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The Workforce Composition of Young Firms and Product Innovation – Complementarities in the Skills of Founders and their Early Employees

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Abstract

We investigate the extent to which complementarities between technical and business skills of founders and employees matter for the generation of market novelties by new ventures. Using data about German start-ups, we find that there are no complementarities between technical and business skills within the group of founders, but that there are significant complementarities between technically trained founders and employees who have business skills. This suggests that the innovation potential of start-ups by technically trained founders is best explored by hiring employees who are trained in business. However, a reverse relationship does not exist: There are no complementarities between founders with business skills and employees with technical skills.

Keywords: Entrepreneurship, Innovation, Human Capital, Skills, Complementarity
JEL classification: J24, L23, L26, M13, M51, Q31

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1 Introduction

Young firms attract attention from both policy makers and academics because of their expected direct and indirect contribution to innovation (Schumpeter, 1934; Baumol, 2002, 2004). Perhaps the most critical resource for the innovation performance of a firm is the human capital endowment of its workforce. Listening not only to practitioners, but also to policy makers and academics, one often encounters the view that, apart from technical knowledge that is important for the development of the business idea, young firms also need skills in business administration in order to commercialize that idea successfully. To paraphrase this view: "Young firms need business skills to use the full potential of their idea." Translating this into economic language, this understanding suggests that there are complementarities between technical and business skills; in other words, that the marginal return on one skill type is higher if the other skill type is used as well. While this seems to be a widespread view - either explicitly articulated or implicitly assumed - little is known about complementarities in the human capital of young firms.

We aim to contribute to the literature in two important ways. First, we explore the role of complementarities between technical and business skills for the probability that a young firm introduces a market novelty. With this research focus, our paper belongs to the literature on the effects of skill diversity on firms' innovation outcomes. As the authors of previous studies have noted, diversity is associated with both gains and costs (Hambrick et al., 1996; Ensley and Amason, 1999; Lazear, 1999). While the costs consist mainly of difficulties in inter-personal communication, complementarities can be regarded as the gains from diversity (Lazear, 1999). Thus, by analyzing complementarities we explore whether gains from diversity in technical and business skills exist with regard to the innovation outcomes of young firms.

Second, we integrate the human capital of early employees alongside that of the firms' founders into the analysis. With regard to the discussion of the role of human capital for the innovation outcomes of young firms, the focus in the entrepreneurship literature is usually on the human capital of the founders (e.g. Corrocher and Lenzi, 2015; Kato et al., 2015; Marvel and Lumpkin, 2007). However, this view is too narrow because the hired employees also bring their knowledge and experience to a firm's pool of knowledge. We aim to overcome this limitation by analyzing the relationship between the complete stock of young firms' human capital and their probabilities of launching market novelties. Particularly, we differentiate between skill inputs of founders and employees.

For the empirical analyzes, we use a new linked employer-employee data set that matches the employer data from the KfW/ZEW Start-up Panel to register data on employees from the employment statistics of the German Federal Employment Agency. The KfW/ZEW Start-up Panel is a random sample of young German firms from almost all sectors (Fryges et al., 2010) and provides information about the human capital of the firms' founders and the firms' innovation activities. The register data from the German Federal Employment Agency cover relevant information about the educational and professional qualifications of all employees.

Our results show that, overall, technical and business skills are complementary, but that this outcome is not driven by complementarity between the two skill types within the groups of founders. Instead, we find complementary relationships between the skills of the founders and the skills of the employees, as well as within the group of employees. Interestingly, the complementary relationship between founders and employees is asymmetric. We find complementarities between technically trained founders and employees with business skills, but we cannot detect complementarities between founders with business skills and employees with technical skills.

The paper is organized as follows: In Chapter 2 we review the relevant literature on the relationship between human capital and innovation. In Chapter 3 we relate general theories about complementarity to complementarities in human capital in the innovation process. In Chapter 4 we present our empirical strategy, and discuss limitations to the identification of causal effects in the chosen setting. In Chapter 5, we present details about the data we use. In Chapter 6, we present descriptive and multivariate empirical evidence and classify and discuss the findings. The conclusion follows in Chapter 7.

2 Related literature: Human capital and innovation

Human capital (i.e., the knowledge, experience, abilities and skills of individuals) has been regarded to be a key factor in the innovation process since researchers are interested in innovation (early studies include, for example, Mansfield, 1977; Griliches, 1979). Consistent with this consideration, empirical studies that analyze the relationship between human capital and innovation usually find that there is a positive association between these two factors (Acs and Audretsch, 1988; Bantel and Jackson, 1989; Smith et al., 2005; Marvel and Lumpkin, 2007; De Winne and Sels, 2010; Østergaard et al., 2011; Andries and Czarnitzki, 2014; Kato et al., 2015).

A recurring idea for describing the emergence of innovation is that innovations occur through combining existing knowledge in a novel way (Schumpeter, 1934; Kogut and Zander, 1992, 1996). At the same time, a large part of the relevant knowledge is stored in individuals as tacit knowledge (Grant, 1997; Kogut and Zander, 1992, 1996) which makes individuals important knowledge carriers. In addition, it is individuals who must create the combinations even in cases when knowledge is not tacit but is available in codified form. Accordingly, also team diversity is regarded to be beneficial for the innovation outcomes of firms. When a group is composed of individuals with different skills, knowledge, and ability, more problems - or, more opportunities - are identified and a larger set of possible solutions is considered because different perspectives are united in a diverse group (Bantel and Jackson, 1989). In addition, the different perspectives resulting from different skills form the basis for combinations of knowledge to create something new (Østergaard et al., 2011). Diversity in knowledge also increases the ability to take up and exploit external knowledge, or what Cohen and Levinthal (1990) call the "absorptive capacity".

However, when it comes to testing the proposition that skill diversity is good for innovation, the results are mixed and partly contradictory. When considering diversity in educational fields, Bantel and Jackson (1989) find no relation with innovation. Parrotta et al. (2014) find a positive effect of diversity in educational backgrounds on innovation in their basis regressions but this effect does not persist when the authors instrument their measures. By contrast, Østergaard et al. (2011) report a positive effect for diversity in educational fields and Corrocher and Lenzi (2015) find positive effects for heterogeneity in areas of expertise. Regarding age as a measure for general experience skills, according to Zajac et al. (1991) and Østergaard et al. (2011), age diversity has a negative effect on innovation, while Bantel and Jackson (1989) find no effect. However, the latter authors find a positive effect for the heterogeneity of functional backgrounds. Van der Vegt and Janssen (2003) use a measure of perceived differences in views and attitudes to analyze the effect of cognitive group diversity on the innovative behavior of groups. They find no effect of this diversity measure on the behavior of groups to search for and implement new ideas.

These inconclusive results gave rise to the conjecture that diversity is not only associated with benefits but that it also entails costs, i.e., that it is a "double-edged sword" (Hambrick et al., 1996; Ensley and Amason, 1999). On one hand, it increases the range of perspectives but, on the other hand, it can also result in communication problems which lead to conflict. The latter could offset the advantage of having a broader skill base due to different backgrounds. As Lazear (1999) points out gains from diversity in skills arise if "skills [...] can be combined to create a whole that is greater than the sum of its parts" (Lazear, 1999, p. C21), or if skills are complementary. Thus, by searching for complementarities in the human capital stock of young firms and describing its pattern we touch on the sources for gains from skill diversity.

Many previous studies analyzing teams' characteristics and firms' performance are inspired by the upper-echelon theory, which regards "organizations as a reflection of their top managers" (Hambrick and Mason, 1984, p. 193). Consequently, the main interest in earlier studies has been in the characteristics of the members of the top management team (TMT). In our view, this is a shortcoming for the study of young entrepreneurial firms because the outcome of a young firm can be regarded as joint effort of both the founders and the employees (Baron and Hannan, 2002; Ruef et al., 2003; Aldrich and Ruef, 2006).

There have been recent attempts to widen the focus and to include the human capital of employees into the analysis of the innovation performance of firms. Examples are Østergaard et al. (2011), who consider the impact of the diversity of the entire workforce on innovation; Andries and Czarnitzki (2014) distinguish between ideas originating from managers and ideas being suggested by employees, and De Winne and Sels (2010) study the relationship between the human capital of both owners/managers and employees and firms' innovation strategies. However, with the exception of the last paper, these studies do not focus on young entrepreneurial firms, but on established firms that have a reasonable size of 15 employees or more on average. In addition, Østergaard et al. (2011) are forced to treat the workforce as one group and cannot distinguish between managers and employees due to data restrictions. Although De Winne and Sels (2010) focus explicitly on start-ups, they are interested in the levels of human capital of founders/managers and employees, and not in the interrelationship of specific combinations of skills which is the focus of our study.

3 Theory: Complementarity in human capital and innovation

In the following, we combine arguments from the literature on innovation with those from personnel economics and the literature on the theory of the firm. First, we derive a hypothesis regarding the general role of complementarities between business and technical skills in the innovation process of young firms. Subsequently, we derive two hypotheses concerning boundary conditions for observing complementary relationships at the levels of the founders and the employees.

Different theoretical considerations suggest that complementarities in human capital are relevant for the innovation outcomes of young firms. Teece (1986) argues that the extent to which a firm can benefit from an invention depends on its access to assets or capabilities that are complementary. He defines an invention as consisting of certain technological knowledge and recognizes that the development of this new knowledge is only the first step in the innovation process. In order for a company to benefit from the new development, the invention must be brought to the market (for example, by developing a new marketable product or service, or by integrating it into a given product or service). For the market launch, abilities in marketing and distribution, or to secure the required funds, are needed and are used in conjunction with the new technological knowledge created. These considerations seem to correspond well with what practitioners, policy makers and academics have in mind when they claim that young firms need business skills in order to benefit from their business idea to the fullest extent.

By classifying complementarities to be the gains from diversity, Lazear (1999) identifies three conditions that determine whether these gains arise in practice: a) individuals in a team must have different information or knowledge sets, b) the information of the individuals must be relevant for each other or for the object of the company, and c) it must be possible that team members can get their knowledge across to their teammates easily; in other words, they must be able to communicate at little costs. Following the arguments of Teece (1986), it is plausible that business and technical skills fulfill conditions a) and b). The fulfillment of condition c) is slightly more difficult, which gives rise to one of our boundary conditions below. At this point in the analysis, we consider that, given their (in most cases) small size, it is possible to communicate at sufficiently low cost within young firms in general. We therefore hypothesize that

> ***Hypothesis 1****: Technical and business skills are complementary in the generation of market novelties in new businesses.*

We now derive boundary conditions necessary for Hypothesis 1 to hold. These are rooted in the question of who should provide the relevant skills to the knowledge pool of the firm. Lazear

(2004, 2005) argues that the entrepreneur him- or herself must have knowledge of all relevant areas, at least at a basic level, because it is he or she who combines the factors of production.

This contrasts with the view that different, potentially complementary, skills can be brought to the firm via a team of founders (Fabel, 2004) or through employees whose skills expand the skills of the founders (Dahl and Klepper, 2015). We argue in the following that it matters for complementarities between technical and business skills to exist, whether the entrepreneurs or the employees contribute the relevant skills.

Based on the transaction cost perspective of the theory of the firm (Coase, 1937; Williamson, 1975, 1985; Grossman and Hart, 1986; Hart and Moore, 1990; Hart, 1995), Rajan and Zingales (2000, 2001) contend that ensuring the cooperation of employees without running the risk of being expropriated is the fundamental problem in entrepreneurship. As the authors identify, at the root of most businesses is an entrepreneur with a unique resource, such as an idea, good customer relationships, a new tool or a superior management technique, who needs assistance in bringing the resource to the market (Rajan and Zingales, 2001). The latter requires that the entrepreneur provides his or her collaborators with access to the resource which, to the extent that the critical resource cannot be protected by law, gives the collaborators the opportunity to exploit the resource themselves and to deceive the entrepreneur. Thus, an important task in a new organization is to ensure that all parties have the appropriate incentives to remain together and to work jointly on the commercialization of the unique resource.

As a solution to this problem, Rajan and Zingales (2000) suggest creating complementarities between the organization and its workforce.[1] "Complementarities" in this context are considered to be a link that leads to a situation in which the organization and its workforce can generate more value together than if the parties were to split up and go their separate ways. In other words, complementarities are the glue that holds the firm together (Hart, 1995). From this, it follows that being able to build complementarities between themselves and their collaborators is an important step for entrepreneurs in the formative stages of their businesses in order to bind the collaborators so that it is in their interest to exploit the resource jointly.

Based on this line of theory, we suggest that the need to build complementarities differs between founders and employees. While complementarities are needed between founders and employees, this is not necessarily the case within the group of founders. For founders, ownership can serve as an alternative means to tie people to an organization. According to Grossman and Hart (1986), ownership is a mechanism that confers residual rights of control over the firm's assets, which allows the holder to specify how a particular asset is used and to exclude others from the use of the asset if needed. The resulting bargaining power ensures that the owner can secure a fraction of the value generated in the relationship and therefore provides incentives to invest in the relationship. While ownership can, in principle, also ensure that employees are tied to the organization (for example, if the employees need the assets the entrepreneur owns to

[1] One way of creating complementarities is by "persuading" employees to make firm-specific investments. This can be achieved by giving employees privileged access to valuable resources (Rajan and Zingales, 2000).

be productive), Rajan and Zingales (1998) point out this may only be effective when physical assets are concerned. When it comes to intangible assets, which represent the unique resources at the beginning of a firm's life in most cases, this might not apply because intangible assets are more difficult to protect. Therefore, ties must be constructed in a different way, such as through complementarities, in order to prevent employees resigning and leaving the organization, taking the unique resource itself or at least knowledge about it. We therefore propose that

> ***Hypothesis 2:*** *Complementarities in the generation of market novelties are stronger between founders and employees than they are within the group of founders.*

Taking this a step further, the most relevant question from the viewpoint of an entrepreneur is whether - given his or her own skills - s/he could benefit from diversifying the firm's pool of knowledge through hiring employees. It is reasonable to assume that potential complementarities between founders and employees are asymmetrical with regard to technical and business skills because these two types of skills have different degrees of transferability between people. In this regard, we refer to condition c) as stated by Lazear (1999) above. As we discuss below, arguments from the literature on personnel economics and the literature on the theory of the firm lead to two competing hypotheses concerning whether complementarities exist depending on which group provides the respective skill to the firm.

Based on research in personnel economics, we suggest that complementarities tend to exist when a founder has technical skills and employs staff with business skills, rather than in the opposite case. We argue that business knowledge can be transferred to others more easily than can technical knowledge. A large number of the members of the workforce in young firms gained work experience prior to setting up or joining the new firm (Brixy and Murmann, 2016; Murmann, 2016). Thus, it can be assumed that the members of the workforce of a young firm have at least a basic understanding of business administration processes. In addition, basic business skills are an element of organizing everyday life. Hence, while specific skills in business administration are necessary in the innovation process, it should be possible to transfer the basic knowledge about these processes to others quite easily. We argue that this is different for technical knowledge. Technical knowledge requires special training in most cases in order to understand it sufficiently well for it to be transferred easily. Thus, the communication costs are higher when technical knowledge needs to be transferred than they are when businesses knowledge is to be transferred.

The "jack-of-all-trades" approach of entrepreneurship suggested by Lazear (2004, 2005) matches this line of thinking. According to Lazear, the essence of entrepreneurship is putting together factors of production to "create a new product or to produce an existing one at a lower or competitive cost" (Lazear, 2005, pp. 649-650). He acknowledges that different skills need to be combined in order to bring an innovation onto the market. Lazear (2004, 2005) argues that the entrepreneur him- or herself must have knowledge of all relevant areas, at least on a basic level, because it is s/he who assembles the factors of production. Hence, s/he can only (successfully) employ personnel for tasks that s/he is able to understand to a basic degree. This basic understanding is necessary to secure good employer-employee matches and to monitor personnel.

Linking the thought that business knowledge can be transferred at a lower cost than can technical knowledge to the reasoning suggested by Lazear (2004, 2005) that an entrepreneur must have at least a basic understanding of different areas in order to combine and manage the talents of others, we suggest that a founder finds it easier to benefit from the skills of employees the lower the communication costs involved in transferring the knowledge from the employees across to the founder.

> ***Hypothesis 3a:*** *Complementarities in the generation of market novelties are stronger between founders with technical skills and employees with business skills than they are when the situation is reversed.*

By contrast, taking the view mentioned by Rajan and Zingales (2000, 2001), which is that it is the role of complementarities to hold the firm together and to prevent employees from deceiving the entrepreneur and leaving with the valuable resource, leads to a different conclusion.

Assuming again that business knowledge is easier to transfer between people than is technical knowledge, it follows that an entrepreneur with business skills who needs the help of an employee with technical skills faces a comparably high risk of being deceived by the employee. This is because the entrepreneur needs to disclose critical details about his or her idea to the employee to allow the employee to implement the idea technically. The employee, in turn, experiences rather low costs to understand roughly how the entrepreneur plans to market the idea. Therefore, the employee will find it rather easy to deceive the entrepreneur and to exploit the resource with a different partner.

On the contrary, an entrepreneur who has the technical skills to implement the idea him- or herself but needs help with the business administrative processes faces a lower risk since active disclosure of critical details is not necessary and the employee specializing in business administration faces comparably high costs in an attempt to understand the critical technical details. According to the perspective of Rajan and Zingales (2000, 2001), the necessity of keeping the employee attached to the firm by building complementarities between the entrepreneur's skills and the employee's skills is much stronger in the former case than it is in the latter. Hence, based on this perspective, we propose that

> ***Hypothesis 3b:*** *Complementarities in the generation of market novelties are stronger between founders with business skills and employees with technical skills than they are when the situation is reversed.*

4 Empirical setup

4.1 Operationalizing complementarities

We formalize the considerations above and build the connection to our empirical analysis by applying a knowledge production framework. The idea of knowledge production functions is that, equivalent to the production of physical goods, new knowledge or innovation is generated by combining different input factors (Griliches, 1979). Human capital is typically regarded as being one of the basic input factors in this production process. In order to test for the impacts of business skills and technical skills, as well as for the joint effect of the two types of skills on the innovation output, we divide the human capital inputs into 'business' components and 'technical' components. More specifically, we assume that innovation in firm i takes place according to the function

$$INNO_i = I(BS_i, TS_i, X_i), \tag{1}$$

where BS_i denotes business skills, TS_i denotes technical skills, and X_i is a vector of other firm and industry variables that are related to innovation. Complementarity between business skills and technical skills exists if it can be shown that equation (1) is supermodular in the respective human capital measures. In a framework in which the skill measures in equation (1) would be continuous and twice differentiable, this would be equivalent to the condition that the cross-partial derivatives with regard to BS and TS are positive. However, our variables measuring the human capital inputs of the founders and the employees are discrete. We therefore refer to a framework based on the mathematical theory of lattices that was developed by Topkis (1978) and applied in a series of studies on complementarities of discrete activities (e.g. Milgrom and Roberts (1990); Leiponen (2005); Mohnen and Röller (2005); Cassiman and Veugelers (2006)).

4.2 Testing for complementarity

Determining the supermodularity of a function in a discrete setting involves testing the validity of inequality constraints. In order to keep the description of the applied testing framework as concise as possible in the following, we concentrate on the case related to Hypothesis 1, in which the focus is on business and technical skills without the differentiation between founders and employees. The testing procedure for the more complex case that includes the founder/employee dimension can be found in Appendix B.

If we assume that both variables BS and TS can take on the values "0" and "1" (business skill yes/no; technical skills yes/no), then equation (1) is supermodular and business skills and technical skills are complements if

$$I(1, 1; X_i) - I(0, 1; X_i) > I(1, 0; X_i) - I(0, 0; X_i). \tag{2}$$

This means that the incremental effect of adding one skill component on the innovation output of a firm is higher if the other skill component is already in place in the initial situation than it is when none of the skill components is present. Supermodularity of the innovation function (1) can therefore be determined by estimating the equation

$$I_i = \beta_0 s_{oo} + \beta_1 s_{o1} + \beta_2 s_{10} + \beta_3 s_{11} + \gamma' X_i + \epsilon_i, \tag{3}$$

where s_{ij} are binary variables reflecting the respective states in equation (2), and then testing whether

$$\hat{\beta}_3 - \hat{\beta}_1 > \hat{\beta}_2 - \hat{\beta}_0 \tag{4}$$

(see Leiponen, 2005; Mohnen and Röller, 2005; Cassiman and Veugelers, 2006).

While this testing procedure is straightforward to apply when two factors are concerned, it becomes more complex when more than two factors are involved. In the case of multiple factors, multiple inequality constraints of the type in Equation (4) have to be tested simultaneously. Tests of whether these inequalities hold simultaneously have to rely on asymptotically derived critical values that have large indecisive areas within which complementarity can neither be concluded nor rejected (Mohnen and Röller, 2005). As a solution to this problem, Carree et al. (2011) suggest that complementarity can be tested alternatively by rearranging the estimation equation from a notation as mutually exclusive state dummies (as in equation (3)) into a notation as interaction terms. For the purposes of consistency, we test for complementarity using the procedure suggested by Carree et al. (2011) and stay within the framework for the case with only two factors to be tested. In our illustrative case that includes two potentially complementary factors, the test can be implemented by rearranging s_{01} and s_{10} from equation (3). Doing so and adding a time dimension provides the regression equation to test Hypothesis 1:

$$I_{it} = \alpha_0 + \alpha_1 s_{.1,t-1} + \alpha_2 s_{1.,t-1} + \alpha_3 s_{11,t-1} + \gamma' X_i + \delta' Z_{i,t} + \epsilon_{it}, \tag{5}$$

where "." indicates that the other skill components can take on any value ("0" or "1").[2] In this formulation, complementarity exists if the estimated coefficient of the interaction term α_3 is significantly larger than zero.[3] As discussed below, all skill measures enter the regressions as one-period lagged values. $X_{i,t-1}$ is a vector for additional firm-specific explanatory variables lagged by one year, $Z_{i,t}$ is a vector for contemporaneous or time-invariant firm-specific explanatory variables, and ϵ_{it} is a firm- and time-specific error term.[4] The innovation variable I_{it} is a dummy variable indicating whether firm i launched a market novelty either nationwide or worldwide in year t.

When both business skills and technical skills can be provided by both founders and by employees, this results in four different human capital input factors for a firm in the innovation process ($BS_{F,i}, TS_{F,i}, BS_{E,i}, TS_{E,i}$). The subscripts F and E denotes that a skill is brought to the firm by a founder or an employee respectively. In our binary setting, this results in 16 different

[2] The dummies are then no longer mutually exclusive, as they are in equation (3).

[3] To see that this is equivalent, note that $\beta_0 = \alpha_0$; $\beta_1 = \alpha_0 + \alpha_1$; $\beta_2 = \alpha_0 + \alpha_2$ and $\beta_3 = \alpha_0 + \alpha_1 + \alpha_2 + \alpha_3$.The test for inequality Equation (4) can then be rewritten as $\alpha_0 + \alpha_1 + \alpha_2 + \alpha_3 - \alpha_0 - \alpha_2 > \alpha_0 + \alpha_1 - \alpha_0$, which is equivalent to $\alpha_3 > 0$.

[4] $X_{i,t-1}$ and $Z_{i,t}$ are specified below.

states of possible combinations of skills s_0 to s_{15} (where s_0 corresponds to state (0,0,0,0), s_1 to state (0,0,0,1), and ..., s_{15} to (1,1,1,1)). Accordingly, for this more detailed case, equation (3) is extended to

$$I_{it} = \sum_{l=0}^{15} \alpha_l s_{l,i,t-1} + \gamma' X_{i,t-1} + \delta' Z_{i,t} + \epsilon_{it}, \tag{6}$$

To test for complementarity between a pair of skills (for example, between $BS_{F,i}$ and $TS_{F,i}$), all possible combinations of the other two skills (in this case $BS_{E,i}$ and $TS_{E,i}$) have to be considered. Therefore, the number of inequality constraints that have to be fulfilled for supermodularity to hold increases to four compared to only one for the "simple" case presented in equation (2). We present more details regarding the inequality constraints in the case of four practices and the applied testing procedure in Appendix B.

4.3 Estimation and identification

There are econometric issues that need to be taken into account. The first relates to the estimation method of choice. Since our dependent variable is binary, we use standard probit estimates with robust standard errors whenever we include our skill measures as mutually exclusive dummies. However, the approach to test for complementarities suggested by Carree et al. (2011) involves estimating a series of interaction effects. The interpretation of interaction effects in nonlinear models, such as probit or logit models, is not straightforward and may require graphical analysis (Ai and Norton, 2003; Greene, 2010). Since this is not feasible in our context because a large number of interaction terms needs to be considered simultaneously we estimate the regression equations for the complementarity tests using linear probability models. This model has been shown to deliver results that are very close to the marginal effects in binary choice models in practice (Angrist and Pischke, 2009), although it does not ensure that the predicted values lie between zero and one. As a robustness check, we double-checked the complementarity test using probit models and found no considerable differences (see Section 6.3).

Another issue is that of potential endogeneity, which arises because firms may adjust their hiring strategies in response to introducing a market novelty. We use lagged human capital inputs to reduce the potential bias caused by reverse causality. Obviously, this does not exclude the case of strategic employment behavior of firms with well-developed, almost market-ready, new products. However, we think that the use of one-period lagged inputs is the best we can do to address the problem in our setting. Instrumental variable estimation is hardly feasible in a context with 16 state dummies, while using longer lag structures leads to noisy measures for human capital inputs and reduces the number of observations to a significant degree. We again run robustness checks to study the effects of the lag length on our results (see Section 6.3).

5 Data and summary statistics

We use matched employer-employee data from the KfW/ZEW Start-up Panel and the employment statistics provided by the German Federal Employment Agency. The KfW/ZEW Start-up Panel is a representative survey of German start-ups. It was established in 2008 by the Centre for European Economic Research (ZEW), KfW Bankengruppe (Germany's and the world's largest state-owned promotional bank), and Creditreform (Germany's largest credit rating agency). The sampling frame for the KfW/ZEW Start-up Panel is the Mannheim Enterprise Panel (Mannheimer Unternehmenspanel - MUP), which contains basic information such as addresses, year of start-up, sector of activity, and legal form, for almost all German firms including start-ups (see Bersch et al., 2014, for a detailed description). The KfW/ZEW Start-up Panel is a random sample of legally independent new ventures founded in the three years prior to the year of the survey and is drawn from almost all sectors of the MUP population (the primary sector, the energy sector, and the public sector are not included). Subsidiary businesses and ventures that resulted from merger activities are excluded. The sample is stratified according to three criteria: (i) year of the firm's formation, (ii) the industry, and (iii) whether or not the firm has received financial support from KfW. Stratification is controlled for by including dummy variables for the stratification cells in all regressions. Ventures that participate once in the survey are subsequently followed in successive panel years until they are eight years' old (see Fryges et al., 2010, for a detailed description).

The panel data are collected using computer-aided telephone interviews and provide information about the founders' characteristics (i.e. educational background, prior employment status, and managerial and leadership experience) and venture characteristics (i.e. innovation and R&D activities). We draw on information from the first six survey waves that contain information about 15,300 firms that were established between 2005 and 2012.

We match the firm-level information with individual-level information from the 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. 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 firms in order to calculate the contributions to the social security system. This implies that we observe the employment biography of all individuals who were employed in one of the young firms in the KfW/ZEW Start-up Panel for at least one day. The employment statistics provide details regarding employee characteristics (i.e. qualifications levels, start and end dates of employment in a given firm, professions, and occupational status, such as full or part-time employment).

As there is no common firm identifier in the two data sets, we matched firms from the KfW/ZEW Start-up Panel with reporting establishments using a text search algorithm via firm/establishment names and addresses. We were able to match about 90 % of the new ventures from the KfW/ZEW-Start-up Panel that are reported to have employees who are subject to social insurance contributions during the yearly telephone surveys with one or more establishments from the employment statistics. Firms that are reported to have employees subject to social insurance contributions, but which were not found in the employment statistics, were removed from the sample. In addition, to adjust for incorrect matches and for erroneous data in either data set we excluded matches in the 1st and 100th percentiles of the difference between self-reported and process-produced employment sizes from the sample. In order to determine the quality of the match, we calculated the correlation coefficient between self-reported (from the KfW/ZEW-Start-up Panel) and process-produced numbers of employees (from the employment statistics of the Federal Employment Agency) in the final firm-year panel dataset, which is slightly above 0.95. Thus, we are confident that the matching procedure led to reliable results.

Since we use lagged values for the human capital inputs and the R&D intensity in the knowledge production function, we are left with 13,527 firm-year observations for estimation in our final (unbalanced) panel.

5.1 Variables

Our dependent variable is whether or not a young firm introduced a national or worldwide market novelty in a given year. We favor market novelties as a measure of innovation instead of new-to-the-firm innovations, since we consider market novelties to be better comparable across firms and industries in the context of new firms. Since market novelties necessarily entail a significant innovative step, we only consider innovations that have a certain degree of radicalness. Furthermore, we decided to concentrate on the yes/no response to introducing a market novelty instead of using a measure of innovation performance such as the percentage of sales from new products in total sales, because young firms usually only offer a small number of products or services, which implies that measuring the percentage of sales generated by innovative product would be subject to large basis effects for some firms. In addition, the yes/no information for introducing an innovation is available for a larger number of observations in our data. The share of sales from a new product is only available one year after the new product has been introduced; thus, relying on this information would clearly increase the sensitivity of our results to panel attrition biases.

Our main variables of interest on the right-hand side of our estimation equations are whether or not business or technical skills exist in a given firm and whether they are brought to the firm by the founders or by the employees. From the KfW/ZEW Start-up Panel, we know the fields of study for founders with a university degree, the profession for which a founder received vocational training if a vocational training is a founder's highest qualification, as well as the previous profession if a founder has no formal qualification. These types of information are coded using the five-digit occupation code KldB2010 (the German adaption of ISCO-08) devised by the Federal Employment Agency. With regard to the employees, we know their occupations in prior jobs from the employment statistics that are readily available in coded form according to the KldB2010. We decided to use the occupation in the last job before entering a focal young firm in our sample for employees because we consider this to be the most relevant information for a firm's hiring decision.

To construct our measures for business and technical skills, we use aggregates for STEM and business-related occupations provided by the German Federal Employment Agency as guidelines to classify the information about the skill backgrounds of both the founders and the employees.[5] We define that there are technical skills within a firm if either a founder or an employee has a background in engineering or technology. With this, technical skills refer to "E" and "T" in STEM. Business skills within a firm are defined accordingly and cover backgrounds in commercial as well as management fields.

As mentioned above, our set of control variables is divided into two parts, namely those variables that we lag by one year ($X_{i,t-1}$ in equations (5) and (6)) and those that are time-invariant, or contemporary ($Z_{i,t}$). $X_{i,t-1}$ includes the R&D intensity (R&D spending/sales) and the size of the firm measured by the logarithm of the number of employees. We lag these variables by one year to account for potential reverse causality. $Z_{i,t}$ includes the logarithm of the age of the firm, a dummy variable indicating whether a firm conducts R&D continuously, the logarithm of the size of the founding team, a dummy variable indicating whether the firm received support from the KfW bank, and industry and year dummies. The exact definition of the variables is provided in Table 6 in Appendix A.

5.2 Summary statistics

We provide summary statistics for our dependent and our main explanatory variables in Table 7 in Appendix A. A correlation table is shown in Table 8 in Appendix A. Around 9% of the firm/year observations are from firms that launched a national or worldwide market novelty. Of the observations, 39% come from firms equipped with business skills, and 61% from firms equipped with technical skills. Both measures are higher for the actual innovators. Dividing the skill measures for founders and employees reveals that differences in the human capital endowment between innovators and other firms are clearly driven by the skills of the employees. Differences in the skills of founders are less pronounced. This indicates that founders of innovative firms augment their own skills via the skills of their employees. This is the first evidence of the importance of also considering the skills of employees with regard to the innovation performance of young firms. The correlation table shows no high correlation among the variables. A VIF test (variance inflation factor) shows an average VIF of 1.91 and a maximum VIF of 2.88. Thus, the VIF test does not indicate problems at the conventionally applied critical levels (Kutner et al., 2004).[6]

[5] `https://statistik.arbeitsagentur.de/Navigation/Statistik/Grundlagen/Klassifikation-der-Berufe/KldB2010/Arbeitshilfen/Berufsaggregate/Berufsaggregate-Nav.html`, only available in German.

[6] A conventionally used rule of thumb is that VIF values of 10 and above can indicate problems of multicollinearity.

6 Results

6.1 Technical skills and business skills (Hypothesis 1)

In Table 1, we show the frequency at which technical and business skills occur in our data in mutually exclusive combinations, as well as the share of observations with market novelties in each of these groups. The most frequent combination is technical skills without business skills. 42% of the observations belong to firms of this category. The other combinations occur in roughly equal shares of 18-20%.

Table 1: Frequency of skill patterns and innovation outcomes

All firms (N = 13,527)	**Frequency of skill pattern**	**Share with market novelty**
No technical & no business skills in firm $_{t-1}$	19%	7%
Only business skills in firm $_{t-1}$	21%	8%
Only technical skills in firm $_{t-1}$	42%	7%
Technical & business skills in firm $_{t-1}$	18%	15%

The results suggest that having both business and technical skills in a firm is associated with a higher probability of innovating: The skill pattern that is most frequently related to introducing a market novelty is "technical & business skills in firm". The share of observations for which the introduction of a market novelty is recorded is as much as twice as high as that associated with the other skill combinations (15% compared to 7%-8% in other groups). There is also already evidence that business and technical skills are complements for innovation because the difference between "technical & business skills" minus "only technical skills" is larger than is the difference between "only business skills" and "no technical & no business skills".[7]

A multivariate analysis confirms the descriptive patterns. Table 2 shows the marginal effects from multivariate probit models for the case without differentiation between founders and employees (see Table 9 in Appendix A for detailed results). For easier interpretability of the marginal effects, we first retain the specification of the skill indicators as mutually exclusive dummy variables.

When firms have only one of the two skills (business or technical skills) in their human capital base, they are not more likely to innovate than are firms that have none of them (Column A). However, for firms with both skills, the likelihood of introducing a market novelty is 1.5 percentage points higher than it is for firms with neither business nor technical skills. Rearranging the estimation equation according to equation (5) to test for complementarity shows that technical and business skills are complementary.[8] Thus, these results support our Hypothesis 1.

An interesting result appears if we focus on the founding team only, which corresponds to the hitherto usual approach in the entrepreneurship literature (Column B). There is no comple-

[7]The same holds for "technical & business skills" minus "only business skills" and "only technical skills" and "no technical & no business skills", which would be the other concrete variant for equation (2).

[8]We follow the work of Carree et al. (2011) and evaluate complementarities in their framework at significance levels of 10%.

Table 2: Business skills, technical skills, and innovation - Probit models

Dependent variable: National or worldw. market novelty	A Whole workforce Marginal effect (S.E.)		B Only founders Marginal effect (S.E.)	
Only business skills in firm_{t-1} $^{1)}$	0.009	(0.009)		
Only technical skills in firm_{t-1} $^{2)}$	-0.004	(0.008)		
Business and techn. comp. in firm_{t-1}	0.015	(0.009)*		
Only founder w. business skills_{t-1} $^{1)}$			0.013	(0.008)*
Only founder w. technical skills $_{t-1}$ $^{2)}$			-0.002	(0.007)
Founder(s) with business and techn. skills_{t-1}			-0.002	(0.011)
R&D intensity_{t-1} (R&D/sales)	0.044	(0.007)***	0.044	(0.007)***
Continuous R&D	0.135	(0.006)***	0.136	(0.006)***
Firm age (log)	-0.028	(0.005)***	-0.028	(0.005)***
Number of founders (log)	0.008	(0.006)	0.010	(0.006)
Number of dep. employees_{t-1} (log)	0.005	(0.004)	0.008	(0.004)**
Founder with tertiary educ._{t-1}	0.027	(0.006)***	0.027	(0.006)***
Employees with tertiary edu._{t-1} (share)	0.014	(0.010)	0.014	(0.010)
Industry & Year Fixed Effects	Yes		Yes	
Constant	Yes		Yes	
N / (Pseudo) R	13527 / 0.251		13527 / 0.251	
Complementarity test (see equation 5)	1.73*		-0.61	

Notes: $^{1)}$= no technical skills in firms. Other skills might be present. $^{2)}$= no business skills in firm. Other skills might be present. Marginal effects from probit models. Significance levels: *** 1%, ** 5%, * 10%. Cluster robust standard errors in parentheses. Baseline category for human capital patterns: 'no technical & business skills in firm_{t-1}'. Additional control variable in all regressions: funding by KfW bank. A dummy variable adjustment as performed in Bloom et al. (2013) is applied to the logarithmically transformed number of employees when the number of employees is zero.

mentarity detectable between business and technical skills when we ignore the human capital of employees. This underpins the importance of a broader view of the human capital base of young firms, which also includes employees and is indicative of our Hypothesis 2. In addition, it is in line with prior findings by De Winne and Sels (2010), who show that the level of human capital of founders mainly affects innovation outcomes indirectly through the choice of employees.

6.2 Skills of founders and skills of employees (Hypothesis 2 and Hypothesis 3)

In Table 3, we take into account the skills that are brought into the firm by the founders and those that are provided by the employees; in other words, we differentiate between the 16 states s_0 = (0,0,0,0) to s_{15} = (1,1,1,1) of the four binary indicators ("Founder with business skills", "Founder with technical skills", "Employee with business skills", "Employee with technical skills"). The most frequent pattern is State 4, with technical skills in the founding team and no other technical or business skills in the firm.[9] This corresponds to that what we found in Table 1 and shows that the firms in the sample rely on technical skills only to a large extent, and that these technical skills are provided primarily by the founders. This result may be reinforced by the over-stratification of high tech start-ups in the sample which we control for in the

[9]There are still over 100 observations in each of the cases that occur quite rarely. We are therefore confident that the comparably small share of observations does not bias the results of the subsequent multivariate analyses.

multivariate analyses.

Table 3: Frequency of skill patterns and innovation - Business and technical skills of founders and employees

State	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Skill pattern[1)]	0000	0001	0010	0011	0100	0101	0110	0111	1000	1001	1010	1011	1100	1101	1110	1111
Share of all (%)	19	2	3	1	31	10	4	5	13	1	4	1	3	1	1	1
Innovators (%)	7	11	8	25	6	9	12	15	8	8	9	20	13	13	19	17

Notes: 1) Skill pattern = $(BS_{F,i}, TS_{F,i} BS_{E,i}, TS_{E,i})$ where BS_F = Founder with business skills; TS_F = Founder with technical skills; BS_E = Employee with business skills; TS_E = Employee with technical skills).

Consistent with what we saw in Table 1, we find that most skill patterns with both business and technical skills are associated with above-average innovation propensities, while the opposite is true for almost all states in which only one skill type is present. All patterns in which both skill types are present - either within the group of founders (states 12-15) or within the group of employees (patterns 3, 7, 11, and 15) - are associated with above-average innovation outcomes. The same holds true when technical skills are present in the founding team and business skills are present among the employees (patterns 6, 7, 14, and 15). By contrast, when business skills are present in the founding team and technical skills are present among employees, the results are more mixed (patterns 9, 11, 13, and 15). While this combination is associated with above-average innovation propensities for states 11, 13, and 15, innovation propensities are below average when a founder trained in business is combined with an employee with technical skills only (State 9).

Table 4 presents marginal effects from probit models when we differentiate between the human capital inputs of founders and those of employees in the multivariate context by including the 15 state dummies s_1 (0,0,0,1), ..., s_{15} (1,1,1,1) in the model (s_0 (0,0,0,0) serves as a reference category).

The most favorable state for innovation outcomes is state 11, with a founder who has business skills and employees with both business and technical skills, but with no technical skills in the founding team. State 11 is associated with a 5.5 percentage point higher probability of innovation than is state 0, in which no business or technical skills are present (however, as can be seen from Table 3, state 11 is quite rare). Other states that are associated with significantly positive innovation propensities compared to state 0 are state 3 (business and technical skills among the employees but no such skills within the founding team), state 6 (technical skills in the founding team and business skills among the employees), state 7 (with technical skills in the founding team and technical and business skills among the employees), and state 8 (with business skills within the founding team only). In none of the 15 states in which either business or technical skills are present firms do perform significantly worse than does the reference group of firms without any such skills.

A closer look reveals that none of the states in which both business and technical skills are

Table 4: Business and technical skills of founders and employees - Probit models

Dependent variable: **National or worldwide market novelty**	**A** **Founders and Emloyees** **M.E. (S.E.)**	
Skill pattern (BS_F,TS_F,BS_E,TS_E)[1)]		
s_1 $(0,0,0,1)_{t-1}$	0.027	(0.018)
s_2 $(0,0,1,0)_{t-1}$	-0.008	(0.016)
s_3 $(0,0,1,1)_{t-1}$	0.036	(0.020)*
s_4 $(0,1,0,0)_{t-1}$	-0.010	(0.008)
s_5 $(0,1,0,1)_{t-1}$	0.013	(0.012)
s_6 $(0,1,1,0)_{t-1}$	0.029	(0.014)**
s_7 $(0,1,1,1)_{t-1}$	0.027	(0.014)*
s_8 $(1,0,0,0)_{t-1}$	0.017	(0.010)*
s_9 $(1,0,0,1)_{t-1}$	-0.007	(0.022)
s_{10} $(1,0,1,0)_{t-1}$	0.010	(0.015)
s_{11} $(1,0,1,1)_{t-1}$	0.055	(0.018)***
s_{12} $(1,1,0,0)_{t-1}$	0.005	(0.014)
s_{13} $(1,1,0,1)_{t-1}$	-0.003	(0.023)
s_{14} $(1,1,1,0)_{t-1}$	0.017	(0.024)
s_{15} $(1,1,1,1)_{t-1}$	0.002	(0.021)
Control variables	Yes	
Industry & Year Fixed Effects	Yes	
Constant	Yes	
N / (Pseudo) R	13.527 / 0.254	

Notes: 1) BS_F = Founder with business skills; TS_F = Founder with technical skills; BS_E = Employee with business skills; TS_E = Employee with technical skills; marginal effects from probit models; significance levels: *** 1%, ** 5%, * 10%; cluster robust standard errors in parentheses; baseline category for human capital patterns $s_0(0,0,0,0)_{t-1}$; additional control var. in all regressions: funding by KfW bank. A dummy variable adjustment as performed in Bloom et al. (2013) is applied to the logarithmically transformed number of employees when the number of employees is zero.

present in the founding team (states 12-15) yield significant results. The marginal effect for state 13 is even slightly negative. By contrast, all states in which both types of skills are present among the employees (states 3, 7, 11, and 15) are associated with positive marginal effects, of which three are significant. Furthermore, marginal effects for all combinations of founders with technical skills and employees with business skills (states 6, 7, 14, and 15) are positive, with two of the four combinations significantly so. By contrast, the results are more mixed if we look at the opposite combination, namely that of founders with business skills and employees with technical skills (states 9, 11, 13, and 15). While founders with business skills seem to do well when they lead a diverse pool of employees with both business and technical skills, the marginal effects are negative (although insignificant) when founders with business skills have employees who only have technical skills. In summary, based on the marginal effects of the state dummies in the multivariate model, we expect to find a complementary relationship between founders with technical skills and employees with business skills, as well as between employees with business skills and employees with technical skills. By contrast, we neither expect complementarity between founders with business skills and employees with technical skills, nor between founders with business skills and founders with technical skills.

The results of the formal complementarity test to confirm these expectations are shown in Table 5. In this table, the lowest and the highest t-statistic from the four regressors in equation (9) in

Appendix B are shown for each pairwise combination of skills. Complementarity between a pair of skills exists if the highest t-statistic is positive and exceeds the Bonferroni corrected critical value for a chosen significance level, while the lowest t-statistic is either positive or its total value does not exceed this critical value. The Bonferroni corrected critical values for the t-statistic are 2.241 for the 10% significance level, 2.498 for the 5% significance level and 3.023 for the 1% significance level. Following Carree et al. (2011), we evaluate the test for complementarity at a significance level of 10%.

Table 5: Test for complementarity between technical and business skills of founders and employees - Highest and lowest t-statistics

All firms - N = 13,527	Founder_technical	Employee_business	Employee_technical
Founder w. business skills	-0.811 ; 0.460	-0.348 ; 0.966	-1.510 ; 0.121
Founder w. technical skills		-1.475 ; 2.441*	-1.777 ; 0.225
Employee w. business skills			-0.624 ; 2.367*
Employee w. technical skills			

Notes: Significance levels: *** 1%, ** 5%, * 10%. t-statistics are derived from OLS regressions. All control variables are included. Critical values are Bonferroni corrected. Bonferroni corrected critical values for the presented t-statistics are 2.241 for the 10% significance level, 2.498 for the 5% significance level and 3.023 for the 1% significance level.

We find complementarity between founders with technical skills and employees with business skills, as well as within the group of employees. By contrast, we do not find complementarity within the group of founders or between founders with business skills and employees with technical skills.

These results are consistent with Hypotheses 2 and 3a. Confirming Hypothesis 2, while we find complementarities between founders and employees, we do not find complementarities within the group of founders. This is consistent with the view that complementarities are important to bind employees to the organization, but are not relevant to the same extent within the group of founders because founders are connected to the organization through ownership. In addition, it seems reasonable to suggest that, within the group of founders, the costs of diversity outweigh the benefits of diversity in a significant number of cases because founders have to agree on a joint strategy, which is likely to be more difficult if the founders have different backgrounds.

Whether a founder succeeds in building complementarities between him- or herself and his or her employees depends on the founder's skill set. In support of Hypothesis 3a (and rejecting the competing Hypothesis 3b), while technically skilled founders seem to benefit from business skills provided by employees, founders with business skills do not benefit equivalently from technical skills provided by employees. A consistent explanation for this asymmetry is that technical knowledge and business knowledge differ with respect to their transferability between persons and that this affects founders' ability to build complementarities between themselves and their employees. While some basic understanding of processes in business administration is likely to be achieved by technical founders during their prior career and facilitates them to select and monitor business personnel adequately, it might be considerably more difficult for an entrepreneur who lacks technical skills to understand technical tasks well enough to adequately manage technical personnel.

6.3 Robustness checks

We run a series of robustness checks to examine the validity of our results. For these checks we concentrate on the general case in which we distinguish between the skills of the founders and the skills of employees, and present the results of the respective complementarity tests in Table 10 in Appendix A. Overall, the complementary relationship between founders with technical skills and employees with business skills forms a highly robust pattern, while the complementarity within the group of employees is somewhat less robust.

For our first robustness check, we restrict our sample to firms that follow an innovation strategy. The rationale behind this check is that some firms might decide not to be innovative since they expect higher pay-offs from a pure imitation strategy. If such behavior is correlated with the skills of the founders (for example, if founders with a business administration background are more likely to follow a pure imitation strategy than are founders with a technical background) and with the firms' hiring choices, this would affect the validity of the conclusions drawn from our results. We define ventures as following an innovation strategy when they have conducted research and development or have launched a market novelty within the last two years (in periods t or $t-1$). Limiting our sample to firms that follow an innovation strategy does not alter our results qualitatively.

Second, we performed the complementarity test using estimates from probit models instead of those from OLS regressions. Again, there is no qualitative change in our results.

Third, since a combination of technical and business skills for innovation might not necessarily be important for firms in sectors such as trade or low-tech services sectors (for example, restaurants or cleaning services), we excluded these sectors from the estimation sample. Despite a significant reduction in sample size, the results do not change qualitatively.

Fourth, we also experimented with the lag length of human capital inputs in the knowledge production function in order to gain some insights into whether the results depend on longer or shorter lags. Using contemporaneous inputs instead of one-year lagged inputs allows us to include market novelties that are introduced in the founding year in the analysis. In this case, the complementarity between founders with technical skills and employees with business skills remains, while the complementarity within the group of employees is no longer measurable. A potential reason for this result is that it takes longer before complementarities among employees lead to measurable innovation outcomes. As employees are usually hired to perform a specific task in relation to the founders it is reasonable to expect that it takes comparatively more time before fruitful interaction within the group of employees leads to measurable results at the firm level. When we use second and third lags, sample sizes, as well as the precision of the estimates, decrease and the effects gradually become insignificant. However, they do not contradict the main results in any event.

Fifth, as explained earlier, we categorize occupations and fields of education into business and technical skills based on classifications provided by the German Federal Employment Agency. These classifications are based on the German adaption of the STEM fields, the so-called “MINT” fields (Mathematics, Informatics, Natural sciences, and Technics). Comparing MINT and STEM classifications, it remains unclear whether information scientists belong to the mathematicians, or to the technicians and engineers, or build a separate group. Hence, we decided to follow a narrow classification and did not group information scientists into technical occupations for our main analyses. In order to check whether this decision affects our results we run a robustness check with information science included in the group of technical skills. In this case, the combination of founders with technical skills and employees with business skills remains complementary while the complementarity between employees becomes insignificant.

Our last robustness check addresses issues concerning the measurement of the skills of founders and employees. As mentioned above, due to the information in our data, we obtain our measures for the business and technical skills of founders from their field of education, while we use information on the occupations in prior jobs for the employees. In general, we do not regard this to be a big issue because in Germany people usually start to work in the field in which they are trained (Fitzenberger and Kunze, 2005) and job mobility is comparatively low, as is mobility between different occupations (Allmendinger, 1989; Rhein et al., 2013). If transitions between occupations still occur it seems reasonable to expect that a move from a technical to a business occupation is the more likely event than a move the other way round. This leads to that we potentially under-record the business skills of a part of the founders because our measure for business skills does not include management experience which founders obtained during their career. It could however be possible that generalists - those, who obtained an education in a technical field and gained management experience during their previous working life - are responsible for the asymmetric complementary relationship between founders with technical skills and employees with business skills. In order to check whether our results are affected via this channel we use information on founders leadership experience from the KfW/ZEW Start-up Panel and change the dummy for business skills to “1” - if it was not already “1” because of the information from the educational background - if the founders previously worked as a director or an executive employee in a private company or in public service. Including this information again does not change our results qualitatively.

7 Conclusion

A common view among practitioners, policy makers and academics is that young firms need both technical skills and management skills to introduce an innovation to the market. Formulated in economic language, it is assumed that technical and business skills are complementary in the innovation process of young firms; in other words, that the returns from technical skills, which are relevant for the business idea, are higher if they are accompanied by business skills.

In this paper, we analyze the extent to which complementarities between technical and business skills exist with regard to the probability that young firms launch a national or worldwide market novelty. Unlike previous papers that analyze the effect of the human capital of the founders on the performance of young businesses, we consider the complete human capital base, including employees. The rationale for this approach is that employees also contribute to the firms' pool of knowledge, which is commonly regarded as an important source of ideas for new products and services and competencies for their implementation. In addition, distinguishing between founders and employees allows us to identify between which groups in a young firm complementarities in the two considered types of skills exist and which combinations are particularly fruitful for the innovation performance.

Our results are consistent with the existence of complementarities between technical and business skills. A more detailed look reveals that this overall effect is due to complementarities between founders and employees, as well as within the group of employees. Within the team of founders, we cannot detect any complementarity between technical and business skills. This shows that it is important to include employees in the analysis of the effects of the human capital of young firms with regard to their innovation outcomes.

A further result of our analysis is that the complementarity between founders and employees is asymmetrical. While we find complementarity between technically trained founders and employees with business skills, we do not find complementarity for the opposite combination of founders with business skills and technically trained employees. This asymmetry points to challenges in monitoring employees in the event that a firm's pool of knowledge has to be augmented by technical skills. This has interesting implications for the hiring strategies of entrepreneurial firms: While founders with technical education can benefit more from their skills when they employ a specialist with business skills, founders without a technical education cannot expect these additional benefits if they hire technically trained employees. Therefore, it is crucial to consider who provides which skills to the human capital base of young firms in order to reap the benefits of diversity.

As is the case in other studies, our study is not without limitations. First, an instrumentation of the skill measures is not feasible in the complex setting of the complementarity analysis in this study. Hence, we cannot fully differentiate between causal effects of skills on innovation and a mere description of personnel strategies of successful innovators. We use lagged skill measures to reduce the risk of such reverse causality. However, this does not entirely exclude the possibility of anticipatory strategic personnel planning strategies by successful innovators. Second, the asymmetric effect in the complementarity between founders and employees might be driven by a negative selection in terms of the quality of the technical personnel employed in new ventures. If the founders of new ventures have difficulty finding good technicians, they might have problems establishing complementarities between themselves and their technical employees. While it is beyond the scope of this study to control for this effect, we think that it is unlikely that it influences our results substantially because we find positive effects of technically trained personnel on innovation in several skill combinations.

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Appendix A

Table 6: Derivation of measures - Details

Variable	**Construction**
National or worldwide market novelty	Dummy variable - Takes a value of one for a firm-year observation if a firm intoduces a product innovation that is a national or worldwide market novetly in a year
Technical skills	Dummy variable - Previous occupation or eductional background grouped using ISCO-08 (KldB 2010) codes according to classifications of the German Federal Employment Agency (see main text for details)
Business skills	Dummy variable - Previous occupation or background grouped using ISCO-08 (KldB 2010) codes according to classifications of the German Federal Employment Agency (see main text for details)
R&D intensity	R&D expenses/total sales - largest percentile is windsorized and missing values are imputed by one period lagged values if possible
Continuous R&D	Dummy variable - Takes a value of one if a firm conducts either internal or external R&D for at least half of the firm-year observation it is observed
Number of founders	Number of founders in the founding team
Number of dep. Employees	Number of full-time or part-time employees subject to social insurance contributions
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

Table 7: Detailed summary statistics

Variable	Unit	All firms (N = 13.527) Mean	S.D.	Min	Max	Innovators (N = 1.184) Mean	S.D.	Min	Max
National or worldw. market novelty	(y/n)	0.09	0.28	0.00	1.00	1.00	0.00	1.00	1.00
Business competence in firm$_{t-1}$	(y/n)	0.39	0.49	0.00	1.00	0.51	0.50	0.00	1.00
Technical competence in firm$_{t-1}$	(y/n)	0.61	0.49	0.00	1.00	0.66	0.48	0.00	1.00
Business # techn. comp. in firm$_{t-1}$	(y/n)	0.18	0.39	0.00	1.00	0.31	0.46	0.00	1.00
Founder w. business profession$_{t-1}$	(y/n)	0.25	0.44	0.00	1.00	0.30	0.46	0.00	1.00
Founder w. technical profession$_{t-1}$	(y/n)	0.55	0.50	0.00	1.00	0.56	0.50	0.00	1.00
Employee w. business profession$_{t-1}$	(y/n)	0.21	0.41	0.00	1.00	0.32	0.47	0.00	1.00
Employee w. technical profession$_{t-1}$	(y/n)	0.23	0.42	0.00	1.00	0.32	0.47	0.00	1.00
R&D intensity$_{t-1}$ (R&D/sales)	Share	0.06	0.23	0.00	1.75	0.26	0.46	0.00	1.75
Continuous R&D	(y/n)	0.22	0.41	0.00	1.00	0.74	0.44	0.00	1.00
Firm follows an innovation strategy	(y/n)	0.49	0.50	0.00	1.00	1.00	0.00	1.00	1.00
Firm age	Years	3.66	1.58	1.08	8.00	3.45	1.52	1.08	8.00
Number of founders	Count	1.42	0.81	1.00	15.00	1.77	1.03	1.00	9.00
Number of dependent employees	Count	1.86	3.64	0.00	75.00	2.81	4.20	0.00	32.00
Founder with tertiary educ.$_{t-1}$	(y/n)	0.42	0.49	0.00	1.00	0.68	0.47	0.00	1.00
Employees with tertiary edu.$_{t-1}$	Share	0.08	0.22	0.00	1.00	0.17	0.29	0.00	1.00
High-technology manufacturing	(y/n)	0.11	0.31	0.00	1.00	0.27	0.44	0.00	1.00
Technology-intensive services	(y/n)	0.23	0.42	0.00	1.00	0.20	0.40	0.00	1.00
Software supply and consultancy	(y/n)	0.07	0.26	0.00	1.00	0.15	0.36	0.00	1.00
Non-high-tech manufacturing	(y/n)	0.12	0.33	0.00	1.00	0.11	0.32	0.00	1.00
Skill-intensive services	(y/n)	0.07	0.26	0.00	1.00	0.08	0.27	0.00	1.00
Other business-oriented services	(y/n)	0.05	0.21	0.00	1.00	0.02	0.14	0.00	1.00
Consumer-oriented services	(y/n)	0.11	0.31	0.00	1.00	0.05	0.21	0.00	1.00
Construction	(y/n)	0.12	0.32	0.00	1.00	0.02	0.15	0.00	1.00
Retail & wholesale	(y/n)	0.13	0.34	0.00	1.00	0.09	0.29	0.00	1.00
Year 2008	(y/n)	0.15	0.35	0.00	1.00	0.14	0.35	0.00	1.00
Year 2009	(y/n)	0.19	0.40	0.00	1.00	0.20	0.40	0.00	1.00
Year 2010	(y/n)	0.20	0.40	0.00	1.00	0.22	0.41	0.00	1.00
Year 2011	(y/n)	0.23	0.42	0.00	1.00	0.21	0.40	0.00	1.00
Year 2012	(y/n)	0.23	0.42	0.00	1.00	0.24	0.43	0.00	1.00

Additional control variable: funding by KfW bank. The number of founders, the number of dependent employees, and the firms' age are presented in counts/years in the summary statistics table but enter the regressions as logarithmic transformations.

Table 8: Correlation table

	Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**	**(15)**
(1)	National or worldw. market novelty	1														
(2)	Technical competence in firm_{t-1}	0.0320*	1													
(3)	Business competence in firm_{t-1}	0.0746*	-0.2178*	1												
(4)	Business # techn. comp. in firm_{t-1}	0.1046*	0.3824*	0.5947*	1											
(5)	Founder w. business profession_{t-1}	0.0305*	-0.3440*	0.7313*	0.2017*	1										
(6)	Founder w. technical profession_{t-1}	0.0035	0.8953*	-0.2866*	0.2271*	-0.3944*	1									
(7)	Employee w. business profession_{t-1}	0.0858*	0.0407*	0.6493*	0.6160*	0.1282*	-0.0365*	1								
(8)	Employee w. technical profession_{t-1}	0.0711*	0.4347*	0.1029*	0.4150*	-0.0777*	0.2261*	0.2415*	1							
(9)	R&D intensity_{t-1} (R&D/sales)	0.2752*	0.0173*	0.0429*	0.0741*	0.0166	0.0021	0.0467*	0.0287*	1						
(10)	Continuous R&D	0.3985*	0.0572*	0.0664*	0.1308*	-0.0042	0.0263*	0.1103*	0.0686*	0.4297*	1					
(11)	Firm age (log)	-0.0407*	0.0431*	0.0282*	0.0501*	-0.0357*	0.0290*	0.0865*	0.0855*	-0.0258*	-0.0059	1				
(12)	Number of dep. employees_{t-1} (log)	0.0847*	0.1891*	0.3663*	0.4817*	0.0288*	0.0454*	0.6148*	0.6261*	0.0368*	0.1125*	0.1140*	1			
(13)	Number of dep. $\text{employees}_{t-1} = 0$	-0.0610*	-0.1706*	-0.3177*	-0.3945*	-0.0183*	-0.0497*	-0.5634*	-0.5866*	-0.0158	-0.0658*	-0.1121*	-0.7745*	1		
(14)	Number of founders (log)	0.1400*	0.0817*	0.2157*	0.2409*	0.1922*	0.0587*	0.1667*	0.1246*	0.1492*	0.2294*	-0.0087	0.1900*	-0.1575*	1	
(15)	Founder with tertiary educ._{t-1}	0.1661*	0.0071	0.1316*	0.1067*	0.1012*	-0.0194*	0.1198*	0.0218*	0.1844*	0.2723*	0.0027	0.0871*	-0.0663*	0.3297*	1
(16)	Employees w. tertiary $\text{educ.}_{t-1}(sh)$	0.1264*	0.0421*	0.1214*	0.1485*	0.0046	-0.0106	0.2136*	0.1571*	0.1679*	0.2045*	0.0513*	0.2378*	-0.2943*	0.1914*	0.2583*

Notes: * significant at 5 % level. Additional control variables in all regressions: year fixed effects, industry fixed effects, funding by the KfW bank.

Table 9: Business skills, technical skills, and innovation - Detailed probit models

Dependent variable: National or worldw. market novelty	A Whole workforce Marginal effect (S.E.)	B Only founders Marginal effect (S.E.)
Only business skills in firm$_{t-1}$	0.009 (0.009)	
Only technical skills in firm$_{t-1}$	-0.004 (0.008)	
Business and techn. comp. in firm$_{t-1}$	0.015 (0.009)*	
Only founder w. business skills$_{t-1}$		0.013 (0.008)*
Only founder w. technical skills$_{t-1}$		-0.002 (0.007)
Founder(s) with business and techn. skills $_{t-1}$		-0.002 (0.011)
R&D intensity$_{t-1}$ (R&D/sales)	0.044 (0.007)***	0.044 (0.007)***
Continuous R&D	0.135 (0.006)***	0.136 (0.006)***
Firm age (log)	-0.028 (0.005)***	-0.028 (0.005)***
Number of founders (log)	0.008 (0.006)	0.010 (0.006)
Number of dep. employees$_{t-1}$ (log)	0.005 (0.004)	0.008 (0.004)**
Founder with tertiary educ.$_{t-1}$	0.027 (0.006)***	0.027 (0.006)***
Employees with tertiary edu.$_{t-1}$ (share)	0.014 (0.010)	0.014 (0.010)
Technology-intensive services	-0.056 (0.009)***	-0.057 (0.009)***
Software supply and consultancy	-0.028 (0.010)***	-0.029 (0.010)***
Non-high-tech manufacturing	-0.031 (0.010)***	-0.032 (0.009)***
Skill-intensive services	-0.030 (0.011)***	-0.032 (0.011)***
Other business-oriented services	-0.062 (0.016)***	-0.064 (0.016)***
Consumer-oriented services	-0.044 (0.012)***	-0.046 (0.012)***
Construction	-0.072 (0.014)***	-0.074 (0.014)***
Retail & wholesale	-0.014 (0.010)	-0.015 (0.010)
Year 2009	0.010 (0.007)	0.011 (0.007)
Year 2010	0.013 (0.007)*	0.013 (0.007)*
Year 2011	-0.004 (0.007)	-0.004 (0.007)
Year 2012	0.004 (0.008)	0.004 (0.008)
Constant	Yes	Yes
N / (Pseudo) R	13527 / 0.251	13527 / 0.251
Complementarity test (see equation 5)	1.73*	-0.61

[1)] = no technical skills in firms. Other skills might be present. 2) = no business skills in firm. Other skills might be present. Marginal effects from probit models; significance levels: *** 1%, ** 5%, * 10%; cluster robust standard errors in parentheses; baseline category for human capital patterns: "no technical & business competence in firm$_{t-1}$". Additional control variable in all regressions: funding by KfW bank.

Table 10: Robustness checks: Test for complementarity between technical and business skills of founders and employees - Highest and lowest t-statistic

Firms with innovation strategy N = 6,653	Founder_technical	Employee_business	Employee_technical
Founder w. business skills $_{t-1}$	-1.019 ; 0.033	-0.162 ; 1.080	-1.396 ; -0.035
Founder w. technical skills $_{t-1}$		-1.222 ; 2.292*	-1.710 ; 0.207
Employee w. business skills $_{t-1}$			-0.903 ; 2.266*
Employee w. technical skills $_{t-1}$			

All firms Probit estimates N = 13,527	Founder_technical	Employee_business	Employee_technical
Founder w. business skills $_{t-1}$	-1.455; 0.480	-0.966 ; 1.609	-1.833 ; 0.017
Founder w. technical skills $_{t-1}$		-1.628 ; 2.460*	-1.998 ; 0.478
Employee w. business skills $_{t-1}$			-1.381 ; 2.495*
Employee w. technical skills $_{t-1}$			

Without low tech services N = 8,085	Founder_technical	Employee_business	Employee_technical
Founder w. business skills $_{t-1}$	-0.991 ; 0.727	-0.518 ; 1.204	-1.543 ; -0.236
Founder w. technical skills $_{t-1}$		-1.750 ; 2.271*	-2.050 ; 0.390
Employee w. business skills $_{t-1}$			-0.539 ; 2.137
Employee w. technical skills $_{t-1}$			

No lags (simultaneous inputs) N = 22,675	Founder_technical	Employee_business	Employee_technical
Founder w. business skills $_{t}$	-0.298 ; 0.982	-0.596 ; 0.787	-1.544 ; -0.217
Founder w. technical skills $_{t}$		-0.61 ; 2.289*	-1.605 ; 0.274
Employee w. business skills $_{t}$			-0.152 ; 1.547
Employee w. technical skills $_{t}$			

Second lags N = 8,158	Founder_technical	Employee_business	Employee_technical
Founder w. business skills $_{t-2}$	-1.789 ; 0.012	-0.396 ; 1.562	-1.324 ; 0.611
Founder w. technical skills $_{t-2}$		-1.717 ; 0.767	-1.816 ; -0.511
Employee w. business skills $_{t-2}$			0.560 ; 2.757**
Employee w. technical skills $_{t-2}$			

Third lags N = 4,432	Founder_technical	Employee_business	Employee_technical
Founder w. business skills $_{t-3}$	-2.100 ; 0.495	-0.362 ; 2.117	-1.092 ; 1.699
Founder w. technical skills $_{t-3}$		-0.955 ; 2.051	-1.853 ; 0.651
Employee w. business skills $_{t-3}$			-0.643 ; 1.927
Employee w. technical skills $_{t-3}$			

Technical skill incl. informatics N = 13,527	Founder_technical	Employee_business	Employee_technical
Founder w. business skills $_{t-1}$	-0.808 ; 0.705	-0.776 ; 0.789	-1.019 ; 0.223
Founder w. technical skills $_{t-1}$		-0.69 ; 2.389*	-1.724 ; -0.109
Employee w. business skills $_{t-1}$			-0.463 ; 1.679
Employee w. technical skills $_{t-1}$			

Executive experience of founder N = 13,527	Founder_technical	Employee_business	Employee_technical
Founder w. executive exper. $_{t-1}$	-1.174 ; 0.855	-0.867 ; 1.263	-1.360 ; 0.901
Founder w. technical skills $_{t-1}$		-1.639 ; 2.507**	-2.625 ; 0.982
Employee w. business skills $_{t-1}$			-0.918 ; 2.862**
Employee w. technical skills $_{t-1}$			

Notes: Significance levels: *** 1%, ** 5%, * 10%. t-statistics are derived from OLS regressions. All control variables are included. Critical values are Bonferroni-corrected. Bonferroni corrected critical values for the presented t-statistic are 2.241 for a 10% significance level, 2.498 for a 5% significance level and 3.023 for a 1% significance level.

Appendix B

Analogous to equation (2), but when four potentially complementary factors are tested for complementarity, the four constraints for complementarity between human capital components 1 and 2 are

$$\begin{aligned} I(1,1,0,0;X_i) &\geq I(1,0,0,0;X_i) + I(0,1,0,0;X_i) - I(0,0,0,0;X_i), \\ I(1,1,0,1;X_i) &\geq I(1,0,0,1;X_i) + I(0,1,0,1;X_i) - I(0,0,0,1;X_i), \\ I(1,1,1,0;X_i) &\geq I(1,0,1,0;X_i) + I(0,1,1,0;X_i) - I(0,0,1,0;X_i), \\ I(1,1,1,1;X_i) &\geq I(1,0,1,1;X_i) + I(0,1,1,1;X_i) - I(0,0,1,1;X_i), \end{aligned} \tag{7}$$

where at least one of the inequalities must hold strictly. Equivalent sets of constraints are related to the complementarity between human capital components 1 and 3, 1 and 4, 2 and 3, and 2 and 4, as well as between 3 and 4.

As four inequality constraints have to be fulfilled for supermodularity to hold between a pair of skills and as there are six different pairwise combinations of binary skill measures, the total number of constraints that have to be tested increases to 24. A useful result in this context is that it is sufficient to test pairwise combinations for the human capital components in order to determine whether equation (1) is supermodular in a pair of skills (Topkis, 1978).

In accordance with the increasing number of constraints, the coefficients to be estimated increase when the founder/employee dimension is considered. In total, we have $2^4 = 16$ possible combinations for the considered human capital input of founders and employees, for which we define the binary state variables $s_0 - s_{15}$ binary state variables for the regression. We define these variables according to the convention of binary algebra and relate the first two digits to the human capital input of the entrepreneurs and the last two digits to the human capital input of the employees. This means that s_0 corresponds to state (0,0,0,0), s_1 to state (0,0,0,1), ..., s_{15} to (1,1,1,1), and that (0,0,0,1) indicates that there is no entrepreneur with business skills, no entrepreneur with technical skills, and no employee with business skills but at least one employee with technical skills. Since we include a constant term, state s_0 (0,0,0,0) serves as reference category in the estimations.

We again follow Carree et al. (2011) to redefine the state variables s_0 to s_{15} for this situation, such that the test of complementarity can be applied directly to regression coefficients using t-tests on combined hypotheses. Given this notation, the equivalent to Equation (5) with four human capital inputs becomes

$$
\begin{aligned}
I = \alpha_0 + & \alpha_1(.,.,.,1) + \alpha_2(.,1,.,.)_{+}\alpha_3(.,.,1,.) + \alpha_4(.,.,.,1) + \alpha_{12}[(1,1,.,.) \\
& + (1,1,1,1 - (1,1,1,.) - (1,1,.,1 + \alpha_{13}(1,.,1,.) + \alpha_{14}(1,.,.,1) \\
& + \alpha_{23}(.,1,1,.) + \alpha_{24}(.,1,.,1) + \alpha_{34}(.,.,1,1) + (\alpha_{12} \\
& + \alpha_{123})[(1,1,1,.) - (1,1,1,1)] + (\alpha_{12} + \alpha_{124})[(1,1,.,1) \\
& - (1,1,1,1)] + \alpha_{134}(1,.,1,1) + \alpha_{234}(.,1,1,1) + (\alpha_{12} + \alpha_{123} \\
& + \alpha_{124} + \alpha_{1234})(1,1,1,1) + \rho X_{i,t-1} + \eta Z_{i,t} + \epsilon_{it}
\end{aligned} \tag{8}
$$

Where, again, all skill measures enter the regression as one-period lagged values (but indices are dropped for improved readability) and "." indicates that a skill component can take a value of either zero or one. Complementarity between human capital components 1 and 2 exists if $\alpha_{12} \geq 0$ and $\alpha_{12} + \alpha_{123} \geq 0$ and $\alpha_{12} + \alpha_{124} \geq 0$ and $\alpha_{12} + \alpha_{123} + \alpha_{124} + \alpha_{1234} \geq 0$ and at least one of the inequalities holds strictly. For details, see Carree et al. (2011). The test is implemented by estimating Equation (8) and considering the significance of the estimated coefficients of the four regressors:

$$
\begin{aligned}
& 1.\ (1,1,.,.) + (1,1,1,1 - (1,1,1,.) - (1,1,.,1, \\
& 2.\ (1,1,1,.) - (1,1,1,1), \\
& 3.\ (1,1,.,1) - (1,1,1,1), and \\
& 4.\ (1,1,1,1).
\end{aligned} \tag{9}
$$

For complementarity to exist at least one of the coefficients of the four regressors needs to be positively significant and none of the coefficients of the four regressors may be negatively significant. We perform this procedure analogously for all possible pairwise combinations of human capital measures. To avoid multiplicity of type I errors, the significance levels for the separate hypotheses in the case of four human capital components are corrected using the Bonferroni procedure. For the case of four separate hypotheses, this procedure suggests critical values for the t-statistic of 2.241 for a 10% significance level, 2.498 for a 5% significance level, and 3.023 for a 1% significance level.