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Wages in high-tech start-ups – Do academic spin-offs pay a wage premium?

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ABSTRACT

Due to their origin in universities, academic spin-offs operate at the forefront of technological development. Therefore, academic spin-offs exhibit a skill-biased labour demand, i.e. academic spin-offs have a high demand for employees with cutting-edge knowledge and technical skills. In order to accommodate this demand, academic spin-offs may have to pay a relative wage premium compared to other high-tech start-ups. However, neither a comprehensive theoretical assessment nor the empirical literature on wages in start-ups unambiguously predicts the existence and the direction of wage differentials between academic spin-offs and non-spin-offs. This paper addresses this research gap and examines empirically whether or not academic spin-offs pay their employees a wage premium. Using a unique linked employer-employee data set of German high-tech start-ups, we estimate Mincer-type wage regressions applying the Hausman-Taylor panel estimator. Our results show that academic spin-offs do not pay a wage premium in general. However, a notable exception to this general result is that academic spin-offs that commercialise new scientific results or methods pay a wage premium to employees with links to the university sector – either as university graduates or as student workers.

1. Introduction

Academic spin-offs (referred to below as "spin-offs" for convenience) are an important means for transferring specific skills, research results and technologies developed at universities and research institutions[1] to the for-profit private sector. Due to their origin in universities, spin-offs are regarded as operating at the forefront of technological development (Clarysse et al., 2011; Wright et al., 2007a), which leads to a skill-biased labour demand, i.e. spin-offs have a high demand for employees with cutting-edge knowledge and technical skills. In order to attract and hire adequately skilled workers from the labour market, spin-offs may be required to provide higher wages even compared to other high-tech start-ups that emanate from outside the university sector ("non-spin-offs"). However, neither a comprehensive theoretical assessment nor the empirical literature on wages in start-ups unambiguously predicts the existence and the direction of wage differentials between spin-offs and non-spin-offs. This paper addresses this research gap and provides the first empirical evidence on whether spin-offs pay their employees a wage premium.[2]

Wage determination in spin-offs and the analysis of wage differentials across high-tech start-ups also has important policy implications. Some scholars argue that spin-offs need to compen-

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[1] In this paper, we use the term "university" to refer to all kinds of publically funded, not-for-profit research organisations. For Germany, this includes extra-university research institutes like those of the Max Planck Society or the Fraunhofer Society.

[2] As pointed out by an anonymous reviewer, the group labelled non-spin-offs may nevertheless contain so-called corporate spin-offs. Parhankangas and Arenius (2003, p. 464) define a corporate spin-off as a "new business formation based on the business ideas developed within the parent firm being taken into a self-standing firm." Unfortunately, we are unable to identify corporate spin-offs in our data set. Thus, throughout this paper we exclusively focus on academic spin-offs that originate from universities and refer as non-spin-offs to all high-tech start-ups that are not academic spin-offs.

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sate the societal costs that arise from the spin-off process, basically resulting from the academic "brain drain" from the incubator university (Czarnitzki et al., 2014; Toole and Czarnitzki, 2010). Against an abundance of studies focussing on job creation or survival of spin-offs, wages have largely been neglected in this discussion so far, although a wage premium paid by spin-offs could be a potential source to compensate for the societal costs of the creation of spin-offs.

Our empirical study uses a comprehensive linked employer-employee (LEE) panel data set that was generated by matching the ZEW High-Tech Start-Up Survey 2007 with administrative data on employees and establishments provided by the Institute for Employment Research (IAB). Our data set comprises 807 German high-tech start-ups including 120 spin-offs, founded in the period from 2003 to 2005, with their full workforce for at least the first three years of the existence of the firms. Most importantly, the data set further enables us to differentiate between different types of spin-offs with respect to the knowledge that has been transferred into the spin-off. Following Egeln et al. (2003a,b), we distinguish between two types of spin-offs: competence and transfer spin-offs. The latter involve the transfer of scientific results or methods to the spin-offs, while the former are based on the transfer of specific skills from the university to the new venture.

Our descriptive analysis reveals that on average full-time employees in both types of spin-offs receive higher wages than their counterparts in non-spin-offs. However, using a multivariate regression framework in the tradition of Mincer (1974) and a Hausman-Taylor panel estimator we are able to explain these unadjusted wage differentials entirely by differences in worker and firm characteristics of spin-offs and non-spin-offs. Being employed by either a competence or a transfer spin-off does not imply higher wage levels than working in a non-spin-off. A notable exception is university graduates working for transfer spin-offs, who receive a significant wage premium of about 14% compared to their counterparts working for non-spin-offs. For university graduates in transfer spin-offs, a potential negative relationship (e.g., due to non-monetary benefits of working in a transfer spin-off) is dominated by an opposing positive link between transfer spin-offs and wages (e.g., due to sorting of more productive employees).

Our study contributes to the literature in three ways: First, our findings support the notion of sorting of relatively productive high-skilled workers who demand higher wages into R&D intensive environments as provided by transfer spin-offs. Second, we provide evidence that policy makers should consider that the societal costs of spin-offs are, at least to some extent, offset by a wage premium paid by transfer spin-offs to their university graduates. Third, according to our knowledge this paper is the first study where the unit of analysis is the individual employee working for a spin-off. Although the quality of human resources is frequently emphasised as an important source of firm performance and development (see the comprehensive survey of Rothaermel et al. (2007) and the literature quoted therein), existing studies focus on the team of entrepreneurs, their human capital, their transition from academia to their spin-off and their return to academic entrepreneurship (e.g., Åstebro et al., 2013). In contrast, our study provides first evidence of recruitment and remuneration policies of spin-offs at the level of the individual employee.

The remainder of the paper is structured as follows: Section 2 documents the definition of spin-offs we use for our analysis and embeds this definition into the existing literature on spin-offs. In Section 3, we outline the related literature on employment in spin-offs and provide theoretical arguments why wages may differ between transfer spin-offs, competence spin-offs and non-spin-offs. Section 4 documents the linked employer-employee data set and provides descriptive statistics. The econometric model is outlined in Section 5. Section 6 presents and discusses the results from the multivariate wage regressions along with the results of alternative specifications and robustness checks. Section 7 concludes with a summary of the implications and limitations of our study.

2. Definition of spin-offs

There are many different definitions of spin-offs used in the literature. In their typology of spin-offs, Pirnay et al. (2003) point out what most definitions have in common: Spin-offs are new firms with a distinct legal status that originate from research institutions in order to commercially exploit knowledge produced by academic activities.[3] Apart from these commonalities, Pirnay et al. (2003) characterise spin-offs by two dimensions in which existing definitions differ from each other: the academic status of individuals involved in the new business venturing process and the nature of knowledge transferred (see also Djokovic and Souitaris, 2008).

The ZEW High-Tech Start-Up Survey that is used to identify spin-offs in our data set applies a definition developed by Egeln et al. (2003a,b), who extensively investigated spin-offs in Germany. The founders (or at least one member of the team of founders) of a spin-off either must have studied or must have worked at a university. The latter group comprises not only university researchers but also academic and non-academic staff members, e.g., lecturers or technical staff (Rappert et al., 1999; Smilor et al., 1990). The formation of spin-offs by former university employees further involves at least a partial employment transition of the university employee from academia to the spin-off, although the university employee may remain affiliated with the incubator university. Thus, the definition used by Egeln et al. allows for spin-offs set up by former students (Bathelt et al., 2010). However, in contrast to the definitions of Nicolaou and Birley (2003) or Pirnay et al. (2003), the definition by Egeln et al. does not include firms where the academic inventor is not part of the team of founders.

With respect to the nature of the knowledge transferred from the university to the spin-off, Pirnay et al. (2003) show that the type of knowledge transferred influences a spin-off's growth potential or its access to financial resources (see also Bathelt et al., 2010; Clarysse et al., 2011). In this study, we define two types of spin-offs according to the nature and the level of the knowledge transferred (Egeln et al., 2003a,b):

- **Transfer spin-offs:** Either new research results the founders themselves developed during their employment at the university or new scientific methods or techniques the founders acquired during their time at the university were essential to the creation of their firms.
- **Competence spin-offs:** Specific skills the founders acquired during their time at the university were essential to the formation of the new firm.

The differentiation between transfer and competence spin-offs shows parallels to the taxonomy provided by Hindle and Yencken (2004), which also classifies spin-offs according to the type of knowledge commercialised. Transfer spin-offs encompass both so-called direct research spin-offs and technology transfer companies (Hindle and Yencken, 2004). Direct research spin-offs commercialise intellectual property (IP) generated at the incubator institution involving, e.g., licensed patents or copyrights. Technology transfer companies are based on tacit knowledge of the founder(s) that is not protected by formal IP rights. De Cleyn

[3] Strictly speaking, the study of Pirnay et al. (2003) is restricted to spin-offs that originate in universities, excluding other research institutions. In this paper, we apply the same characteristics to spin-offs from universities and other publicly funded research institutions.

and Braet (2009) consider direct research spin-offs and technology transfer companies as new ventures started by researchers. However, similar to Pirnay et al. (2003), we allow research results to be commercialised by (doctoral) students too. The fact that our definition requires that the founders' research results were "essential" emphasises that the firm would not have been started without the transfer of this knowledge (Roberts, 1991).

Competence spin-offs broadly correspond to indirect spin-offs that are founded by university employees or students in order to commercialise experience acquired during their time at the university (Hindle and Yencken, 2004). In contrast to mere joint classroom experience (Bathelt et al., 2010), to be classified as a competence spin-off it is required that the commercialised tacit knowledge in the form of specific skills was essential for the formation of the firm.

Transfer spin-offs and competence spin-offs are defined as two mutually exclusive groups whereby the group of transfer spin-offs (higher level of technology transfer) dominates the group of competence spin-offs (lower level of technology transfer). Thus, if interviewees indicate that both research results and specific skills were essential to the creation of their firms, these firms are classified as transfer spin-offs but not as competence spin-offs.[4]

The identification of spin-offs via a survey has the significant advantage that it covers spin-offs that are unknown to their incubator university and its technology transfer office because they were established without a link to their incubator institutions (Egeln et al., 2003b). This applies in particular to those spin-offs that were established with a significant time-lag between the founder's leaving academia and the creation of her or his new venture (Müller, 2010). Moreover, De Cleyn and Braet (2009) point out that indirect spin-offs (i.e., competence spin-offs in our definition) usually occur unnoticed by the university and are not supported by the incubator institution.[5]

3. Related literature

3.1. Employment in spin-offs

Employment in spin-offs is usually discussed in the literature with respect to the number of jobs created by these firms (see Rothaermel et al., 2007). Most studies hypothesise that spin-offs grow faster than other start-ups because of differences in market opportunities (Lacetera, 2009), the human and social capital of the founders (Colombo and Piva, 2005) and superior endowment with intangible assets, basically the knowledge and technology that was transferred from the university to the spin-off (Clarysse et al., 2011). From a societal perspective, it is desirable that spin-offs grow faster than other start-ups because ventures set up by researchers have to produce a net gain in social welfare (a "performance premium") in order to offset the social costs of spin-off generation (Czarnitzki et al., 2014). Such social costs arise when university researchers transition to the private sector, involving a potential decrease in both the production and the disclosure of academic research output (academic "brain drain", Toole and Czarnitzki, 2010). Empirical evidence for an academic "brain drain" is documented by Buenstorf (2009).[6]

However, empirical studies produced mixed results on whether or not spin-offs create more jobs than other start-ups (e.g. Cantner and Goethner, 2011; Czarnitzki et al., 2014; Egeln et al., 2010; Gottschalk et al., 2007; Lindholm-Dahlstrand, 1997; Mustar, 1997; Shane, 2004). Some studies even find that start-ups founded by researchers exhibit a significantly lower employment growth rate than other new technology-based firms (e.g. Colombo and Piva, 2005; Wennberg et al., 2011). The authors of these studies argue that inferior growth performance results from a lack in managerial and commercial competence among spin-offs. Indeed, extant literature emphasises the importance of the human capital of both the entrepreneurs and the firms' employees for the performance of spin-offs (e.g. Clarysse and Moray, 2004; De Cleyn et al., 2011; Visintin and Pittino, 2014; Wright et al., 2007b).

Thus, the recruitment of skilled employees is an important task for spin-offs. Recently, the recruitment policies and constraints start-ups face when hiring new personnel have been the subject of a number of empirical studies (e.g. Bublitz et al., 2015; Dahl and Klepper, 2015; Nyström and Elvung, 2014, 2015; Sorensen et al., 2015). These studies describe various competitive disadvantages of start-ups, like the liability of newness or the lack of established recruiting routines. In conjunction with the inability to adequately compensate for opportunity costs (e.g. higher risk of job loss) by means of wages, non-random sorting of specific groups of workers (e.g. young and unexperienced workers, unemployed persons) into start-ups is documented (Nyström and Elvung, 2014, 2015).

In addition to sorting with regard to firm size and age, there are two additional mechanisms that may induce sorting of certain types of workers especially into high-tech start-ups or spin-offs. First, due to high innovation performance (Egeln et al., 2010), spin-offs have a labour demand that is biased towards high-skilled employees with task specialisations, for instance in engineering and technical occupations. In order to accommodate this demand for specific human capital, spin-offs need to provide potential employees with a working environment that matches their preferences and offsets individual opportunity costs, in particular when they leave other (better paid) positions in academia or in the industry. Second, a distinctive characteristic of spin-offs is their close and enduring contact with the academic sector. This contact provides them with an important competitive advantage over non-spin-offs with respect to the recruitment of high-skilled employees (Berggren and Lindholm-Dahlstrand, 2009). Another labour supply advantage of spin-offs is the employment of students within the context of student jobs (e.g. internships) or by offering students support for their university theses.[7] Transfer spin-offs use this channel more often than competence spin-offs (Egeln et al., 2003b). It can be assumed that this advantage also gives transfer spin-offs a more favourable position in hiring university graduates.

3.2. Wage differentials between spin-offs and non-spin-offs

Hiring employees requires start-ups to pay competitive wages. These wages reflect the outcome of a bargaining process between employer and employee and account for opportunity costs that require monetary compensation as well as for preferences of workers for non-pecuniary aspects of jobs. This trade-off in the bargaining for jobs and wages by utility-maximising agents is described in the theory of compensating wage differentials.[8]

4 Table A1 in the Appendix documents the exact wording used to identify spin-offs and shows how the two groups of spin-offs are defined based on the answers given by the interviewees. In order to be classified as a spin-off, the interviewees had to be able to name the university or public research institution the research results or specific skills originated in. If no research institution was indicated, the firms were not classified as spin-offs.

5 In Section B.1 of the Supplementary online Appendix, we also provide the reader with an overview of relevant legal rules of spin-off formation in Germany.

6 Of course there might be other channels through which a spin-off can generate a net gain in social welfare. For example, it might be argued that a spin-off's contribution to the structural change of an economy exceeds that of a non-spin-off because the spin-off commercialises more advanced technologies. These kinds of social benefits are, however, beyond the scope of this paper.

7 Other forms of contact between the university and a spin-off include joint research projects, the sale of the spin-off's products or services to the university or training of the spin-off's employees by the university.

8 For the rationale of compensating differentials see Rosen (1986).

Workers, for instance, demand a wage premium that compensates them for working in more uncertain job environments associated with a higher risk of job displacement and long term costs of job loss (e.g., Huttunen et al., 2011; Moretti, 2000; Schnabel et al., 2011). Among high-tech start-ups and academic spin-offs job uncertainty is highly correlated with the degree of experimentation (Kerr et al., 2014). Additionally high-tech start-ups often operate in small niche markets and at the technological edge that exposes them to a higher risk of failure (Audretsch, 1995; Hyytinen et al., 2015; Manigart and Van Hyfte, 1999). Hence, transfer spin-offs that exhibit the highest R&D intensity should be forced to pay (*ceteris paribus*) higher wages than competence spin-offs or non-spin-offs. However, empirical studies suggest that the opposite is true. Both a high R&D intensity and strong university ties of spin-offs are related to a higher probability of survival and job security (Cantner and Goethner, 2011; Egeln et al., 2007; Rothaermel and Thursby, 2005). If employees perceive an *a priori* lower risk of job loss when working for an R&D-intensive transfer spin-off, they might more readily accept lower wages compared to a job in a competence spin-off or a non-spin-off.

Assortative matching of workers into different types of firms is documented extensively in the context of wage inequality (e.g. Abowd et al., 1999; Acemoglu and Autor, 2011; Card et al., 2013; Hartog 1986). In the case of high-tech start-ups a wage differential could result from sorting due to specific types of jobs and working environments. Generally, high-tech start-ups require a disproportionately high share of academically trained workers. The literature suggests that many of these workers have a strong "taste for science" (Roach and Sauermann, 2010) that leads them to sort into research careers and to accept lower wages in return for more science-related working conditions or contents (Dupuy and Smits, 2010; Roach and Sauermann, 2010, 2015; Stern, 2004). In the context of our study, assortative matching of university graduates[9] into start-ups with R&D-intensive jobs and more intense university linkages could provide a rationale for wage differentials across high-tech start-ups. If university graduates have a "taste for science" that leads them to perceive rather the opportunities than the risks of R&D-intensive environments, the most R&D-intensive type of start-ups, namely transfer spin-offs, might be able to pay (*ceteris paribus*) lower wages compared to non-spin-offs or competence spin-offs.

However, mostly start-ups do not compete among each other but with incumbent firms. Given the competitive disadvantages start-ups face against incumbents (see Nyström and Elvung, 2015), start-ups will have to pay higher wages, at least at the level of their competitors. Paying a wage premium is unavoidable for high-tech start-ups because specific human capital can hardly be substituted by any other means (e.g. workers with different skills, technology), especially in the early years after firm foundation. Therefore, on competitive labour markets higher exposure to competition for more academically trained workers or technical specialists could require these start-ups to pay disproportionately high wages compared to other start-ups. If so, R&D-intensive transfer spin-offs would face this situation more often than other (non-)spin-offs. If transfer or competence spin-offs can accommodate their specific labour demand by exploiting their relative labour supply advantage through university linkages, competition-driven higher wage payments are expected for non-spin-offs.

Financial constraints of start-ups affect their ability to compete for highly skilled workers. A potential remedy to these constraints is the acquisition of external financing such as venture capital (VC) or informal equity financing (often referred to as business angel financing). Since spin-offs in general and transfer spin-offs in particular have an advantage in receiving equity financing (Fryges et al., 2007; Shane and Stuart, 2002; Toole and Czarnitzki, 2007), it can be assumed that spin-offs use this financial advantage for hiring purposes and to incentivise their workers by paying higher wages (Bengtsson and Hand, 2013).

Overall, the literature provides only an ambiguous prediction for the direction of wage differentials across different types of spin-offs and non-spin-offs. Theoretical arguments can be found both in favour of a wage premium (risk of business failure in R&D-intensive and experimental start-ups; availability of external equity; labour market competition) and against higher wages (sorting and "taste for science"; access to the academic labour market). The net effect of these partly counteracting mechanisms remains unclear and is thus subject to empirical investigation.

4. Data and descriptive analysis

4.1. Data

In this study, we use a linked employer-employee data set that combines survey data of newly-founded high-tech firms with administrative employee data from the German employment statistics. The employer data originate from the ZEW High-Tech Start-Up Survey conducted in 2007 by the Centre for European Economic Research (ZEW). The survey data were collected via Computer-Aided Telephone Interviews (CATI). The data set includes information on the year and process of firm formation, the human capital of firm founders and innovation activities.

The survey covers newly founded legally independent firms. The survey's sample was stratified by industry sector and year of firm formation. Firms included in the sample were founded in the period from 1998 to 2005. Start-ups from both high-tech manufacturing sectors (cutting-edge technology manufacturing and high-tech manufacturing) and high-tech service sectors (software firms and other technology-intensive services like telecommunication firms, R&D laboratories or engineering services) were interviewed (for NACE codes see Table A2 in the Appendix).

The survey data were linked with comprehensive employment biography data from the German Employment Statistics and from administrative data of the Federal Employment Agency. This data set, the Integrated Employment Biographies (IEB), was provided by the Institute of Employment Research (IAB).[10] It contains process-produced person-specific biographical data on a daily basis on all employees subject to obligatory social insurance (i.e. pension funds, health and unemployment insurance) as well as episodes of registered unemployment or job search along the biographies. The individual-level data encompass socio-demographic characteristics like gender, age, nationality and education. On the other hand, rich information on employment-related characteristics is available: the exact start and end date of employment episodes, gross earnings subject to social insurance, occupational and employment status.

Since there is no unique firm identifier in the two data sets, the firms comprised in the survey had to be matched with the adminis-

[9] University researchers or non-scientific personnel with tenure positions are unlikely to join spin-offs because of a substantial negative wage differential and the higher risk of job loss. However, the regulation of the German academic labour market only provides a relatively low number of tenured positions (9%) for which a disproportionally high number of PhD students and post-docs eventually compete (Hohendanner et al., 2016).

[10] For an outline of the IEB data set see Dorner et al. (2010), who describe the Sample of Integrated Labour Market Biographies (SIAB), a 2% random sample of the IEB data which is available for scientific research.

Table 1
Overview of the samples of spin-offs and non-spin-offs.

	Firms		Employees		Person-year observations (full sample)		Person-year observations (estimation sample)	
	#	%	#	%	#	%	#	%
Non-spin-offs	687	85.1	9747	85.0	24,239	86.1	20,803	85.8
Spin-offs								
Competence spin-offs	65	8.1	816	7.1	1880	6.7	1620	6.7
Transfer spin-offs	55	6.8	910	7.9	2039	7.2	1817	7.5
Total	807	100	11,473	100	28,158	100	24,240	100

Source: ZEW High-Tech Start-Up Survey, Integrated Employment Biographies of the IAB, authors' calculations.

trative data via firm names and addresses using methods of record linkage.[11]

Our final sample comprises 807 firms founded in the period from 2003 to 2005, among them 55 transfer spin-offs and 65 competence spin-offs. For our empirical analyses, we set up a person-year panel data set. The employment data available to us cover all employment episodes from 2003 to 2008. During this period, a total of 11,473 employees liable to social insurance worked in the firms of our sample – either part time or full time, for the entire year or for a shorter period. On average, an employee was employed 2.5 (not necessarily consecutive) years. This results in 28,158 person-year observations. Table 1 shows the number of firms, employees and person-year observations for spin-offs and non-spin-offs.[12]

The last column of Table 1 depicts the person-year observations for the sample that is eventually used for the econometric analyses. All descriptive statistics are based on this reduced sample. However, the conclusions would remain unchanged if we used the full sample.

4.2. *Employment and hiring pattern in high-tech start-ups*

The literature provides very little information on recruitment policies and workforce composition of high-tech start-ups in general and of spin-offs in particular. However, this information is essential for understanding potential differences in remuneration policies between spin-offs and non-spin-offs. We therefore describe concisely where employees worked before they joined the high-tech start-up, what they earned in these jobs, how the workforce of high-tech start-ups is composed in terms of employment status and what tasks employees execute in high-tech start-ups.

Analysing the biographies of recruits in high-tech start-ups, we find that transfer spin-offs significantly more often hire labour market entrants (e.g. university graduates) than non-spin-offs (Table 2). The two groups of spin-offs, however, do not differ with respect to the share of entrants among their employees. The share of employees recruited from unemployment is higher in non-spin-offs than in both types of spin-offs, while between transfer and competence spin-offs the difference is not significant.

The share of recruits who were employed at a university or a public research institute directly prior to joining the start-up is significantly higher in spin-offs than in non-spin-offs. Transfer spin-offs exploit this hiring channel more extensively than competence spin-offs. When restricting the inflow of employees to local universities only, the same pattern across start-up types is evident, indicating a strong local dimension of knowledge transfer via the labour market. On the other hand, there are no significant differences across all three types of start-ups with regard to the share of workers that joined the start-up from a job in the same local labour market.

Full-time employees in their last job prior to the employment transition into a spin-off received significantly higher wages[13] than workers who joined a non-spin-off. Across the two types of spin-offs it appears that recruits of transfer spin-offs drive this differential. When comparing the individual pre-start-up wage with the entry wage in the start-up for all employees who had worked full-time in both jobs, we find that employment transitions into start-ups frequently involve wage cuts. Wage cuts, however, are more common for employees in both types of spin-offs.

Table 3 provides an overview of the number of employees and the composition of the firms' workforces within our three groups of start-ups. The number of employees is measured as the headcount per year, based on the number of days the individual employees worked in the start-up (e.g. 1 = 365 days or 0.16 = 60/365 days). Competence spin-offs are significantly smaller than both transfer spin-offs and non-spin-offs, whereas there is no significant difference between transfer spin-offs and non-spin-offs.

The middle panel of Table 3 depicts the composition of the start-ups' workforces according to the employees' highest level of education. The categories are: no (completed) training, completed vocational training and university degree. The share of each education category is calculated as the share of a start-up's total person days that are allotted to employees with this level of education.[14] Non-spin-offs exhibit a significantly smaller share of both employees with a university degree and those without (completed) training than do spin-offs. Conversely, spin-offs show a significantly smaller share of employees with a vocational qualification. The share of employees with a university degree in the group of transfer spin-offs is even higher than in the group of competence spin-offs.[15]

[11] Details how the two data sets were matched and on the matching quality are provided in section B.2 of the Supplementary online Appendix.

[12] If a start-up operates under the legal form of an incorporated firm it is possible that the start-up's founders and owners are recorded as dependent employees and are thus included in the administrative employment data. In the case of a private company, however, the income of the founders is a part of the start-up's profit. In order to avoid a potential bias, we excluded all employees of incorporated firms that are recorded as the start-ups' CEOs. This applies to 308 persons, or 856 person-year observations, in our data set.

[13] For illustrative purposes we report projected wages that are based on daily wages recorded in the administrative data for each employment episode, multiplied by the factor 365, to obtain an approximation of the gross annual wage. Throughout this paper, nominal wages are deflated using the consumer price index and reported in euros of 2006. We decided to use the consumer price index because producer price indices are not available before 2006 for some service sectors covered by our data set.

[14] Note that the level of education of an individual employee can change over time. A change of the highest level of education usually takes place within one calendar year. In order to obtain consistent person-year observations, we always included those individual-level data into our estimation data set that correspond to the employment episode with the highest daily wage.

[15] The shares of the three education categories do not add up to 100% in Table 3. This results from the fact that a small number of employees in the full sample do not have any valid information on their level of education recorded in the Employment Statistics. Employees without valid information on their level of education do not enter the estimation sample but they impact the firm-level shares that are computed using the full sample.

Table 2
Employment transitions into high-tech start-ups.

Indicator	Description	(1) Non-spin-off	(2) Transfer spin-off	(3) Competence spin-off	(4) *t*-test (2) vs. (3) (*p*-value)
Employment of labour market entrants	Average share of workers (%) without any prior employment spell (after January 1, 2000) among the recruits.	8.30%	**10.19%**	8.78%	0.354
Job transitions from unemployment	Average share of unemployed workers (%) among the recruits.	21.32%	**15.63%**	**17.82%**	0.279
Hiring from local labour market	Share of recruits (%) originating from a firm in the local labour market of the start-up.	48.41%	45.37%	48.11%	0.313
Hiring from university or research institute	Share of recruits (%) originating from a university or research institute (identified using 3-dig. NACE codes).	3.46%	**21.02%**	**9.62%**	0.000
Hiring from local university or research institute	Share of recruits (%) originating from a university or research institute (identified using 3-dig. NACE codes) in the local labour market of the start-up.	1.61%	**12.59%**	**4.73%**	0.000
Prior wage	Average gross annual wage (in euros of 2006) in last job prior to joining start-up.	30,668.38	**37,610.29**	**33,513.76**	0.003
Higher wage in high-tech start-up	Share of workers (%) with employment transition into start-ups who earned a higher wage (in euros of 2006) after joining the start-up (wage in entry year).	54.72%	**47.72%**	**48.25%**	0.899

Source: ZEW High-Tech Start-Up Survey, Integrated Employment Biographies of the IAB, authors' calculations.
Figures in columns (2) and (3) printed in bold indicate significant differences from column (1) at the level of statistical significance $p < 0.10$.

Table 3
Employees in high-tech start-ups.

	Non-spin-offs			Competence spin-offs			Transfer spin-offs			Differences across spin-offs	
	Mean	*t*-test non-spin-offs vs. spin-offs		Mean	*t*-test competence s-o vs. non-spin-offs		Mean	*t*-test transfer s-o vs. non-spin-offs		*t*-test transfer s-o vs. competence s-o	
		diff.	p-value		diff.	p-value		diff.	p-value	diff.	p-value
Number of employees [a]	6.193	0.625	0.168	4.989	−1.204	0.018	6.232	0.040	0.952	1.244	0.088
Level of education [b]											
No (completed) training	15.88	−4.09	0.004	21.09	5.21	0.008	18.69	2.81	0.143	−2.40	0.360
Completed vocational training	57.53	19.28	0.000	44.48	−13.04	0.000	31.09	−26.44	0.000	−13.40	0.000
University degree	23.59	−15.13	0.000	31.55	7.96	0.000	46.97	23.38	0.000	15.42	0.000
Employment status [b]											
Trainee	4.56	0.43	0.535	5.06	0.50	0.594	3.06	−1.50	0.102	−2.00	0.104
Mini-jobber	36.51	3.11	0.084	33.77	−2.73	0.258	32.96	−3.55	0.147	−0.82	0.802
Part-time employee	5.30	−1.48	0.113	9.19	3.89	0.007	4.01	−1.29	0.175	−5.18	0.002
Full-time employee	53.64	−2.07	0.267	51.99	−1.65	0.508	59.98	6.34	0.012	8.00	0.018
	100			100			100				
Student workers [b]	1.65	−1.15	0.032	2.04	0.39	0.546	3.66	2.01	0.014	1.62	0.109

Source: ZEW High-Tech Start-Up Survey, Integrated Employment Biographies of the IAB, authors' calculations.
Annual firm-level data averaged over the observation period 2003 to 2008. Firm-year observations: 2455 observations for non-spin-offs, 246 for competence spin-offs, 214 for transfer spin-offs.
[a] Headcounts based on person days per year (1 = 365 person days).
[b] Share (%) of high-tech start-up's total person days.

For all three groups of start-ups, full-time employees account for more than half of a start-up's person days, with transfer spin-offs showing a significantly higher share of full-time employees than the other two groups (lower panel of Table 3). Interestingly, high-tech start-ups heavily rely on mini-jobbers.[16] It is, however, important to emphasise that the data set does not allow us to determine how many hours a part-time employee or a mini-jobber worked for the start-up. A full-time employee and a mini-jobber who were both employed by the start-up for the whole year represent 365 person days each. The last row in Table 3 displays the share of total person days for the small albeit interesting group of student workers. Student workers are a distinctive category of employees because they can exhibit all three levels of education and can work as mini-jobbers or part-time employees.

The occupational structure of high-tech start-ups is informative for the skill-task matches that these firms require. Spin-offs employ a higher proportion of highly skilled technical and engineering staff than non-spin-offs (Table 4, using 12 occupational fields as proposed by Blossfeld, 1987). Transfer spin-offs, which have the

[16] According to German social insurance law, mini-jobbers are marginally employed persons who either work on a short-term contract (less than two months during a year) or who earn a maximum monthly salary of 400 euros (325 euros before 01.04.2003).

Table 4
Employees in high-tech start-ups by occupational fields.

Occupational field		Examples	Non-spin-offs %	Competence spin-offs %	Transfer spin-offs %
1	Agricultural occupations	Farmers, other paper products makers, fishermen	0.36	0.12	0.39
2	Simple manual occupations	Assistants (no further specification), welders, oxy-acetylene cutters, packagers, goods receivers, despatchers	15.38	8.52	5.12
3	Skilled manual occupations	Electrical fitters, mechanics, engine fitters, locksmiths, turners	23.62	13.64	9.91
4	Technicians	Technical draughtspersons, electrical engineering technicians, mechanical engineering technicians	9.08	16.17	13.10
5	Engineers	Electrical engineers, mechanical engineers, motor engineers, chemists, chemical engineers	5.47	9.44	14.14
6	Simple service	Household cleaners, stores and transport workers, warehouse managers, warehousemen	5.57	5.00	2.64
7	Qualified service	Visual, commercial artists, safety testers, artistic and assisting occupations (stage, video and audio)	3.01	0.93	1.21
8	Semi-professions	Journalists, interpreters, translators, librarians, archivists, museum specialists	0.47	0.25	0.33
9	Professions	Economic and social scientists, statisticians, university teachers, lecturers at higher technical schools and academies, legal representatives, advisors	0.52	0.56	4.57
10	Simple commercial and administrative occupations	Office auxiliary workers, salespersons, stenographers, shorthand-typists, typists	4.23	5.68	5.17
11	Qualified commercial and administrative occupations	Office specialists, data processing specialists, wholesale and retail trade buyers, buyers, accountants	27.52	36.17	31.32
12	Managers	Entrepreneurs, managing directors, divisional managers, management consultants, organisers	1.70	2.47	3.19
13	NA	Occupation not reported, unknown (category omitted in regressions)	3.08	1.05	8.92
Total			100	100	100
Person-year observations (estimation sample)			20,803	1620	1817

Source: Integrated Employment Biographies of the IAB, authors' calculations.
The classification of occupations (3-digit level, see Bundesagentur für Arbeit, 1988) is based on occupational fields proposed by Blossfeld (1987). Descriptive statistics based on person-year observations (N = 24,240).

highest share of engineering tasks, are also the type of start-up with the highest R&D and technological intensity (see Table A4 in the Appendix). Nevertheless, the importance of qualified production workers, technical staff and engineers in non-spin-offs underlines the high-tech orientation of these firms. Both spin-offs and non-spin-offs further require employees in services, administrative and commercial tasks. The majority of administrative and commercial jobs demand qualifications usually obtained from university education (e.g., business, logistics, marketing) or at least specific vocational training. Jobs in service fields with lower skill requirements (e.g., cleaning services, office assistants) are often filled with mini-jobbers. The relative importance of managerial jobs and tasks is found to be higher in spin-offs than in non-spin-offs, with transfer spin-offs employing the highest share of management personnel. This difference could result from a lack of applied managerial skills among the team of founders.

Our variable of primary interest is the wage paid to start-ups' employees. Gross annual wages differentiated by employment status are displayed in the upper panel of Table 5. Full-time employees in both groups of spin-offs earn significantly higher wages than full-time employees working for non-spin-offs. Since we do not know the actual working hours, differences in gross annual wages for part-time employees or mini-jobbers can result from both varying remunerations per working hour or varying numbers of hours these workers are contracted to work per day or per week. Full-time employees who hold a university degree receive significantly higher wages in spin-offs than in non-spin-offs, whereas there is no difference between the two groups of spin-offs (lower panel of Table 5). Full-time employees with a university degree earn 12% more in spin-offs than their counterparts in non-spin-offs. For both employees without qualification and employees with completed vocational training, there are no significant wage differentials between spin-offs and non-spin-offs.

5. Econometric model

5.1. Estimation method

We estimate logarithmic daily (gross) wages using the instrumental-variable estimator developed by Hausman and Taylor (1981). As a panel estimator, it allows for individual specific effects capturing unobserved factors that are not entirely reflected by the control variables of the regressions. The advantage of the Hausman-Taylor (HT) estimator is that it allows for some covariates to be correlated with the individual-specific random effect. Moreover, it enables us to estimate the effect of time-invariant regressors including our core indicator variables for competence and transfer

Table 5
Gross annual wages by employment status and level of education.

	Non-spin-offs			Competence spin-offs			Transfer spin-offs			Differences across spin-offs	
	Mean	*t*-test non-spin-offs vs. spin-offs		Mean	*t*-test competence s-o vs. non-spin-offs		Mean	*t*-test transfer s-o vs. non-spin-offs		*t*-test transfer s-o vs. competence s-o	
		diff.	p-value		diff.	p-value		diff.	p-value	diff.	p-value
Employment status											
Trainee	6,513.12	552.62	0.059	5,856.34	−656.78	0.082	6,110.35	−402.77	0.360	254.01	0.531
Mini-jobber	3,861.09	−253.63	0.058	3,581.79	−279.31	0.119	4,656.34	795.24	0.000	1,074.55	0.001
Part-time employee	13,771.32	−2,451.60	0.053	16,983.19	3,211.87	0.044	14,917.79	1,146.47	0.529	−2,065.40	0.459
Full-time employee	30,589.71	−4,461.09	0.000	33,354.18	2,764.48	0.001	36,360.09	5,770.38	0.000	3,005.91	0.010
Student worker	8,418.56	−231.82	0.756	9,471.93	1,053.37	0.385	8,257.08	−161.47	0.844	−1,214.84	0.439
Level of education (full-time employees only)											
No (completed) training	25,817.36	−1,294.76	0.320	25,660.08	−157.28	0.927	28,594.41	2,777.04	0.114	2,934.33	0.317
Completed vocational training	28,601.86	−811.41	0.253	28,953.16	351.30	0.719	29,913.31	1,311.45	0.181	960.15	0.470
University degree	37,056.80	−4,466.72	0.000	41,289.86	4,233.07	0.007	41,647.79	4,590.99	0.000	357.93	0.846

Source: ZEW High-Tech Start-Up Survey, Integrated Employment Biographies of the IAB, authors' calculations.
Wages are reported in euros of 2006. Standard errors for *t*-tests are cluster-adjusted for the clusters on the level of the individual employee.

spin-offs, which is not possible with the fixed-effects estimator.[17] Hausman and Taylor consider the following model to explain the dependent variable *y* (the logarithmic daily gross wage in our case):

$$y_{it} = X_{Ex\_it}\beta_1 + X_{En\_it}\beta_2 + Z_{Ex\_i}\delta_1 + Z_{En\_i}\delta_2 + \mu_i + \varepsilon_{it} \quad (1)$$

with $i = 1, \ldots, N$ indicating the number of individuals (employees) and $t = 1, \ldots, T_i$ indicating the number of years individual i is observed. μ_i is the unobserved individual-specific random effect with mean zero and finite variance σ_μ^2 and is independently and identically distributed over the individuals. ε_{it} is an idiosyncratic error term with mean zero and finite variance σ_ε^2 that is independently and identically distributed over all observations in the data set. The k covariates in $X = [X_{Ex}; X_{En}]$ are time-varying, whereas the g covariates in $Z = [Z_{Ex}; Z_{En}]$ are time-invariant. All covariates in X and Z are assumed to be uncorrelated with ε_{it}. Hausman and Taylor decompose the vectors of covariates X and Z so that

X_{Ex_it} is a vector of k_1 time-varying variables that are uncorrelated with μ_i (exogenous variables),

X_{En_it} is a vector of k_2 time-varying variables that are correlated with μ_i (endogenous variables),

Z_{Ex_i} is a vector of g_1 time-invariant variables that are uncorrelated with μ_i (exogenous variables),

Z_{En_i} is a vector of g_2 time-invariant variables that are correlated with μ_i (endogenous variables).

For this model, Hausman and Taylor derived an instrumental-variable estimator, using X_{Ex_it}, Z_{Ex_i}, $\left(X_{En\_it} - \overline{X_{En\_i}}\right)$ and $\overline{X_{Ex\_i}}$ as instruments with $\overline{X_{\_i}}$ as the individual-specific means. Hence, the exogenous variables that are uncorrelated with μ_i serve as their own instruments. The time-varying variables X_{En_it} are instrumented by the deviations from their individual-specific means (within transformation), and the time-invariant variables Z_{En_i} are instrumented by the individual-specific means $\overline{X_{Ex\_i}}$. For the coefficients of Z_{En_i} to be identified, the number of variables in X_{Ex_it} must be at least as large as the number of variables in Z_{En_i}, i.e. $k_1 \geq g_2$. Moreover, there must be sufficient correlation between the instruments and the variables in Z_{En_i} to avoid a weak-instrument problem (Baltagi, 2013; Hausman and Taylor, 1981). The assumption of strictly exogenous regressors that are used as instruments can be directly tested using Hausman tests against the fixed-effects model as noted by Baltagi et al. (2003).

The HT estimator has been applied in various studies to estimate wage equations (e.g., Heineck, 2005; Light and Ureta, 1995; Salehin and Breunig, 2012). The estimator is also appropriate for our study since the Hausman tests that compare the fixed-effects models and the random-effects models reveal that some variables are correlated with the individual-specific random effect μ_i (see Section B.3 in the Supplementary online Appendix).

5.2. Explanatory and control variables

In the HT estimations, the vector of explanatory variables contains both employee-specific and employer-specific variables.[18] As a general rule, we treat employee-specific variables as endogenous, i.e., as correlated with the individual-specific random effect μ_i. The only exceptions to this rule are two time-invariant dummy variables indicating the employee's gender and citizenship that are modelled as exogenous variables. Employer-specific variables, on the contrary, whether time-varying or time-invariant, are assumed to be exogenous to the individual-specific random effect.

At the individual level our main time-varying, endogenous regressors are the three levels of education (see Section 4.2). Moreover, we control for employee age, firm tenure, occupational fields and a dummy variable indicating censored wages (see Table A3 for details). Since we do not know how many hours a part-time employee or a mini-jobber is working per day, the regression equation we use to estimate the daily gross wage of all employees includes additional, time-varying controls identifying the different employment statuses with full-time employees as the base category. Moreover, the wage equation for all employees contains a time-varying dummy variable indicating employment episodes of student workers.

The only time-invariant, endogenous variable measured at the employee level is the duration (in days) of a potential unemployment episode before entering the start-up. This variable captures the fact that prior unemployment is assumed to reduce the reservation wage the employee is willing to accept when joining the start-up.

All employer-specific variables are treated as exogenous. In the first place we include the two indicator variables identifying trans-

[17] The HT estimator was chosen following a thorough model-selection process. For details please refer to section B.3 in the Supplementary online material.

[18] Table A3 in the Appendix provides details about the generation of all explanatory and control variables used in our econometric analysis. In Table A4 in the Appendix, we present the related summary statistics of the variables for non-spin-offs, competence spin-offs and transfer spin-offs and document the data source of the variables.

fer and competence spin-offs. In order to account for potential sorting of employees with different education levels into different types of start-ups, we composed interaction terms between the two spin-off variables and the dummy variables reflecting an employee's level of education. In the wage equation for all employees, we also added an interaction term with the variable that identifies student workers (see Section 4.2).

Further firm-level variables are generated to control for heterogeneity of performance indicators that affect wage determination across start-ups. We plug in time-invariant controls for firm-level R&D activities, industry sector and dummy variables that characterise the start-up's team of founders. The set of time-varying firm characteristics comprises firm size, the share of workers that hold a university degree, the share of trainees and the availability of external equity from private investors.[19] However, most time-varying, exogenous variables (the instruments) show a low correlation with the time-invariant, endogenous duration of prior unemployment. Therefore, we also include the share of previously unemployed workers that is, by design, highly correlated with the individual-specific duration of prior unemployment so that we avoid a weak-instrument problem.

We further control for differences in the structural type of the regions start-ups are located in (like core cities or rural areas) and include an indicator for East Germany. We also plug in year dummies to account for temporal variations in the business cycle.

The credibility of the results of the HT estimator strongly depends on the choice of which variables are treated as exogenous and endogenous, respectively. Assuming exogeneity means that a variable is not correlated with the individual-specific random effect μ_i, which reflects characteristics of the individual employee that are not captured by observed individual-specific variables but that may nevertheless impact individual wages. Examples of unobserved factors are motivation, work enthusiasm and effort or unobserved differences in capabilities and labour productivity. Our choice to treat firm-specific variables as exogenous is in line with previous research using the HT estimator (Baltagi and Khanti-Akom, 1990; Heineck, 2005). It can also be justified on *a priori* grounds. For instance, it can be assumed that an employee's motivation and work effort does not depend on whether the employer uses equity from business angels or cash flow to pay the employee's salary. Classifying the employee's gender and origin (ethnicity in studies for the US, citizenship in our case) as exogenous also corresponds to extant literature (Baltagi and Khanti-Akom, 1990; Hausman and Taylor, 1981; Light and Ureta, 1995).

6. Econometric results

The econometric results of the wage regressions are reported in Table 6, where we first show a sequence of models using the sample of full-time employees only. We present several base-line regressions to show the base effects of the education levels and spin-off types on wages. By introducing interaction terms of these variables we account for sorting of employees with different education levels. Our main results that include these interaction terms are drawn from the HT estimation depicted in model IV a. Since almost half of the start-ups' total person days relate to employees who do not work full time we present the estimation of the main specification for the sample of all employees as a robustness check (model IV b).

Table 7 displays the wage differentials for competence and transfer spin-offs based on the main specifications. All differentials are computed as average marginal effects, considering the various interactions between spin-offs and education levels. For example, the wage differential for university graduates of transfer spin-offs compared to employees with a university degree working for a non-spin-off is given by the linear combination of the coefficient for transfer spin-offs plus the coefficient of the interaction term for transfer spin-offs and university graduates.[20]

6.1. Main results and robustness tests

The base-line OLS specification (I) that uses only firm level regressors shows that wage differentials of full-time employees across high-tech start-ups are mostly captured by the firm-level controls, while the type of spin-off is not statistically significant. In the subsequent model (II), we use the HT estimator to provide base-line estimates for the individual returns to education while controlling for employee and job characteristics. In line with extant human capital literature, we find significantly positive returns to education for the completed vocational training and university degree categories. In model (III), the full scope of our LEE data is exploited. Introducing additional variables that account for the different spin-off types and a comprehensive set of firm-level controls does not change the significance or the magnitude of the individual returns to education. The spin-off type dummies indicate a positive wage differential of 9.3% (coefficient 0.090) for full-time employees in transfer spin-offs compared to employees in non-spin-offs that is significant at the 10% level of significance.

In our main specification (Table 6, model IV a), we address the effect of sorting on wages by estimating a model that includes all interactions between education levels and spin-off types. Two main findings are evident: First, in contrast to the descriptive results, spin-offs show very little differences in their wage levels compared to non-spin-offs. Second, for full-time employees, most wage differentials as indicated by the interactions with competence and transfer spin-offs are insignificant. There is, however, one notable exception to this pattern: The positive coefficient found for transfer spin-offs in the previous specification is now entirely picked up by the interaction term of university graduates and transfer spin-offs. Working for a transfer spin-off is associated with a significant wage premium of 14.0% for employees with a university degree when compared with university graduates working for a non-spin-off (left column of Table 7). Although the point estimate of the wage differential for university graduates is much higher for transfer spin-offs than for competence spin-offs, this difference is statistically not significant (standard error of the difference: 0.088; t-value = 1.21).

The overall wage differential (averaged over all three groups of start-ups) for university graduates compared to employees without (completed) training amounts to 3.6% and is significant at the 1% level of significance. This wage differential can be interpreted as a return to university education. Similarly, the wage differential for employees with completed vocational training amounts to 3.1%, again significant at the 1% level.[21]

The results for the remaining covariates accord with the literature and are documented in Table A5 in the Appendix. However, two findings deserve particular attention given the theoretical background of the paper. First, the intensity of R&D activities is

[19] Informal equity from private investors (e.g. business angels) is much more widespread among high-tech start-ups than formal equity from VC funds (Fryges et al., 2007). In our regression, we therefore control for informal equity financing only.

[20] Throughout this paper, all wage differentials that show the relationship between a dummy variable and the level of wages in our semilogarithmic regression equations are transformed as proposed by Kennedy (1981). The approximate unbiased variance estimator of the transformed wage differentials was derived by van Garderen and Shah (2002, Eq. 2.4).

[21] The two marginal effects, i.e. the returns to education for university graduates and employees with a vocational training respectively, are not significantly different from each other (standard error of the difference: 0.010; t-value = 0.427).

Table 6
Determinants of the (logarithmic) daily gross wage.

	Full-time employees				All employees
Specification	(I)	(II)	(III)	(IV a)	(IV b)
Estimator	OLS	HT	HT	HT	HT
Education: no (completed) training		*ref.*	*ref.*	*ref.*	*ref.*
Completed vocational training	–	0.031***	0.028**	0.029**	−0.012
		(0.012)	(0.012)	(0.012)	(0.013)
University degree	–	0.03**	0.033***	0.027**	0.012
		(0.012)	(0.013)	(0.013)	(0.015)
Employment status: full time-employee					*ref.*
Trainee	–	–	–	–	−0.957***
					(0.022)
Part-time worker	–	–	–	–	−0.463***
					(0.017)
Marginal worker	–	–	–	–	−1.751***
					(0.012)
Student worker	–	–	–	–	0.773***
					(0.031)
High-tech start-up: non-spin-off	*ref.*		*ref.*	*ref.*	*ref.*
Competence spin-off	0.026	–	0.029	0.031	0.016
	(0.027)		(0.057)	(0.069)	(0.058)
Transfer spin-off	0.006	–	0.090*	0.017	0.140**
	(0.024)		(0.053)	(0.075)	(0.057)
Interaction effects					
Competence s.-o. × compl. voc. training	–	–	–	0.002	−0.074
				(0.048)	(0.050)
Competence s.-o. × university degree	–	–	–	0.030	−0.077
				(0.059)	(0.052)
Transfer s.-o. × compl. voc. training	–	–	–	−0.003	−0.089
				(0.052)	(0.055)
Transfer s.-o. × university degree	–	–	–	0.115*	0.013
				(0.061)	(0.043)
Competence s.-o. × student worker	–	–	–	–	0.082
					(0.104)
Transfer s.-o. × student worker	–	–	–	–	0.056
					(0.056)
Employee social demographics	No	Yes***	Yes***	Yes***	Yes***
Job characteristics	No	Yes***	Yes***	Yes***	Yes***
Occupational fields dummies	No	Yes***	Yes***	Yes***	Yes***
Firm characteristics	Yes***	No	Yes***	Yes***	Yes***
Industry sector dummies	Yes***	No	Yes***	Yes***	Yes***
Structural type of region dummies	Yes***	Yes***	Yes***	Yes***	Yes***
Observation year dummies	Yes***	Yes***	Yes***	Yes***	Yes***
Integer	4.126***	−4.846***	−5.066***	−5.071***	−0.681
	(0.038)	(0.896)	(0.869)	(0.869)	(0.829)
Hausman test (fixed effects vs. HT)	–	$\chi^2(4) = 8.71$	$\chi^2(18) = 21.66$	$\chi^2(18) = 21.65$	$\chi^2(18) = 23.74$
		p = 0.069	p = 0.248	p = 0.248	p = 0.164
R^2	0.244	–	–	–	–
σ_μ	–	1.428	1.223	1.219	1.328
σ_ε	–	0.139	0.139	0.139	0.221
ρ	–	0.991	0.987	0.987	0.973
Person-year observations	16,082	16,082	16,082	16,082	24,240
Number of employees	6215	6215	6215	6215	9815

Source: ZEW High-Tech Start-Up Survey, Integrated Employment Biographies of the IAB, authors' estimations.
σ_μ: Standard error of the individual-level random effect; σ_ε: Standard error of the idiosyncratic error term; ρ: Fraction of variance attributed to μ_i.
Levels of statistical significance for control variables are obtained from Wald F-tests of joint significance.
*/**/*** 10%/5%/1% level of significance; standard errors clustered at the individual level in parentheses.

insignificant, both individually for the two intensity categories and jointly (test of joint significance: χ^2 (2) = 0.63; (p > χ^2) = 0.731). Apparently, R&D-intensive start-ups do not pay higher wages per se. If individual employees involved in R&D activities receive higher wages this is likely to be captured by sorting that operates via the employee's occupation or level of education. Second, the estimates reveal that wage levels are affected by the availability of informal equity from external investors. The dummy variable capturing the fact that the high-tech start-up has received informal equity financing shows a significantly positive relationship with wage levels of full-time employees. This finding is in line with studies that suggest a link between equity financing and recruitment policies or the provision of wage incentives.

Model IV b shows the results for the main specification using the unrestricted sample of all employees instead of full-time employees only. Despite some slight changes in the coefficients of the interactions (see Table 6 and Table A5, IV a and IV b), the wage differentials indicated by the average marginal effects remain robust to the extension of the sample (right column of Table 7). In accordance with the results for full-time employees, we do not find any significant wage differentials for employees in competence spin-offs. Transfer spin-offs, however, pay their university graduates significantly higher wages. The estimated wage differential is 16.4% and thus slightly exceeds the corresponding value in the model for full-time employees. Contrary to our previous results, we also discover a significantly positive wage differential of 14.9% for employees without (completed) training. As a result, the overall relationship

Table 7
Wage differentials of competence and transfer spin-offs.

	Full-time employees			All employees		
	Wage differential in %	Std.error		Wage differential in %	Std.error	
Transfer spin-offs	7.09	5.74		10.37	5.25	**
Competence spin-offs	2.95	5.91		−4.74	4.48	
Transfer spin-offs						
No (completed) training	1.49	7.56		14.93	6.52	**
Completed vocational training	4.72	5.96		6.39	5.81	
University degree	14.01	6.33	**	16.44	5.96	***
Student worker	–	–		16.43	8.22	**
Competence spin-offs						
No (completed) training	2.86	7.04		1.63	5.86	
Completed vocational training	3.08	6.33		−5.61	5.03	
University degree	2.57	6.66		−7.02	5.54	
Student worker	–	–		2.72	11.31	

Source: ZEW High-Tech Start-Up Survey, Integrated Employment Biographies of the IAB, authors' estimations.
Wage differentials (average marginal effects) for discrete change of dummy interactions. Average marginal effects are transformed according to Kennedy (1981), standard errors are computed according to van Garderen and Shah (2002).
/* 5%/1% level of significance.

between being a transfer spin-off and wages is positive and significant in the model for all employees (wage differential of 10.4%).[22]

A driver for the positive wage differential for employees without training could be student workers employed by transfer spin-offs. Student workers are almost exclusively classified as employees without a vocational degree. As Table 7 displays, the regression results indicate a wage differential of 16.4% for student workers in transfer spin-offs, similar to the size of the wage differential for university graduates. It has to be noted, however, that the number of student workers in our sample is rather small. Therefore, the estimated size of the wage differential for student workers should be interpreted with caution since it may overestimate the true value.

In order to further assess the robustness of our results, we tested two alternative specifications of our regression models. First, in our data we cannot distinguish between managers hired by the start-ups' owners and the founders themselves who work in their firm as owner-managers. To avoid biased estimates that might arise from the inclusion of owner-managers, we excluded 3.4% person-year observations from the initial sample referring to employees that were recorded as the start-ups' CEOs.[23] However, we regard employed CEOs as an important group of start-ups' employees that ought to be considered in our analysis, not least because they are likely to earn above-average wages. Therefore, we re-estimated the models including all person-year observations of CEOs as a robustness check. Our main results regarding the wage premia paid by transfer and competence spin-offs remain unchanged.

In a second alternative specification of the HT models we switched the two time-invariant dummy variables indicating gender and citizenship from the group of exogenous to the group of endogenous variables. The two indicators were the only individual-specific variables that were treated as exogenous, although it can be argued that these two variables might also be correlated with the individual-specific random effect. The choice of exogenous variables is crucial for the credibility of the HT model and might therefore affect our results. Re-estimating the model shows that the wage premia for transfer and competence spin-offs are essentially the same as in our preferred model. However, based on the alternative specification the estimated wage differentials due to gender and citizenship are implausibly high, presumably because of a weak-instrument problem.

We evaluate the validity of all specifications that apply the HT estimator by using a Hausman test as proposed by Baltagi (2013). The test statistics are χ^2-distributed with $(k_1 - g_2)$ degrees of freedom.[24] As reported in Table 6, the null hypotheses of no systematic difference between the fixed-effects specification and the HT model cannot be rejected, confirming the validity of our HT estimations.

6.2. Researcher and student spin-offs

This paper focuses on two groups of spin-offs that differ from one another by the kind of knowledge that is transferred from the incubator university to the newly founded spin-off. But spin-offs are defined by two dimensions. In this section, we investigate an alternative definition that distinguishes between spin-offs founded by (former) researchers and those set up by students (Pirnay et al., 2003; Rappert et al., 1999; Smilor et al., 1990).[25] On the one hand, this analysis serves as a robustness check since it allows us to test whether our previous results depend on our definition of spin-offs. On the other hand, we extend our previous analysis by examining whether higher wages paid by certain spin-offs depend on the founder's academic background.[26]

It is reasonable to expect that the wage-setting behaviour of researcher spin-offs differs from that of student spin-offs. Lacetera (2009) argues that academic scientists possess a full set of opportunities that they have developed during their scientific career. If

[22] In contrast to the model for full-time employees, the wage equation for all employees does not indicate a general return to education. Summarising over all three groups of start-ups, the wages of employees with a university degree do not differ from those without training. Employees with vocational training even appear to earn 2.3% less than unskilled workers, although the difference is significant only at the 10% level of significance. A reason for this result might be that the level of education is correlated with the employment status (e.g. mini-jobbers are more likely to be unskilled workers).

[23] The bias can go in both directions. Founders may earn disproportionately high wages compared to the rest of the workforce. However, founders may also relinquish their own wage to reduce the costs of the firm in the early years of firm existence. There is indeed some evidence that supports a downward bias of wages due to founders working as owner-managers. Almost 20% of the CEOs in the initial sample receive a wage that is below the median wage of full-time workers. Nevertheless, on average wages of CEOs are almost 40% higher than wages of other full-time employees and the percentage of censored wages is about five times higher (5% vs. 26%).

[24] A more detailed description of the validation tests is provided in Section B.3 of the Supplementary online Appendix.

[25] We distinguish between researcher spin-offs and student spin-offs based on questions 1 and 2 in Table A1 in the Appendix, assuming that founders who hold a university degree and were employed by a university worked there as researchers.

[26] It is important to note that both researcher spin-offs and student spin-offs are required to commercialise university knowledge in the form of either new research results or specific skills. Thus, the sample of spin-offs in this section is identical with that investigated in previous sections.

Table 8
Wage differentials of researcher and student spin-offs.

	Full-time employees	
	Wage differential in %	Std.error
Researcher spin-offs	6.03	7.80
Student spin-offs	6.47	5.17
Researcher spin-offs		
No (completed) training	3.75	10.58
Completed vocational training	6.36	9.13
University degree	5.77	8.26
Student spin-offs		
No (completed) training	3.57	6.48
Completed vocational training	4.19	5.32
University degree	12.24	5.80**

Source: ZEW High-Tech Start-Up Survey, Integrated Employment Biographies of the IAB, authors' estimations.
Wage differentials (average marginal effects) for discrete change of dummy interactions. Average marginal effects are transformed according to Kennedy (1981), standard errors are computed according to van Garderen and Shah (2002).
/* 5%/1% level of significance.

a researcher decides to leave academia and to commercialise one of their research results, she/he can pick the opportunity with the highest expected revenue. This leads to a better performance of researcher spin-offs and, as a consequence, to an improved ability to pay higher wages. PhD students, on the contrary, develop only the limited scope of research results that is related to their PhD project.

On the other hand, some scholars argue that the human capital of academic scientists is "too academic" (Czarnitzki et al., 2014; Dasgupta and David, 1994; Nelson, 2004). This may suggest that researcher spin-offs may lack commercial and managerial skills, leading to inferior performance compared to other start-ups (Wennberg et al., 2011). Conversely, students may have gained these skills by attending courses in entrepreneurship or business while studying at university. The literature further suggests that spin-offs differ in terms of their innovation capabilities based on the human capital of the entrepreneurs (Czarnitzki et al., 2014; Zucker et al., 2002). Thus, a possible structural sorting process of employees into R&D-related tasks and working conditions might be more relevant for spin-offs founded by academic scientists than for student spin-offs.

In our sample, 30% of all spin-offs were founded by (former) researchers, while 70% are student spin-offs. Student spin-offs dominate the group of competence spin-offs (86% vs. 14%), whereas transfer spin-offs were set up in equal parts by researchers and students (presumably PhD students). The wage differentials derived from the HT estimation are displayed in Table 8 (full-time employees only).[27]

In accordance with our previous results, there is no general wage premium – neither for researcher spin-offs nor for student spin-offs. We find a significantly positive wage differential of 12% for university graduates working for student spin-offs. The remaining wage differentials for the different levels of education are not significant. The Hausman test on the validity of our model cannot reject the null hypothesis of no systematic difference between the fixed-effects model and the HT model (χ^2 (18) = 21.68; ($p > \chi^2$) = 0.246).

[27] We restrict this robustness check to full-time employees only because there are almost no student workers employed by spin-offs that were founded by former students. Moreover, in the model with all employees the Hausman test on the validity of the HT estimator rejects the null hypothesis of no correlation between the time-varying, exogenous variables and the individual-specific random effect ((χ^2 (18) = 433.08; ($p > \chi^2$) = 0.000). The results of the HT estimator are available from the authors on request.

6.3. Discussion

The most important result of our econometric analysis is that although there is no general relationship between spin-offs and wage levels, we find a significant correlation for a very particular group of employees, namely university graduates working for transfer spin-offs. One implication of this result is that the relationship between spin-offs and wages depends on the nature and level of the knowledge transferred from the incubator university to the spin-off.

Generally speaking, the mechanisms that determine the wage levels of university graduates are the same in both transfer spin-offs and competence spin-offs and, as the literature review revealed, work in opposing directions. Our results show that positive and negative effects on wages are balanced for competence spin-offs. For university graduates in transfer spin-offs, on the contrary, a potential negative relationship between transfer spin-offs and wages is unambiguously dominated by an opposing positive link. From both a theoretical and an empirical point of view this is not necessarily the expected result. Many theoretical reasons that argue for lower wages (e.g. willingness to accept lower wages in R&D-intensive environments) apply particularly to university graduates working in a transfer spin-off. The descriptive analysis shows that transfer spin-offs are more R&D-intensive than competence spin-offs and that they employ a higher number of employees who transitioned from a position at a university to the transfer spin-off, militating in favour of a negative relationship between transfer spin-offs and wages.

Nevertheless, for university graduates working at transfer spin-offs positive links are more important. Transfer spin-offs require highly specialised university graduates. The hiring pattern of transfer spin-offs reveals that they have a higher demand for employees from occupational fields like engineering and the professions (i.e. statisticians or economic and social scientists). The highly specific knowledge that transfer spin-offs demand involves sorting of specialised employees who demand higher wages than employees with more general knowledge. Moreover, the salaries earned by employees in their last job before joining a transfer spin-off exceed the salaries paid to employees of competence spin-offs in their previous job. Therefore, the opportunity costs of joining a transfer spin-off are higher and potential employees will thus claim higher wages. Transfer spin-offs are also more likely to receive external equity, increasing their ability to pay those higher wages. Assuming further that employees are remunerated according to their marginal value product, the estimated wage differential partly captures unobserved productivity differentials of university graduates working for different types of high-tech start-ups.

The literature provides us with additional arguments that we cannot rule out as explanations for the positive wage differential of university graduates working for transfer spin-offs but that cannot be backed by the empirical data available. The perceived risk of failure could be higher for transfer spin-offs than for competence spin-offs. If we interpret a start-up's R&D intensity as an indicator of the riskiness of its business model, we have evidence that the business models of transfer spin-offs are riskier than those of competence spin-offs. However, we do not know whether riskier business models lead to a higher perceived risk of failure among employees of transfer spin-offs. Similarly, it is likely that the competition with incumbent firms for the highly specialised employees that transfer spin-offs require affects the wage differential for university graduates, but we cannot prove this notion by empirical data.

A remarkable result of our econometric analysis is that the estimated wage differential for university graduates working for transfer spin-offs is even slightly higher than the average wage differential discovered by the descriptive analysis (14% based on the econometric estimation for full-time employees, compared to 12% according to Table 5). The estimated relationship measures the wage differential after controlling for employee-specific and employer-specific characteristics. In other words, university graduates with the same socio-demographic characteristics would earn 14% higher wages working for a transfer spin-off than working for a non-spin-off with the same firm characteristics. Another result we find is that transfer spin-offs not only employ younger workers (average age of full-time employees in transfer spin-offs is 36 years; in non-spin-offs, 39 years) and more job-market entrants, they also have more female employees. In transfer spin-offs, 26% of person days are performed by female full-time employees, as compared to 22% in non-spin-offs.

In contrast to university graduates, wages of both unskilled employees and employees with completed vocational training do not differ between transfer spin-offs, competence spin-offs and non-spin-offs. Unskilled employees, many of them in casual employment, may not demand a wage premium for a perceived higher risk of failure of a spin-off. Similarly, unskilled workers are unlikely to have a preference for a more science-related working environment. Employees who have completed vocational training may demand compensation for a perceived higher risk of firm failure. Some employees with vocational education possess specialised knowledge and perform skilled tasks. However, most employees in this category work in occupations (e.g. simple manual or administrative occupations) that are unrelated to the technological core of a high-tech start-up. These employees can easily be substituted, so that neither transfer nor competence spin-offs are willing to pay higher wages than non-spin-offs.

The wage regression for all employees reveals that student workers benefit from the higher wages paid by transfer spin-offs. Although the number of student workers in our data set is small, we conclude that transfer spin-offs provide higher wages to all employees with ties to the university sector – either as students or as graduates. This mirrors the strong links of transfer spin-offs to the university sector. The descriptive analysis further shows that in our data set student workers are almost exclusively employed by researcher spin-offs. It is likely that former researchers employ students because they have specialised knowledge in the technological field of the spin-off because the researchers have educated the students and already worked with them at the incubator university. For this specialised knowledge, they are willing to offer a monetary incentive. Indeed, we observe student workers who have an employment spell in a university before they enter a spin-off. Moreover, we observe some students who work for a transfer spin-off in one year returning to the same transfer spin-off in later years. Transfer spin-offs not only require university graduates with specialised knowledge, they are able to find and hire those university graduates due to their close and enduring contacts to the university sector.

The alternative specification estimating the wage differential between student spin-offs and researcher spin-offs indicates that university graduates earn significantly higher wages in spin-offs founded by students. It is likely that this result is driven by transfer spin-offs founded by PhD students, since competence spin-offs do not pay higher wages. Spin-offs founded by former researchers and PhD students are likely to require a similar specificity of knowledge and human capital, so that theory would suggest that both types of spin-offs pay a positive wage premium. However, as demonstrated in the previous paragraph, researcher spin-offs take advantage of the internal university labour market by hiring their former students and job-market entrants leaving university. Conversely, spin-offs set up by PhD students rely more on the external labour market. Thus, potential employees of student spin-offs have higher opportunity costs and demand higher wages.

7. Conclusions and implications

In this paper, we study wage differentials between transfer spin-offs, competence spin-offs and other high-tech start-ups in Germany using unique linked employer-employee data. From a theoretical point of view, there is no unambiguous prediction of whether wages paid by spin-offs should be higher or lower than those paid by non-spin-offs. The descriptive analysis reveals that on average full-time employees in both competence and transfer spin-offs receive higher wages than their counterparts in non-spin-offs. Applying the HT instrumental-variable estimator, we find that for competence spin-offs the descriptive wage differential can be explained by employee-specific and employer-specific characteristics. For transfer spin-offs there is no general relationship between being a transfer spin-off and the wage level either. However, the econometric analysis yields a wage premium of 14% for university graduates working for a transfer spin-off over equally educated employees working for a non-spin-off. Moreover, student workers, who are an important way to maintain close ties with the university sector, earn significantly higher wages in transfer spin-offs, too.

We extend the existing literature by presenting the first evidence on wages paid by spin-offs. Moreover, the paper provides first insights on recruitment and remuneration policies of spin-offs and high-tech start-ups in general. Whereas existing studies focus on the team of founders of high-tech start-ups, our unit of analysis is the individual employee, her/his monetary incentives to join a high-tech start-up and the occupations she/he performs within a start-up.

Our study also contributes to the academic discussion on whether spin-offs exhibit a higher employment growth rate than other start-ups and offers a possible explanation of why many empirical studies find that spin-offs do not grow faster. We do not argue that higher wages are *per se* an obstacle for the growth of spin-offs. However, from a static perspective a spin-off with a fixed budget faces a trade-off between investing in an additional recruit and paying higher wages to its current workforce. In other words, with a fixed budget, transfer spin-offs, which depend on the specific human capital of their (more expensive) university graduates, can only employ a smaller number of employees. Of course, our analysis does not rule out that from a dynamic perspective transfer spin-offs are able to set a higher mark-up on their product prices because of their technological leadership. In this case, transfer spin-offs might be able to generate additional financial resources both to pay higher wages and to hire more employees in order to grow faster than non-spin-offs.

From a policy perspective, our paper provides policy makers with an additional indicator in the evaluation of academic entrepreneurship. Governmental policies that promote the formation of spin-offs can only be justified if the social costs involved in the foundation of a spin-off (e.g. from lost knowledge accumulation and disclosure in the university sector) are offset by the social benefits generated by spin-offs (Czarnitzki et al., 2014). This study provides first evidence that spin-offs generate more social benefits than non-spin-offs in terms of higher wages, so that at least some social costs of spin-off formation can be compensated by a mechanism that is endogenously related to academic spin-offs. However, these benefits are confined to transfer spin-offs and to employees that emanate from the university sector, i.e. university graduates and student workers.[28]

[28] Please note that we do not make any statement about whether higher wages for a particular group of employees are socially desirable. We argue that *ceteris paribus* better paid jobs are socially more desirable than poorly paid jobs. Nevertheless, as pointed out by an anonymous reviewer, there might be a trade-off because higher wages may lead to a lower return on investment (ROI) on the production factor

One limitation of our study is that we observe a limited number of spin-offs, notably 55 transfer spin-offs with more than 1800 person-year observations only. Therefore, we cannot fully account for the heterogeneity of transfer spin-offs, for instance those whose foundation is financially supported by the government or spin-offs that are granted a patent or licence by their incubator university. Our analysis is further limited by the cross-sectional nature of the survey. Firm-level variables like the amount of R&D expenditures and, in particular, information on a start-up's financial situation (e.g., cash flow, debt financing) is not available in a panel data format. Longitudinal information on different sources of financing would improve our ability to measure a start-up's ability to pay and, in this way, to account for an important source of heterogeneity of spin-offs (Mustar et al., 2008).

Another shortcoming is that our sample might suffer from a potential survival bias. Since the firm-level data were collected in 2007 by a survey, we know that all start-ups survived at least until 2007, and our firm sample is representative for these "successful" start-ups only. If it is true that non-spin-offs are less likely to survive, our results might be biased downwards because we compare spin-offs with a sample of disproportionately "successful" non-spin-offs. Moreover, if the survival of a firm is endangered this may affect wages even in years before the actual market exit of the firm, e.g. in case the firm reduces wages or wage growth with the goal of ensuring survival. The question of how the probability of survival and the occurrence of a company crisis are related to both the wage level of spin-offs and its development over time is a topic for future research.

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Appendix A.

Table A1
Identification and definition of academic spin-offs.

Wording of questions that identify academic spin-offs	
1 Did the founder study at a university or does she/he currently study?	☐ yes ☐ no
2 After finishing her/his education, was the founder employed by a university or by a public research institution?	☐ yes ☐ no
3 I will read out several factors that might have been relevant for the formation of your firm. Please tell me whether these factors were 'essential', 'of great importance', or 'of minor or no importance.'	
3–1 Specific skills that the founder has acquired during her/his employment at the scientific institution. Specific skills that the founder has acquired during her/his university studies.	☐ essential ☐ great importance ☐ minor/no import.
3–2 New scientific methods or techniques which the founder has acquired during her/his activities at the scientific institution. New scientific methods or techniques which the founder has acquired during her/his university studies.	☐ essential ☐ great importance ☐ minor/no import.
3–3 Results of the founder's own research activities at the scientific institutions, for instance, the development of a new product or service. New research results the founder herself/himself contributed to during her/his university studies.	☐ essential ☐ great importance ☐ minor/no import.
Definition of academic spin-offs	
Competence spin-offs: The founder either must have studied or must have worked at a university or public research institution (answer "yes" to question 1 or question 2) AND specific skills must have been essential for the formation of her/his firm (answer "essential" to questions 3-1). Transfer spin-offs: The founder either must have studied or must have worked at a university or public research institution (answer "yes" to question 1 or question 2) AND new scientific methods or new research results must have been essential for the formation of her/his firm (answer "essential" to question 3-2 or question 3-3).	

Source: ZEW High-Tech Start-Up Survey 2007.

Table A2
Composition of high-tech industry sectors.

	Industry sector	NACE Rev. 1
1	Cutting-edge technology manufacturing	23.3, 24.2, 24.41, 24.61, 29.11, 29.6, 30.02, 31.62, 32.1, 32.2, 33.2–3, 35.3
2	High-technology manufacturing	22.33, 24.11–14, 24.17, 24.3, 24.42, 24.62-64, 24.66, 29.12–14, 29.31-32, 29.4, 29.52-56, 30.01, 31.1, 31.4-5, 32.3, 33.10.1-3, 33.4, 34.1, 34.3, 35.2
4	Software supply and consultancy	72.2
3	Technology-intensive services	64.2, 72 (without 72.2), 73.1, 74.20.5–6, 74.20.9, 74.3

Source: own classification, high-technology manufacturing industries based on Grupp and Legler (2000), high-technology service sectors based on Nerlinger and Berger (1995).
Cutting-edge technology manufacturing: manufacturing industries with average R&D expenditure > 8.0% of total sales. High-technology manufacturing: manufacturing industries with average R&D expenditure 3.5-8.0% of total sales.

capital and some policy makers might regard a higher ROI as socially more desirable than higher wages. But this discussion is beyond the scope of our paper.

Table A3
Description of explanatory variables.

Variable	Description
Time-invariant exogenous variables	
Spin-off type	Type of spin-off (Table A1).
Founder with university degree	At least one founder holds a university degree.
Founder with industry experience	At least one founder has prior experience in the industry sector of the start-up.
Team foundation	Start-up was founded by more than one founder.
R&D activities	Classification of R&D activities as reported by start-up: (i) no R&D activities; (ii) occasional R&D activities; (iii) continuous R&D activities.
Industry sector	Industry sector of the start-up (Table A2).
Female employee	Employee is of female gender.
German citizenship	Employee holds German citizenship.
Time-varying exogenous variables	
Firm location in East Germany	Start-up is located in East Germany.
Firm size in person days	The number of employees multiplied by the individual employment duration in dimension year x start-up.
Share of university graduates	Person days of employees with university degree or technical college degree in % of person days.
Share of trainees	Person days of trainees in % of all person days.
Share of previously unemployedemployees	Person days of employees who joined the firm from unemployment in % of person days.
External equity from private investors	Indicator variable that is one from the year a start-up has received external equity from a private investor (e.g. a business angel). Prior to an investment the indicator variable takes the value zero.
Age of firm	Age of the firm in years based on the year of firm formation as reported in the survey.
Structural type of region	Structural type of regional labour market: (i) core city; (ii) urban fringe; (iii) city outside of agglomerations; (iv) rural areas. Typology is based on data settlement structure and density for NUTS3 regions provided by the Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR).
Time-invariant endogenous variables	
Duration of prior unemployment episode	Duration of a prior unemployment episode in days before entering the start-up. Variable is recoded to the value zero if the duration of unemployment was less than 30 days or if employee joined start-up directly from another firm (job-to-job transition).
Time-varying endogenous variables	
Employee age	Age of the employee in years.
Education	Educational level of the employee (Table 3, upper panel).
Firm tenure	Cumulated tenure in days since the employee has joined the start-up.
Censored wage	This indicator records wages that exceed the social security contribution ceiling in the administrative data. The annual threshold amounted to €61,200 in 2003 and €63,600 in 2008 for employees in West Germany. For East German employees, the respective values were €51,000 in 2003 and €54,000 in 2008.
Occupational fields	Occupational field of the employee (Table 4).
Employment status	Employment status of the employee (Table 3, lower panel).
Student worker	(Student) interns or student jobs according to the employment status of the employee.

Table A4
Descriptive statistics of explanatory variables by start-up group.

Variable	Source		Non- spin-offs	Competence spin-offs	Transfer spin-offs
Founder with university degree	ZEW	%	65.31	90.56	95.87
Founder with industry experience	ZEW	%	83.42	87.72	78.54
Team foundation	ZEW	%	57.80	62.65	82.39
R&D activities: No R&D	ZEW	%	38.28	32.28	8.92
Occasional R&D	ZEW	%	42.64	18.27	3.63
Continuous R&D	ZEW	%	19.08	49.44	87.45
Industry sector: Cutting-edge manufacturing	ZEW	%	25.50	46.98	25.65
High-technology manufacturing	ZEW	%	43.55	13.40	37.26
Software	ZEW	%	11.62	13.21	10.73
Technology-intensive services	ZEW	%	19.33	26.42	26.36
Female employee	IEB	%	31.25	31.67	29.17
Employee with German citizenship	IEB	%	91.23	93.21	91.69
Firm location in East Germany	IEB	%	18.30	21.48	14.53
Firm size in person days	IEB	mean	33.30	11.76	16.16
		median	13.25	8.58	10.13
		std. dev.	47.50	11.85	14.24
Share of university graduates (in % of person days)	IEB	mean	23.13	32.84	45.91
		median	16.40	31.67	48.10
		std. dev.	22.95	26.88	26.87
Share of trainees (in % of person days)	IEB	mean	3.64	4.98	2.74
		median	0	0	0
		std. dev.	9.37	11.23	7.44
Share of previously unemployed employees (in % of person days)	IEB	mean	20.50	16.79	14.78
		median	14.95	11.97	9.47
		std. dev.	20.61	19.81	16.45
External equity from private investors	ZEW	%	6.76	8.64	25.43
Age of firm (in years)	ZEW	mean	2.56	2.77	2.64
		median	3	3	3
		std. dev.	1.49	1.47	1.40
Structural type of region: Core city	IEB	%	27.26	40.93	42.43
Urban fringe	IEB	%	47.61	36.98	53.88
Cities outside agglomerations	IEB	%	7.08	12.35	0.55
Rural areas	IEB	%	18.06	9.75	3.14

Table A4 (*Continued*)

Variable	Source		Non- spin-offs	Competence spin-offs	Transfer spin-offs
Duration of prior unemployment episode (in days)	IEB	mean	22.73	20.47	12.89
		median	0	0	0
		std. dev.	111.85	106.37	70.88
Employee age (in years)	IEB	mean	38.26	36.97	34.80
		median	38	36	32
		std. dev.	11.89	12.11	10.74
Education: No (completed) training	IEB	%	12.13	13.52	16.35
Completed vocational training	IEB	%	60.00	47.72	34.12
University degree	IEB	%	23.40	32.47	46.06
Firm tenure (in days)	IEB	mean	590.50	534.31	513.40
		median	457	415	366
		std. dev.	491.72	441.68	427.38
Censored wage	IEB	%	2.81	5.68	7.43
Employment status: Trainee	IEB	%	3.97	5.06	3.14
Mini-jobber	IEB	%	25.23	30.86	27.02
Part-time employee	IEB	%	3.81	6.36	3.30
Full-time employee	IEB	%	67.00	57.72	66.54
Student worker	IEB	%	1.81	2.84	5.17
Person-year observations (estimation sample)			20,803	1620	1817

Source: ZEW High-Tech Start-Up Survey, Integrated Employment Biographies (IEB) of the IAB, authors' calculations.
Descriptive statistics based on person-year observations (N = 24,240).

Table A5
Results from Hausman-Taylor estimator (full specifications of Table 6).

	Full-time employees (IV a)			All employees (IV b)		
	Coeff.	Std.error		Coeff.	Std.error	
Time-invariant exogenous variables						
High-tech start-up: non-spin-off	*ref.*			*ref.*		
Competence spin-off	0.031	0.069		0.016	0.058	
Transfer spin-off	0.018	0.075		0.140	0.057	**
Founder with university degree	0.109	0.034	***	0.127	0.028	***
Founder with industry experience	−0.004	0.038		0.046	0.033	
Team foundation	0.029	0.030		0.060	0.026	**
R&D activities (ref.: no R&D)	*ref.*			*ref.*		
Occasional R&D	0.012	0.041		0.003	0.035	
Continuous R&D	0.027	0.034		−0.010	0.029	
Industry sector: cutting-edge manufacturing	*ref.*			*ref.*		
High-technology manufacturing	0.022	0.035		0.020	0.031	
Software	0.130	0.051	**	0.093	0.043	**
Technology-intensive services	0.070	0.044		−0.023	0.036	
Female employee	−0.281	0.032	***	−0.271	0.026	***
Employee with German citizenship	−0.009	0.051		−0.023	0.045	
Time-varying exogenous variables						
Firm location in East Germany	−0.101	0.021	***	−0.126	0.025	***
Firm size in person days (log)	0.012	0.003	***	0.025	0.004	***
Share of university graduates (person days)	0.026	0.014	*	0.027	0.017	
Share of trainees (person days)	−0.152	0.038	***	0.016	0.038	
Share of previously unemployed employees (person days)	−0.025	0.015	*	−0.011	0.018	
External equity from private investors	0.032	0.015	**	0.010	0.019	
Time-invariant endogenous variables						
Duration of prior unemployment episode in days (log)	−0.106	0.013	***	−0.100	0.013	***
Time-varying endogenous variables						
Competence spin-off × completed vocational training	0.002	0.048		−0.074	0.050	
Competence spin-off × university degree	−0.003	0.052		−0.089	0.055	
Transfer spin-off × completed vocational training	0.030	0.059		−0.077	0.052	
Transfer spin-off × university degree	0.115	0.061	*	0.013	0.043	
Competence spin-off × student worker	–			0.082	0.104	
Transfer spin-off × student worker	–			0.056	0.056	
Employee age in years (log)	4.260	0.567	***	1.511	0.518	***
Squared employee age in years (log)	−0.461	0.095	***	−0.046	0.083	
Education: no (completed) training	*ref.*			*ref.*		
Completed vocational training	0.029	0.012	**	−0.012	0.013	
University degree	0.027	0.013	**	0.012	0.015	
Firm tenure in days (log)	0.034	0.003	***	0.019	0.004	***
Censored wage	0.100	0.008	***	0.122	0.013	***
Employment status: full-time employee				ref.		
Trainee	–			-0.957	0.022	***
Mini-jobber	–			−1.751	0.012	***
Part-time employee	–			−0.463	0.017	***
Student worker	–			0.773	0.031	***
Age of firm dummies	Yes ***			Yes ***		
Structural type of region dummies	Yes ***			Yes ***		
Occupational fields dummies	Yes ***			Yes ***		

Table A5 (*Continued*)

	Full-time employees (IV a)			All employees (IV b)	
	Coeff.	Std.error		Coeff.	Std.error
Observation year dummies	Yes ***			Yes ***	
Integer	−5.073	0.869	***	−0.681	0.829
Hausman test (fixed effects vs. HT)	$\chi^2(18) = 21.65$			$\chi^2(18) = 23.74$	
	p = 0.248			p = 0.164	
Person-year observations	16,082			24,240	
Number of employees	6215			9815	
σ_μ	1.219			1.328	
σ_ε	0.139			0.221	
ρ	0.987			0.973	

Source: ZEW High-Tech Start-Up Survey, Integrated Employment Biographies of the IAB, authors' estimations.
σ_μ: Standard error of the individual-level random effect; σ_ε: Standard error of the idiosyncratic error term; ρ: Fraction of variance attributed to μ_i.
Levels of statistical significance for dummy variables (age of firm, structural type of region, occupational fields, observation years) are obtained from Wald F-tests of joint significance.
*/**/*** 10%/5%/1% level of significance; standard errors clustered at the individual level.

Appendix B. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.respol.2016.09.002.

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