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Abstract

This paper examines how university research alliances and other cooperative links with universities contribute to startup employment growth. We argue that "scientific absorptive capacity" at the startup is critical for reaping the benefits from university research alliances, but not necessarily for other university connections. We also estimate the aggregate employment contribution from startup firms and attribute those employment gains to university research alliances and other university connections. We find significant contributions to employment growth from university research alliances and other university connections, but scientific absorptive capacity is critical for university research alliances. Only 7% of the startup population maintained a university research alliance, but among these firms, 3.4% of their total jobs created were attributable to their alliances. These results suggest university connections are quite important for job growth and university research alliances contributed substantially to job creation for those firms that had such alliances.

Keywords: Academic Entrepreneurship, Startups, Firm performance, Technology Transfer, University Spinoff Policy, Human Capital

JEL-Classification: L25, L26, J24

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1 Introduction

An emerging body of research focuses on the role of startup companies in job creation. One finding from this work identifies startups as a major source of new jobs. For instance, Haltiwanger (2012) found that new firms accounted for 18 percent of gross job creation in the U.S. between 1980 and 2009. Neumark, Zhang, and Wall concluded that "new firms contribute more to job creation than do new branches of existing firms, with the former contribution sometimes as much as twice as large." (2006, 90). A second finding from this work identifies startups as more volatile than mature firms. Haltiwanger, Jarmin, and Miranda (2013) call this an "up-or-out" dynamic. Young firms that survive often grow rapidly, but many startups exit and this leads to higher rates of job destruction. The new insight from this work is the "up" dynamic. It moves the literature beyond the question of survival toward a focus on how startups create jobs post-entry.

In this paper, we examine how research alliances and other cooperative links with universities contribute to startup employment growth.[3] It is well known from prior work that new and young companies face serious challenges when trying to access the resources needed to build strong capabilities for growth, especially in knowledge-intensive industries (Baum, Calabrese, and Silverman 2000). Relationships with established and reputable organizations such as research universities can provide market credibility or access to valuable intangible and tangible assets such as knowledge, skilled personnel, and specialized equipment (Teece 1986; Stuart 2000). Although a growing literature exists on small and medium-sized enterprises, we did not find any studies that examined how university research alliances or other university linkages contribute to employment growth for startup companies outside of the biotechnology sector (Link and Wessner 2012).

Our research makes three main contributions. First, it not only examines the direct effects of university research alliances and other linkages on startup performance, but goes further to argue that the scientific absorptive capacity of the startup is critical for harnessing the benefits from university research alliances. Second, the up-or-out dynamic suggests only the most

[3] Throughout the paper we will use "university" as shorthand for all public research organizations (PROs) in the not-for-profit sector.

robust firms survive. To account for potential upward bias from survivorship, we use a Heckman selection model with data for the selection equation drawn from a separate comprehensive source that documents the annual population of startup companies. Third, the employment analysis is based on a representative sample of all startups in knowledge-intensive industries in Germany. The survey design allows us to estimate the aggregate employment contribution from startup firms and attribute any employment gains to university research alliances and other university connections.

The rest of the paper is organized as follows. In Section 2 we briefly summarize prior work and state our hypotheses. Section 3 describes the empirical model and the data. Section 4 presents the empirical results, and section 5 concludes with some reflections on the main findings and policy implications.

2 Literature and Hypotheses

Exploring the sources of job creation in the US and Europe, an emerging literature emphasizes the central role of firm age as opposed to firm size (Haltiwanger, Jarmin, Miranda 2013; Anyadike-Danes et al. 2013; Czarnitzki and Delanote 2012; Neumark, Zhang, and Wall 2006). Conditional on survival, a main finding is that startup companies contribute a disproportionate share to total job creation. When startups survive for some defined period of time, they can also be called "young firms." As described in section 3, all of the startups analyzed in this paper are young firms that had survived one to six years at the time of analysis. For Haltiwanger, Jarmin, and Miranda (2013) young firms are particularly important. They found that companies between one and five years old made the largest contributions to employment growth. In a follow-on study, Hathaway (2013) offered further insights into the sector composition of these findings. He found that young firms in high technology sectors were responsible for creating most of the job growth in the U.S. Industries with large shares of technology-oriented workers, which closely match the knowledge-intensive sectors we analyze below for Germany, created jobs at twice the average rate compared to the overall private sector. These studies suggest that surviving startups (i.e. young firms) in knowledge-intensive industries are an important source of economy-wide employment growth.

But how do young firms in knowledge-intensive industries create jobs? The conventional framework models growth as a function of the characteristics of the founding team, resource endowments of the new venture at the time of entering the market, and aspects of its external environment (see Storey 1994). In a recent review of the literature, McKelvie and Wiklund (2010) found that relatively few studies went beyond this framework to address how firms grow. They argued that research should incorporate the modes of growth: organic (i.e. through internal resources), acquisition, and hybrid. The hybrid mode involves "contractual relationships that bind external actors to the firm at the same time as the firm maintains a certain amount of ownership and control over how any assets are used" (McKelvie and Wiklund 2010, 274).[4] Our analysis follows their recommendation and focuses on employment growth due to a particular form of hybrid growth, that is, university research alliances. These alliances are contractual relationships between young enterprises and universities formed in the first years after market entry.[5] They involved pooled and coordinated research and development (R&D) activities using joint R&D projects.

University research alliances are likely to be valuable to young firms in knowledge-intensive industries and may help explain how these companies achieve superior employment growth. Unlike traditional industries, knowledge-intensive industries such as biopharmaceuticals and telecommunications are highly competitive, technologically dynamic, and driven by innovation. Teece (1986; 1992) argued convincingly that highly competitive environments that are driven by innovation are well suited for various forms of cooperation. His framework suggests young firms in technologically dynamic environments are likely to form relationships with the owners of complementary assets as long as transaction costs and the risk of appropriation are sufficiently low. Using a sample of relatively young technology-based firms in Italy, Columbo, Grilli, Piva (2006) found support for the idea that complementary assets are a motivation for alliance formation. Okamuro, Kato, Honjo (2011) argued that the background of the founding team determines the type of partner. Using a

[4] Hybrid growth is a broad category that encompasses a variety of inter-organizational arrangements including inter-firm strategic alliances, franchising, technology licensing, and so forth. See Hagedoorn, Link, and Vonortas (2000) for a summary of prior literature as well as the various theoretical perspectives on research partnership motivations.

[5] In the literature, joint R&D projects are sometimes referred to as partnerships, collaborations, or cooperation agreements. As long as these alternatives meet the definition of the hybrid mode given in the text, they are conceptually equivalent.

sample of Japanese startups, their results show a positive association between the presence of an academic founder and having a university research alliance.[6]

To stimulate employment growth, university research alliances need to increase the workforce at the startup. This can happen by boosting labor demand through greater innovation and sales or by freeing up resources by increasing labor productivity or lowering search and hiring costs. In the framework of Teece (1992), these effects would flow from access to complementary assets through interactive research alliances. For instance, engagement in the research process with a university offers exposure to new knowledge that can facilitate the development of new products and services. Joint R&D projects may allow access to specialized equipment that would otherwise be cost prohibitive. These projects also bring the company founders and research personnel into direct working relationships with the skilled university personnel and graduate students.

For startups or young firms, the empirical literature offers few results on these potential impacts, but some findings exist in the literature on biotechnology firms.[7] For a sample of startups, Baum, Calabrese, and Silverman (2000) found that university alliances were associated with increased revenue and patenting while alliances with research institutes increased employees and R&D expenses. Haeussler, Patzelt, and Zahra (2012) found that the number of university research alliances is positively related to new product development using a sample of relatively young firms from the United Kingdom and Germany. Zucker, Darby, and Armstrong (2002) used co-authorship on publications between academic and industry scientists to proxy for collaboration through joint R&D projects. Their results showed that various measures of success such as patents, products on the market, and products in development significantly increased with the degree of collaboration with university scientists. They also found that the level of employment at the firms increased with the number of collaborations. Based on this literature we postulate:

[6] A much broader literature exists on the motivations for forming university research alliances and other university links; however, young firms are rarely discussed (see, for instance, Fontana, Geuna, and Matt 2006; Belderbos, Carree, and Lokshin 2004; Veugelers and Cassiman 2005).

[7] There are many more studies in the literature that generally find positive effects of university research alliances on innovation, sales, and labor productivity if one does not restrict attention to startups or young firms. For this literature, refer to the following papers and the references therein: Falk (2013), Robin and Schubert (2013), Aschhoff and Schmidt (2008), and Arvanitis, Sydow, and Woerter (2008).

H1: Startups grow faster in terms of employment when they engage in university research alliances, ceteris paribus.

Beyond cooperative research alliances, startups and young firms can establish a wide range of other types of connections to universities such as performing contract research for the university, contracting research out to the university, sending employees for training, or maintaining informal contacts such as attending seminars (Meyer-Krahmer and Schmoch 1998; Schartinger, Rammer, and Fischer 2002).[8] These other types of connections may also allow young firms to increase innovation, sales, labor productivity, or lower search and hiring costs. In this sense, research alliances and other university connections could be substitutes. In Teece's (1986) framework, hybrid modes such as research alliances will be preferred when R&D projects require transaction-specific investments by each party. Detailed project-level data would be required to examine these alternatives in any detail. Cassiman, Di Guardo, and Valentini (2010) analyzed project-level data from a large microelectronics firm and concluded that alliances will be used for more basic research projects while contracting is preferred for strategically important projects where only specific components are contracted out to the university (also see Hall, Link and Scott 2003). With this background, we postulate:

H2: Startups grow faster in terms of employment when they engage in other types of university connections (such as contract research, contracting-out to the university, personnel exchange and other more informal means of information exchange) in addition to collaborative research alliances, ceteris paribus.

Employment growth at startups may also depend on interactions between elements of the conventional growth framework such as the characteristics of the founding team and the mode of growth. In particular, the human capital of the founders may moderate the employment impacts from university research alliances. Because startups are typically small companies, the human capital of the founders constitutes an important part of the startup's absorptive

[8] Locating in a university science park may help faciliate access to unversity infrastructure, faculty and students (see Link and Scott 2007).

capacity. As argued by Cohen and Levinthal (1990), absorptive capacity is the ability to recognize, assimilate and exploit external information. It depends not only on the knowledge and experience of the individuals in an organization, but especially on those individuals who play “boundary-spanning” communication roles at the firm. In our context, we postulate that the presence of a research-experienced academic founder at the startup provides the necessary “scientific absorptive capacity” for getting the most out of university research alliances. In the literature, Zucker, Darby, and Brewer (1998) emphasized that absorptive capacity is embodied in people based on the observation that intellectual human capital is often tacit knowledge held by the academic inventor that is difficult to codify and communicate except through person-to-person interaction in the laboratory. More recently, Haeussler, Patzelt, and Zahra (2012) argued that the specialization of a biotech firm’s internal technological capabilities mediates potential alliance benefits and risks.[9] Based on this and other literature, we postulate:

> H3: The employment growth effects of university research alliances are greater when the startup has high scientific absorptive capacity, ceteris paribus.

3 Empirical Model and Data

Model

To investigate our hypotheses about the employment effects of university research alliances and scientific absorptive capacity, we must account for the up-or-out dynamic of startup companies. To do this, we use Heckman selection models to control for potential survivor bias in the population of new ventures over time.[10] The outcome equation models employment growth as a function of the conventional characteristics (founding team, resource

[9] A number of studies in the literature examine the moderating and mediating effects of absorptive capacity, but most do not focus on startups or young firms. For this literature, refer to the following papers and the references therein: Subramanian, Lim, and Soh (2013), Lin et al. (2012), Flatten, Greve, and Brettel (2011), and Baba, Schichijo, and Sedita (2009).

[10] See e.g. Heckman (1976; 1979), or Verbeek (2012, 248-252) for details on the Heckman selection model.

endowments, and external environment), but adds three dichotomous explanatory variables representing university research alliances, other connections to universities, and the presence of a research-experienced academic founder. Using the presence of a research-experienced academic founder to proxy for startup scientific absorptive capacity is consistent with the idea that communicating and understanding research results often requires tacit knowledge based on experience. To test hypotheses #1 and #2, the outcome equation in the Heckman model has the following form:

$$Emp\_Growth_i = \beta_0 + \beta_1\, U\_Res\_Alliance_i + \beta_2\, Other\_U\_Connect_i + \beta_3\, Res\_AF_i + \beta_4\, Control\_Variables_i + \beta_5\, \lambda_i + \varepsilon_i$$

where the subscript i represents surviving startups and "*Control Variables*" is shorthand for all other covariates in the regression specification. Employment growth (Emp_Growth) is measured in terms of the annualized logarithmic change in the number of employees between the first year of commercial operation of a new venture (s), and the end of 2001. We are primarily interested in the signs and significance of β_1 and β_2. Hypotheses #1 and #2 predict these coefficients will be positive and significant. While not our main focus, we also expect β_3 to be positive and significant. Prior research shows that the presence of a research-experienced academic founder is associated with better startup performance.[11] λ_i denotes the selection term also known as Heckman's lambda or Inverse Mills Ratio. A significant coefficient on the inverse mills ratio indicates adjusting for survivor bias is important. ε_i is the error term denoting all unobserved shocks to growth.

To examine our hypothesis about the moderating role of absorptive capacity, we use interaction terms between the presence of a research-experienced academic founder (called *Res_AF*) and variables indicating whether the startup had a university research alliance (*U_Res_Alliance*) or other university connections (*Other_U_Connect*). The outcome equation in the Heckman model has the following form:

$$Emp\_Growth_i = \beta_0 + \beta 1\, Res\_AF_i + \beta_2\, Res\_AF_i \cdot U\_Res\_Alliance_i +$$

[11] Toole and Czarnitzki (2007, 2009) found that firms with an academic entrepreneur perform better in terms of proof of concept research, patenting, and the receipt of follow-on venture capital investment. Czarnitzki, Rammer, and Toole (2014) found that startups with an academic entrepreneur showed a performance premium over industry startup companies in terms of employment growth.

$$\beta_3\ No\_Res\_AF_i \cdot U\_Res\_Alliance_i + \beta_4\ Res\_AF_i \cdot Other\_U\_Connect_i + \beta_5\ No\_Res\_AF_i \cdot Other\_U\_Connect_i + \beta_6\ Control\_Variables_i + \beta_7\ \lambda_i + \varepsilon_i$$

As above, the subscript i represents surviving startups and "Control Variables" is shorthand for all other covariates in the regression specification. We are primarily interested in the signs and significance of β_2 and β_3. If scientific absorptive capacity is important for realizing employment benefits from university strategic alliances, then β_2 should be positive and significant. Also, the combination of scientific absorptive capacity with university research alliances, ($\beta_1 + \beta_2$), should be significantly larger than β_3 (cf. H3). The variable $Other\_U\_Connect_i$ captures all other forms of university connections used by the startup such as contract research, training, and informal relationships. Therefore β_4 and β_5 are expected to be positive. We do not have any prior beliefs that scientific absorptive capacity is an important moderator of non-scientific university connections (i.e. no hypothesis about the differences in magnitude between β_4 and β_5).

Sample and Survey Method

Our empirical analysis is based on a survey of German firms that were founded in the five years 1996 to 2000 in "knowledge intensive industries", i.e. in high-tech manufacturing and those service sectors where new technologies and human capital are important for competitiveness (see Appendix 1 for a definition of the sectors used). The new ventures were surveyed through standardized telephone interviews, using stratified random sampling combined with quota sampling. For each stratum in the gross sample, new ventures were ordered randomly and interviews were conducted until a target figure of successful interviews in each stratum was reached. We used sector groups (high-tech manufacturing, technology-oriented services, knowledge-intensive consulting), year of foundation (1996-2000), and region as stratification criteria and applied a disproportional weighting scheme that oversampled high-tech manufacturing and regions with research universities. This was done to increase the likelihood of sampling young firms with university alliances or other university connections and was accounted for in the sampling weights used to make the population estimates. Interviews were conducted with a person who was part of the founding team. The interviews took place from late October to early December 2001. The new ventures were between one year (for start-ups founded at the end of 2000) and almost 6 years (for start-ups founded at the beginning of 1996) old at the time of the interviews.

The sample was drawn from the Mannheim Foundation Panel (MFP) of the Centre for European Economic Research (ZEW). This data set contains almost all firms founded in Germany since 1989 and rests on information from Germany's largest credit rating agency, *Creditreform*. In principle, only firms meeting a minimum threshold of economic activity enter the database. *Creditreform* transmits information twice a year on newly founded firms to ZEW where it is transformed into a panel data structure (see Almus, Engel, and Prantl 2000).

The total number of new ventures surveyed is 20,241. In order to realize this number of interviews, a total of 57,022 firms had to be contacted. Those firms that were contacted but with whom no interview could be performed fell into two groups: (1) firms that refused to participate in the survey or could not be contacted during the interview period because the interviewee was not available (n=25,359) and (2) firms for which the existing contact details turned out to be incorrect and no better contact information was available (n=11,422). The response rate of surveyed firms to the total number of successfully contacted firms at the time of survey was 44.2%.

For those new ventures that could not be successfully contacted due to incorrect contact details (e.g. invalid phone number), we analyzed whether the firms exited the market prior to the time of interviews. We used information contained in the MFP on bankruptcy, insolvency, deregistration from company registers, voluntary closures and other rating-related information for this purpose. About ninety-seven percent (11,100 out of the 11,422 not successfully contacted) were identified as non-surviving firms. This means that about 19.5% of all contacted new ventures ceased business operations soon after starting. Given the high rate of startup failure, we control for survivor bias using a Heckman selection model.

Among the 20,241 surveyed firms, it turned out that 19.4% were founded prior to 1996. In most of these cases, the MFP database showed a change in legal form of the company. A further 3.0% of the surveyed firms were subsidiaries of other companies and did not qualify as independent new ventures. After omitting these firms, we also filtered out extreme observations by trimming the top and bottom of the employment distribution growth at the 99.5 and 0.5 percentiles, respectively. The net sample we use for further analysis consists of

14,844 new ventures. These represent about 5% of the total estimated number of new ventures in Germany within the 5 year period and in the sectors covered by the survey.

Data and variables in the Selection (Survival) Model

The selection model for the Heckman procedure uses data from the MFP to model the probability of survival for new ventures in knowledge intensive industries. The endogenous variable in the survival model is a dummy variable that takes the value of one if the startup was active in 2001 and zero if the startup was identified as not economically active at the end of 2001. The covariates in the selection equation collected from the MFP include the following: founding year dummy variables, industry dummy variables, regional dummy variables, a dummy variable indicating whether the startup's equity is held (in part) by another firm, the formal educational attainment of the founders, a dummy variable indicating whether real estate property is owned by firm founders, and a dummy variable indicating whether the real estate is business property (see Appendix 3).

Variables in Growth Model

The endogenous variable, employment growth, is measured by the annualized logarithmic change in the number of employees in the first year of firm activity to the end of 2001. The explanatory variables fall into three categories. The first category includes characteristics of the founding team. Our indicator of scientific absorptive capacity for the new ventures is based on whether the founding team contains a university researcher. The following founding team covariates are used:

Res_AF	A dummy variable that is equal to one if the startup had at least one research-experienced academic founder. This individual had been employed as a scientist at a university prior to founding the firm.
% Academic Degree	This variable captures the general human capital of the founding team. It is measured as the percentage of founding team members with an academic degree. Academic degree refers to any tertiary education level.
Team Size	The number of people on the founding team.

The second category includes characteristics of the new venture at the time of founding. The following covariates are used:

Firm Patent	A dummy variable indicating the new venture had at least one patent.
Firm R&D (cont)	A dummy variable indicating that the new venture conducts in-house research and development (R&D) activities on a continuous basis. The survey used the same definition and phrasing as the Community Innovation Surveys of Eurostat.
Firm R&D (occ)	A dummy variable indicating that the new venture conducts in-house research and development (R&D) activities on an occasional basis. The survey used the same definition and phrasing as the Community Innovation Surveys of Eurostat.
Employees at founding	The number of employees at the new venture in the first year of economic activity. The number of employees is measured in full time equivalents and includes the founders themselves (as long as they actively contribute labor), salaried employees, trainees, student apprentices and freelancers.
Credit rating	The credit rating of the new venture was obtained from *Creditreform*. This covariate controls for access to external financial capital. *Creditreform* uses a scale from 100 to 600 with 100 representing the best and 600 representing the worst rating. We adjust the scale to be between 1 and 6.
Limited liability Comp	A dummy variable indicating that the new venture was founded under a legal form that limits the founders liability. For instance, one legal form limits the founders' liability to the amount of equity invested at the start of the business. However, it requires a higher minimum equity for starting the business and may complicate access to external capital.

The third category includes characteristics related to the new venture's external environment which includes any connections to universities. The covariates in this category include:

U_Res_Alliance	A dummy variable indicating that the new venture maintained a joint research alliance with a university in the post-foundation period.
Other_U_Connect	A dummy variable indicating that the new venture maintained other connections to a university in the post-foundation period besides joint research. These other connections include contracting in, contracting out, employee training, and regular informal contacts.
Industry	A set of eight dummy variables controlling for the industry in which the new venture is active. The list of industries appears in Appendix 1.
Cohort	This is a set of year dummy variables that indicate the year the new venture was founded. It controls for annual cohort effects for new ventures founded in different years, 1996-2000, which may result from a variety of conditions such as differences in business climate.

4 Empirical Results

Table 1 presents the descriptive statistics for the sample of new ventures in Germany's knowledge intensive industries. The top panel reports the variables for startups without university research alliances and the bottom panel reports this information for startups with university research alliances. Firms with alliances are a relatively small proportion of total new ventures in knowledge intensive industries, representing only 7.4% of the surviving firms in 2001. About 32% of the startups with alliances have high scientific absorptive capacity as indicated by the presence of a research-experienced academic founder(s) on the founding team. The percentage of founding team members with academic degrees is also larger for these startups, about 78% versus 47% on average.

Among the company characteristics, startups with university research alliances have more full-time employees at founding, conduct R&D more often, and maintain extensive connections to universities. Startups with alliances show higher average values across all the innovation indicators such as patents, R&D conducted continuously, and R&D conducted occasionally. For instance, about 62% of these companies invest continuously in R&D compared to 15% for non-alliance startups. Regarding access to external financial capital, however, both types of startups have similar average credit ratings. The largest difference occurs among other connections to universities. Nearly 96% of the startups that have research alliances also have contracting, training, or informal relationships versus 24% for non-research alliance startups.

Table 2 shows the multivariate regression results using Heckman selection models to adjust for survival bias and sampling weights to reflect the population of German startup companies in knowledge-intensive industries as defined in Appendix 1. The Heckman procedure shows that correcting for startup survival is important. The Inverse Mills Ratio given at the bottom of the table is statistically significant at the 1% level. Model 1 gives baseline results that exclude any interaction effects between university research alliances and scientific absorptive capacity. The coefficient for university research alliances is positively and significantly related to startup employment growth. It indicates that startups with university research alliances grew 1.8 percentage points faster in term of employment than startups without such alliances. Note that 1.8 percentage points amount to an acceleration of growth of about 20%, as the average growth of firms without an university research alliance amounts to 9.1 percentage points [= (9.1+1.8)/9.1 ≈ 120%]. The estimate for other university connections such as contracting, training and informal relationships is also significant and increases average employment growth by 4.1 percentage points. A startup's scientific absorptive capacity, as indicated by the presence of a research-experienced academic founder (*Res_AF*), is positive and statistically significant at the 1% level. These findings are consistent with results found in prior studies and support hypothesis #1 and #2.

Models 2 and 3 in Table 2 introduce interaction effects to examine how a startup's scientific absorptive capacity moderates its employment benefits. Both models examine the moderating effect of scientific absorptive capacity by estimating separate slope coefficients for startups with research-experienced academic founders and those without such individuals. In Model 2, both slope coefficients on the interaction variables are positive and significant. This indicates that both types of startups experienced employment growth from university research alliances. However, the combination of scientific absorptive capacity with university research alliances, ($\beta_1 + \beta_2$), is significantly larger than β_3 ($\chi^2(1) = 6.56$ with p-value < 0.01). This shows that startups with scientific absorptive capacity (i.e. with a research AF) experienced significantly higher employment growth from university research alliances. The size of this difference suggests scientific absorptive capacity allowed a marginal employment boost of 3.2 percentage points, on average. Note that 3.2 percentage points amount to an employment growth acceleration of about 35% relative to the average growth rate of firms without the scientific absorptive capacity. These results are consistent with hypothesis #3 and suggest that research-based human capital is vital for getting the more out of university research alliances.

Model 3 adds separate interaction coefficients for other university connections. In this model, scientific absorptive capacity is allowed to moderate every type of startup connection to universities. The interaction effect between scientific absorptive capacity and university research alliances is very similar to Model 2 in both magnitude and significance. For startups without scientific absorptive capacity, the results from Model 2 showed a marginally significant effect of research alliances on employment growth; however, this effect disappears in Model 3. In this more general model, university research alliances only stimulate employment growth for the startup if one of the founders had prior research experience at a university. This suggests that university research alliances are quite specialized. Turning to other university connections such as contract work, training, and informal relationships, both interaction terms are positive and significant. Scientific absorptive capacity does not provide any employment growth advantage to startups with these other connections. The marginal effects on employment growth of 3.8 and 4.2 percentage points, respectively, are not economically or statistically different. This result suggests that other university contacts may be a useful alternative to research alliances when in-house scientific capabilities are low, at least for employment growth.

For the other explanatory variables, the results are quite stable across the models in Table 2 and are largely consistent with expectations. New ventures that perform R&D, those with better credit ratings, and those organized as limited liability companies show higher employment growth. The general human capital of the founding team, measured as the percentage of the founders with an academic degree, is also associated with higher employment growth. The patent dummy variables and the size of the founding team have no significant effects on employment growth. The initial size of the new venture is negatively related to employment growth.

Aggregate Employment Estimates

With a representative sample from the population of Germany startup companies in knowledge intensive industries, the survey data can be used to estimate the total net jobs created by these companies.[12] Even more, we can use our empirical model to estimate the fraction of total net jobs created by startup companies attributable to connections to universities and specifically to university research alliances. The attribution of total jobs to these sources is obtained as the difference between actual startup jobs created and predicted startup jobs created. The prediction is based on a counterfactual that assumes no partial effect for the variables of interest. So, for instance, the counterfactual for university connections (research alliances and other types) assumes the coefficients for these two covariates are zero and calculates the predicted net jobs created.

For the period from 1996 through 2001, German National Account statistics show total employment in the knowledge intensive sectors covered by our survey increased by 701,000 jobs. Based on the survey responses and sampling weights, 453,422 of these jobs were created by 171,833 companies founded between 1996 and 2000 that survived until the end of 2001 (see Table 3). This is about 65% of total net jobs in the sectors covered. Among all startups of this cohort, the survey data show that 51,908 companies had some kind of university connection(s) in the post-foundation period and created 223,969 jobs. Using the Heckman regression model results, we estimate that university connections (research alliances and all others) accounted for 9.2% (or 20,535) of these jobs. Turning to university research alliance relationships, the survey data show a total of 11,896 startups in the population had such relationships and created a total of 72,857 jobs. The model results indicate that 3.4% (or 2,453) jobs can be attributed to university research alliances.

5 Conclusion

By all appearances a fundamental reorientation is taking place among researchers and policymakers from firm size to firm age as the critical characteristic associated with employment growth. As discussed in Section 2, mounting evidence points to young companies, particularly in high-technology industries, as a primary source driving the overall rate of economy-wide employment growth. The important and challenging question is: how

[12] Net jobs created by startups measures the difference between total jobs created through expansions minus total jobs destroyed through startup failures or contractions, 1996-2001. We do not count full-time employees at founding as part of jobs created. This allows us to measure job creation by young firms as analyzed in Haltiwanger, Jarmin, and Miranda (2013).

do young companies in knowledge-intensive industries create jobs? This paper explored this question by analyzing the contribution from university research alliances, which is a particular form of hybrid organizational growth, along with other connections that startups can make with universities such as contract research, training, and informal contacts.

To stimulate employment growth these university connections would need to expand the workforce at the startup by increasing labor demand though greater innovation and sales or by freeing up resources by increasing labor productivity or lowering recruitment costs. For university research alliances, we postulated that employment growth is moderated by the ability of the startup to access, assimilate, and exploit knowledge exchanged through collaborative R&D projects. That is, the "scientific absorptive capacity" at the startup is a critical for reaping the benefits of university research alliances, but not necessarily for other university connections.

These basic insights were largely confirmed by the empirical results. University research alliances added 3.4 percentage points to startup employment growth, but only for those young firms that had scientific absorptive capacity, which we measured using the employment background of the startup's founding team. Specifically, this higher growth rate was associated with startups that had a former academic researcher(s) as part of the founding team and no statistically significant effect was found for other startups. This result highlights the specialized character of university research alliances. Perhaps not surprisingly, it suggests that these alliances are not appropriate for all startups in knowledge-intensive industries, but they may be appropriate for a larger number of startups as only 31% of the startups in our sample with an academic founder also had a university research alliance. Research alliances constitute a relevant way of transferring research at universities into economic wealth. When evaluating transfer activities of universities, this channel is often ignored and less valued compared to the creation of spinoff companies, patenting or research alliances with established companies.

Other university connections (contacting, training, and informal contacts) contributed significantly employment growth among German startups in knowledge-intensive industries. Those startups with scientific absorptive capacity had 3.8 percentage points higher employment growth while those without such capacity had 4.2 percentage points higher growth. As the difference between these estimates is not economically or statistically significant, scientific absorptive capacity did not provide any advantage for harnessing the employment effects from other university connections. Without the requirement for scientific absorptive capacity, other university connections may be a feasible strategy for a larger group of startups. Only about 30% of the sample startups maintained these other university connections in Germany's knowledge-intensive industries.

Another unique contribution of our analysis was the attribution of aggregate sector-level employment impacts to university research alliances and other university connections. Consistent with the emerging literature, the startups we analyzed contributed about 65% of the total net jobs to Germany's knowledge-intensive sectors in 1996-2001. In this population of startups, 30% had university connections of any kind (research alliances and other) and theses firms added 223,969 jobs. Of these, 20,535 jobs (or 9.4%) were due to any kind of university connections. Only 7% of the startup population maintained a university research alliance, but among these firms, 3.4% of their total jobs created were attributable to their alliances. These results suggest university connections are quite important for job growth and university research alliances contributed substantially to job creation for those firms that had such alliances.

For policymakers, our research suggests opportunities exist to stimulate employment by supporting startup survival and growth through university research alliances and other university connections, particularly in knowledge-intensive industries. One might consider university research alliances with young enterprises as a viable mode of technology transfer. This would extend spinoff policies to the post-foundation period. So, for instance, young firms are likely to benefit from greater access to university facilities such as labs. Policies that incentivize the formation of university research alliances on the university-side might also be valuable as traditional norms and reward structures do not support such activities.

While our research addresses the important and challenging question of how young companies in high-technology industries grow, it is just a beginning. Access to longitudinal data would help to hold unobservable influences constant and push the findings toward a causal interpretation. Along these lines, highly detailed startup and project-level data would permit one to explore the deeper mechanisms underlying our employment growth findings. For instance, such data might identify labor productivity as the main link between university research alliances and employment growth. In future research it will also be important to implement more sophisticated models that test for and address other potential sources of endogeneity. For instance, assuming suitable instruments are available, it would be informative to model the choice of university connections in addition to our correction for survivor bias. Based on the up-or-out dynamic, we believe survivor bias is the most serious form of estimation bias, but future research could explore such issues.

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Appendix 1: Definition of Technology Sectors

High-tech manufacturing: This sector comprises manufacturing activities characterized by high R&D inputs and includes the following NACE rev. 1.1 codes: 24, 29, 30, 31, 32, 33, 34, 35 (chemicals and pharmaceuticals, machinery and equipment, computer and office machinery, electrical equipment, electronics, medical and measurement instruments, automotive and other vehicles).

Technology-oriented services: This sector covers services that are heavily relying on the use of new technology, particularly information and communication technology, and includes the NACE rev. 1.1 codes: 64.3, 72, 73, 74.2, 74.3, 92.11 (telecommunication, computer services and software, R&D services, engineering, testing, film making).

Knowledge-intensive consulting: This sector represents services that are largely based on high qualified labor while relying less on new technology and includes NACE rev. 1.1 codes: 74.1, 74.4, 74.85.1, 74.85.2, 74.87.2, 74.87.4, (business consulting, advertising, design activities, etc.)

Appendix 2: Tables

Table 1: Startup descriptive statistics by University Research Alliance

Startups without a University Research Alliance = 13,744				
	Mean	**Std. Dev.**	**Min**	**Max**
Employment growth (average annual)	0.091	0.162	-0.448	0.805
Founding team characteristics				
Research-experienced Founder(s)	0.058	0.234	0	1
Percent founding team members with academic degrees	0.467	0.466	0	1
Size of founding team	1.594	1.044	1	15
New venture characteristics				
Employees at founding (FTE)	3.415	4.552	0.5	50
Patent	0.015	0.121	0	1
R&D (continuous)	0.149	0.356	0	1
R&D (occasional)	0.101	0.301	0	1
Credit rating at founding	2.670	0.461	1.46	6
Limited liability company	0.370	0.483	0	1
External environment characteristics				
Other University connections	0.244	0.429	0	1

Startups with a University Research Alliance = 1,100	**Mean**	**Std. Dev.**	**Min**	**Max**
Employment growth (average annual)	0.167	0.183	-0.448	0.805
Founding team characteristics				
Research-experienced Founder(s)	0.321	0.467	0	1
Percentage of founding team with academic degrees	0.776	0.367	0	1
Size of founding team	2.188	1.488	1	15
New venture characteristics				
Employees at founding (FTE)	5.405	6.117	0.5	50
Patent	0.119	0.324	0	1
R&D (continuous)	0.618	0.486	0	1
R&D (occasional)	0.174	0.379	0	1
Credit rating at founding	2.682	0.430	1.97	6
Limited liability company	0.684	0.465	0	1
External environment characteristics				
Other University connections	0.955	0.206	0	1

Note: Eight industry dummy variables and five founding year cohort dummy variables are not reported.

Table 2: Startup employment growth (1996-2000), Heckman selection models using Sampling Weights

Variable	Model 1	Model 2	Model 3
U_Res_Alliance	0.018***		
	(0.007)		
Other_U_Connect	0.041***	0.041***	
	(0.004)	(0.004)	
Res_AF	0.017***	0.012*	0.014*
	(0.006)	(0.007)	(0.009)
Res_AF * U_Res_Alliance		0.033***	0.034**
		(0.012)	(0.014)
No_Res_AF * U_Res_Alliance		0.013*	0.013
		(0.009)	(0.008)
Res_AF * Other_U_Connect			0.038***
			(0.012)
No_Res_AF * Other_U_Connect			0.042***
			(0.004)
Firm Patent (yes/no)	0.017	0.016	0.016
	(0.012)	(0.012)	(0.012)
Firm R&D (continuous)	0.045***	0.044***	0.044***
	(0.005)	(0.004)	(0.004)
Firm R&D (occasional)	0.027***	0.027***	0.027***
	(0.005)	(0.005)	(0.005)
Percentage of Founding Team with Academic degrees	0.004	0.004	0.004
	(0.003)	(0.003)	(0.003)
Size of Founding Team	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)
Employees at Founding	-0.003***	-0.003***	-0.003***
	(0.0004)	(0.0004)	(0.0004)
Credit rating at Founding	-0.008**	-0.008**	-0.008**
	(0.003)	(0.003)	(0.003)
Limited Liability Comp.	0.035***	0.035***	0.035***
	(0.003)	(0.003)	(0.003)
Intercept	0.067***	0.067***	0.067***
	(0.010)	(0.010)	(0.010)
Founding year dummy variables	Y	Y	Y
Industry dummy variables	Y	Y	Y
Inverse Mills Ratio	-0.213***	-0.213***	-0.217***
Total Observations	23,803	23,803	23,803
Censored Observations	8,959	8,959	8,959

Note: Standard errors in parentheses. *** (**,*) indicate a significance level of 1% (5%, 10%). All second stage regressions include industry and founding year dummy variables.

Table 3: Job Creation of Startups by type of university link (startups in knowledge intensive industries in Germany founded 1996 to 2000 that survived until the end of 2001)

	No. of startups 1996-2000 surviving through 2001	No. jobs created 1996-2001
All startups	171,833	453,422
Startups with any type of university connection	51,908	223,969
- of which: jobs attributable to any connection		20,535
Startups with University Research Alliances (URAs)	11,896	72,857
- of which: jobs attributable to URAs		2,453

Note: All data from survey except the attribution of jobs created, which is based on the empirical model.

Appendix 3: The survival equation controlling for selection

As described in section 3 of the main text, all regressions results were obtained using sample selection models. In order to model the survival of the firms (as only surviving firms could be included in the surveys) we rely on available data for firms that exited before the survey. Although somewhat limited, we can use information from the Mannheim Foundation Panel (MFP) to model the probability of survival for the new ventures. In particular, we use the founding year, industry, firm location, equity ownership by other firms, real estate property of firm founders, and the level of formal educational attainment among the founders.

The industry dummies and foundation cohort dummies are analogous to those included in the growth equation. In addition, we use 13 regional dummies to model survival. The regional dummies are omitted from the growth equations as they always turned out to be insignificant. In the survival equation, they are jointly significant at the 5% level (the χ^2 test value amounts to 126.64). In the growth equation, we do not include the education-related variables that appear in the selection equation as we have the survey reported data on the education of the academic entrepreneurs and the share of founders with academic degrees. Also, we do not use the real estate variables in the growth equation, but instead include the firm's credit rating, which is a more general financial performance variable. Part of this decision was based on data limitations. For the non-surviving firms the rating had too many missing values as it was possibly never constructed for firms that exited soon after foundation.

Table 4: Estimates of the survival equation (first stage of the selection model); N = 23,803

Variable	Coeff.	Std. err.
Equity ownership by at least one firm	0.194***	0.036
Dummy whether founders or firm own real estate	0.283***	0.028
dummy indicating whether real estate is business property	0.448***	0.137
Dummy indicating that real estate information was 'missing'	-0.010	0.063
Education of founders		
at least one founder with doctoral degree	0.028	0.041
at least one founder with engineering master degree	0.231***	0.028
at least one founder with business/econ degree	0.129***	0.036
at least one founder with other university degree	0.080**	0.041
at least one founder is master craftsman	0.184***	0.046
at least one founder has no higher education degree	0.043	0.058
Dummy indicating that education variables were 'missing'	-.166***	0.020
Intercept	1.536***	0.065
Industry dummies	Included.	
Foundation cohort dummies	Included.	
Regional dummies	Included.	

*** (**,*) indicate a significance level of 1% (5%, 10%).