In der vorliegenden Studie untersuchen wir, ob die Einführung einer mittleren Führungsebene die Innovationsleistung von Startups beeinflusst. Hierarchische Strukturen stehen oft im Verdacht, innovative Aktivitäten in Unternehmen zu hemmen. Die Kapazitäten, die Unternehmensgründer für Informationsverarbeitung und Ressourcenallokation aufbringen können, sind in der Regel jedoch stark begrenzt, während gleichzeitig Entscheidungen im Bereich von Forschung und Entwicklung (FuE) zu den folgenreichsten in Startups gehören. Wir argumentieren daher, dass die Einführung einer mittleren Führungsebene in Startups positiv mit der Einführung von Produktinnovationen zusammenhängt, da dadurch die Wahrscheinlichkeit, vorhandenes Wissen erfolgreich zu rekombinieren, erhöht und das Management von FuE-Personal verbessert wird. Darüber hinaus argumentieren wir, dass die Wirksamkeit dieser Mechanismen vom Risikograd der Geschäftsidee eines Startups abhängt. Diese Hypothesen werden durch Auswertungen umfangreicher Daten zu einer Stichprobe deutscher High-Tech-Startups gestützt.

JEL-Klassifikation: L26, M13, M12, M51, L22, L23, J21

Keywords: Middle management, innovation performance, R&D, startups, organizational design, R&D management.

1 Introduction

Launching innovative products onto the market is a central element in the strategies of most startups in high-technology sectors (Wiklund and Shepherd, 2003). Having discovered an entrepreneurial opportunity, many startups find themselves in a race to realize that opportunity and to introduce new products ahead of competitors or before their funding runs out (Venkataraman, 1997; Shane, 2000). Opportunities are realized when startups decide to act upon them by deploying resources and investments in the pursuit of perceived opportunities (Shane and Venkataraman, 2000; Eckardt and Shane, 2003; Shane, 2003). An important part of this process are decisions on research and development (R&D) activities that are challenging since technologies and market conditions are by definition novel and uncertain (Amit, Glosten, and Muller, 1990) while funding sources are limited (Hall, 2005). While we learn from existing literature how demanding and error prone R&D decisions are for the management of established firms (Koput, 1997; Katila, 2002), we know comparatively little about the management of R&D in startups. Faced with many competing demands for attention, the burden on startup management, often times the founder or founding team, to evaluate many technological alternatives and to arrive at the most promising ones is high (Dencker and Gruber, 2015).

In this study, we investigate whether startups can improve the likelihood for successful innovation by altering their organizational design through the introduction of a middle management. We expect a startup's middle management to allow for better managing competing demands for attention and processing information related to R&D and technology development in order to successfully realize innovation. We draw theoretical mechanisms from the literature on how middle managers increase a startup's information processing capacity as well as free up attention of founders (Colombo and Grilli, 2013) and integrate them into models of R&D decision making. We reason that startups with middle management will increase their innovation performance in general, but also indirectly by re-using existing knowledge bases of the startup and managing R&D personnel more effectively. Further, we hypothesize that the latter will be more beneficial for startups with risky business opportunities while the former effects occur when opportunities are comparatively less risky. We test our theoretical reasoning using a unique sample of almost 3,700 firm-year observations of 1,708 high-tech startups founded in Germany between 2005 and 2012. The information on these firms stems from linked employer-employee data that merges firm data from a panel survey with official register data on the employees who work in these firms. The results broadly confirm our theoretical expectations.

Our theoretical model addresses a gap in existing literatures that are on the one hand rather critical of the effects of added hierarchical levels on innovation performance for the average firm (Burns and Stalker, 1961) but on the other hand recognize the establishment of middle management as a crucial milestone in the maturing of startups (Colombo and Grilli, 2013). Intuitively, we would associate middle management with a higher level of formalization and bureaucracy, a more “mechanistic” and less “organic” organizational structure that facilitates control and productivity but often stifles creativity and innovation (e.g., Burns and Stalker, 1961; Thompson, 1965; Dess, Lumpkin, and McKee, 1999; Shane and Venkataraman, 2000; Ireland, Covin, and Kuratko, 2009; Foss, Lyngsie, and Zahra, 2015). More recently, however, scholars have begun to argue for the benefits of formal structure to realize opportunities. Ireland and Webb (2009) suggest that centralization allows unambiguous resource allocation decisions and facilitates monitoring and control. Foss et al. (2015) find that both decentralization and formalization help opportunity discovery and realization. Yet most research in this area assumes an established firm while scant attention has been paid to organizational structure in startups. Moreover, while Sine, Mitsuhashi and Kirsch (2006) show that startups with higher founding team formalization, specialization, and administrative intensity perform better than those with more organic structures, we know little about the relationship between organizational structure and innovation, a central outcome of opportunity realization.

In that sense, we advance existing literature in two important ways. First, entrepreneurship literature has largely acknowledged that startups adjust their organizational design while they mature (Baron, Burton, and Hannan, 1999; Colombo and Grilli, 2013) through a process of professionalization (Hellmann and Puri, 2002). However, we know comparatively little about how these changes in organizational design affect their innovation performance, arguably a core strategic goal of most high-tech startups. Our theoretical model introduces information processing and monitoring mechanisms from existing middle management literature into models of R&D decision making, thereby providing a basis for future theorizing. What is more, existing literature that investigates innovation outcomes of high-tech startups but ignores its organizational design, particularly the presence of an additional hierarchical level, is likely to suffer from biased results.

Second, an active stream in the strategic entrepreneurship literature focusses on how the internal organization of startups interacts with industry characteristics such as the business opportunities in an industry. These theoretical models largely equate the management capacity of a startup with its founder. Prior knowledge and experience of founders are assumed to be the primary source of success for startups and these effects are contingent on the startups’ business opportunity (e.g., Dencker and Gruber, 2015). We extend this contingency perspective to the organizational design choices of a startup by arguing that (a) a startup’s capacity for R&D decision making is not limited to its founder but can be extended through middle management and (b) the positive effects of these organizational design choices are contingent on the startup’s business opportunity. Our theoretical model can be a pathway for future theorizing on how the effectiveness of other organizational design choices of startups (apart from middle management) is contingent on their business opportunities.

These academic insights have immediate implications for decision making in startups. Our results provide evidence for how the establishment of a middle management level increases the odds for innovation success in high-tech startups. This evidence can alleviate concerns among startup founders and/or owners about whether the introduction of a middle management makes startups more bureaucratic and less innovative. Our results show the opposite. These insights are also valuable to investors, consultants or government agencies advising high-tech startups. We show that the innovativeness of a high-tech startup is not merely a function of its technological decisions but also whether it puts an organization design in place that increases the management capacities for making these decisions.

2 Therory and Hypotheses

2.1 Innovation opportunities and decision making

New technologies have long been characterized as a basis for the creation of new products, new processes, new markets, or new ways of organizing (Schumpeter, 1934), and entrepreneurs must discover and identify opportunities in which such new technologies could be used (e.g., Venkataraman, 1997; Shane, 2000; Dencker and Gruber, 2015). Opportunities are realized when entrepreneurs decide to act upon them through a process of resource acquisition and organization (Shane, 2003). As a consequence, opportunity realization in entrepreneurial ventures depends often times on the founder or founding team and the decision to engage in identified opportunities. Following previous studies, we will refer to the founder(s) as the startup's highest management level making these strategic decisions (e.g. Dencker and Gruber, 2015), given that very few startups hire professional top managers early in their life cycle. Our terminology assumes that the hierarchical level below the founders (i.e. top management) is the middle management.

Our theoretical reasoning is concerned with the realization of innovation opportunities. In other words, we predict the likelihood with which startups manage to introduce product innovations built from new technologies or the recombination of existing ones. The introduction of new products allows firms to alter current patterns of competition and cooperation, facilitate market entry, and gain market share based on a superior offering compared to incumbent firms (Venkataraman, 1997; Wiklund and Shepherd, 2003). However, the realization of such opportunities puts considerable demands on decision makers because investments in R&D have to be made, forcing deciders in startups to dedicate attention to the recombination of existing resources and the acquisition of new ones.

While successful product innovations create important benefits for startups, making the necessary investment decisions is challenging for two primary reasons. First, the outcomes of investments in R&D are uncertain (Amit et al., 1990). On the technological side, experimentation with novel or untested materials and procedures is by nature error prone and likely to fail. Even technologically feasible solutions often fail commercially due to a lack of customer acceptance (Gourville, 2006). Second, large parts of R&D expenditures consist of salaries for scientists and engineers or investments in specialized, non-fungible laboratories (Hall, 2005). Accordingly, firms are constrained in the available financing for R&D to equity capital or cash flows since external lenders find it difficult to finance uncertain investments with little collateral. Decision making in innovation activities is therefore particularly crucial for new ventures lacking the internal funds for sustaining innovation failures.

Decision making in innovation activities can be conceptualized as a search process in which firms make heterogeneous decisions about which technologies to select or combine (Katila and Ahuja, 2002). Some of these choices lead to higher innovation performance than others. The quality of these technology choices depends on the amount of attention that a firm can devote to screening potential alternatives (Koput, 1997). A lack of attention results in erroneous technology choices, missing out on important trends or spreading existing screening capacities too thinly. Management attention has often been described as one of the most important resources of the firm (Ocasio, 1997), but startups, in particular, are challenged to commit sufficient attention to realizing innovation opportunities.

2.2 Hypotheses

Startup decision making is typically dominated by the founders whose decisions have vital influence on the firm (Wasserman, 2012). As a consequence, prior literature has extensively studied the role of founder knowledge and experience in facilitating the recognition of entrepreneurial opportunities and startup performance (e.g., Shane, 2000, 2003; Dencker and Gruber, 2015). Since founder decision making is not only concerned with the startup's innovation domain but encompasses all kinds of related and unrelated activities that are crucial for the survival of the firm, it is likely that capacity constraints impede the recognition and exploitation of innovation opportunities. We reason that startups can alleviate capacity constraints of the founders and facilitate innovation through organizational design choices. Organizational structure, in that sense, allocates the authority to make decisions, to deploy resources, and to select the opportunities to pursue (e.g., Galbraith, 1977). Specifically, we argue that startups with a middle management possess higher information processing capacities compared to startups without such a hierarchical level, leading to better opportunity recognition and realization.

The term middle management originates from the perspective that firms consist of at least two levels, i.e. a top management and line workers (Rajan and Wulf, 2003). The typical startup starts with these two levels, and the introduction of a hierarchical level in between, i.e. the middle management, constitutes a major organizational design change (Colombo and Grilli, 2013). Middle managers are managerial or administrative specialists with delegated decision rights (Baron et al., 1999). They can reduce the ambiguity about the organization of work in a firm and thereby improve coordination and efficiency (Sine et al., 2006).

Since all individuals are naturally limited in their capacity to acquire, store, process and transmit information (Simon, 1948), the establishment of a middle-management level can improve the information processing capacity of startups (Colombo and Grilli, 2013). The middle management of an organization allows it to handle a given amount of information more efficiently by enabling parallel information processing in which middle managers share information processing tasks with top management (Radner, 1993).

Besides, the establishment of a middle management level allows firms to use existing information processing capacities more efficiently. Garicano (2000) conceptualizes the hierarchical decision making in firms based on the knowledge that is available to each employee for solving problems. Organizational hierarchies emerge because some employees are better equipped than others to deal with particularly hard problems. Line workers can deal with regular problems based on their own knowledge and turn to middle managers for increasingly exceptional or difficult problems. Middle managers turn to top management only if their knowledge is insufficient to deal with a particular problem. Hence, a middle management level frees up top management to focus on the most challenging problems of the organization.

Moreover, middle management allows an organization to predict more accurately when problems or projects have reached a scope that benefit from organization-wide solutions (Harris and Raviv, 2002). The latter are most effectively addressed by top management since they have the broadest set of knowledge about the organization while lower level projects or problems do not require top management attention. In sum, middle management increases the information processing capacity of startups by enabling parallel processing and allowing decision making of its founders to focus on strategic and higher-value decisions while other decisions can be delegated to middle managers.

We conjecture that the improvement in startup's information processing capacity from introducing middle managers can be extended to improving decision making in R&D. R&D decisions are particularly complex and uncertain, requiring management attention and thorough decision making. Middle managers allow founders to specialize in solving more strategic problems and to use their skills and competences more productively. Since innovation is a domain of strategic importance for successfully entering markets and gaining market share, middle management is therefore likely to improve a startup's ability to innovate and position its offering vis-à-vis the incumbents in the market. As a result, our first hypothesis reads:

> *Hypothesis 1: Startups with middle management are more likely to introduce product innovations.*

Existing literature has frequently highlighted that startups are differentially endowed with resources upon market entry, including prior technological knowledge, invested capital, or managerial, entrepreneurial and industry experience of the founder (e.g., Shane, 2000; Dencker and Gruber, 2015). We focus on a startup's prior technological knowledge base because the recombination of existing knowledge is a central determinant of a firm's ability to innovate (Rosenkopf and Nerkar, 2001; Katila and Ahuja, 2002). We suggest that startups with a middle management will be more effective in recombining existing knowledge.

Literature describing innovation performance based on the re-use of a firm's existing technologies (i.e. deep search) summarizes its advantages across the dimensions of reliability, predictability and efficiency (Katila and Ahuja, 2002). We reason that new ventures with middle management will experience advantages across all three dimensions. First, the added information-processing capacity decreases the likelihood of errors and false starts when using the same knowledge elements repeatedly so that search becomes more reliable (Levinthal and March, 1993). Second, middle management can be assumed to render the startup's search more predictable because it enables a better understanding of the requirements that need to be met for successful innovation. Higher information processing capacity facilitates an understanding of how product development tasks can be decomposed into manageable sub-problems, how recombination activities should be sequenced, and what elements are unnecessary and can thus be disregarded. Third, middle management allows for a deeper understanding of the existing knowledge base which increases a startup's ability to identify valuable knowledge elements that may not have been obvious to the founder. In sum, our second hypothesis reads:

> *Hypothesis 2: Startups with middle management are more likely to introduce product innovations, and this likelihood increases with the size of the startup's existing knowledge base.*

Apart from the positive influence of middle management on a startup's ability to recombine existing knowledge, we argue that middle management can further influence current knowledge production by reducing the span of control for a startup's employees. Tighter spans of control imply that the plans of an organization can be implemented more quickly if workers receive instructions from their managers more effectively (Keren and Levhari, 1979). These theoretical models rest on the assumption that the goals and incentives of the owners and the employees of a firm differ, requiring monitoring or incentive alignments to overcome principal-agent problems from employees following their self-interests (Calvo and Wellisz, 1978; Qian, 1994).

Jensen and Meckling (1995) suggest that the agency problems are especially pronounced when employees possess specific knowledge that is difficult to transfer. The R&D activities of startups create such conditions. Given that R&D evolves around experimentation with novel and untested procedures and materials, it is difficult to codify and monitor. Many R&D outcomes occur as tacit knowledge in the understanding of R&D personnel and would be costly to codify comprehensively (Agrawal, Cockburn, and McHale, 2006). Besides, the knowledge from failed experiments is rarely codified but may be as valuable for eventually identifying promising R&D trajectories.

The motivations of scientists and engineers for their work have also been found to differ from the goals of their firms (Gambardella, Ganco, and Honoré, 2015): R&D decisions of individuals can be driven by curiosity, an interest in learning about or confidence in particular technologies. This can lead to biased decision making of R&D personnel. One of the best documented biases of R&D personnel is the systematic negative bias about the quality or usability of knowledge from external sources ("not invented here syndrome") (Katz and Allen, 1982; Antons and Piller, 2015). In the absence of a middle management, it falls on the startup's founders to monitor the technological choices of its R&D personnel and ascertain that these choices are aligned with the overall goals of the startup. We reason that middle managers can share this management task either by supervising R&D personnel directly or freeing up founder capacities from monitoring other startup activities.

We acknowledge that hierarchical layers can constrain the information flow between knowledge production and top management of organizations since the transfer of information rests on aggregation with potential losses of important details (Keren and Levhari, 1989; Stein, 2002). However, we suggest that on balance middle management will be particularly helpful for effectively managing R&D personnel because it can provide direction, set priorities and correct mistakes. Based on the added monitoring capacity, market opportunities can be more reliably identified and evaluated so that R&D personnel can be focused on them. Monitoring by middle management allows for the targeted provision of resources in order to increase the likelihood of innovations. As a consequence, our third hypothesis reads as follows:

> *Hypothesis 3: Startups with middle management are more likely to introduce product innovations, and this likelihood increases with the size of the startup's R&D personnel.*

Finally, Dencker and Gruber (2015) shed light on the business opportunity itself that a startup seeks to exploit and suggest that its riskiness will not only directly influence firm performance but also condition the role of the founder's industry and managerial experience. Miller (1992, 1993) relates the risk of a business to the dynamics of its environment, e.g. changes in input prices, competitor behavior, etc. On the one hand, such risks increase the odds of a startup's failure (Miller, 1992). On the other hand, riskier businesses enable startups to find dissatisfied customers or niche markets that are not served by incumbent firms (Wiklund and Shepherd, 2003). Dencker and Gruber (2015), based on the intuitive assumption of a positive risk-return relationship, find that riskier opportunities are associated with greater startup performance above and beyond the characteristics of the founder. Accordingly, we reason that the benefits that middle managers bring to the management of prior knowledge and R&D in startups are conditioned by the riskiness of a startup's business opportunity.

Risky business opportunities affect the R&D decision making of startups in two ways. First, they aggravate the consequences of failing innovations, e.g. due to a lack of reliability or desired functionality, for the startup. Startups with risky business opportunities may not have the financial resources and goodwill from customers, investors or suppliers to sustain a failed innovation. Accordingly, screening technologies and predicting success rates requires comparatively more attention from founders. Second, risky business opportunities imply that the technological and market demands for successful innovation are comparatively less predictable. Hence, they benefit from increasingly intense testing and adapting. The latter requires more intensive management of current R&D activities. In sum, risky business opportunities tax the attention of founders especially with decision making in current R&D activities. As a consequence, startups with risky business opportunities are also particularly likely to experience positive effects from middle management in directing current R&D activities and personnel. We propose:

> *Hypothesis 4a: Startups with middle management are more likely to introduce product innovations, and the effect of middle management on the startup's R&D personnel is stronger for risky business opportunities.*

Conversely, startups with comparatively less risky business opportunities benefit from more predictable environments. Technological and market conditions can be analyzed more reliably, creating opportunities for exploiting existing technologies. Within such settings, the benefit from involving middle management emerges from increased information processing capacities for identifying unrealized market potentials of existing *technologies. We predict:*

> *Hypothesis 4b: Startups with middle management are more likely to introduce product innovations, and the effect of middle management on the prior knowledge base is stronger for comparatively less risky business opportunities.*

3 Data and Methods

3.1 Data

We construct a dedicated dataset combining multiple data sources to test our hypotheses. It rests on a linked employer-employee panel dataset that matches firm-level data from the KfW/ZEW Startup Panel with the official employment statistics provided by the German Federal Employment Agency. The KfW/ZEW Startup Panel is a survey of German startups of the cohorts 2005-2012. It was established in 2008 as a joint project of the Centre for European Economic Research (ZEW), the KfW Bankengruppe (Germany's and the world's largest state-owned promotional bank), and Creditreform (Germany's largest credit rating agency). The KfW/ZEW Startup Panel is a stratified random sample of legally independent new ventures drawn from the Mannheim Enterprise Panel (Mannheimer Unternehmenspanel - MUP). The MUP contains basic information such as addresses, year of startup, sector of activity, and legal form, for almost all German firms (see Bersch et al., 2014, for a detailed description). The sample of the KfW/ZEW Startup Panel is drawn from almost all sectors of the MUP population (the primary sector, the energy sector, and the public sector are not included) and stratified according to three criteria: (i) the year of a firm's formation, (ii) the industry, and (iii) whether or not a firm has received financial support from KfW. Stratification is controlled for by including dummy variables for the stratification cells in all regressions.

When drawn into the sample firms are allowed to be not older than three years. Subsidiary businesses and ventures that resulted from merger activities are excluded. Startups that participate once in the survey are subsequently followed for up to seven successive years (i.e. until they are eight years old. See Fryges, Gottschalk, and Kohn, 2010, for a detailed description). Data are collected using computer-assisted telephone interviews. In the present study, the survey data provide information about the founders' characteristics (i.e. educational background and managerial and entrepreneurial leadership experience) and venture characteristics (including innovation and R&D activities).

We match the firm-level information with employee-level information from the official employment statistics provided by the Federal Employment Agency. The employment statistics contain person-specific register data on all employees subject to social security contributions in Germany.[1] This dataset is a rich source of employee records and allows us, most importantly, to identify middle managers and R&D personnel based on occupation codes (see variable description below). Moreover, the employment statistics also provide details regarding further employee characteristics for the purpose of the present study.

As there is no common identifier in the two data sets, we matched startups from the KfW/ZEW Startup Panel using a text search algorithm via startup names and addresses. The text search algorithm is described in detail in the Appendix B of Czarnitzki et al. (2015) and has proven to deliver very reliable results in various settings.

We were able to match about 90 percent of the startups from the KfW/ZEW-Startup Panel that self- reported to have employees who are subject to social security contributions (during a telephone interview) with one or more establishments from the official employment statistics. Firms that self-reported to have employees subject to social security contributions, but which were not found in the official employment statistics, were removed from the sample. In addition, we adjusted for the possibility of

1 In addition to regular full-time and part-time employees, this includes apprentices, interns, and marginally employed personnel. All notifications on employment and unemployment spells of an individual can be linked with the aid of a unique person-specific identifier thereby obtaining the complete employment history of each employee. A further identifier makes it possible to match the employees to establishments. The data are reported by the employing establishment and are collected by the social security agencies. Reporting data about the employees is mandatory for the employing establishments in order to calculate the contributions to the social security system.

incorrect matches or erroneous data in either dataset by excluding matches in the 1st and 100th percentiles of the difference between employment sizes reported during telephone interviews and to the social security agencies. To assess the quality of the matches in the resulting firm-year panel dataset, we calculated the correlation coefficient between the numbers of employees reported in the KfW/ZEW-Startup Panel and the numbers of employees reported in the official employment statistics. The correlation is slightly above 0.95 which makes us confident that the matching procedure led to reliable results.

We obtain information from 3,407 startups that operate in knowledge-intensive industries and have at least one employee.[2] Because we apply a one year time lag between independent and dependent variables (see details below), we are able to draw on 3,699 observations from 1,708 startups in the panel dataset that we use for estimations.

3.2 Variables

Dependent variable

Our hypotheses predict the likelihood with which startups introduce product innovations. Accordingly, we create a dummy variable for the introduction of a product innovation in a given year. Product innovations can have various degrees of novelty. We require that a startup's new product is new to the market, not just new to the startup itself.

Explanatory variables

Our main variables of interest on the right-hand side of our estimation equation are whether or not a firm employs at least one employee who is appointed with delegated decision making authority ("middle manager"), the size of the existing knowledge stock of a firm, the number of R&D employees, and the riskiness of the business opportunity a firm exploits.

We construct our binary indicator for the presence of a middle manager from occupation codes available in the employment statistics of the German Federal Employment Agency. In the individual level data, occupations are coded using the five-digit occupation code KldB2010 (the German adaption of ISCO-08, devised by the Federal Employment Agency) which allows identifying employees with supervisory or executive competences.[3] We classify such employees as "middle managers". Analogously, we

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[2] "Knowledge-intensive industries" include "cutting-edge" and high-technology manufacturing, technology-intensive services, software supply and consultancy, and skill-intensive services in line with Fryges et al. (2010).

[3] Employees with supervisory or executive competences are identified by a "9" as fourth digit of the five-digit KldB2010 occupation code.

construct the number of R&D employees by summing up those employees that have occupation codes relating to R&D occupations.[4]

We approximate a firm's existing knowledge stock by the number of patents the founder(s) of a firm held prior to the registration of the firm. We retrieve this information from the survey data of the KfW/ZEW Startup Panel.

Following Dencker and Gruber (2015), we measure the riskiness of the business opportunity of a firm using the average credit rating score of all other German firms of the same age in the same three-digit NACE industry. Credit rating scores reach from 100 (best) to 600 (worst, indicating default) and are retrieved from the credit rating agency Creditreform. The measure reflects the average likelihood of failure of comparable firms. Since information about startups is typically scarce, the probability of failure of comparable firms oftentimes determines the financing conditions and the financial pressure a new venture faces and hence measures the inherent riskiness of its business opportunity. Dencker and Gruber (2015) argue that this measure reflects the risk-return potential inherent in opportunities. Risk ratings, in that sense, proxy for the likelihood of insolvency in a given industry, and higher risk ratings should therefore also provide the basis for building high-performing startups (Stinchcombe, 1965; Dencker and Gruber, 2015).

We control for a number of factors that have frequently been shown to be associated with the likelihood to innovate (Ahuja, Lampert, and Tandon, 2008). Details on the construction of all variables are provided in Table 4 in Appendix A. We control for the resource availability of the startup by controlling for the number of founders and employees as well as for R&D in particular by including R&D expenditures (scaled by startup sales). Besides, we control for the quality of the startup's human capital by including a dummy variable if at least one of the founders had tertiary education as well as the share of employees with tertiary education. Besides, founder experience has been found to impact startup performance (Colombo, Delmastro, and Grilli, 2004; Colombo and Grilli, 2005). We capture these effects with two dummy variables indicating whether the founder had managerial or entrepreneurial experience as well as the number of years of industry experience of the founder.

Taking into consideration structural differences among startups, we control for the startup's age and whether it is incorporated (limited liability). We further add three industry dummies for technology intensive services, software supply and consultancy as well as skill-intensive services. High-tech manufacturing startups will serve as our reference group.

[4] We apply the definition of R&D occupations of the German Federal Statistical Offices (https://www.klassifikationsserver.de/klassService/jsp/variant/variantList.jsf)

3.3 Estimation approach and identification

Since our dependent variable is binary, we choose probit estimates with standard errors robust to clustering at the startup level as our main estimation method. In our analyses, we estimate a series of interaction effects. The interpretation of interaction effects in nonlinear models, such as probit or logit models, is not straightforward (Ai and Norton, 2003; Greene, 2010). Therefore, we first re-calculated all interaction effects following Ai and Norton (2003). In addition, we double-checked all results with linear probability models as a robustness check. We did not find qualitative differences to the reported marginal effects in both checks.

Endogeneity is a potential issue in our empirical setting. A first source of endogeneity might stem from simultaneity/omitted variable bias. It seems plausible to assume that startups of higher quality might simultaneously have a higher probability of doing both, hiring a middle manager and introducing an innovation. If we cannot control for startup quality adequately, we might spuriously attribute changes in innovation propensity to the introduction of a middle management. We address this problem by a two-step strategy: We first pre-balance our sample with respect to firm-year observations with middle management and those without over a large number of indicators for firm quality that are determined before a startup introduces a middle management (and potentially confounds the measures). Second, we control for a wide range of contemporary or one period lagged indicators for firm quality directly in all estimated models.

We apply entropy balancing to implement the pre-balancing empirically. Entropy balancing achieves balance over specified moments of selected covariates by deriving sample weights. The retrieved weights are then used in subsequent weighted estimations (Hainmueller, 2011; Hainmueller and Xu, 2013). Intuitively, this can be understood as the creation of a synthetic control group, where the observations in the control group are reweighted so that their specified sample moments mimic those of the treatment group as closely as possible (cf. Abadie, Diamond, and Hainmueller, 2010). In contrast to other related methods, for instance propensity score matching, entropy balancing induces covariate balance directly, and not as the result of a propensity score matching procedure (which requires iterated re-specifications of the propensity score estimation to achieve covariate balance). Entropy balancing has been applied for sample balancing in several recent studies (e.g., Bansak, Hainmueller, and Hangartner, 2016; Malesky and Taussig, 2016; Satyanath, Voigtländer, and Voth, 2017). Technical details on the derivation of the entropy balancing weights are provided in Appendix B.

Our choice of indicators for startup quality that we use in the balancing exercise follows the results of Colombo and Grilli (2013) who analyze the antecedents of the emergence of a middle management layer in Italian high-tech startups. We balance on the full-time equivalent employment size of the startup at the time of foundation including founders, whether the firm was incorporated with limited liability at the time of foundation, industry dummies, whether the firm reported to have equity investors in the first interview, the number of patents a firm founder held at the time of firm foundation, and measures for founder human capital (whether the founder has tertiary education, the founder's years of industry experience, whether the founder had started a firm before, and whether the founder has experience as a manager in dependent employment).[5] The data show that, as expected, startups with middle management clearly outperform those without middle management with respect to nearly all firm quality indicators. After balancing, though, original differences are leveled entirely (see Table 5 in Appendix A for results).

A second, closely related, source of endogeneity might arise from direct reverse causality, when firms appoint a middle manager in response to the introduction of a market novelty. We use only lagged values of middle management to reduce the potential bias caused.

To assess the robustness of our identification strategy, we re-estimate our main models and instrument the presence of a middle manager by two measures that we regard as plausibly exogenous to a startup's innovation performance: (1) the number of executives in firms that filed bankruptcy in the same district and one-digit NACE industry in a given year and (2) the propensity that other firms in the sample, which operate in the same one-digit NACE industry and are in the same size category, have a middle management.[6] The first instrument introduces exogenous variation due to a local supply shock of potential candidates for middle management positions. The second instrument introduces exogenous variation in the firms' demands for middle managers.

Because our IV model is over-identified (i.e., we use more instruments than endogenous regressors we instrument for) we use a (pooled) GMM approach to estimate the IV model and adjust the GMM weighting matrix and the standard errors for a potential clustering at the firm level. We find the proposed instruments to be valid and our identification strategy to be supported by the results of IV regressions (see results section for details).

4 Results

Summary statistics and a table of pairwise correlations are provided in Table 1 and Table 2. We learn from the descriptive statistics that 16 percent of startups in our sample report product innovations which gives some indication that achieving inno-

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5 For founding teams we use information on the founder with the highest education/most experience in the team. For improving the precision of the balancing of continuous variables (i.e. startup size and number of founder patents), we require that the first three moments of these variables are balanced, i.e. mean, variance and skewness.

6 According to existing research, the necessity to introduce a hierarchical structure depends crucially on industry and firm size (Rajan and Zingales, 2001). However, the probability that other firms hire a middle manager should not directly influence a focal firm's probability to launch an innovation on the market. For the generation of the instrument, we defined six size categories to achieve an as uniform as possible distribution of observations over size categories: (1) 1 employee, (2) 2 employees, (3) 3 or 4 employees, (4) 5 to 7 employees, (5) 8 to 14 employees, (6) more than 14 employees.

vation success is challenging for the average high-tech startup. Startups are on average 3.87 years old, have 1.7 founders and employ 4.89 employees. They spend 12 percent of sales on R&D and employ 0.14 R&D employees, albeit with a substantial standard deviation. The number of R&D employees provides some indication that R&D positions are difficult to finance for startups. Similarly, founders hold 0.48 patents when creating the startup but also with a large standard deviation.

Most of the startups operate in service sectors, especially technology-intensive services (42 percent). Thirty percent of startup operate in high-tech manufacturing sectors which typically have higher entry barriers, e.g. from necessary fixed capital investments. The riskiness of the business opportunities of startups in our sample is at an intermediate level at 308 on the scale between 100 and 600. Most startups are incorporated as limited liability companies (64 percent) but few have equity investors from the start (4 percent). Moreover, 10 percent of startups in our sample have a middle management. Hence, a sizable number of startups makes this organizational design choice but the majority of startups does not. This indicates that the introduction of a middle management has the potential to be a strategic decision differentiating startups from their peers.

None of the correlations between the explanatory variables reach levels that indicate collinearity problems. This is supported by the variance inflation factor (VIF) that has an average value of 1.45 for our main models. The VIF is far below usually applied critical levels of 10 (Belsley, Kuh, and Welsh, 1980).

------ Table 1 about here ------

------ Table 2 about here ------

In line with Hypothesis 1, our main multivariate regression estimates from weighted Probit models reveal a significant and positive relationship between middle management and a startup's likelihood to introduce a product innovation (Column A of Table 3; see Column A of Table 6 in Appendix A for results of the unbalanced/non-weighted model). Employing at least one middle manager increases the likelihood to introduce a market novelty by 7.2 percentage points. Given that the average propensity to introduce a market novelty in the sample is 16 percent, this effect size stands for a substantial increase.

------ Table 3 about here ------

The marginal effects of the wide range of included control variables show the expected signs. Most noteworthy, the R&D intensity has a positive and significant effect, as does the size of the existing knowledge stock (patents at time of foundation), the number of R&D employees, and the share of employees with tertiary education.

We apply interaction and split sample analyses, to test the moderating effects on the relationship between middle management and innovation performance that we proposed in Hypotheses 2 to 4b (Table 3; Column B-F). In support of Hypothesis 2, we find a positive and significant interaction effect between the presence of a middle management level and a startups' existing knowledge stock. Hence, middle management seems to become especially effective in managing innovation when middle managers can draw on larger stocks of existing knowledge. In addition, it seems reasonable to assume that middle managers help startups to translate inventions into marketable innovations and hence facilitate the commercialization of previously recognized opportunities. In contrast, our data does not support Hypothesis 3: The interaction effect between middle management and the number of R&D employees is positive but insignificant in the full sample. As we will show in the following, understanding the relationship between middle management, the number of R&D employees, and innovation requires a more nuanced explanation.

To assess how the riskiness of a firm's business opportunity influences the moderating effects of the prior knowledge stock and the R&D personnel (Hypotheses 4a and 4b), we split our sample at the industry median of the riskiness of the business opportunity.[7] In support of Hypothesis 4a, we find that the interaction between middle management and the number of R&D employees is only positive and significant for firms that exploit risky opportunities. In contrast, and in support of Hypothesis 4b, the interaction term between middle management and the size of a startup's prior knowledge stock is only positive and significant for less risky business opportunities. These results support the hypothesized rationale that in highly risky businesses, which need to adapt to their business environment constantly and keep the cost of these adaptions under control, middle management plays an important role in supporting the founders in monitoring ongoing R&D. In contrast, in less risky but more stable environments that allow recombining a startup's existing knowledge stock middle management seems to facilitate innovation by rendering the search for innovation through the recombination of existing technologies more efficiently and reliably.

4.1 Robustness checks

As described before, we apply an instrumental variables approach as a robustness check (Table 7 in Appendix A). In a first step, we instrument lagged middle management to replicate our main analyses (i.e. we replicate Table 3, Column A). Both instruments have a positive and statistically significant impact on the probability to employ a middle manager in the first stage of the IV regression. The joint first stage F-statistics of the instruments is 10.45. As a rule of thumb, first stage F-statistics of 10 and below indicate critically weak instruments. The Hansen-J test for over-identification has a p-

[7] We split the sample at the industry medians of the industries used for the stratification of the KfW/ZEW Startup Panel. We control for these stratification industries by industry fixed effects in all models. Since the opportunity risk measure is generated on a three-digit NACE level, this procedure implies that we compare "more risky" opportunities to opportunities that are less risky but generally comparable.

value of 0.106: over-identification and the validity of our instruments cannot be rejected at a 10 percent significance level. When instrumented, the effect of middle management remains positive and significant.

In a second step, we re-run the IV model but use contemporary (and not lagged) explanatory variables. Since the effect of middle management is identified by exogenous variation in the IV model, a specification without lags yields unbiased estimates. However, the precision of the estimates should increase due to the increase in the sample size. This allows us to provide some evidence whether the fact that the coefficient and the standard error of middle management become somewhat inflated in the lagged IV specification can be attributed to the rather week instruments. As in the first specification, both instruments have a significantly positive relationship with the propensity to employ a middle manager in the first stage. The power of the instruments is higher with a first stage F-statistic of 20.75 and a p-value of the Hansen-J test for over-identification of 0.511. As a consequence of the stronger instruments, the inflation of the estimated coefficient for middle management decreases considerably (to 0.247). Hence, we conclude that overall the IV specifications support a causal interpretation of our results.

As a second robustness check, we increase the level of detail of the included industry fixed effects. We do so to assure that our estimates are not driven by industry differences in the propensity to innovate we do not control for. The industry controls in our main models reflect the stratification criteria of the KfW/ZEW-Startup Panel and are included on the level of stratification to control for firms' probabilities to be drawn into the sample. When we increase the level of detail of the industry fixed effects up to the two digit NACE level, the marginal effect of middle management changes only slightly (see Columns C and D of Table 6 in Appendix A). Hence, we are confident that controlling for industry differences at the level of the industry stratification of the sample yields unbiased results.

5 Discussion

Do middle managers help startups to introduce innovative products to the market? And if so, when are middle managers most effective? Our research addresses a fundamental puzzle in the literature on organizational design. On the one hand, middle management is typically associated with a higher level of formalization and bureaucracy and therefore bears the risk of hampering creativity and innovation in the average firm (e.g., Burns and Stalker, 1961; Thompson, 1965). On the other hand, organizational structure such as a middle management level can help firms to allocate resources, to facilitate monitoring and control, and therefore to realize opportunities (Ireland and Webb, 2009; Foss et al. 2015).

Our research provides a number of compelling findings to address this gap in existing research for a high-tech startup context. Based on a unique sample of almost 3,700 firm-year observations between 2005 and 2012, we find that high-tech startups with middle management have a higher likelihood of introducing product innovations. We attribute this finding to the fact that the establishment of middle management leads to increased information processing and monitoring capacity in the startup (Colombo and Grilli, 2013). Middle management frees up founders to focus on the most challenging problems of the organization. It also allows an organization to predict more accurately when problems or projects require organization-wide solutions (Harris and Raviv, 2002). In that sense, middle management enables parallel processing and allows decision making of its founders to focus on strategic and higher-value decisions while other decisions can be delegated to middle managers. This should be particularly true for decision making in R&D. Since R&D decisions are complex and uncertain, they require management attention and thorough decision making. Middle managers allow founders to focus on these decisions and therefore improve a startup's ability to innovate.

Moreover, we find evidence that middle managers facilitate the recombination of existing knowledge, a central determinant of a firm's ability to innovate (Rosenkopf and Nerkar, 2001; Katila and Ahuja, 2002). Middle managers, through the added information-processing capacity, apparently decrease the likelihood of errors and false starts when using the same knowledge elements repeatedly so that search becomes more reliable (Levinthal and March, 1993). They also make the search for innovation more predictable due to a better understanding of the requirements that need to be met for successful innovation. The increased information processing capacity helps understand how product development tasks can be decomposed into manageable sub-problems, how they should be sequenced, and which elements to disregard.

Contrary to our expectations, we do not find a positive and significant interaction effect between middle management and the size of a startup's current R&D personnel. We had expected middle management to be of value in directing and focusing current knowledge production and technology development by reducing the span of control for a startup's employees, leading to quicker implementation of plans because of tighter spans of control (Keren and Levhari, 1979). However, our results indicate that this relationship is more complex and requires an understanding of the riskiness of the startup's business opportunity. Splitting the sample into two groups with below and above median riskiness reveals that the interaction between middle management and current R&D personnel is positive and significant for firms that operate in industries with risky business opportunities. However, there is no significant interaction effect for less risky opportunities. In contrast, the interaction term between middle management and the startup's existing knowledge is only positive and significant in industries with less risky business opportunities. These results support our expectations that startups in highly risky businesses need to continuously adapt and dedicate management attention which is why middle management is particularly helpful in supporting founders. In more stable environments, middle managers help with recombining a startup's existing knowledge stock.

Taken together, our findings advance academic research along two dimensions. First, existing entrepreneurship literature emphasizes how startups mature and professionalize through their organizational design choices (Baron et al., 1999; Colombo and Grilli, 2013; Hellmann and Puri, 2002). Our theoretical model focusses on one particular organizational design choice, i.e. the establishment of a middle management layer in a startup, and links it to innovation performance, arguably one of the most crucial strategic outcomes for high-tech startups. We integrate mechanisms on information processing and monitoring from existing middle management literature into models of R&D decision making. On the one hand, this provides a basis for future studies to theorize about how middle management affects other strategic outcomes of startups, e.g. internationalization. On the other hand, it highlights a weakness in existing literature investigating innovation outcomes of high-tech startups. Studies ignoring the hierarchical levels are likely to suffer from biased results.

Second, recent research in strategic entrepreneurship emphasizes how the riskiness of a startup's business opportunity conditions the value of founder knowledge and experience for startup success (e.g., Dencker and Gruber, 2015). We find that this contingency effect of a startup's business opportunity is not limited to founder characteristics. Instead, we show how middle management can extend the management capacities of a startup for making R&D decisions and that the effects differ depending on the riskiness of the startup's business opportunities. Our theoretical model can be a pathway for future theorizing on how the effectiveness of other organizational design choices of startups (apart from middle management) is contingent on their business opportunities.

Apart from these academic contributions, our findings have relevance for decision making in startups. We provide evidence of the benefits of middle management for startups and outline conditions under which the establishment of a middle management level is most effective. These insights translate into direct recommendations for the management of startups. They suggest that startups should hire middle managers as soon as the startup finances allow to do so (Michelacci and Quadrini, 2005) in order to improve the realization of opportunities. There is a particularly strong case for the establishment of middle management in high-tech startups that have a strong technological base and whose prior knowledge offers numerous opportunities for recombination. Moreover, high-tech startups that continue to invest into R&D because the business opportunity they exploit features high-risk and return prospects also benefit from middle managers. Founders should critically question their own information processing capabilities and to what extent they can dedicate attention to innovation. Similarly, startup advisors such as investors, consultants or government agencies should take these mechanisms into account. We show that the likelihood for innovation success of a startup is not limited to technological decisions of its founders but includes organizational design choices which will make it more likely that the startup will have the information processing and monitoring capacities in place to arrive at promising R&D decisions.

6 Concluding remarks

We have argued theoretically and shown empirically that establishing a middle management layer can help startups to introduce product innovations. The positive effects of middle management seem to arise through improved capabilities for information processing, monitoring and decision making. These improvements help startups prioritize between the creation of new knowledge and the exploitation of existing knowledge, dependent on the riskiness of a startup's business opportunity.

Nevertheless, our research is not without limitations. First, our research investigates only an individual organizational design choice and seeks to isolate its effect on innovation. However, the organizational structure of startups can be characterized by several other dimensions that may interact with the establishment of a middle management level. Future research should therefore also consider other design choices and study their interrelationships. Second, while our research design allows us to capture the effect of middle management across a number of startups and industries, smaller scale and/or qualitative studies may be better positioned to delineate communication and coordination patterns by which middle managers and founders interact in their R&D decisions. Finally, while we use panel data that enables us to control for a large number of firm- as well as individual-specific factors in our models and to use one period lagged explanatory variables to reduce the risk of reverse causality, the remaining time dimension in our panel dataset is not large enough to estimate meaningful fixed effects specifications. Hence there may be some remaining unobserved heterogeneity in individual or firm characteristics that can offer alternative explanations for our empirical results. However, since we are able demonstrate the robustness of our results by using different methods of identification, including a pre-balancing of our sample and instrumental variables models, we consider the potential remaining bias to be very small at most.

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Tables

Table 1
Descriptive statistics

Variable	Unit	All firms (N = 3,699)			
		Mean	S.D.	Min	Max
Product innovation (y/n)	(y/n)	0.16	0.37	0.00	1.00
Firm has middle management (y/n) - lag	(y/n)	0.10	0.30	0.00	1.00
Risk of business opportunity	Score	308.32	14.64	239.00	461.58
Number of R&D employees - lag	Count	0.14	0.64	0.00	13.00
Number of patents bef. foundation	Count	0.48	7.40	0.00	180.00
R&D intensity (R&D/sales) - lag	Share	0.12	0.34	0.00	2.00
Number of founders	Count	1.70	0.98	1.00	9.00
Founder with tertiary education (y/n)	(y/n)	0.65	0.48	0.00	1.00
Founder has managerial experience (y/n)	(y/n)	0.51	0.50	0.00	1.00
Founder has entrepreneurial experience (y/n)	(y/n)	0.47	0.50	0.00	1.00
Years of industry experience	Count	19.48	9.06	2.00	48.00
Number of dep. employees - lag	Count	4.89	5.16	1.00	45.00
Employees with tertiary edu. (share) - lag	Share	0.25	0.33	0.00	1.00
Equity capital in year of foundation	(y/n)	0.04	0.20	0.00	1.00
Limited liability	(y/n)	0.64	0.48	0.00	1.00
Firm age	Count	3.87	1.56	1.08	8.00
High-technology manufacturing	(y/n)	0.30	0.46	0.00	1.00
Technology-intensive services	(y/n)	0.42	0.49	0.00	1.00
Software supply and consultancy	(y/n)	0.14	0.35	0.00	1.00
Skill-intensive services	(y/n)	0.14	0.35	0.00	1.00
Year 2008	(y/n)	0.12	0.32	0.00	1.00
Year 2009	(y/n)	0.19	0.39	0.00	1.00
Year 2010	(y/n)	0.20	0.40	0.00	1.00
Year 2011	(y/n)	0.24	0.43	0.00	1.00
Year 2012	(y/n)	0.26	0.44	0.00	1.00

Notes: Additional control variable: funding by KfW bank.
Source: Own calculations from the KfW/ZEW Start-up Panel and linked employee data.

Table 2
Pairwise correlations of dependent and main explanatory variables (n = 3,699)

	Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1)	Product innovation (y/n)	1														
(2)	Firm has Middle Management (y/n) - lag	0.1114*	1													
(3)	Risk of business opportunity (log)	0.0715*	0.0347*	1												
(4)	Number of RnD Employees - lag	0.0610*	0.0878*	-0.0148	1											
(5)	Number of Patents bef. foundation	0.0266	-0.0167	0.0081	-0.0039	1										
(6)	R&D intensity (R&D/sales) - lag	0.2771*	0.1024*	0.0532*	0.0519*	0.0694*	1									
(7)	# Founders in team (log)	0.1162*	0.1026*	0.0573*	0.0495*	0.0176	0.1227*	1								
(8)	Founder with tertiary education (y/n)	0.1116*	0.0582*	-0.0076	0.0683*	0.0405*	0.1394*	0.2787*	1							
(9)	Founder has managerial experience (y/n)	0.0316	0.0479*	-0.0377*	0.0405*	-0.0107	0.0301	-0.0016	0.0517*	1						
(10)	Founder has entrepreneurial experience (y/n)	0.1115*	0.0688*	0.1082*	0.0224	0.0457*	0.0750*	0.2699*	0.1011*	-0.2094*	1					
(11)	Years of industry experience	-0.0169	0.0042	-0.0328*	0.0452*	0.0542*	-0.0276	0.0085	-0.0953*	0.1209*	0.0419*	1				
(12)	Number of dep. Employees (log) - lag	0.0877*	0.2525*	-0.007	0.2144*	-0.0332*	0.0442*	0.1548*	0.0076	0.0450*	0.0837*	0.0416*	1			
(13)	Employees with tertiary edu. (share) - lag	0.0724*	0.0845*	0.0212	0.0867*	-0.0263	0.1840*	0.1556*	0.3152*	0.0296	0.0815*	-0.0500*	-0.0072	1		
(14)	Equity capital in year of foundation	0.1025*	0.1105*	0.0015	0.0691*	-0.0039	0.2892*	0.1093*	0.0705*	-0.0146	0.0652*	-0.0662*	0.1129*	0.1280*	1	
(15)	Limited liability	0.1984*	0.1568*	0.1742*	0.1039*	0.0362*	0.2007*	0.3519*	0.3064*	-0.0187	0.2911*	0.0102	0.2246*	0.2120*	0.1508*	1
(16)	Firm age (log)	-0.0804*	0.0199	0.1528*	0.0036	0.0029	-0.0712*	-0.0232	-0.0353*	-0.0422*	-0.0350*	0.1569*	0.1236*	0.0055	-0.0329*	-0.1146*

Notes: * denotes the statistical significance of a pairwise correlation at a 5 percent level.

Source: Own calculations from the KfW/ZEW Start-up Panel and linked employee data.

Table 3
Main results

Dependent variable: **Product innovation**	**A** **Full Sample** **M.E. (S.E.)**	**B** **Full Sample** **M.E. (S.E.)**	**C** **Full Sample** **M.E. (S.E.)**	**D** **Full Sample** **M.E. (S.E.)**	**E** **Risk > MED** **M.E. (S.E.)**	**F** **Risk <= MED** **M.E. (S.E.)**
Firm has middle management (y/n) - lag	0.072 (0.026)***	0.054 (0.026)**	0.069 (0.028)**	0.054 (0.027)**	0.059 (0.039)	0.042 (0.037)
Number of patents before foundation	0.002 (0.001)*	0.001 (0.001)**	0.002 (0.001)*	0.001 (0.001)**	0.002 (0.001)***	-0.001 (0.001)
Number of R&D employees - lag	0.040 (0.019)**	0.033 (0.016)**	0.032 (0.023)	0.032 (0.023)	0.020 (0.031)	0.038 (0.023)
Middle management * # patents bef. found. - lag		0.167 (0.079)**		0.167 (0.080)**	0.083 (0.080)	0.285 (0.105)***
Middle management * # R&D empl. - lag			0.012 (0.025)	0.001 (0.026)	0.073 (0.042)*	-0.038 (0.028)
Risk of business opportunity (log)	0.397 (0.299)	0.406 (0.299)	0.394 (0.299)	0.406 (0.299)	0.549 (0.389)	0.115 (0.779)
R&D intensity (R&D/sales) - lag	0.120 (0.029)***	0.115 (0.028)***	0.120 (0.029)***	0.115 (0.028)***	0.102 (0.032)***	0.110 (0.045)**
# Founders in team (log)	0.022 (0.029)	0.024 (0.029)	0.022 (0.029)	0.024 (0.029)	0.006 (0.035)	0.052 (0.039)
Founder with tertiary education (y/n)	0.014 (0.035)	0.013 (0.034)	0.014 (0.035)	0.013 (0.034)	0.028 (0.044)	-0.012 (0.045)
Founder has managerial experience (y/n)	0.055 (0.028)*	0.054 (0.028)*	0.055 (0.028)*	0.054 (0.028)*	0.081 (0.038)**	0.035 (0.038)
Founder has entrepreneurial exp. (y/n)	0.029 (0.029)	0.025 (0.029)	0.028 (0.029)	0.025 (0.029)	0.026 (0.039)	0.014 (0.035)
Founder’s years of industry experience	-0.000 (0.002)	-0.000 (0.002)	-0.000 (0.002)	-0.000 (0.002)	0.001 (0.002)	-0.003 (0.002)
Number of dep. employees (log) - lag	-0.022 (0.014)	-0.021 (0.014)	-0.022 (0.014)	-0.021 (0.014)	-0.024 (0.020)	-0.020 (0.019)
Employees with tertiary edu. (share) - lag	0.123 (0.039)***	0.122 (0.038)***	0.125 (0.039)***	0.122 (0.038)***	0.111 (0.053)**	0.102 (0.050)**
Equity capital in year of foundation	0.016 (0.052)	0.004 (0.050)	0.016 (0.052)	0.004 (0.050)	0.038 (0.070)	-0.038 (0.064)
Limited liability	0.063 (0.048)	0.059 (0.048)	0.063 (0.048)	0.059 (0.048)	0.051 (0.061)	0.077 (0.066)
Firm age (log)	-0.047 (0.032)	-0.047 (0.031)	-0.048 (0.032)	-0.047 (0.031)	-0.045 (0.041)	0.001 (0.044)
Technology-intensive services	-0.186 (0.035)***	-0.183 (0.034)***	-0.187 (0.035)***	-0.183 (0.034)***	-0.142 (0.046)***	-0.207 (0.043)***
Software supply and consultancy	-0.008 (0.041)	0.001 (0.040)	-0.008 (0.041)	0.001 (0.040)	0.020 (0.055)	-0.018 (0.066)
Skill-intensive services	-0.133 (0.043)***	-0.128 (0.042)***	-0.133 (0.043)***	-0.128 (0.042)***	-0.153 (0.054)***	-0.105 (0.057)*
Constant and year fixed effecs	Yes	Yes	Yes	Yes	Yes	Yes
N / Pseudo R-sq.	3699 / 0.12	3699 / 0.13	3699 / 0.12	3699 / 0.13	1904 / 0.14	1795 / 0.16

Notes: Marginal effects from probit models. Significance levels: *** 1 percent, ** 5 percent, * 10 percent. Cluster robust standard errors in parentheses. Baseline category for industry controls: high-tech manufacturing. Additional control var. in all regressions: Funding by KfW bank

Source: Own calculations from the KfW/ZEW Start-up Panel and linked employee data.

Appendices

Appendix A: Tables and figures

Table 4
Details on measures

Variable	Construction
Product innovation	Dummy variable - Takes a value of one for a firm-year observation if a firm introduces a product innovation that is a national or world-wide market novelty in a year
Firm has middle management	Dummy variable - At least one dependent employee in firm is classified as having supervisory or executive competence according to the KldB2010 (ISCO-08) occupation code
R&D employees	Number of dependent employees who are classified as R&D personnel according to the KldB2010 (ISCO-08) occupation code
Patents before foundation	Number of patents a founder self-reported to hold at the time of firm foundation
R&D intensity	R&D expenses/total sales - largest percentile is winsorized and missing values are imputed by one period lagged values if possible
Riskiness of business opportunity	Credit rating score of other firms of the same age in the same NACE4 industry - credit rating scores reach from 100 (best) to 600 (worst)
Number of founders	Number of founders (in the founding team) according to the survey data
Number of dep. employees	Number of reportable employees subject to social insurance contributions. This includes regular full-time and part-time employees, apprentices, interns, and marginally employed personnel.
Founder with tertiary education	Dummy variable - Takes a value of one if the founder (or at least one founder in the team) has a tertiary degree
Employees with tertiary education	Share of dependent employees with tertiary degree
Entrepreneurial experience	Dummy variable - Takes a value of one if the founder (or at least one founder in the team) started up an own company before.
Managerial experience	Dummy variable - Takes a value of one if the founder (or at least one founder in the team) has managerial experience as employee from prior employment
Industry experience	Years of industry experience of the founder (or the founder with the longest experience in the team)
Equity capital in year of foundation	Dummy variable – Takes a value of one if a firm reported any equity investors during the first interview
Limited liability	Dummy variable – Takes a value of one if a firm is incorporated with limited liability
Firm age	Age of startup in years

Table 5
Entropy balancing outcomes

	Treatment group			Control group		
	Before weighting					
	Mean	Variance	Skewness	Mean	Variance	Skewness
Equity capital in year of foundation	0.112	0.100	2.460	0.036	0.035	4.989
Limited liability at foundation	0.871	0.113	-2.216	0.611	0.238	-0.455
Founder with tertiary education (y/n)	0.740	0.193	-1.091	0.646	0.229	-0.609
Years of industry experience	19.590	81.620	0.405	19.460	82.100	0.466
Founder has managerial experience (y/n)	0.583	0.244	-0.335	0.502	0.250	-0.006
Founder has entrepreneurial experience (y/n)	0.577	0.245	-0.312	0.461	0.249	0.157
Full-time eq. empl. size at foundation (incl. founders)	3.186	23.060	2.850	1.997	6.929	2.547
High-technology manufacturing	0.364	0.232	0.565	0.291	0.206	0.921
Technology-intensive services	0.339	0.225	0.681	0.429	0.245	0.288
Software supply and consultancy	0.165	0.138	1.802	0.136	0.117	2.126
	After weighting					
	Mean	Variance	Skewness	Mean	Variance	Skewness
Equity capital in year of foundation	0.112	0.100	2.460	0.112	0.099	2.463
Limited liability at foundation	0.871	0.113	-2.216	0.870	0.113	-2.195
Founder with tertiary education (y/n)	0.740	0.193	-1.091	0.739	0.193	-1.089
Years of industry experience	19.590	81.620	0.405	19.590	81.610	0.406
Founder has managerial experience (y/n)	0.583	0.244	-0.335	0.583	0.243	-0.335
Founder has entrepreneurial experience (y/n)	0.577	0.245	-0.312	0.577	0.244	-0.310
Full-time eq. empl. size at foundation (incl. founders)	3.186	23.060	2.850	3.183	23.030	2.852
High-technology manufacturing	0.364	0.232	0.565	0.364	0.232	0.565
Technology-intensive services	0.339	0.225	0.681	0.339	0.224	0.680
Software supply and consultancy	0.165	0.138	1.802	0.165	0.138	1.804

Source: Own calculations from the KfW/ZEW Start-up Panel and linked employee data.

Table 6
Additional specifications and robustness check estimates

Dependent variable: **Product innovation**	**A** **Not balanced** **M.E. (S.E.)**	**B** **Full Sample** **M.E. (S.E.)**	**C** **Full Sample - OLS** **M.E. (S.E.)**	**D** **Full Sample - OLS** **M.E. (S.E.)**
Firm has middle management (y/n) - lag	0.047 (0.019)**		0.074 (0.028)***	0.064 (0.027)**
Number of patents before foundation	0.001 (0.000)*			
Number of R&D employees - lag	0.017 (0.010)*			
Middle management in firms in risky environment - lag		0.052 (0.036)		
Middle management in firms in non-risky environment - lag		0.050 (0.035)		
Middle management * # Patents bef. foundation (firms in risky env.) - lag		0.090 (0.086)		
Middle management * # Patents bef. foundation (firms in non-risky env.) - lag		0.266 (0.099)***		
Middle management * # R&D employees (firms in risky env.) - lag		0.072 (0.043)*		
Middle management * # R&D employees (firms in non-risky env.) - lag		-0.044 (0.028)		
# Patents bef. foundation in firms in risky environment		0.003 (0.001)***		
# Patents bef. foundation in firms in non-risky environment		-0.001 (0.001)		
# R&D employees in firms in risky environment - lag		0.027 (0.031)		
# R&D employees in firms in non-risky environment - lag		0.037 (0.022)*		
Risk of business opportunity (log)	0.399 (0.161)**	0.289 (0.293)	0.436 (0.309)	0.199 (0.404)
R&D intensity (R&D/sales) - lag	0.139 (0.017)***	0.117 (0.027)***	0.159 (0.038)***	0.143 (0.037)***
# Founders in team (log)	0.009 (0.015)	0.025 (0.028)	0.017 (0.031)	0.011 (0.029)
Founder with tertiary education (y/n)	0.047 (0.018)***	0.009 (0.033)	0.023 (0.035)	0.021 (0.034)
Founder has managerial experience (y/n)	0.031 (0.014)**	0.059 (0.028)**	0.043 (0.030)	0.048 (0.029)*
Founder has entrepreneurial experience (y/n)	0.043 (0.015)***	0.022 (0.028)	0.029 (0.031)	0.027 (0.029)
Years of industry experience	-0.001 (0.001)	-0.000 (0.002)	0.000 (0.002)	-0.001 (0.002)
Number of dep. employees (log) - lag	0.006 (0.008)	-0.023 (0.014)	-0.017 (0.016)	-0.017 (0.015)
Employees with tertiary edu. (share) - lag	-0.000 (0.020)	0.118 (0.038)***	0.146 (0.045)***	0.127 (0.044)***
Equity capital in year of foundation	0.003 (0.035)	0.001 (0.049)	0.024 (0.064)	0.011 (0.056)
Limited liability	0.078 (0.019)***	0.066 (0.048)	0.055 (0.037)	0.042 (0.035)
Firm age (log)	-0.058 (0.016)***	-0.039 (0.030)	-0.039 (0.034)	-0.048 (0.033)
Stratification industry fixed effects	Yes	Yes		
NACE 1-digit fixed effects			Yes	
NACE 2-digit fixed effects				Yes
Year fixed effects and constant	Yes	Yes	Yes	Yes
N / Pseudo R-sq.	3699 / 0.14	3699	3699	3699

Notes: Marginal effects from probit models in Column A and B). Significance levels: *** 1 percent, ** 5 percent, * 10 percent. Cluster robust standard errors in parentheses. Baseline category for industry controls: high-tech manufacturing. Additional control var. in all regressions: Funding by KfW bank.

Source: Own calculations from the KfW/ZEW Start-up Panel and linked employee data.

Table 7
GMM-IV Estimation

Dependent variable: **Product innovation**	**A** **1st stage - lags** **M.E. (S.E.)**	**B** **2nd stage - lags** **M.E. (S.E.)**	**C** **2nd stage - no lags** **M.E. (S.E.)**
Firm has middle management (y/n) - lag		0.370 (0.204)*	
Firm has middle management (y/n)			0.247 (0.139)*
Executives involved in firms (same NACE-1 and district)	0.000 (0.000)*		
Share of firms with middle manager (same NACE-1 and size class)	0.580 (0.138)***		
Risk of business opportunity (log)	0.108 (0.131)	0.324 (0.190)*	0.083 (0.069)
R&D intensity (R&D/sales) - lag	0.038 (0.025)	0.215 (0.031)***	
R&D intensity (R&D/sales)			0.204 (0.023)***
Number of Patents bef. foundation	0.000 (0.000)*	0.001 (0.001)	0.001 (0.001)
Number of R&D employees - lag	0.008 (0.012)	0.019 (0.014)	
Number of R&D employees			0.017 (0.01)*
# Founders in team (log)	0.012 (0.017)	0.010 (0.018)	0.007 (0.014)
Founder with tertiary education (y/n)	-0.001 (0.015)	0.051 (0.017)***	0.052 (0.013)***
Equity capital in year of foundation	0.075 (0.042)*	-0.014 (0.055)	-0.004 (0.042)
Founder has managerial experience (y/n)	0.024 (0.012)**	0.022 (0.015)	0.02 (0.012)*
Founder has entrepreneurial experience (y/n)	0.013 (0.014)	0.037 (0.016)**	0.032 (0.012)**
Years of industry experience	0.000 (0.001)	-0.001 (0.001)	-0.001 (0.001)
Number of dep. employees (log) - lag	0.015 (0.012)	-0.021 (0.015)	
Number of dep. employees (log)			-0.004 (0.013)
Employees with tertiary edu. (share) - lag	0.043 (0.019)**	-0.015 (0.023)	
Employees with tertiary edu. (share)			-0.007 (0.019)
Full-time eq. empl. size at foundation (incl. founders)	0.000 (0.003)	0.002 (0.003)	0.000 (0.002)
Limited liability	0.032 (0.014)**	0.044 (0.018)**	0.053 (0.013)***
Firm age (log)	0.004 (0.014)	-0.058 (0.018)***	0.001 (0.009)
Technology-intensive services	-0.024 (0.018)	-0.116 (0.021)***	-0.091 (0.016)***
Software supply and consultancy	-0.004 (0.025)	-0.026 (0.030)	-0.017 (0.023)
Skill-intensive services	-0.002 (0.020)	-0.113 (0.024)***	-0.082 (0.018)***
Year fixed effects and constant	Yes	Yes	Yes
First stage F-statistic of instruments		10.45	20.75
First stage Hansen's J-Test p-value		0.106	0.511
N / (Pseudo) R-sq.	3699 / 0.10	3699 / 0.08	5847 / 0.09

Notes: Significance levels: *** 1 percent, ** 5 percent, * 10 percent. Cluster robust standard errors in parentheses. Baseline category for industry controls: high-tech manufacturing. Additional control var. in all regressions: Funding by KfW bank.

Source: Own calculations from the KfW/ZEW Start-up Panel and linked employee data.

Appendix B: Entropy balancing

In contrast to other related methods, for instance propensity score weighting, entropy balancing induces covariate balance directly, and not as the result of a propensity score matching procedure, which requires iterated re-specifications of the propensity score estimation to achieve covariate balance. The sampling weights are chosen as the solution to the minimization problem

$$\min_{w_i} H(w) = \sum_{\{i|D=0\}} h(w_i)$$

Under the constraints that

$\sum_{\{i|D\,=\,0\}} w_i c_{ri}(X_i) = m_r$ with $r \in 1, \ldots R$ and

$\sum_{\{i|D\,=\,0\}} w_i = 1$ and

$w_i \geq 0$ for all i such that $D = 0$

w_i denotes the weights for each observation from the control group. $h(w_i)$ is a distance measure which measures the distance between the chosen weights and a set of base weights. $w_i c_{ri}(X_i) = m_r$ denotes the balance constraints for the R moments to balance for each covariate (for further details we refer to Hainmueller, 2011; Hainmueller and Xu, 2013). Entropy balancing therefore induces covariance balance directly and explicitly minimizes the weight given to each observation from the control group.

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