Institute for Employment Research

The Research Institute of the Federal Employment Agency

IAB-Discussion Paper 17/2015

Articles on labour market issues

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

Matthias Dorner
Helmut Fryges
Kathrin Schopen

ISSN 2195-2663

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

Matthias Dorner (Max-Planck Institute for Innovation and Competition, Institute of Employment Research (IAB))

Helmut Fryges (Australian Innovation Research Centre, University of Tasmania),

Kathrin Schopen (ZEW Centre for European Economic Research)

Mit der Reihe „IAB-Discussion Paper“ will das Forschungsinstitut der Bundesagentur für Arbeit den Dialog mit der externen Wissenschaft intensivieren. Durch die rasche Verbreitung von Forschungsergebnissen über das Internet soll noch vor Drucklegung Kritik angeregt und Qualität gesichert werden.

The “IAB-Discussion Paper” is published by the research institute of the German Federal Employment Agency in order to intensify the dialogue with the scientific community. The prompt publication of the latest research results via the internet intends to stimulate criticism and to ensure research quality at an early stage before printing.

Contents

Abstract

Due to their origin from universities, academic spin-offs operate at the forefront of the technological development. Therefore, spin-offs exhibit a skill-biased labour demand, i.e. spin-offs have a high demand for employees with cutting edge knowledge and technical skills that distinguish them even from other high-tech start-up firms. In order to accommodate this demand, 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 spin-offs and non-spin-offs. This paper addresses this research gap and examines empirically whether or not 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 spin-offs do not pay a wage premium in general. However, a notable exception from this general result is that spin-offs that commercialise new scientific results or methods provide higher wages to employees with linkages to the university sector – either as university graduates or as student workers.

Zusammenfassung

Wegen ihres Ursprungs an Universitäten operieren akademische Spinoffs an der Spitze der technologischen Entwicklung. Sie haben daher auch im Vergleich mit anderen High-Tech Gründungen eine relativ hohe Nachfrage nach Arbeitskräften mit hochentwickeltem Wissen und technischen Fähigkeiten. Folglich müssen Spinoffs potenziell eine Lohnprämie zahlen, um hinreichend ausgebildete Arbeitskräfte auf dem externen Arbeitsmarkt zu attrahieren und diese im Unternehmen zu halten. Theoretische Studien zu Bestimmungsfaktoren von Löhnen liefern jedoch auch Gegenargumente, die für niedrigere Löhne in Spinoffs sprechen können. Die vorliegende Studie untersucht ob akademische Spinoffs tatsächlich eine Lohnprämie bezahlen und welche Bestimmungsfaktoren mögliche Lohnunterschiede erklären. Zu diesem Zweck werden umfangreiche Employer-Employee-Paneldaten erstellt und mittels Mincer Lohnregressionen sowie erweiterten Panel Schätzverfahren nach Hausman-Taylor analysiert. Die Ergebnisse zeigen, dass Beschäftigte in akademischen Spinoffs nicht grundsätzlich eine Lohnprämie erhalten. Eine Ausnahme von diesem generellen Befund stellen akademischen Spinoffs dar, die universitäre Forschungsergebnisse oder Methodenentwicklungen kommerzialisieren. Diese Firmen zahlen ausschließlich Beschäftigten mit akademischem Abschluss (sowie studentischen Mitarbeitern) signifikante höhere Löhne als vergleichbaren Beschäftigten in anderen Spinoffs bzw. High-Tech Gründungen.

JEL classification: J31, L26, M13, O34

Keywords: wages, high-tech start-ups, academic spin-offs, linked employer-employee data

Acknowledgements: This study was financially supported by the Federal Ministry of Economics and Technology, Microsoft Germany GmbH, the ZEW Sponsors' Association for Science and Practice and the ZEW Centre for European Economic Research. Matthias Dorner acknowledges funding from the GradAB scholarship programme of the Institute for Employment Research (IAB). Kathrin Schopen acknowledges funding from the ZEW Centre for European Economic Research where she was employed until May 2012. We thank Udo Brixy for useful comments and Thorsten Doherr for matching the data that build the linked employer-employee data set used in this study. Previous versions of this paper were presented at the 11th Comparative Analysis of Enterprise Data & COST Conference 2012 (CAED 2012) in Nuremberg, at the 16th Annual Interdisciplinary Entrepreneurship Conference 2012 (G-Forum) in Potsdam and at seminars at the IAB in Nuremberg, at the University of Marburg and at a Max-Planck Institute Research Seminar in Kochel am See. Helpful suggestions and remarks from participants are gratefully acknowledged. All remaining errors are our sole responsibility.

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[1] to the for-profit private sector. Due to their origin from universities, spin-offs are regarded as operating at the forefront of the technological development (Wright et al. 2007a; Clarysse et al. 2011). The more sophisticated business ideas of spin-offs and their tendency to use more complex technologies distinguishes spin-offs even from other high-tech start-ups that emanate from outside the university sector (‘non-spin-offs’). Indeed, empirical evidence supports that spin-offs have a higher R&D intensity and a higher inclination to patenting than non-spin-offs (Egeln et al. 2010). These structural characteristics of spin-offs result in a skill-biased labour demand, i.e. spin-offs have a high demand for employees with cutting edge knowledge and technical skills. Hiring high skilled workers requires start-ups to pay competitive wages in order to accommodate this demand with adequate employees. As a consequence, compared to other start-ups a relative wage premium for employees in spin-offs could result from the fact that spin-offs need to provide higher wages in order to attract and hire adequately skilled workers from the external labour market and retain them in the firm.

However, theoretical studies on the determinants of wages also provide contrary arguments that militate in favour of lower wages in spin-offs. In R&D intensive environments, employees might trade-off non-monetary utility arising from these jobs with actual remuneration. Essentially, 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 first empirical evidence whether spin-offs, due to their structural differences in terms of R&D intensity and skill biased labour demand, pay their employees a wage premium.

Wage determination in spin-offs and the analysis of wage differentials across high-tech start-ups has also important policy implications. From a societal point of view, the creation of spin-offs involves both costs and benefits. Some scholars argue that spin-offs need to compensate the societal costs that arise from the spin-off process, basically resulting from the academic “brain drain” from the incubator university (Toole and Czarnitzki 2010; Czarnitzki et al. 2014). Regarding the benefits of spin-off creation, the number of newly created jobs is the most frequently examined economic indicator, although empirical evidence on the hypothesised superior job creation performance of spin-offs compared to other start-ups is mixed (see for example Mustar 1997, Egeln et al. 2010, Cantner and Goethner 2011, Wennberg et al. 2011, Czarnitzki et al. 2014). Wages have been largely neglected in this discussion so far,

---

[1] In this paper, we use the term “university” to refer to all kind 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.

although a wage premium paid by spin-offs could be an additional source to compensate for the societal costs of the creation of spin-offs. Essentially, this would imply that spin-offs do not necessarily create more jobs than non-spin-offs – as evident in many studies – but create better paid, i.e., more productive jobs.

Our empirical study uses a comprehensive linked employer-employee panel data set that was generated from the ZEW High-Tech Start-Up Survey 2007 and from administrative data on employees and establishments provided by the Institute for Employment Research (IAB). These linked data comprise 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. The scope of our data enables us to exploit precise daily wage information from social security data and control for worker and firm heterogeneity. 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.

The 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 wage differentials entirely by differences in worker and firm characteristics of spin-offs and non-spin-offs. Being either a competence or a transfer-spin-off does not imply higher wage levels than in non-spin-offs. A notable exception to this general finding, however, are 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 effect on wages (e.g., due to non-monetary benefits of working in a transfer spin-off) is dominated by opposing positive impacts (e.g., due to sorting).

Our study contributes to the literature in two ways: First, our findings support the proposed notion of sorting of relatively productive high skilled workers who demand higher wages into R&D intensive transfer spin-offs. Second, we provide evidence that the societal costs of spin-offs might be, at least to some extent, offset by a wage premium paid by transfer spin-offs to their university graduates. Based on our results, policy makers should consider employee wages an additional source of potential benefits when evaluating governmental programmes supporting spin-off activities.

The remainder of the paper is structured as follows: In section 2, we outline the related literature on employment in spin-offs and provide theoretical arguments why wages may differ between spin-offs and non-spin-offs. Section 3 documents the generation of our linked employer-employee data set. A comprehensive descriptive analysis and details about the identification of spin-offs are provided in section 4.

Section 5 outlines the econometric model. Section 6 presents and discusses the results from the multivariate wage regressions and additional robustness checks. The paper concludes in section 7 with a discussion of policy implications and limitations of our study.

2 Related literature

2.1 Employment in spin-offs

Employment in spin-offs is usually discussed in the literature with respect to the number of jobs created by spin-offs. 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).

Most existing studies, however, are unclear why, from a societal perspective, it is desirable or even necessary that spin-offs grow faster than other start-ups. An exception is the study of Czarnitzki et al. (2014). The authors argue that spin-offs have to produce a net gain in social welfare in order to offset the social costs of spin-off generation. Such social costs arise when university researchers transition from the public research sector 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). Analysing the research output of scientists from the Max Planck Society, Buenstorf (2009) finds that spin-off founders experience long-run declines in their research output. If spin-offs grow faster than other start-ups, they generate a social benefit in the form of a “performance premium” that contributes to offset the social costs of spin-off formation (Czarnitzki et al. 2014).[2]

However, empirical studies produced mixed results whether or not spin-offs create more jobs than other start-ups. Analysing a sample German knowledge-intensive start-ups founded in the period from 1996 to 2000, Czarnitzki et al. (2014) find that spin-offs exhibit a 3.4 percentage points higher employment growth rate than other start-ups in knowledge-intensive industries. Lindholm-Dahlstrand (1997) examines a sample of Swedish technology-based start-ups and shows that spin-offs increase their number of employees faster than non-spin-offs. Similarly, Shane (2004) reports that spin-offs create more jobs than the average start-up in the United States.

On the contrary, most studies cannot confirm that employment growth rates of spin-offs exceed those of other start-ups. Mustar (1997) concludes that major increases in the number of newly created jobs are rare among French spin-offs. This finding is

[2] 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.

supported by Egeln et al. (2010) for Austria and by Cantner and Goethner (2011) for the German state of Thuringia. Both studies use matching techniques and do not find any significant differences in employment growth between spin-offs and a control group of other start-ups which are similar in their firm characteristics. Using the same data set the start-up firm information of this study originate from, Gottschalk et al. (2007) cannot show that being a spin-off leads to a significantly higher employment growth rate if compared to other high-tech start-ups in Germany.

Zhang (2009) examines a sample of venture capital (VC) backed start-up companies in the United States. Multivariate OLS regressions reveal that the absolute number of employees either does not differ between spin-offs and non-spin-offs or, depending on the specification of the regression model, that spin-offs even employ fewer persons than non-spin-offs. When comparing a sample of Italian spin-offs with a matched sample of other new technology-based firms, Colombo and Piva (2005) find that spin-offs exhibit a significantly lower employment growth rate. The authors suspect that the lower growth rate results from a lack in managerial and commercial competences among spin-offs. This presumption is confirmed by Wennberg et al. (2011) for a sample of Swedish spin-offs.

Indeed, extant literature on spin-offs emphasises the importance of human capital for the performance and the development of spin-offs (e.g. Wright et al. 2007b; De Cleyn et al. 2011; Clarysse and Moray 2004; Visintin and Pittino 2014). However, spin-offs' human capital is almost exclusively discussed regarding the human capital of the team of founders or the board of directors. This focus fails to address the importance of employees for the knowledge base of high-tech start-ups (Cardon and Stevens 2004). Employees are one of the most critical resources of a young firm (Aldrich and Ruef 2006; Baron and Hannan 2002). By recruiting employees, a start-up can integrate diverse knowledge it lacks (Song et al. 2003).

A distinctive characteristic of spin-offs is their close and enduring contact to the university sector in general and to their incubator institutions in particular. One important form of contact between spin-offs and academic institutions is the employment of students within the context of internship or by offering students support for their university theses (Egeln et al. 2003b).[3] The contact of spin-offs to universities and their students facilitates the recruitment of high-skilled employees (Berggren and Lindholm-Dahlstrand 2009).

2.2 Wage differentials between spin-offs and non-spin-offs

Start-ups need to attract and hire their employees from a labour market external to the firm. In particular, hiring high skilled employees from the labour market requires start-up firms to pay competitive wages. Besides providing an adequate compensa-

[3] 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.

tion for human capital investments and skills of the employee, the level of wages needs to reflect characteristics of the employer such as working conditions, career prospects and, not least, particularities of the local labour market (Becker 1964; Mincer 1974). While this applies to both spin-offs and non-spin-offs, the literature on wage determination does not provide a straightforward prediction about why and how wages should actually differ between these two types of start-ups. In the following, we discuss compensating differentials, sorting and financial constraints as potential sources for wage differentials between spin-offs and non-spin-offs.

To explain wage differentials in the context of small firms, the theory of compensating wage differentials[4] serves as a common reference. The theory predicts that utility maximising workers might trade off wages with other factors related to their employment in a firm, such as the risk of job loss or non-monetary benefits that are associated with their jobs. A general characteristic of start-ups is that their future is highly uncertain. In particular, start-ups which operate in small niche markets and at the technological edge face both a high probability of outstanding performance but also a high risk of business failure. Manigart and Van Hyfte (1999) find that VC backed firms that commercialise cutting-edge technologies show a lower probability to survive than non-venture backed companies. According to Audretsch (1995), the probability of survival is lower for firms that operate in highly innovative industries than for firms in industries with limited innovative activities – at least during the initial years of a firm's life cycle. For employees in start-ups this risk of failure is directly reflected in a high risk of job loss (Schnabel et al. 2011). Therefore, the literature on firm size and firm age differentials argues that observed wage gaps might be related to practices of compensation for differences in the risk of job loss (Brixy et al. 2007). Assuming that employees associate spin-offs with a higher risk of business failure spin-offs might be, ceteris paribus, required to pay a compensating wage differential for the risk of displacement. However, empirical studies reveal that spin-offs actually exhibit a higher probability of survival than other start-ups (Egeln et al. 2007; Cantner and Goethner 2011). If employees perceive a lower risk of job loss when working for a spin-off they might rather accept lower wages compared to a job in a non-spin-off.

Another source of compensating wage differentials among start-ups are non-monetary returns associated with certain jobs. These factors have been documented as a major determinant for the actual labour market behaviour of employees (Freeman 1978). The literature on the returns to entrepreneurship lists higher work satisfaction of entrepreneurs resulting from, for instance, greater autonomy, flexible working hours or a higher identification with the business idea of the firm (Benz and Frey 2004; Benz 2009; Hyytinen et al. 2013). It can be argued that the non-monetary returns of working for start-ups might also be valued by the employees of start-ups, in particular with regard to organisational features or identification. Anoth-

[4] For the general rationale of compensating differentials see Rosen (1986).

er important non-monetary aspect frequently documented for high-skilled academic workers is their preference and willingness to pay for doing science, i.e., accepting lower wages for more science related working conditions and content (Stern 2004; Dupuy and Smits 2010; Roach and Sauermann 2010). Since spin-offs are characterised by a relatively high R&D intensity which tends to go along with more research affine working conditions, we expect that non-monetary returns could be higher in spin-offs at least for high-skilled academic workers who value these factors in their labour supply decision. Hence, if spin-offs provided sizable non-monetary rewards they could afford to pay wages below the level of less R&D intensive non-spin-offs, in particular for research affine workers.

Given the importance of labour and human capital in the early phase of the life cycle of a firm, wage differentials at this stage and across start-ups might simply reflect productivity differentials as a result of both sorting (and matching) and the composition of the workforce. Assortative matching of workers with different personal characteristics into different types of firms has been documented extensively in the context of wage inequality (Hartog 1986; Abowd et al. 1999; Acemoglu and Autor 2011; Card et al. 2013). While large firms on average hire more experienced and productive workers (Gerlach and Hübler 1998), small and young firms tend to employ a disproportionately high share of young and relatively unexperienced workers (Ouimet and Zarutski 2014).[5] Nyström and Elvung (2013) analyse whether systematic sorting of certain groups of entrants occurs into start-ups. They show that workers with less labour market experience tend to sort into start-ups and that this selectivity of workers with inferior human capital endowments explains lower wages in these firms as a result of lower aggregate firm productivity when compared to established firms.

Another important sorting mechanism that is expected to distinguish in particular spin-offs from non-spin-offs is determined by differences in R&D intensities. Spin-offs are more likely to develop complex products and services as well as cutting-edge technologies when compared to non-spin-offs. Therefore, spin-offs require more high-skilled technical workers which should be reflected by the composition of spin-offs' labour demand and wage setting behaviour. Since human capital of high-skilled technical workers can be hardly substituted by any other means for spin-offs in their early stage of the life cycle, it is likely that they will need to pay relatively high wages for these kinds of skills.[6]

---

5 This finding is consistent with the heterogeneity of the costs of job displacements which are, due to specific human capital, higher for older and experienced workers (e.g., Jacobsen et al. 1993; Schmieder et al. 2009).

6 There is no direct evidence in the literature that explicit sorting on R&D tasks occurs. Acemoglu and Autor (2011) describe heterogeneous worker skills, job tasks and the diffusion of new technologies as a source for sorting and wage inequality.

Financial constraints of start-ups might affect their ability to offer competitive wages. A potential remedy to these constraints is the acquisition of external financing such as VC or informal equity financing (often referred to as business angel financing). Bengtsson and Hand (2014) report that employees in VC backed firms receive about 14% higher wages than employees in founder-dominated firms. Since Bengtsson and Hand also find that VC controlled firms employ more skilled workers they argue that VC is used both to attract better workers and to retain them. The embeddedness of spin-off founders in the scientific community as well as the use of more advanced technologies have both been found to increase the likelihood of receiving formal or informal equity financing (Shane and Stuart 2002; Toole and Czarnitzki 2007; Fryges et al. 2007). Hence, it is straightforward to assume that spin-offs are more likely than non-spin-offs to use equity financing for hiring purposes and to implement wage incentive schemes which result in higher wage payments for their employees.

To summarise, we conclude that there are theoretical arguments which might explain the presence of wage differences in any direction between spin-offs and non-spin-offs. The net effect, however, remains unclear and is subject to empirical evaluation. Furthermore, it appears that indirect channels affecting wages like sorting or equity financing, which are correlated with aggregate firm characteristics or performance measures might be more significant for the actual process of wage determination than clear structural differences between spin-offs and non-spin-offs.

3 Data

In this study, we use a linked employer-employee (LEE) data set that combines survey data of newly-founded high-tech firms with employee data from the German Employment Statistics of the Federal Employment Agency. The employer data originate from the ZEW High-Tech Start-Up Survey conducted in 2007 by the Centre for European Economic Research (ZEW) and financed by the German Federal Ministry of Economics and Technology and the high-tech start-up initiative “unternimm was.” of Microsoft Germany. 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. 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. NACE codes of industry sectors covered by the survey are depicted in Table 7 in the appendix. Firms included in the sample were founded in the period from 1998 to 2005.

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)7, was provided by the Institute of Employment Research (IAB). It contains process-produced person-specific data on all employees subject to obligatory social insurance (i.e., pension funds, heath and unemployment insurance) as well as episodes of registered unemployment or job search along the biographies. The employment data are reported by the employing establishment and collected by the social security administration. On the one hand, the data encompass socio-demographic characteristics like gender, age, nationality, school education and professional qualifications. On the other hand, rich information on employment-related characteristics is available: the exact start and end date of employment, gross earnings subject to social insurance, occupational and employment status (trainees, marginal, part-time or full-time employment). The IEB data on the individual employees are collected continuously and are updated on an annual basis or whenever major changes in the employer-employee relationship occur, e.g. a change in the establishment identifier, indicating an employee's move to another firm. This implies that we are able to observe individual level employment data on both employees who permanently worked in a high-tech start-up and employees with employment episodes shorter than a year.

Since there is no unique firm identifier in the two data sets, the firms comprised in the survey had to be matched via their firm names and addresses. However, firm addresses were not available in the required form from the address file of the administrative employment data before 2003. In order to avoid imprecise matching results, only firms founded in the period from 2003 to 2005 were used to set up the linked employer-employee data set. Among all firms interviewed in the context of the ZEW High-Tech Start-Up Survey, 1,623 firms were founded in the year 2003 or later. Record linkage was conducted applying the specialised software "SearchEngine", a programme that has been developed at the ZEW and proved to be efficient in identifying the same firm in different data sets via the employed string matching algorithm.

947 of the 1,623 firms surveyed could be matched to at least one establishment recorded in the administrative employment data. Of course, many firms that participated in the start-up survey did not have any employees liable to social insurance in any year. The survey data set contains 1,117 firms founded from 2003 to 2005 of which the workforce measured at the end of the year 2006 exceeded the number of

[7] 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 external researchers.

firm founders. From this group of firms, 838 firms (75%) could be matched.[8] The remaining 109 firms did not have any dependent employees at the end of the year 2006, but had employees liable to social insurance at any other time during our observation period. If a firm was matched to more than one establishment, the data of the employment statistics were aggregated in order to make them comparable with the firm level data from the start-up survey. Only 3% of start-ups have more than one establishment during their initial years covered by our data.

The employment data available to us cover all employment episodes from 2003 to 2008, which are all employees working in the firms of our sample at least during their first three business years.

4 Identification of spin-offs and descriptive statistics

4.1 Definition and identification of spin-offs

There are various definitions of spin-offs available 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[9] in order to commercially exploit knowledge produced by academic activities. Apart from these communalities, Pirnay et al. (2003) characterise spin-offs by two dimensions in which existing definitions distinguish from each other: the academic status of individuals involved in the new business venturing process and the nature of knowledge transferred.

The ZEW High-Tech Start-Up Survey and, consequently, this study apply a definition developed by Egeln et al. (2003a, b) who extensively investigated spin-offs in Germany. The definition of Egeln et al. is in line with all features outlined by Pirnay et al. (2003) as communalities throughout the literature. Regarding the individuals involved in the foundation process, we require an academic background of the spin-offs' founders. The founders (or at least one member of the team of founders) must have studied at a university or must have worked at a university. The latter group does not only comprise university researchers but also academic and non-academic

8 The questionnaire of the ZEW High-Tech Start-Up Survey did not distinguish between different groups of employed persons. Thus, employees working in the surveyed firms are not necessarily liable to social insurance but might be family members who do not receive payment or freelancers. The questionnaire explicitly asked interviewees to include owners, family members and freelancers into the number of employees. This implies that not all of those 1,117 firms have a data entry in the administrative employment data. Results from the KfW/ZEW Start-Up Panel, a representative panel data set of German start-ups, reveal that among all high-tech start-ups that report employees at the end of their third business year, 14% do not have any employees liable to social insurance but rely on family members or freelancers only. We thank Martin Murmann (ZEW) for providing us with this information.

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

staff members (e.g., lecturers, technical staff). 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 for-profit private sector, although the university employee may remain affiliated with the incubator university.

With respect to the nature of the knowledge transferred from a university to the spin-off, we define two types of spin-offs:

- **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 have acquired during their time at the university were essential to the creation of their firms.
- **Competence spin-offs.** Specific skills the founders have acquired during their time at the university were essential to the formation of the new firm.

The two types of spin-offs differ in their level of knowledge and technology transferred to the spin-off. While transfer spin-offs represent a high level of technology transfer, competence spin-offs stand for a lower level of technology transfer. Moreover, transfer and competence spin-offs distinguish in their specificity of the knowledge transferred. While new research results may be linked to a concrete product and, thus, have a narrow application range, competences can be exploited for the production of a wider range of products (Müller 2010).

Transfer spin-offs and competence spin-offs define two mutually exclusive groups whereas the group of transfer spin-offs (those with higher level of technology transfer) dominates the group of competence spin-offs (those with 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. The exact wording used to identify spin-offs is documented in Table 8 in the appendix.[10]

It is important to note that both the academic background of the founder and the transfer of knowledge from a university to the start-up are necessary to identify a spin-off. Start-ups that were set up by students or university employees without the transfer of essential research results, methodologies or skills are not classified as spin-offs. Similarly, start-ups that commercialise new research results or methodologies but do not have at least one founder with an academic background in their team of founders do not qualify as spin-offs either.

The identification of spin-offs via a survey has the significant advantage that it covers all possible incubator institutions and all high-tech industry sectors. Further-

[10] 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 from. In the case that no research institution was indicated, the firms were not classified as spin-offs.

more, we do not use incubator institutions or technology transfer offices as our source of information but the start-ups themselves that indicate whether or not they have commercialised skills and knowledge originating from a university. In this way, we also include spin-offs that are unknown to the incubator university and the 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 of academia and the creation of her/his new venture (Müller 2010).

4.2 Descriptive statistics

According to our definition, 8% of the firms in the sample belong to the group of competence spin-offs (65 firms), 7% of the firms are transfer spin-offs (55 firms). The remaining 85% of the firms are classified as non-spin-offs (687 firms).

For our empirical analyses, we set up a person-year panel data set. From 2003 to 2008, 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 individual employee was employed by a high-tech start-up in 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.

<<< Table 1 about here >>>

The last column of Table 1 depicts the person-year observations for the sample that is eventually used for the econometric analyses in section 6. All descriptive statistics in this section are based on this reduced sample. However, the conclusions would remain unchanged if we used the full sample.[11]

Table 2 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. An employee that worked for the start-up for the whole year (employment episode of 365 days) counts for one full employee. An employee with an employment episode of 60 days in a particular year counts for a 60/365 = 0.16 employee in that year. The first row of Table 2 shows the average headcount per year during the observation period from 2003 to 2008.

<<< Table 2 about here >>>

[11] 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 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. Nevertheless, our main results do not change if we retain observations for CEOs in our regressions.

The average number of employees of non-spin-offs amounts to 6.2 persons. Competence spin-offs employed 5.0 persons per year, transfer spin-offs had 6.2 employees. According to *t*-tests on the equality of means, competence spin-offs are significantly smaller than non-spin-offs. However, there is no significant difference between transfer spin-offs and non-spin-offs. The last column of Table 2 shows that the number of employees in competence spin-offs is also smaller than the comparative value for transfer spin-offs. The difference is significant at the 10% level of significance.

The distribution of the number of employees is, however, highly right-skewed. The median number of employees of non-spin-offs is equal to 2.3 employees, competence and transfer spin-offs have a median of 2.5 and 3.0 employees respectively. Tests on the equality of the medians reveal that the median number of employees in transfer spin-offs is significantly different from the medium value in non-spin-offs (at the 10% level of significance), whereas, contrary to the mean, the medium number of employees does not differ between competence spin-offs and non-spin-offs.[12]

The mid panel of Table 2 depicts the composition of the start-ups' workforces according to the employees' highest level of education. We distinguish three different levels of education: employees without a (completed) qualification, employees with a vocational qualification, and employees with a university degree. Note that the level of education of an individual employee can change over time.[13] For example, a trainee who is recorded as an employee without a completed qualification and who worked for a start-up during his vocational training may have finished his training and may continue to work for this start-up, now recorded as an employee with a completed vocational training.[14]

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. Consider a start-up that has one employee with a university degree, who worked for the start-up for the whole year, and a second employee with a vocational qualification who was employed by the start-up for 60 days. This start-up's share of employees with a uni-

---

[12] *p*-values of Pearson's χ^2 tests on the equality of medians: non-spin-offs vs. spin-offs: 0.139; competence spin-offs vs. non-spin-offs: 0.492; transfer spin-offs vs. non-spin-offs: 0.084; transfer spin-offs vs. competence spin-offs: 0.191.

[13] Inconsistencies, i.e., implausible variations of the education information for individuals along their employment biographies were corrected as proposed by the algorithm described for the IAB employment biography data in Fitzenberger et al. (2006).

[14] The change from a trainee (no completed qualification) to an employee with a completed vocational training 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. Thus, in the year of their change from a trainee to an employee with a completed vocational training, the individual in our example enters the regression as an employee with a vocational training and the daily wage that corresponds to this employment episode.

versity degree amounts to 365/(365+60) = 86%. Accordingly, the share of employees with a vocational training is equal to 60/(365+60) = 14%.

Non-spin-offs exhibit a significantly smaller share of both employees with a university degree and those without (completed) training than 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]

The lower panel of Table 2 outlines the distribution of a start-up's total person days according to the employees' employment status. 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. Both part-time employees and trainees play a minor role within a start-up's workforce, each group contributing about 5% to a start-up's total person days. On the contrary, start-ups heavily rely on mini jobbers.[16] For both spin-offs and non-spin-offs, the share of mini jobbers amounts to around one third of total person days. It is, however, important to emphasise that the data set does not allow determining 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. This implies that we are unable to calculate the number of employees in terms of full-time equivalents and have to revert to headcounts.

The last row in Table 2 displays the share of total person days for the small albeit interesting group of student workers. In transfer spin-offs, student workers are equally important as trainees. 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.

Our variable of primary interest is the wage paid to start-ups' employees. For every employment episode, the Employment Statistics provides us with data on the employees' daily gross wages[17] that are the assessment basis for the contributions to mandatory social insurances. In our econometric model, we will use the logarithmic

---

[15] The shares of the three education categories do not sum up to 100% in Table 2. 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 German 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.

[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 Euro (325 Euro before 01.04.2003).

[17] The employer is obligated to report the employees' income subject to social insurance for the full employment episode. This figure may also include bonus payments which are not included in monthly salaries. Gross daily wages included in our data are computed from the ratio of this income and the length of the employment episode.

daily gross wage as the endogenous variable. In this section, however, we use annual gross wages for illustrative purposes. For those employees that worked in a start-up for less than a year, we report a projected gross annual wage assuming that the employees earned the recorded daily wage on all 365 days of the year. Throughout this paper, nominal wages are deflated by the consumer price index and displayed in Euro of 2006.[18]

Gross annual wages differentiated by employment status are displayed in Table 3. Full-time employees of spin-offs earn significantly higher wages than full-time employees working for non-spin-offs. The wage differential between full-time employees in transfer spin-offs and those in non-spin-offs amounts to 19%, in competence spin-offs the wage differential comes to 9%. Conversely, trainees who do their vocational training in a spin-off receive significantly lower wages than their counterparts in non-spin-offs. The gross annual wages of part-time employees and mini jobbers are difficult to interpret. Since we do not know how many hours a part-time employee or a mini jobber works for the start-up, differences in gross annual wages can result from both varying remunerations per working hour and varying numbers of hours the part-time employee or the mini jobber is contracted to work per day or per week.

<<< Table 3 about here >>>

Therefore, we restrict ourselves to the subsample of full-time employees when discussing gross annual wages by level of education in Table 4. Full-time employees that hold a university degree receive significantly higher wages in spin-offs than in non-spin-offs, whereas there is no difference between transfer spin-offs and competence spin-offs. Full-time employees with a university degree earn 12% more in spin-offs than their counterparts in non-spin-offs. Employees with a vocational qualification in the German dual education system that work for a non-spin-off have to content with 3% lower wages compared to corresponding employees in spin-offs. Employees without a qualification earn significantly more in transfer spin-offs (wage differential 11%), the wage differential to competence spin-offs is not significant.

<<< Table 4 about here >>>

5 Econometric model

5.1 Model selection and estimation method

Various econometric methods are available for estimating a wage equation, using the logarithmic daily gross wage as the endogenous variable. We first estimated a pooled OLS model. This model ignores the panel structure of our micro data set. Most importantly, the pooled OLS assumes that there is no serial correlation be-

[18] 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.

tween observations belonging to the same individual, i.e. that there is no unobserved individual heterogeneity. The null hypotheses of no serial correlation is rejected by Breusch-Pagan Lagrange-Multiplier tests for both the model with full-time employees ($\chi^2(1) = 8{,}616.53$; $(p > \chi^2) = 0.000$) and the model with all employees ($\chi^2(1) = 9{,}761.32$; $(p > \chi^2) = 0.000$).

In contrast to the pooled OLS model, the random effects model and the fixed effects model allow for individual specific effects. However, the fixed-effects model is unable to estimate the effect of time-invariant factors. Since the core variables that are of primary interest for this paper are two time-invariant dummy variables indicating competence spin-offs and transfer spin-offs respectively, the fixed-effects model is not appropriate for our study. Therefore, in a second step we estimated a random effects model. The random effects model assumes that the individual-specific random effect is uncorrelated with the set of explanatory variables. This assumption is tested by a Hausman test that compares the subset of coefficients that are estimated by the fixed-effects model (i.e. the coefficients of all time-varying variables) with the corresponding coefficients estimated by the random-effects model. The null hypothesis of equality of coefficients implies no correlation between the random effects and the covariates. In our case, however, the null hypothesis is rejected for both the model with full-time employees ($\chi^2(35) = 884.71$; $(p > \chi^2) = 0.000$) and the model with all employees ($\chi^2(45) = 1{,}111.17$; $(p > \chi^2) = 0.000$). We present the results of the pooled OLS model, the random effects model and the fixed effects model in Table 9 in the appendix. Since these results have been proven to be biased – or do not answer our main research question as in the case of the fixed effects model – we do not discuss the results for reasons of space.

As an alternative to the standard random-effects model, Hausman and Taylor (1981) developed an estimator that allows for some covariates to be correlated with the individual-specific random effect. 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 $i = 1, \dots, N$ indicating the number of individuals (employees) and $t = 1, \dots, T_i$ 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} , $(X_{En\_it} - \overline{X_{En\_i}})$ 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} in order to avoid a weak instrument problem (see Hausman and Taylor (1981) or Baltagi (2013) for more details on the Hausman-Taylor estimator).

The Hausman-Taylor estimator was applied in various studies to estimate wage equations (like Light and Ureta 1995; Heineck 2005; Salehin and Breunig 2012). The estimator is also appropriate for our study since the Hausman test that compares the fixed effects model and the random effects model reveals that at least some variables are correlated with the individual-specific random effect μ_i. The following subsection introduces the explanatory variables of our estimation equation and how they divide into the four different categories of explanatory variables included in the Hausman-Taylor model.

5.2 Explanatory variables

The vector of explanatory variables contains both employee-specific and employer-specific variables. As a general rule, we treat employee-specific variables as endogenous, i.e. as correlated with the individual-specific random effect μ_i. On the contrary, employer-specific variables are assumed to be exogenous to the individual-specific random effect.

The only exceptions from this rule are two time-invariant dummy variables indicating the employee's gender and citizenship (German vs. foreign citizenship) which enter the regression equation as exogenous variables. The remaining set of employee-specific variables includes the time-varying, socio-demographic characteristics age (measured in years), the squared value of age to account for potential non-linear age effects and the employee's level of education (categorised as discussed in section 4.2). An employee's position in the start-up is captured by her/his employment status (full-time or part-time employee, trainee or mini-jobber as discussed in section 4.2), job tenure (measured in person days since the employee's entry into the start-up) and a set of dummy variables for 12 occupational fields according to the classification proposed by Blossfeld (1987), which characterise the job tasks the employee performs in the start-up.[19] Table 10 in the appendix provides a description of the occupational fields including examples. Furthermore, we add a dummy variable that marks wages at or above the social security contribution ceiling.[20]

The only time-invariant, endogenous variable in our regression equation is a variable that measures the duration of a potential unemployment episode before entering the start-up. This variable takes the value zero if no prior unemployment is registered in the data or if the length of the unemployment spell was less than one month. Unemployment is assumed to reduce the reservation wage the employee is willing to accept at the start-up. With increasing duration of a prior unemployment episode we expect a higher reduction of the reservation wage.

The wage equation is estimated for two different samples: the sample of full-time employees only and the sample of all employees including part-time employees, mini jobber and trainees. Since we do not know how many hours a part-time employee or a mini jobber is working per day, the regression equation that estimates the daily gross wage of all employees includes additional, time-varying dummy variables 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.

All employer-specific variables are treated as exogenous. They originate from both the ZEW High-Tech Start-Up Survey and the administrative employment data. Since the start-up survey is a cross-sectional data set only, most variables that were collected by the survey are time-invariant. The survey data allow us to characterise the start-ups' founders. We include three indicator variables that take the value one if at least one founder holds a university degree, if, prior to the formation of the start-up, at least one founder had industry experience in the same sector the start-up operates in, and if the start-up was founded by a team of founders. We expect that these indicators affect the performance of the new firm and thus indirectly affect the wages the start-up is able to pay.

---

19 A 13th category for employees without a reported occupational field is considered in the regression equation.

20 Wages that exceed the social security contribution ceiling are recorded with the threshold value in the administrative employment 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. We control for these censored observations by a dummy variable. Our main results remain unchanged if we exclude all censored observations.

Firm-level variables originating from the survey are in the first place the two dummy variables identifying transfer and competence spin-offs. In order to estimate wage differentials for employees with different levels of education, 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.

Other firm-level variables that were collected in the context of the survey are a set of dummy variables indicating firm age (first to sixth business year) and two dummy variables for the frequency of R&D activities. A distinction between no R&D activities, occasional R&D activities and permanent R&D activities is made. In general, we expect that R&D activities result in more innovative outcome of a firm. However, the relationship between R&D activities and wages is not clear a priori[21]. Industry dummies (corresponding to the industry sectors in Table 7 are derived from self-reported information on the firm's best-selling product or service and are introduced as control variables for unobserved heterogeneity and differences in the markets of the high-tech start-ups. Finally, we control for the start-up's financial situation and, thus, for its ability to pay higher wages by including a time-varying dummy variable that takes the value one in the year the start-up first received external equity from private investors (business angels) and in all years thereafter. It takes the value zero if the start-up did not benefit from an inflow of equity from business angels in the year of observation or in any year before that. Business angel financing is an important element of a start-up's external finance from third parties. In particular, business angel financing is much more widespread among high-tech start-ups than equity from VC funds (Fryges et al. 2007).

Firm-level characteristics obtained from the survey are complemented with variables derived from the administrative data. These variables are available as time-varying panel information. The scope of these variables comprises the number of employees (measured as headcounts based on person days per year), the share of workers that hold a university degree and the share of trainees[22]. The share of workers with an unemployment episode prior to joining the start-up was included primarily for the reason of identifying the effect of the individual-specific duration of prior unemployment. Most time-varying, exogenous variables (the instruments) show a low correlation with the time-invariant, endogenous duration of prior unemployment. The share of previously unemployed workers is, by construction, highly correlated with the individual-specific duration of prior unemployment so that we avoid a weak instrument problem.

---

[21] For firm level evidence on the relationship between innovation and wages, see Van Reenen (1996). At the individual level, it has been documented for inventors that successful patenting activities lead to a wage premium (Toivanen and Väänänen 2012; Depalo and Di Addario 2014).

[22] It has been found that on the job training provided by firms is positively related to a firm's ability to innovate (Bauernschuster et al. 2009; Dostie 2014).

We control for the regional disparities in entrepreneurial activity and the business environment within Germany by implementing a dummy indicating whether the start-up is located in East Germany. We further account for the significant regional variance in the wage levels within Germany that results from urbanity effects. Using a classification of the Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR) we are able to distinguish whether start-ups in our sample are located in core cities of large agglomerations, in the urban fringe, in cities outside of agglomerations or in rural areas. Finally, year dummies are introduced to control for temporal shocks and variations in the business cycle.

Table 11 in the appendix shows the means of the explanatory variables for non-spin-offs, competence spin-offs and transfer spin-offs.

6 Econometric results

The results of the Hausman-Taylor estimations for both the sample of full-time employees and the sample of all employees are displayed in Table 5. Our main results are drawn from the estimation using the sample of full-time employees only. Nevertheless, since almost half of start-ups' total person days relate to employees who do not work full time we estimate the wage equation for all employees as a robustness check.

<<< Table 5 about here >>>

Table 6 displays the wage differentials for competence and transfer spin-offs. The wage differentials are computed as average marginal effects, considering the various interaction terms that are included in the regression equations. Throughout this paper, all wage differentials that show the impact of a dummy variable regressor on the level of wages in our semilogarithmic regression equations are transformed as proposed by Kennedy (1981). The variance estimator of the transformed wage differentials was derived by van Garderen and Shah (2002).[23]

<<< Table 6 about here >>>

6.1 Results for full-time employees

In contrast to the descriptive results, spin-offs show very little differences in their wage levels compared to non-spin-offs. In the model for full-time employees, most wage differentials for both competence and transfer spin-offs are insignificant. There is, however, one notable exception: Working for a transfer spin-off leads to significantly higher wages for employees with a university degree when compared with

[23] According to Kennedy (1981), the percentage impact of a dummy variable on the level of the dependent variable in a semilogarithmic regression equation, $\hat{p}$, is given by $\hat{p} = 100\left(exp\left\{\hat{c} - \frac{1}{2}\hat{V}(\hat{c})\right\} - 1\right)$ with $\hat{c}$ as the estimated coefficient and $\hat{V}(\hat{c})$ as the estimated variance of $\hat{c}$. The approximated unbiased variance estimator of $\hat{p}$ is given by $\tilde{V}(\hat{p}) = 100^2\ exp\{2\hat{c}\}\left[exp\{-\hat{V}(\hat{c})\} - exp\{-2\hat{V}(\hat{c})\}\right]$ as derived by van Garderen and Shah (2002).

university graduates working for a non-spin-off. The estimated wage differential amounts to 14.0% (left column of Table 6). Compared to competence spin-offs, although the point estimate of the wage differential for university graduates is much higher for transfer spin-offs this difference is statistically not significant (Standard error of the difference: 0.088; t-value = 1.21).

Independent of the positive impact transfer spin-offs have on the wage level of university graduates, employees do in general benefit from a higher level of education. The overall wage differential (averaged over all three groups of start-ups) for university graduates compared to employees without (completed) training comes to 3.6% and is significant at the 1% level of significance. This wage differential can be interpreted as a return to education. Similarly, the wage differential for employees with completed vocational training amounts 3.1%, again significant at the 1% level. Our regression results, however, do not show any significant difference between the return to education for university graduates and employees with a vocational training respectively (Standard error of the difference: 0.010; t-value = 0.427).

The results for the remaining covariates accord with the findings of previous studies. The daily gross wages are determined by both characteristics of the employee and employer-specific factors (left column of Table 5). The wages increase significantly with the age of the employee, although at a decreasing rate as indicated by the negative coefficient of the squared term of the age variable. Job tenure has a positive effect on wages, whereas employees that were unemployed for more than one month before entering the start-up have to accept lower wages. The estimated gender wage gap amounts to 24.6% which is close to the value reported by Eurostat 2015).[24] Employees with a foreign citizenship are not discriminated in terms of their wages. As expected, wages depend on the employee's occupation. The dummy variables reflecting the different occupational categories are individually and jointly significant (test of joint significance: χ^2 (12) = 147.70; (p > χ^2) = 0.000).

Among those variables that characterise the start-ups' founders the only variable that has a positive impact on the wage level of the start-ups' employees is the dummy variable indicating founders with a university degree. The frequency of R&D ac-

[24] It has to be noted, however, that Eurostat (2015) documents unadjusted gender wage gaps, i.e. the difference between average gross hourly earnings of male and female employees before controlling for age, occupation or different levels of education. Our regression controls for these effects. Nevertheless, since the gender wage gap is not the focus of this paper, we do not consider other important factors such as individual behaviour in wage negotiations, employment breaks (e.g. a maternity leave) or sorting into industries or jobs that may contribute to the gender wage gap (Fossen 2012; EFI 2013, 2014). Moreover, there is empirical evidence that in R&D related professions the gender wage gap is particularly high. An empirical study of almost 9,000 inventors worldwide shows that female inventors have still substantially lower incomes than their male peers, even after controlling for several sources of heterogeneity across gender such as education, experience or productivity and for the selection of inventors into different types of jobs and tasks (Hoisl and Mariani 2014). Similarly, Toivanen and Väänänen (2012) estimating the monetary returns to patenting report a substantial negative coefficient for females.

tivities does not influence wages paid by the firm. The two dummy variables for R&D activities are jointly insignificant (test of joint significance: χ^2 (2) = 0.63; ($p > \chi^2$) = 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 captured by the employee's occupation or the level of education.

Furthermore, the wages are positively associated with firm size (number or employees), the availability of informal equity from private investors, and the firm-level share of employees with a university degree. Conversely, the wages are negatively associated with the firm-level share of apprentices and the share of workers that were unemployed prior to their entry into the start-up. Software start-ups exhibit a higher wage level than new firms in the manufacturing sectors. Start-ups in Eastern Germany pay lower wages (wage differential of -9.6%), so do firms outside the core cities. Most dummy variables measuring firm age are individually not significant. Nevertheless, the hypothesis of joint significance cannot be rejected (χ^2 (5) = 46.41; ($p > \chi^2$) = 0.000).[25] Similarly, the year dummies are not individually but jointly significant (χ^2 (5) = 16.85; ($p > \chi^2$) = 0.005).

In order to evaluate the validity of our Hausman-Taylor model, we follow Baltagi (2013). The Hausman-Taylor estimator uses the individual-specific means of the time-varying, exogenous variables as instruments for the time-invariant variables that are correlated with the individual-specific random effect μ_i. The choice of the exogenous variables can be tested by a Hausman test that compares the estimated coefficients of the fixed effects model with the results of the Hausman-Taylor estimator. This test can also be interpreted as a test of the overidentifying restrictions in the Hausman-Taylor estimation. Since we have k_1 = 19 time-varying, exogenous variables and g_2 = 1 time-invariant, endogenous variable, the test statistic is χ^2-distributed with $(k_1 - g_2)$ = 18 degrees of freedom. In our model, the null hypothesis of no systematic difference between the fixed effects model and the Hausman-Taylor model cannot be rejected (χ^2 (18) = 21.65; ($p > \chi^2$) = 0.248). Thus, our choice of exogenous variables is adequate and the Hausman-Taylor estimation is valid in our case.

6.2 Results for all employees

In the regression model that considers all employees irrespectively of their employment status, the determinants of the daily gross wages are very similar to the regression results for full-time employees only (right column of Table 5). Socio-

[25] Interestingly, the coefficients of all firm age dummies indicate a negative wage differential compared to firms in their first business year (the base category). This does not imply that the individual employee earns less once the firm gets older. The effect of tenure is still positive. An explanation for the negative coefficients could be that new employees who enter the firm in "later" years receive lower wages because the founder gained more experience in wage negotiations. Alternatively, at the time of start-up the founder might have been too optimistic with respect to the financial success of her/his firm. Consequently, wages offered to new employees during "later" years have to be reduced.

demographic characteristics (age, job tenure, previous unemployment) are likewise decisive for the wage levels of part-time employees, mini jobbers and trainees. The estimated gender wage gap for all employees amounts to 23.8%. Contrary to the results for full-time employees, the dummy variable indicating firms founded by a team of founders shows a significantly positive effect on the wage level, whereas the availability of informal equity from private investors does not reveal a significant impact.

The wages are again positively associated with firm size (number of employees), they are higher for software firms and firms in core cities but lower for start-ups in Eastern Germany. The shares of person days for different groups of employees (employees with a university degree, apprentices, previously unemployed workers) are no longer significant in the model that includes all employees. The dummy variables measuring firm age are jointly significant (test of joint significance: χ^2 (5) = 85.94; (p > χ^2) = 0.000)), so is the set of year dummies (χ^2 (5) = 32.94; (p > χ^2) = 0.000).

The dummy variables that control for employment status show the wage differential of part-time employees, mini jobbers and trainees in relation to the base category, i.e. full-time employees. Part-time employees earn 37.1% less than full-time employees. Assuming that a part-time employee with the same socio-demographic characteristics who works in the same start-up receives the same salary per hour as a full-time employee, the regression results reveal that this part-time employee works 63% of the working hours of a full time job. The estimated wage differential for mini jobbers and trainees also yield plausible results, with mini jobbers earning 82.7% less than a full-time employee and trainees getting a 61.6% lower salary than a full-time colleague.

Our main results regarding the impact of spin-offs on the wage level of all employees is depicted in the right column of Table 6. In accordance with the results for full-time employees, we do not find any significant wage differentials for competence spin-offs. Transfer spin-offs, however, pay significantly higher wages than non-spin-offs. Similarly to the estimation results for full-time employees only, working for a transfer spin-off leads to higher wages for employees who hold a university degree. The estimated wage differential is 16.4% and thus about two percentage points higher than the corresponding wage differential in the model for full-time employees. As before, employees with a vocational training do not distinguish between transfer spin-offs and non-spin-offs. Contrary to our previous results, however, we also discover a positive wage differential of 14.9% for employees without (completed) training. As a result, the overall effect of being a transfer spin-off on wages is positive and significant in the model for all employees (wage differential of 10.4%).[26]

One possible driver for the positive wage differential for employees without training are student workers employed by transfer spin-offs. Most student workers are classified as employees without prior vocational training in the German dual education system. As Table 6 displays, the regression results indicate a wage differential of 16.4% for student workers in transfer spin-off, 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. In particular, the estimated size of the wage differential for student workers should thus be interpreted with caution since it may overestimate the true value.

The Hausman test on the validity of the Hausman-Taylor model confirms that there is no correlation between the chosen time-varying, exogenous variables and the individual-specific random effect (χ^2 (18) = 23.72; ($p > \chi^2$) = 0.164). Consequently, the Hausman-Taylor model is also appropriate for the estimation of the wage equation for all employees.

6.3 Discussion

The most important result of our econometric analysis is that although there is no general impact of being a spin-off on wage levels, we find a significant effect for a very particular group of employees, namely university graduates working for transfer spin-offs. One implication of this result is that the effect spin-offs have on wages depends on the nature of the knowledge transferred from the incubator university to the spin-off. Competence spin-offs do not show any significant wage differential compared to non-spin-offs. For this group of spin-offs, the higher wages that were revealed by the descriptive analysis can be explained by employer-specific and employee-specific characteristics.

There are two possible interpretations for the insignificant wage differentials of competence spin-offs. The first interpretation is that being a competence spin-off has both a positive (e.g., due to skill biased sorting) and a negative (e.g., due to non-monetary benefits provided by the competence spin-off) effect on wages. However, these two opposing impacts balance for competence spin-offs. The alternative interpretation is that being a competence spin-off does not influence wages in any positive or negative way. In this case, competence spin-offs do not distinguish from oth-

[26] In contrast to the model for full-time employees, the wage equation for all employees does not reveal 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 a 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 unskilled workers).

er high-tech start-ups in how wages are determined and there are no unobserved productivity differentials.

For university graduates in transfer spin-offs on the contrary, a potential negative effect of being a transfer spin-off is unambiguously dominated by opposing positive impacts. From a theoretical point of view this is not necessarily the expected result. It can be argued that many theoretical reasons that militate in favour of lower wages apply particularly to university graduates working in a transfer spin-off. These include the enthusiasm and identification with the business idea. In transfer spin-offs, many university graduates are involved in R&D activities. Maybe, they have already contributed to the development of the commercialised research results when they worked in a university lab together with the founder of the transfer spin-off. After they joined the transfer spin-off, university graduates probably contribute to the further development, adaptation and customisation of the research results in order to transform them into marketable products or services. These arguments indicate a presumably high identification of university graduates with a transfer spin-off's business idea so that they might be willing to accept lower wages.

Nevertheless, for university graduates of transfer spin-offs positive impacts are more important. It is very likely that sorting significantly affects the hiring pattern of transfer spin-offs. In order to further develop and adapt a product or service that originates from a university and embodies new and possibly highly sophisticated technologies, transfer spin-offs require more productive university graduates – even if we compare them to university graduates employed by other high-tech start-ups. Assuming that wages reflect university graduates' individual productivity, the estimated wage differential partly captures unobserved productivity differentials.

Furthermore, employees may associate a transfer spin-off with a higher risk of failure due to the novelty and sophistication of a transfer spin-off's products and services. In this case, they demand a compensating wage premium for working in a transfer spin-off. This argument is particularly relevant for university graduates who seek for a longer-term engagement, not least for conducting research in the transfer spin-off. In contrast, unskilled employees, many of them having a casual employment, may not demand a wage premium for a perceived higher risk of failure of a transfer spin-off.[27]

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

---

[27] It has to be emphasised that this argument is based on a risk of failure employees of transfer spin-offs possibly perceive. Empirical results, however, show that even within a sample of spin-offs, strong university linkages – as exhibited by transfer spin-offs – reduce the probability of failure (Rothaermel and Thursby 2005; see also the discussion in section 2).

Table 4). The estimated effect measures the wage differential after controlling for employee-specific and employer-specific characteristics. In other words, university graduates with the same socio-demographic characteristics (same age, same gender etc.) would earn 14% higher wages when working for a transfer spin-off compared to a situation when they worked for a non-spin-off with the same firm characteristics. However, a notable distinction between transfer spin-offs and non-spin-offs is the average age of their employees. Employees of non-spin-offs are on average 39 years old, employees of transfer spin-offs are three years younger (based on the estimation sample for full-time employees). As a consequence, one reason why the wage differential actually paid by transfer spin-offs is smaller than the estimated wage differential is that transfer spin-offs have a younger staff. Moreover, transfer spin-offs employ more female employees. In transfer spin-offs, 26% of person days are performed by female full-time employees compared to 22% in non-spin-offs.

Apart from university graduates, the wage regression for all employees reveals that student workers benefit from higher wages paid by transfer spin-offs. Since the number of student workers in our data set is relatively small, we have to be cautious when interpreting this result. Nevertheless, we conclude that transfer spin-offs provide higher wages to all employees with linkages to the university sector – either as students or as graduates. This mirrors the strong linkages transfer spin-offs themselves have to the university sector in general and to their incubator university in particular. As Egeln et al. (2003b) point out, almost 40% of transfer spin-offs employ university students through internships or offer them the opportunity to conduct studies for their university theses. In our data set, 29% of transfer spin-offs employed a student worker at least once during the observation period. Moreover, for transfer spin-offs the university sector is a source for the recruitment of highly qualified employees. Indeed, we observe some students who worked for a transfer spin-off in one year and who returned to the same transfer spin-off in later years. The recruitment of former student workers corresponds to the observation that transfer spin-offs employ younger workers. Transfer spin-offs do not only require university graduates with highest productivity, they are able to find and hire those university graduates due to their close and enduring contacts to the university sector.[28]

7 Conclusions and implications

In this paper, we study wage differentials between spin-offs and other high-tech start-ups in Germany. For our study, we use a unique linked employer-employee data set that combines survey data of newly-founded high-tech firms with comprehensive employment biography data from social security records and administrative data of the Institute of Employment Research (IAB).

[28] We re-estimated our model including a dummy variable that takes the value one if a trained employee previously worked for the same start-up as a trainee or a student worker. The results show that retained employees earn significantly higher wages. However, these results have to be interpreted with caution since the number of retained employees is very small. The results are available from the authors on request.

From a theoretical point of view, there is no unambiguous prediction whether wages paid by spin-offs should be higher or lower compared to 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 Hausman-Taylor instrumental-variable estimator in a traditional Mincer regression framework, we find that for competence spin-offs the descriptive wage differential can be explained by employee-specific and employer-specific variables. For transfer spin-offs there is no general effect of being a transfer spin-off on the wage level either. However, the econometric analysis proves a significantly positive wage differential of 14% for university graduates working for a transfer spin-off compared to graduates working for a non-spin-off. Moreover, student workers who are an important way to maintain close contacts to the university sector earn significantly higher wages in transfer spin-offs, too.

From a policy perspective, our paper is related to the discussion on the social costs and benefits of spin-off formation. Governmental policies that promote the formation of spin-offs can only be justified if the social costs involved with 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). Against the background that existing studies have produced mixed results for the question whether spin-offs generate social benefits in terms of higher employment growth, this study provides first evidence whether spin-offs generate social benefits in terms of better paid jobs. Based on our results, policy makers should consider the social benefits that result from higher wages paid by transfer spin-offs. In doing so, policy makers have to be aware that social benefits from better paid jobs are confined to employees with contacts to the university sector, i.e. university graduates and student workers. Nevertheless, considering the effect transfer spin-offs have on the wage level will give policy makers a more comprehensive view on the social benefits of spin-off formation.

Finally, our study makes an important contribution to the controversial discussion whether spin-offs exhibit a higher employment growth rate than other start-ups. Studies that examine the growth rate of spin-offs argue that spin-offs should be expected to grow faster. It then comes as a surprise when the empirical analysis does not find significantly higher growth rates for spin-offs and it often remains unclear why, contrary to the theoretical arguments, spin-offs actually do not grow faster. Our study offers one possible answer. Spin-offs and in particular transfer spin-offs do not only heavily rely on university graduates as employees. They also require university graduates with the highest productivity and these graduates must be paid a wage premium. Therefore, transfer spin-offs are restricted in their growth potential because growth, what is to a large degree equivalent to hiring another university graduate, is too expensive.

One limitation of our study is that we are unable to further differentiate spin-offs, in particular the group of transfer spin-offs. Although our estimation sample contains more than 1,800 person-year observations for transfer spin-offs, there are only 55 transfer spin-offs in our data set. Nevertheless, it would be an interesting research question, whether our results are driven by a particular group of transfer spin-offs, for instance those whose spin-off process was financially supported by the government (e.g., in context of the programme EXIST-Seed, cf. Kulicke and Schleinkofer (2008)) or spin-offs who were granted a patent or license by their incubator university. Our data set is further limited by the cross-sectional nature of the ZEW High-Tech Start-Up Survey. We used administrative data to compute annual firm-level variables like firm size or the share of university graduates in order to capture the knowledge-intensity of a start-up. However, firm-level data that were derived from the survey are not available in a panel data format. This limitation applies to the amount of R&D expenditures and, in particular, to information on a start-up's financial situation (e.g., cash flow, availability of debt financing). The regression results already show that the wage level depends on the availability of informal equity. Additional information on other sources of finance would improve our measurement of 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). Observing annual financial data would also allow us to examine which spin-offs are able to provide compensation and monetary incentives (e.g., bonus payments, profit sharing) in order to attract and retain highly skilled employees required for instance for R&D activities (Bengtsson and Hand 2013).

A further shortcoming of our analysis 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-off exhibit a lower probability of survival, 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 the case firms reduce wages or wage growth with the goal to ensure survival. The question 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.

References

Abowd, J.M., Kramarz, F., Margolis, D., 1999. High wage workers and high wage firms. Econometrica 67 (2), 251-333.

Acemoglu, D., Autor, D., 2011. Skills, tasks, and technologies: implications for employment and earnings, in: Ashenfelter, O., Card, D. (Eds.), Handbook of Labor Economics. Elsevier, Amsterdam, pp. 1043-1171.

Aldrich, H.E., Ruef, M., 2006. Organizations Evolving (2nd ed.). SAGE Publications Ltd..

Audretsch, D.B., 1995. Innovation, Growth and Survival. International Journal of Industrial Organization 13 (4), 441-457.

Baltagi, B.H., 2013. Econometric Analysis of Panel Data (5th ed.). Wiley, Chichester,UK.

Baron, J., Hannan, M., 2002. Organizational Blueprints for Success in High-Tech Start-Ups. California Management Review 44 (3), 8-36.

Bauernschuster, S., Falck , O., Heblich, S., 2009. Training and innovation. Journal of Human Capital 3 (4), 323-353.

Becker, G.S., 1964. Human Capital: A theoretical and empirical analysis with special reference to education. Columbia University Press, New York.

Bengtsson, O., Hand, J.R., 2013. Employee Compensation in Entrepreneurial Companies. Journal of Economics and Management Strategy 22 (2), 312-340.

Benz, M., 2009. Entrepreneurship as a non-profit seeking activity. International Entrepreneurship and Management Journal 5, 23-44.

Benz, M., Frey, B. S., 2004. Being independent raises happiness at work. Swedish Economic Policy Review 11, 95-134

Berggren, E., Lindholm-Dahlstrand, A., 2009. Creating an Entrepreneurial Region: Two Waves of Academic Spin-Offs from Halmstad University. European Planning Studies 17 (8), 1171-1189.

Blossfeld, H.-P., 1987. Labor Market Entry and the Sexual Segregation of Careers in the Federal Republic of Germany. The American Journal of Sociology 93 (1), 89-118.

Brixy, U., Kohaut, S., Schnabel, C., 2007. Do Newly Founded Firms Pay Lower Wages? First Evidence from Germany. Small Business Economics 29, 161-171.

Buenstorf, G., 2009. Is commercialization good or bad for science? Individual-level evidence from the Max Planck Society. Research Policy 38, 281-292.

Bundesagentur für Arbeit, 1988. Klassifizierung der Berufe 1988. Statistik der Bundesagentur für Arbeit, Nuremberg.

Cantner, U., Goethner, M., 2011. Performance differences between academic spin-offs and non-academic spin-ups: A comparative analysis using non-parametric matching approach. mimeo, DIME Final Conference, Maastricht University.

Card, D., Heining, J., Kline, P., 2013. Workplace Heterogeneity and the Rise of West German Wage Inequality. The Quarterly Journal of Economics 128 (3), 967-1015.

Cardon, M.S., Stevens, C.E., 2004. Managing human resources in small organizations: What do we know. Human Resource Management Review 14, 295-323.

Clarysse, B., Moray, N., 2004. A process study of entrepreneurial team formation: The case of a research-based spin-off. Journal of Business Venturing 19 (1), 55-79.

Clarysse, B., Wright, M., van de Velde, E., 2011. Entrepreneurial Origin, Technological Knowledge, and the Growth of Spin-Off Companies. Journal of Management Studies 48 (6), 1420-1442.

Colombo, M.G., Piva, E., 2005. Are Academic Start-ups Different? A Matched Pair Analysis. Working Paper ID: A244, Politecnico di Milano.

Commission of Experts for Research and Innovation (EFI) (ed.), 2013. Research, innovation and technological performance in Germany – EFI Report 2013. EFI, Berlin.

Commission of Experts for Research and Innovation (EFI) (ed.), 2014. Research, innovation and technological performance in Germany – EFI Report 2014. EFI, Berlin.

Czarnitzki, D., Rammer, C., Toole, A.A., 2014. University Spinoffs and the "Performance Premium". Small Business Economics 43 (2), 309-326.

De Cleyn, S.H., Braet, J., Klofsten, M., 2011. How do human and social capital contribute to the early development of academic spin-off ventures. Frontiers of Entrepreneurship Research 31 (17), Article 3, 567-581.

Depalo, D., Di Addario, S., 2014. Shedding Light on Inventors' Returns to Patents. IRLE Working Paper No. 115-14, University of California, Berkeley.

Dorner, M., Heining, J., Jacobebbinghaus, P., Seth, S., 2010. The Sample of Integrated Labour Market Biographies. Journal of Applied Social Science Studies 130 (4), 599-608.

Dostie, B., 2014. Innovation, Productivity, and Training. IZA Discussion Paper No. 8506, Bonn.

Dupuy, A., Smits, W., 2010. How Large is the Compensating Wage Differential for R&D Workers? Economics of Innovation and New Technology 19 (5), 423-436.

Egeln, J., Fryges, H., Gottschalk, S., Rammer, C., 2007. Dynamik von akademischen Spinoff-Gründungen in Österreich. ZEW Discussion Paper No. 07-021, Centre for European Economic Research, Mannheim.

Egeln, J., Fryges, H., Gottschalk, S., Rammer, C., 2010. Performance von akademischen Spinoff-Gründungen in Österreich. AStA Wirtschafts- und Sozialstatistisches Archiv 3 (4), 265-283.

Egeln, J., Gottschalk, S., Rammer, C., Spielkamp, A., 2003a. Spinoff-Gründungen aus der öffentlichen Forschung in Deutschland. ZEW Wirtschaftsanalysen, Vol. 68, Nomos, Baden-Baden.

Egeln, J., Gottschalk, S., Rammer, C., Spielkamp, A., 2003b. Public Research Spin-Offs in Germany – Summary Report. ZEW Documentation, No. 03-04, Centre for European Economic Research, Mannheim.

Eurostat, 2015. Gender pay gap in unadjusted form – NACE Rev. 2 (Structure of Earnings Survey methodology), available at http://ec.europa.eu/eurostat/tgm/table.do?tab=table&init=1&language=en&pcode=tsdsc340&plugin=1

Fitzenberger, B., Osikominu, A., Völter, R., 2006. Imputation rules to improve the education variable in the IAB employment subsample. Journal of Applied Social Science Studies 126 (3), 405-436.

Fossen, F.M., 2012. Gender differences in entrepreneurial choice and risk aversion – a decomposition based on a microeconometric model. Applied Economics 44, 1795-1812.

Freeman, R., 1978. Job Satisfaction as an Economic Variable. American Economic Review 68 (2), 135-141.

Fryges, H., Gottschalk, S., Licht, G., Müller, K., 2007. Hightech-Gründungen und Business Angels. Report to the Federal Ministry of Economics and Technology, Centre for European Economic Research, Mannheim.

Gerlach, K., Hübler, O., 1998. Firm Size and Wages in Germany – Trends and Impacts of Mobility. Empirica 25, 245-261.

Gottschalk, S., Fryges, H., Metzger, G., Heger, D., Licht, G., 2007. Start-Ups zwischen Forschung und Finanzierung: Hightech-Gründungen in Deutschland. Research report, Centre for European Economic Research in collaboration with Microsoft Germany, Mannheim.

Grupp, H., Legler, H., 2000. Hochtechnologie 2000: Neudefinition der Hochtechnologie für die Berichtersattung zur technologischen Leistungsfähigkeit. Report to the Federal Ministry of Education and Research, Karlsruhe/Hannover.

Hartog, J., 1986. Allocation and the Earnings Function. Empirical Economics 11 (1), 97-110.

Hausman, J.A., Taylor, W.E., 1981. Panel Data and Unobservable Individual Effects. Econometrica 49 (6), 1377-1398.

Heineck, G., 2005. Up in the Skies? The Relationship between Body Height and Earnings in Germany. Labour, 19 (3), 469-489.

Hoisl, K., Mariani, M., 2014. It's a men's job – Income and the gender gap in industrial research. mimeo.

Hyytinen, A., Ilmakunnas, P., Toivanen, O., 2013. The return-to-entrepreneurship puzzle. Labour Economics 20, 57-67.

Jacobson, L.S., LaLonde. R.J., Sullivan, D.G., 1993. Earnings losses of displaced workers. American Economic Review 83 (4), 685-709.

Kennedy, P.E., 1981. Estimation with correctly interpreted dummy variables in semilogarithmic equations. American Economic Review 71, 801.

Kulicke, M., Schleinkofer, M., 2008. Wirkungen von EXIST-SEED aus Sicht von Geförderten – Ergebnisse einer Befragung im Rahmen der wissenschaftlichen Begleitung von EXIST – Existenzgründungen aus der Wissenschaft. Project report to the Federal Ministry of Economics and Technology (BMWi), Fraunhofer IRB Verlag, Stuttgart.

Lacetera, N., 2009. Academic entrepreneurship. Managerial and Decision Economics 30, 443-464.

Light, A., Ureta, M., 1995. Early-Career Work Experience and Gender Wage Differentials. Journal of Labor Economics 13 (1), 121-154.

Lindholm-Dahlstrand, Å., 1997. Growth and Inventiveness in Technology-Based Spin-Off Firms. Research Policy 26 (3), 331-344.

Manigart, S., Van Hyfte, M. (1999). Post-investment evolution of venture backed companies, in: Reynolds, P., Bygrave, W., Manigart, S., Mason, C., Meyer, G., Sapienza, H.J., Shaver, K. (Eds), Frontiers of Entrepreneurship Research. Babson College, Wellesley, MA, pp. 419-432.

Mincer, J., 1974. Schooling, Experience and Earnings. Columbia University Press, New York.

Müller, K., 2010. Academic Spin-Off's Transfer Speed – Analysing the Time from Leaving University to Venture. Research Policy 39 (2), 189-199.

Mustar, P., 1997. How French Academics Create Hi-Tech Companies: The Conditions for Success or Failure. Science and Public Policy 24 (1), 37-43.

Mustar, P., Wright, M., Clarysse, B., 2008. University Spin-Off Firms: Lessons from Ten Years of Experience in Europe. Science and Public Policy 35 (2), 67-80.

Nerlinger, E., Berger, G., 1995. Technologieorientierte Industrien und Unternehmen: Alternative Definitionen. ZEW Discussion Paper No. 95-20, Centre for European Economic Research, Mannheim.

Nyström, K., Elvung, G.Z., 2014. New firms and labor market entrants: Is there a wage penalty for employment in new firms? Small Business Economics 43 (2), 399-410.

Ouimet, P., Zarutskie, R., 2014. Who works for startups? The relation between firm age, employee age, and growth. Journal of Financial Economics 112 (3), 386-407.

Pirnay, F., Surlemont, B., Nlemvo, F., 2003. Toward a Typology of University Spin-Offs. Small Business Economics 21 (4), 355-369.

Roach, M., Sauermann, H., 2010. A taste for science? PhD scientists' academic orientation and self-selection into research careers in industry. Research Policy 39 (3), 422-434.

Rosen, S., 1986. The theory of equalizing differences, in: Ashenfelter, O., Layard, R. (Eds.), Handbook of Labor Economics. North-Holland, pp. 641-692.

Rothaermel, F.T., Thursby, M., 2005. Incubator Firm Failure or Graduation? The Role of University Linkages. Research Policy 34 (7), 1076-1090.

Salehin, M., Breunig, R., 2012. The Immigrant Wage Gap and Assimilation in Australia: The Impact of Unobserved Heterogeneity. Australian National University, Centre for Economic Policy Research, Discussion Paper No. 661, Canberra.

Schmieder, J.F., von Wachter, T., Bender, S., 2009. The Long-Term Impact of Job Displacement in Germany During the 1982 Recession on Earnings, Income, and Employment. Institute for Employment Research, IAB Discussion Paper No. 2010-1, Nuremberg.

Schnabel, C., Kohaut, S., Brixy, U., 2011. Employment stability in newly founded firms: a matching approach using linked employer-employee data from Germany. Small Business Economics 36 (1), 85-100.

Shane, S., 2004. Academic entrepreneurship: University spin-offs and wealth creation. Edward Elgar, Cheltenham, UK.

Shane, S., Stuart, T., 2002. Organizational endowments and the performance of university start-ups. Management Science 48, 154-170.

Song, J., Almeida, P., Wu, G., 2003. Learning-by-hiring: When is Mobility More Likely to Facilitate Interfirm Knowledge Transfer. Management Science 49 (4), 351-365.

Stern, S., 2004. Do scientists pay to be scientists? Management Science 50 (6), 835-853.

Toivanen, O., Väänänen, L., 2012. Returns to Inventors. The Review of Economics and Statistics 94, 1173-1190.

Toole, A.A., Czarnitzki, D., 2007. Biomedical Academic Entrepreneurship Through the SBIR Program. Journal of Economic Behavior and Organization 63, 716-738.

Toole, A.A., Czarnitzki, D., 2010. Commercializing Science: Is there a university "brain drain" from academic entrepreneurship? Management Science 56 (9), 1599-1614.

van Garderen, K.J., Shah, C., 2002. Exact Interpretation of Dummy Variables in Semilogarithmic Equations. Econometrics Journal 5 (1), 149-159.

van Reenen, J., 1996. The Creation and Capture of Rents: Wages and Innovation in a Panel of U.K. Companies. The Quarterly Journal of Economics 111, 195-226.

Visintin, F., Pittino, D., 2014 Founding Team Composition and Early Performance of University-Based Spin-Off Companies. Technovation 34 (1), 31-43.

Wennberg, K., Wiklund, J., Wright, M., 2011. The effectiveness of university knowledge spillovers: Performance differences between university spin-offs and corporate spin-offs. Research Policy 40 (8), 1128-1143.

Wright, M., Clarysse, B., Mustar, P., Lockett, A., 2007a. Academic entrepreneurship in Europe. Edward Elgar, Cheltenham, UK.

Wright, M., Hmieleski, K.M., Siegel, D.S., Ensley, M.D., 2007b. The Role of Human Capital in Technological Entrepreneurship. Entrepreneurship Theory and Practice 31 (6), 791-806.

Zhang, J., 2009. The Performance of University Spin-Offs: An Exploratory Analysis Using Venture Capital Data. The Journal of Technology Transfer 34 (3), 255-285.

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	9,747	85.0	24,239	86.1	20,803	85.8
Spin-offs								
Competence spin-offs	65	8.1	816	7.1	1,880	6.7	1,620	6.7
Transfer spin-offs	55	6.8	910	7.9	2,039	7.2	1,817	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.

Table 2
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
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]											
Trainees	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 employees	5.30	-1.48	0.113	9.19	3.89	0.007	4.01	-1.29	0.175	-5.18	0.002
Full-time employees	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

Notes: Annual data averaged over the observation period 2003 to 2008. Firm-year observations: 2,455 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.

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

Table 3
Gross annual wages by employment status (in Euro of 2006)

	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
Trainees	6,513.12	552.62	0.003	5,856.34	-656.78	0.014	6,110.35	-402.77	0.072	254.01	0.436
Mini jobber	3,861.09	-253.63	0.023	3,581.79	-279.31	0.073	4,656.34	795.24	0.000	1,074.55	0.000
Part-time employees	13,771.32	-2,451.60	0.006	16,983.19	3,211.87	0.009	14,917.79	1,146.47	0.288	-2,065.40	0.185
Full-time employees	30,589.71	-4,461.09	0.000	33,354.18	2,764.48	0.000	36,360.09	5,770.38	0.000	3,005.91	0.000
Student workers	8,418.56	-231.82	0.712	9,471.93	1,053.37	0.409	8,257.08	-161.47	0.801	-1,214.84	0.373

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

Table 4
Gross annual wages of full-time employees by level of education (in Euro of 2006)

	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
No (completed) training	25,817.36	-1,294.76	0.197	25,660.08	-157.28	0.919	28,594.41	2,777.04	0.022	2,934.33	0.126
Completed vocational training	28,601.86	-811.41	0.050	28,953.16	351.30	0.554	29,913.31	1,311.45	0.016	960.15	0.220
University degree	37,056.80	-4,466.72	0.000	41,289.86	4,233.07	0.000	41,647.79	4,590.99	0.000	357.93	0.734

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

Table 5
Determinants of the (logarithmic) daily gross wage – results of the Hausman-Taylor model

	Full-time employees			All employees		
	Coeff.	Stand. error		Coeff.	Stand. error	
Time-invariant exogenous variables						
Spin-off type (ref.: non-spin-off)						
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)						
Occasional R&D	0.012	0.041		0.003	0.035	
Continuous R&D	0.027	0.034		-0.010	0.029	
Industry sector (ref.: cutting-edge manuf.)						
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 (in person days)	0.026	0.014	*	0.027	0.017	
Share of trainees (in person days)	-0.152	0.038	***	0.016	0.038	
Share of previously unemployed employ-ees (in 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 x completed voca-tional training	0.002	0.048		-0.074	0.050	
Competence spin-off x university degree	-0.003	0.052		-0.089	0.055	
Transfer spin-off x completed vocational training	0.030	0.059		-0.077	0.052	
Transfer spin-off x university degree	0.115	0.061	*	0.013	0.043	
Competence spin-off x student worker		–		0.082	0.104	
Transfer spin-off x student worker		–		0.056	0.056	
Employee age in years (log)	4.260	0.567	***	1.512	0.518	***
Squared employee age in years (log)	-0.461	0.095	***	-0.046	0.083	

continued next page

Continued from Table 5

Education (ref.: no (completed) training)						
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	***
Dummy wages at or above the social security contribution ceiling	0.100	0.008	***	0.122	0.013	***
Employment status (ref.: full-time employee)						
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		Yes			Yes	
Year dummies		Yes			Yes	
Occupational fields dummies		Yes			Yes	
Integer	-5.073	0.869	***	-0.681	0.829	
Person-year observations		16,082			24,240	
Employees		6,215			9,815	
σ_μ		1.219			1.328	
σ_ε		0.139			0.221	
ρ		0.987			0.973	

Notes: 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 .
*/**/*** 10%/5%/1% level of significance; standard errors clustered at the individual level.

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

Table 6
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	

Notes: 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.

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

Appendix

Table 7
Composition of high-tech industry sectors

	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

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.

Source: own classification, high-technology manufacturing industries based on Grupp and Legler (2000), high-technology service sectors based on Nerlinger and Berger (1995).

Table 8
Wording of questions that identify academic spin-offs

1	Did the founder study at a university or does she/he currently study?
2	After finishing her/his education, was the founder employed by a university or by a public research institution?
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. 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. 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.

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

Table 9
Comparison of the pooled OLS, random effects, fixed effects and Hausman-Taylor model

	Pooled OLS		**Random effects**		**Fixed effects**		**Hausman-Taylor**	
	Coeff. (Stand. error)		Coeff. (Stand. error)		Coeff. (Stand. error)		Coeff. (Stand. error)	
Spin-off (ref.: non-spin-off)								
Competence spin-off	0.024		0.019		–		0.031	
	(0.069)		(0.049)				(0.069)	
Transfer spin-off	0.071		0.073		–		0.018	
	(0.081)		(0.057)				(0.075)	
Founder with university degree	0.061	***	0.109	***	–		0.109	***
	(0.013)		(0.013)				(0.034)	
Founder with industry experience	0.024	*	0.054	***	–		-0.004	
	(0.013)		(0.014)				(0.038)	
Team foundation	0.026	**	0.034	***	–		0.029	
	(0.011)		(0.011)				(0.030)	
R&D activities (ref.: no R&D)								
Occasional R&D	0.054	***	0.042	***	–		0.012	
	(0.015)		(0.015)				(0.041)	
Continuous R&D	0.005		0.029	**	–		0.027	
	(0.012)		(0.013)				(0.034)	
Industry sector (ref.: cutting-edge manuf.)								
High-technology manufacturing	0.060	***	0.071	***	–		0.022	
	(0.013)		(0.013)				(0.035)	
Software	0.086	***	0.072	***	–		0.130	**
	(0.021)		(0.021)				(0.051)	
Technology-intensive services	0.021		0.031	*	–		0.070	
	(0.018)		(0.018)				(0.044)	
Female employee	-0.279	***	-0.310	***	–		-0.281	***
	(0.013)		(0.013)				(0.032)	
Employee with German citizenship	0.015		0.007		–		-0.009	
	(0.020)		(0.019)				(0.051)	
Firm location in East Germany	-0.231	***	-0.218	***	-0.047		-0.101	***
	(0.014)		(0.013)		(0.035)		(0.021)	
Firm size in person days (log)	0.047	***	0.027	***	0.010	*	0.012	***
	(0.005)		(0.005)		(0.006)		(0.003)	
Share of university graduates (in person days)	0.187	***	0.105	***	0.013		0.026	*
	(0.028)		(0.022)		(0.026)		(0.014)	
Share of trainees (in person days)	-0.625	***	-0.338	***	-0.133		-0.152	***
	(0.078)		(0.064)		(0.090)		(0.038)	
Share of previously unemployed employees (in person days)	-0.327	***	-0.140	***	-0.024		-0.025	*
	(0.032)		(0.027)		(0.033)		(0.015)	
External equity from private investors	0.020		-0.006		0.036		0.032	**
	(0.019)		(0.024)		(0.045)		(0.015)	
Duration of prior unemployment episode in days (log)	-0.020	***	-0.028	***	–		-0.106	***
	(0.002)		(0.002)				(0.013)	
Competence spin-off x completed vocational training	-0.026		0.003		0.002		0.002	
	(0.073)		(0.049)		(0.060)		(0.048)	
Competence spin-off x university degree	0.008		0.008		-0.013		-0.003	
	(0.073)		(0.056)		(0.060)		(0.052)	
Transfer spin-off x completed vocational training	-0.066		-0.042		0.029		0.030	
	(0.086)		(0.056)		(0.094)		(0.059)	
Transfer spin-off x university degree	-0.064		-0.007		0.107		0.115	*
	(0.083)		(0.062)		(0.118)		(0.061)	

continued next page

Continued from Table 9

Employee age in years (log)	4.744 *** (0.435)	5.563 *** (0.412)	-2.421 (4.503)	4.260 *** (0.567)
Squared employee age in years (log)	-0.634 *** (0.061)	-0.740 *** (0.058)	0.846 (0.889)	-0.461 *** (0.095)
Education (ref.: no (completed) training)				
Completed vocational training	0.100 *** (0.018)	0.064 *** (0.016)	0.030 (0.023)	0.029 ** (0.012)
University degree	0.158 *** (0.020)	0.113 *** (0.021)	0.022 (0.030)	0.027 ** (0.013)
Firm tenure in days (log)	0.063 *** (0.005)	0.040 *** (0.003)	0.035 *** (0.004)	0.034 *** (0.003)
Dummy wages at or above the social security contribution ceiling	0.406 *** (0.016)	0.159 *** (0.019)	0.097 *** (0.021)	0.100 *** (0.008)
Age of firm dummies	Yes	Yes	Yes	Yes
Structural type of region	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Occupational fields dummies	Yes	Yes	Yes	Yes
Integer	-4.944 *** (0.771)	-6.401 *** (0.734)	1.833 (4.649)	-5.073 *** (0.869)
Person-year observations	16,082	16,082	16,082	16,082
Employees	6,215	6,215	6,215	6,215
R^2	0.469		0.095	
σ_μ		0.347	1.076	1.219
σ_ε		0.139	0.139	0.139
ρ		0.862	0.984	0.987

Notes: Model for full-time employees only.

σ_μ: Standard error of the individual-level random effect and the individual-level fixed effects respectively;

σ_ε: Standard error of the idiosyncratic error term;

ρ: Fraction of variance attributed to μ_i.

*/**/*** 10%/5%/1% level of significance; standard errors clustered at the individual level.

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

Table 10
Occupational categories

	Occupational category	share (in %)	examples
1	Agricultural occupations	0.35	Farmers, other paper products makers, fishermen
2	Simple manual occupations	14.15	Assistants (no further specification), welders, oxy-acetylene cutters, packag-ers, goods receivers, despatchers
3	Skilled manual occupations	21.92	Electrical fitters, mechanics, engine fit-ters, locksmiths, turners
4	Technicians	9.86	Technical draughtspersons, electrical engineering technicians, mechanical en-gineering technicians
5	Engineers	6.39	Electrical engineers, mechanical engi-neers, motor engineers, chemists, chemi-cal engineers
6	Simple service	5.31	Household cleaners, stores and transport workers, warehouse managers, ware-housemen
7	Qualified service	2.74	Visual, commercial artists, safety testers, artistic and assisting occupations (stage, video and audio)
8	Semi-professions	0.44	Journalists, interpreters, translators, li-brarians, archivists, museum specialists
9	Professions	0.83	Economic and social scientists, statisti-cians, university teachers, lecturers at higher technical schools and academies, legal representatives, advisors
10	Simple commercial and administrative occupations	4.40	Office auxiliary workers, salespersons, stenographers, shorthand-typists, typists
11	Qualified commercial and administrative occupations	28.38	Office specialists, data processing spe-cialists, wholesale and retail trade buyers, buyers, accountants
12	Managers	1.86	Entrepreneurs, managing directors, divi-sional managers, management consult-ants, organisers
13	NA	3.38	Occupation not reported, unknown (category omitted in regressions)
		100	

Note: The classification of occupations (3-digit level, cf. Bundesagentur für Arbeit (1988)) is based on occupational fields proposed by Blossfeld (1987).

Source: Integrated Employment Biographies of the IAB.

Table 11
Descriptive statistics of explanatory variables by start-up group

		Non-spin-offs	Competence spin-offs	Transfer spin-offs
Founder with university degree	%	65.31	90.56	95.87
Founder with industry experience	%	83.42	87.72	78.54
Team foundation	%	57.80	62.65	82.39
R&D activities: No R&D	%	38.28	32.28	8.92
Occasional R&D	%	42.64	18.27	3.63
Continuous R&D	%	19.08	49.44	87.45
Industry sector: Cutting-edge manufacturing	%	25.50	46.98	25.65
High-technology manufacturing	%	43.55	13.40	37.26
Software	%	11.62	13.21	10.73
Technology-intensive services	%	19.33	26.42	26.36
Structural type of region: Core city	%	27.26	40.93	42.43
Urban fringe	%	47.61	36.98	53.88
Cities outside agglomerations	%	7.08	12.35	0.55
Rural areas	%	18.06	9.75	3.14
Age of firm (in years)	mean	2.56	2.77	2.64
	median	3	3	3
Female employee	%	31.25	31.67	29.17
Employee with German citizenship	%	91.23	93.21	91.69
Firm location in East Germany	%	18.30	21.48	14.53
Firm size in person days	mean	33.30	11.76	16.16
	median	13.25	8.58	10.13
Share of university graduates (in % of person days)	mean	23.13	32.84	45.91
	median	16.40	31.67	48.10
Share of trainees (in % of person days)	mean	3.64	4.98	2.74
	median	0	0	0
Share of previously unemployed employees	mean	20.50	16.79	14.78
(in % of person days)	median	14.95	11.97	9.47
External equity from private investors	%	6.76	8.64	25.43
Duration of prior unemployment episode (in days)	mean	22.73	20.47	12.89
	median	0	0	0
Employee age (in years)	mean	38.26	36.97	34.80
	median	38	36	32
Education: No (completed) training	%	12.13	13.52	16.35
Completed vocational training	%	60.00	47.72	34.12
University degree	%	23.40	32.47	46.06
Firm tenure (in days)	mean	590.50	534.31	513.40
	median	457	415	366
Dummy wages at or above the social security contribution ceiling	%	2.81	5.68	7.43

continued next page

Continued from Table 11

Employment status: Trainee	%	3.97	5.06	3.14
Mini-jobber	%	25.23	30.86	27.02
Part-time employee	%	3.81	6.36	3.30
Full-time employee	%	67.00	57.72	66.54
Student worker	%	1.81	2.84	5.17
Person-year observations (estimation sample)		20,803	1,620	1,817

Descriptive statistics based on person-year observations (N = 24,240).

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

Recently published

No.	Author(s)	Title	Date
2/2015	Stops, M.	Revisiting German labour market reform effects: A panel data analysis for occupational labour markets	1/15
3/2015	Brunow, S. Grünwald, L.	Exports, agglomeration and workforce diversity: An empirical assessment for German Establishments	1/15
4/2015	Osiander, C. Dietz, M.	What could all the money do? Ergebnisse eines faktoriellen Surveys zur Bedeutung von Opportunitätskosten bei Weiterbildungsentscheidungen	1/15
5/2015	Lucht, M. Haas, A.	The productivity effect of migrants: Wage cost advantages and heterogeneous firms	2/15
6/2015	Brenzel, H. Müller, A.	Higher wages or lower expectations? Adjustments of German firms in the hiring process	2/15
7/2015	Vallizadeh, E. Muysken, J. Ziesemer, T.	Offshoring of medium-skill jobs, polarization, and productivity effect: Implications for wages and low-skill unemployment	2/15
8/2015	Busk, H. Jahn, E. J. Singer, C.	Do changes in regulation affect temporary agency workers' job satisfaction?	2/15
9/2015	Eisermann, M. Moritz, M. Stockinger, B.	Multinational resilience or dispensable jobs? German FDI and employment in the Czech Republic around the Great Recession	3/15
10/2015	Walwei, U.	From deregulation to re-regulation: Trend reversal in German labour market institutions and its possible implications	3/15
11/2015	vom Berge, P. Schmillen, A.	Direct and indirect effects of mass layoffs: Evidence from geo-referenced data	3/15
12/2015	Brenzel, H. Reichelt, M.	Job mobility as a new explanation for the immigrant-native wage gap: A longitudinal analysis for the German labor market	3/15
13/2015	Schanne, N.	A Global Vector Autoregression (GVAR) model for regional labour markets and its forecasting performance with leading indicators in Germany	4/15
14/2015	Reichelt, M. Abraham, M.	Occupational and regional mobility as substitutes: A new approach to understanding job changes and wage inequality	4/15
15/2015	Zapf, I.	Individual and workplace-specific determinants of paid and unpaid overtime work in Germany	4/15
16/2015	Horbach, J. Janser, M.	The role of innovation and agglomeration for employment growth in the environmental sector	6/15

As per: 2015-06-09

For a full list, consult the IAB website
http://www.iab.de/de/publikationen/discussionpaper.aspx

Imprint

IAB-Discussion Paper 17/2015

Editorial address
Institute for Employment Research
of the Federal Employment Agency
Regensburger Str. 104
D-90478 Nuremberg

Editorial staff
Regina Stoll, Jutta Palm-Nowak

Technical completion
Jutta Palm-Nowak

Website
http://www.iab.de

Download of this Discussion Paper
http://doku.iab.de/discussionpapers/2015/dp1715.pdf

ISSN 2195-2663

For further inquiries contact the author:

Matthias Dorner
Phone + 49.911.179 8895
E-mail matthias.dorner@iab.de