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Experience Matters: The Role of Academic Scientist Mobility for Industrial Innovation

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EXPERIENCE MATTERS: THE ROLE OF ACADEMIC SCIENTIST MOBILITY FOR INDUSTRIAL INNOVATION

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Research summary: A learning-by-hiring approach is used to scrutinize scientists' mobility in relation to the recruiting firms' subsequent innovation output. Our starting point is that among firm hires, individuals with university research experience — hired from universities or firms — can be particularly valuable. However, conflicting institutional logics between academia and industry makes working with academic scientists challenging at times for firms. We suggest two solutions to this difficulty: hiring 'ambidextrous' individuals with a mix of experience of university research and working for a technologically advanced firm, and a strong organizational research culture in the recruiting firm reflected by the presence of a scientist on the top management team. We track the mobility of R&D workers empirically using patent and linked employer-employee data. (max 125 words).

Managerial summary: An important way to make organizations more innovative is hiring individual researchers with the right types of skills and experience. We show that individuals with university research experience beyond their final degree are particularly likely to help boost firm-level innovation output after hiring compared to R&D workers with other types of skills and experience. However, to obtain good returns to innovation from hiring such individuals, firms need a university research-friendly organizational culture when hiring individuals with university research experience, from either firms or academia. (max 125 words).

KEYWORDS: Innovation output, the science-technology relationship, scientists' mobility, organizational research culture, econometric evidence.

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INTRODUCTION

It is well-established that science and university scientists make central and important contributions to the innovation output of private business firms in a variety of industries (see e.g., Jaffe, 1989; Gambardella, 1992; Fleming and Sorenson, 2004; Gittelman, 2007; Kotha, George, and Srikanth, 2013). However, the conditions allowing firms to benefit from expanding their scientific capacity through inward mobility of academic scientists with heterogeneous work experience are less well understood. In this paper, we examine whether private firms' hiring of scientists with university research experience has a stronger impact on these firms' innovation output than hiring of other types of researchers, and we address the related question of how other knowledge-work experienced hires and the recruiting firm's research culture, might affect the net benefits of scientists' mobility.

The extant literature on learning-by-hiring considers recruitment of research scientists to be an important source of knowledge that affects the hiring firm's innovation process (e.g., Almeida and Kogut, 1999; Rosenkopf and Almeida, 2003; Hoisl, 2007; Tzabbar, 2009; Corredoira and Rosenkopf, 2010; Singh and Agrawal, 2011; Kaiser, Kongsted, and Rønde, 2015; Jain, 2016). The study by Rosenkopf and Almeida (2003) examines pairs of firms, and shows that dyads involved in high levels of mutual labor mobility are involved also in greater knowledge flows. Tzabbar (2009) shows that the recruitment of technologically distant scientists is related positively to firm-level technological repositioning. In a paper that uses the Danish register data employed in our study, Kaiser, Kongsted and Rønde (2015) find that workers recruited from a technologically leading firm compared to individuals recruited from non-leading firms, appear to increase the innovation output of the new employer. However, although this research stream provides valuable insights, it has some limitations. First, work on how scientists affect the innovation output of private business firms generally analyzes hirings from other industrial firms, irrespective of the *type* and *mix of* research experience accumulated by the recruited researchers from disparate organizational contexts (e.g., universities vs. employment in other business firms). Second, this literature looks mostly at how labor mobility affects the hiring firms' technological problem-solving processes (reflected in patent citations) rather than their innovation output.

Taking the learning-by-hiring literature as our point of departure, the present study analyzes the extent of the heterogeneity in the benefits derived from hiring R&D workers with different kinds of knowledge-related experience with respect to firm-level, quality adjusted innovation output. We focus on the joint effects of scientists' previous university research experience combined possibly with experience of working in a firm with a strong technological record, and the recruiting firm's research culture. To our knowledge, ours is the first paper to study the combined influence of newly recruited researchers' different university and private firm experience, and to link this heterogeneity to the firm-level research culture and firm innovation output.

We propose that firms' hirings of individuals with university research rather than other types of experience provide important support for science-based problem solving which in turn, leads to more firm-level innovation output. However, given the potentially conflicting institutional logics between industrial and academic research (Dasgupta and David, 1994; Sauermann and Stephan, 2013), hiring university scientists can present problems, and may not pay off. We hypothesize about two approaches to this problem which may allow firms to benefit from hiring individuals with university research experience in relation to their quality adjusted innovation output. The first approach involves hiring individuals with a mix of industry and university research experience, and the second refers to firms with a research culture which allows them to accommodate individuals with academic research experience and related preferences.

We use unique data on the entire population of Danish firms and their employees over the period 1999 to 2004. These data allow us to measure the average effect on innovation of R&D workers moving to private firms, and to assess the effect of inward mobility of scientists with heterogeneous experience. We link these data to the number of a firm's patent applications to the European Patent Office (EPO) which we use to measure innovation output. The analysis focuses on 5,385 firms (15,984 observations) that employ at least one R&D worker and which are more likely to patent. The econometric analysis takes account of state dependence — previous innovation output is likely to have an impact on current innovation, and on unobserved firm-specific time-invariant heterogeneity since some firms — due perhaps to better management of R&D — may be inherently more innovative than others. We control for these fixed firm effects using a pre-sample variable, the mean of the dependent variable prior to the time period of the study (Blundell, Griffith, and van Reenen, 1995; Bettis, Gambardella, Helfat, and Mitchell, 2014), and control for the inward mobility of science or engineering graduates.

THEORETICAL BACKGROUND

We follow the mainstream literature and consider technological innovations as inventions with commercial application, where inventions refer to the development of a new idea or an act of creation (see, Ahuja and Toh, 2015). Also in line with the literature, we define firm-level innovation output as the sum of the technological innovations created by a firm over a given period. Quality adjusted innovation output is this construct corrected by its economic and technological value (see for instance, Sampson, 2005; Singh, 2008; Hess and Rothaermel, 2011).

With respect to R&D workers' inward mobility we consider two types of scientist experience to be particularly salient in our case: (1) previous university research experience, and (2) experience of working in a firm with a strong technological record. These two dimensions are the basis for the 2×2 matrix depicted in Figure 1 below.

[Insert Figure 1 about here]

Arora and Gambardella (1994) make an important distinction between scientific capabilities whose relative strength is in *evaluation* of technological information, and technological capabilities whose relative strength is in *utilization* of technological information. In the context of the former, Arora and Gambardella (1994: 102) argue that ‘Scientific capability enables the firm to reduce the uncertainty about the outcome of individual projects...science provides information that helps restrict the search for successful innovations at the downstream applied research and development stages’. As Arora and Gambardella (1994) argue, scientific capability is particularly useful for evaluating technological information. We posit that overall, new hires with university research experience increase the focal firm’s scientific capabilities, and that given the importance of the ability to evaluate technological information in the innovation process such hires should increase the firm’s innovation output.

Arora and Gambardella (1994: 96–97) suggest also that the value of an innovation project ‘depends upon the ability of the firm to utilize effectively the [relevant] know-how.’ We argue that this ability can be enhanced by new hires with work experience in a technologically strong firm. In the context of technology spinoffs, Klepper and Sleeper (2005) suggest that firms that are more successful own more knowledge, resulting in there being more knowledge for previous employees to exploit. Also, former employees of patent active compared to non-patenting firms are likely to have deeper and broader technological knowledge (Kaiser *et al.*, 2015). Scientists moving from patent active firms are likely to bring technological experience in the form of knowledge useful for innovation output, and to have the ability to utilize technological information.

Figure 1 Panel (1) includes newly hired individuals with neither type of experience; Panel (2) includes newly hired individuals with university scientific experience but no experience of working in a technology active firm — i.e., the hire will increase ability to *evaluate* technological information; Panel (3) includes newly hired individuals with technological experience but no university scientific experience — i.e., the hire will increase ability to utilize of technological information; and Panel (4) includes newly hired individuals with both types of experience — i.e., the hire will increase both *evaluation* and *utilization* of technological information abilities. Using this 2×2 matrix as our starting point, in what follows we derive our hypotheses.

HYPOTHESES

An important type of external experience that can be acquired by firms through recruitment is experience of academic research in a university context beyond the level of doctoral research. We propose that inward mobility of scientists with academic research experience compared to recruitment of R&D personnel lacking such experience, is particularly useful for solving innovation-related problems, and therefore, for the quality-adjusted innovation output of firms. We suggest that firms will achieve a greater boost to their innovation output from recruiting an individual with the types of experience described in Panels (2) and/or (4) in Figure 1 compared to an individual with the type of experience described in Panels (1) and/or (3). Knowledge transfer in the context of the links between science and technology is 'mainly person-embodied, involving personal contacts, movements, and participation in national and international networks' (Pavitt, 1991: 112). For this reason, recruitment of scientists is an important means for private firms to obtain access to science. Following the literature (see, Pavitt, 1991; Salter and Martin, 2001), we argue that scientific capability enables the evaluation of technological information in innovation projects through scientists' application in the technological setting through three different mechanisms.

First, in relation to the importance of *general scientific research skills and techniques*, Fleming and Sorenson (2004) argue that by providing inventors with a 'map' or a stylized (or theoretical) representation of the solution-space, scientific knowledge can lead to other types of problem-solution than would be possible using regular technological problem solving abilities. Gibbons and Johnston (1974) found that when faced with a problem scientists may be able to provide direct solutions but are more likely to suggest an alternative way to tackle the problem to reduce the range of possible solutions, or to access equipment and procedures to test the feasibility of a proposed solution. Second, *specific problem-solving skills* can be directly useful for technological problem-solving in private firms. For instance, the general principle related to a pharmaceutical drug may be scientific knowledge; however, innovations by electronics firms also exhibit strong links to science (Pavitt, 1991; Klevorick, Levin, Nelson, and Winter, 1995). In this context, Gibbons and Johnston (1974) argued that scientists are particularly critical for 'translating' information from scientific journals into a form that is meaningful to industry problem-solvers. Finally, former university scientists can draw on social *university networks* to help in their technological problem-solving activities (Gibbons and Johnston, 1974), and to exploit international networks of colleagues and co-authors which increases the industry employer's awareness of the leading scientists and relevant scientific resources (Murray, 2004).

We argue that given the potentially major benefit to firms of combining scientific knowledge, skills, and techniques with the firm's already existing technological problem-solving activities, hiring a scientist with university experience will have a stronger effect on quality-adjusted innovation output compared to recruiting someone with no experience of working in academia. Hiring recent university masters and doctoral graduates also allows firms to access scientific knowledge, skills, and techniques (Pavitt, 1991; Salter and Martin, 2001). However, we argue that there are two reasons why new graduates embody fewer scientific capabilities than individuals who have also been employed by a university (we control empirically for such hirings). The first reason is based on an organizational learning argument: It takes time to acquire scientific capability. Graduates spend a significant amount of time on educational activities which reduces the time available to practice science while scientists who are employed by a university after graduating have spent more time conducting research in an academic environment. The have also had more time to develop social networks within the university system compared to graduates employed by private firms immediately after graduation. The second reason is that graduates choosing employment in a university as an initial career choice may be inherently more motivated to perform scientific research than graduates choosing employment in a private firm immediately after graduation. In sum, these arguments suggest that:

Hypothesis 1: Newly hired individuals coming from universities, or individuals with university research experience who are hired from firms, should provide higher positive returns with respect to quality-adjusted innovation output than individuals with no university research experience who are hired from firms.

The non-trivial challenges of hiring university scientists

While there are clear benefits to firms deriving from science and the recruitment of university scientists, hiring scientists imposes on the recruiting firm some non-trivial problems (additional to the usual adjustment problems related to new hires) including the integration of university scientists into the firm's local knowledge production. According to Dasgupta and David (1994), the fundamental differences between scientific and technological knowledge are the types of goals, behavior norms behavior, and reward systems considered legitimate by the two researcher communities. Based on these goals, norms, and incentives, academically trained scientists tend to have a strong 'taste for science' including a preference for basic research, freedom to choose among research projects, and disclosure of research results through publication (Stern, 2004; Roach and Sauermann, 2010; Agarwal and Ohyama, 2013). The strong taste for science among academically trained scientists suggests that employing former university scientists might be problematic for profit-oriented business firms which need an appropriate strategy to exploit potentially valuable knowledge inputs.

Complementarities between academic and industrial research experience

Despite conflicting logics between industrial and academic research, Sauermann and Stephan (2013: 904) maintain that 'the ideal types of 'academic logic' and 'commercial logic' overstate differences between industrial and academic science while ignoring important heterogeneity within each sector.' In other words, bridging between the two spheres is possible but requires explicit attention. One possibility is to hire scientists with a mix of experience from academic and technological/industry contexts. In this case, we argue that individual-level academic research experience can be (even) more productive for a firm when combined with work experience from a highly technology-active firm (Figure 1 Panel 4) compared to other mixes of relevant experience (Figure 1 Panels 1, 2 and 3).

The starting point for our analysis is that heterogeneity in the previous experience of newly hired scientists is central to explaining firm-level innovation outcomes. Agarwal, Echambadi, Franco, and Sarkar (2004) argue that the level of a new employee's technological know-how is to an important extent a function of the previous employer's technological knowledge. Indeed as suggested above, successful firms possess more knowledge, implying that there is more knowledge available to a leaving employee to apply in a new setting (Klepper and Sleeper, 2005). That knowledge includes not only idiosyncratic technological knowledge in the narrow sense but also includes tacit, process-related know-how about how to create innovations

(Thompson, 1967). Thus, it can be argued that recruits with experience from employment in a technologically strong firm (Kaiser *et al.*, 2015), or inward mobility of individuals with academic research experience (Hypothesis 1) will increase the hiring firm's innovation activities more than recruitment of individuals with neither type of experience.

Central to our argument is that we predict a higher increase to the recruiting firm from individuals with both types of experience. In other words, hiring individuals with strong academic research experience combined with strong technological experience should increase innovation output more than recruitment of individuals with just one or neither type of experience. As argued above, given that on balance, academic research experience and the capabilities it endows are directed more towards evaluating technological information, and that technological capabilities are directed more towards utilizing technological information aimed at commercial exploitation, the combination of these capabilities should provide a superior outcome since successful innovation requires both competences (Agarwal and Ohyama, 2013). The literature on individual-level ambidexterity suggests that individual ambidexterity increases with experience (Mom, Bosch, and Volberda, 2009); in our context, scientists with both academic and industry technological experience will be better able to manage the (partially) conflicting logics underlying academic scientific and industrial technological activities. In other words, experience of working in both domains should render the individual better able to bridge those spheres. It follows that experience of working in both domains should outperform having only one type or no such experience. This complementarity logic underpins the following hypotheses:

Hypothesis 2a: Individuals with university research experience newly hired from firms with patenting experience should provide higher positive returns with respect to quality-adjusted innovation output than individuals with university research experience hired from *universities or non-patenting firms.*

Hypothesis 2b: Individuals with university research experience hired from firms with patenting experience should provide higher positive returns with respect to quality-adjusted innovation output than individuals hired from firms with patenting experience but no university research experience.

Hypothesis 2c: Individuals with university research experience hired from firms with patenting experience should provide higher positive returns with respect to quality-adjusted innovation output than individuals hired from non-patenting firms and with no university research experience.

Organizational culture

The tension between the (academic) science and (commercial) technology spheres can be managed through the hiring of individuals with experience in both spheres (see arguments related to Hypotheses 2a/b/c). However, the potential boost to innovation output from hiring a researcher of the type described in Figure 1 Panel 2 or 4 also may depend significantly on the observed heterogeneity in the firms' emphasis on an academic or a commercial logic as highlighted by Sauermann and Stephan (2013). There may be important differences in how well private firms are able to exploit and manage researchers oriented to academic research (Cockburn and Henderson, 1998). For instance, Liu and Stuart (2014: 1136) describe some central organizational features of the 'university research-friendly' firms they analyzed: 'To the extent possible, the firm creates a university-like milieu to cater to the preferences held by their researchers. For biologists, who have almost all spent many years training at universities, BTCO's research division will seem a relatively familiar place.' Organizational culture is defined generally as 'a system of shared values defining what is important, and norms, defining appropriate attitudes and behaviors, that guide members' attitudes and behaviors' (O'Reilly and Chatman, 1996: 166). A university research-friendly organizational culture emphasizes the importance of academic research and the associated norms and practices.

We suggest that relevant experience and a resulting culture of employing academic scientists will alleviate some of the tensions discussed above. A research-friendly organizational culture helps to reduce the problems associated to integrating university scientists into the firm's knowledge production. The absorptive capacity literature regards such a culture as a social integration mechanism which reduces the counter-productive gap between exploration and exploitation (Zahra and George, 2002). Indeed, despite private firms' for-profit objectives, some companies have a research culture which generally accommodates academic research activities. This includes allowing former university scientists a degree of autonomy, and the right to continue to publish (Rosenberg, 1990; Cockburn and Henderson, 1998; Roach and Sauermann, 2010; Ding, 2011) although sometimes after some delay to comply with protection of intellectual property rights (Lei, Juneja, and Wright, 2009). Nevertheless, an academic research-friendly culture reduces frustration in academically-oriented scientists which arguably, should increase their productivity (Mudambi and Swift, 2009). Such a culture is likely to satisfy the firm's profit and coordinated problem-solution goals as well as catering to scientists' research preferences. This should increase the hiring firm's quality-adjusted innovation output.

Scientists with university research experience can be recruited directly from universities, or hired from other firms. We argue that the successful integration of individuals with both types of experience regarding innovation output requires an appropriate research culture. Although researchers with both academic and industrial research experience may have a better understanding of the research requirements in industry compared to researchers hired directly from a university although their industry experience is unlikely to have erased their taste for science. Indeed, it is likely that scientists with academic experience hired from industry will more likely have been employed by a firm characterized by an academic research-friendly culture. In sum, we posit that:

Hypothesis 3: A research friendly organizational culture in the focal firm enhances the positive effect on the quality-adjusted innovation output of individuals with university research experience newly hired from universities or firms.

METHODS

Data

Patent data. The first set of data are patent applications filed with the EPO since 1978 (when the EPO was established) with at least one Danish applicant. These data are taken from the EPO's PatStat ('Worldwide Patent Statistical Database'). This data set is critical since our basic measure of innovation output is patent counts. Although patent counts are imperfect proxies for innovation output (Arundel and Kabla, 1998), they are representative of a specific invention (patent applications refer to single inventions), and can be related to patent value correlates (Trajtenberg, 1990). Patent counts are used extensively in the management (Stuart and Podolny, 1996; Almeida and Kogut, 1999; Song, Almeida, and Wu, 2003) and economics literatures (Griliches, 1990; Blundell *et al.*, 1995; Kim and Marschke, 2005).

Linked employer-employee data. We use linked employer-employee information provided by Statistics Denmark: Our data set includes the whole (not a selected sample) population of Danish firms and workers. The database is a recognized and valuable resource for research in the social sciences (see, for instance, Sørensen, 2007; Marx and Timmermans, 2017 for recent applications of these data). Linked employer-employee data at the workplace level are available from 1980 although information on the firm-level variables is available only from 1999 due to a break in recording of the unique firm identifiers used by Statistics Denmark. To create our data set we linked the unique firm identifiers to the patent applicants in our patent data. We achieved a match for 95 percent of the applicants. The 5 percent unmatched firms exited before 1999 and would have been excluded because our firm-level information begins only in 1999. Since current patent counts are the result of past research efforts, we lag all R&D-related variables by one year as in Blundell, Griffiths, and Reenen (1999). Therefore, the effective starting date of the within-sample period is 2000; 1978–99 is a pre-sample period of information on patents used in the estimation (see below).

Our linked employer-employee/patent assignee data contain information on the highest level of education attained by the individual worker and her/his current occupation. We use this information to define our population of R&D workers. They are defined as individuals with a master's or a doctoral degree in the technical, natural, veterinary, agricultural, or health sciences, occupying a job function that requires a 'high' (professional) or 'intermediate' (technician and associate professional) level of skills, and aged between 20 and 75. The employee-level data were aggregated at firm level before being merged, i.e., our estimations consider each firm's total R&D work force. The information on job functions was retrieved from the International Standard Classification of Occupations (ISCO) published by the International Labor Office.

We do not include firms with no R&D workers since they are unlikely to patent (see the findings in Kaiser, Kongsted, and Rønde, 2008 based on inventor survey data). Therefore, our final data set includes firms with at least one R&D worker. Moreover, we include only private sector firms (although we consider labor mobility from the public sector). The main estimation results are based on 15,964 firm-year observations of 5,385 unique R&D active firms. A total of 293 unique firms patented at least once during the five years 2000–2004.

Dependent Variable. We adopt the terminology used in the literature (see, for instance, Jaffe, Trajtenberg, and Henderson, 1993; Shan, Walker, and Kogut, 1994; Ahuja and Katila, 2001; Joshi and Nerkar, 2011) and measure *innovation output* as each firm's patent count. In order to account for the skewed patent value distribution (Lanjouw, Pakes, and Putnam, 1998; Harhoff, Narin, Scherer, and Vopel, 1999; Hall, Jaffe, and Trajtenberg, 2005), we include also a *quality* dimension of innovation (Joshi and Nerkar, 2011), and hence, use *quality-adjusted innovation output* as our main dependent variable. Specifically, we adopt Trajtenberg's (1990) weighted patent count measure, the number of applications by firm *i* in year *t* plus the total number of forward citations received by those patents within the three years following the year of EPO publication (a 5-year time window is more common; we chose a shorter time because our citation data end less than 4 years after the patent data). For example, if firm *i* applied for 10 patents in *t* and received 15 citations to these patents in the subsequent 3 years, our dependent variable would add to 25. Forward citations constitute a verified measure of both technological impact and private and social value (Hall *et al.*, 2005). Other patent value correlates considered in the literature, such as backward citations, family size, number of technological areas, breadth, and renewal, have been shown to be less reliable predictors of patent value (see Jaffe and de Rassenfosse, 2017 for a recent survey).

Explanatory variables. We separate the population of R&D workers by mobility status. We identify movements of knowledge-intensive R&D workers — workers with high levels of scientific and technological capability — from universities to firms, and movements between non-affiliated firms. We consider as a control variable, *R&D support workers* or workers in positions requiring an intermediate level of scientific and technological capability. We define hires as workers employed by different employers in *t-1* and *t*. We consider the following broad groups of mobile knowledge-intensive R&D workers: (i) *Hires from universities*, (ii) *Hires from* (non-affiliated) *firms,* (iii) *University graduates* (workers employed in a firm in *t* who were university students in *t-1*), and (iv) *Other hires* (workers who joined the firm in *t* whose employment status in *t-1* is unknown). Finally, stayers we define as non-mobile R&D workers i.e., who were employed by the same firm in *t-1* and *t.* We split hires from firms along two further dimensions of experience — hires from a patenting firm vs. hires from a non-patenting firm, and workers previously employed as university researchers vs. those never employed in a university.

Finally, we interact the variables representing hires from firms with and without university experience as well as university hires on the one hand, with a dummy variable that is coded 1 if the present top management team (TMT) includes at least one individual with an R&D education, on the other hand. We use the inclusion of a scientist on the TMT (*Researcher on TMT dummy*) as a proxy for firms with an academic research-friendly organizational culture. Hambrick (2007: 335) notes that 'researchers have generated substantial evidence that demographic profiles of executives (both individual executives and TMTs) are highly related to strategy and performance outcomes.' The composition of the TMT is likely to reflect the general types of problems that the firm can expect to face (Carpenter, Geletkanycz, and Sanders, 2004; Strandholm, Kumar, and Subramanian, 2004). In the context of innovation more specifically, Balsmeier and Buchwald (2015) argue that top-management experience is a central aspect of the firm's innovation strategy since it enhances understanding of the processes involved.

We would argue that having a scientist on the TMT is indicative of the focal firm's objective to encourage an organizational research culture that facilitates the integration of scientists with academic research experience who typically have a 'taste' for academic science. By facilitating and supporting a university research-friendly culture, the TMT member's scientific experience and skillset will be beneficial for managing the integration of newly-recruited scientists with academic research experience.

We control also for a set of variables conventionally considered determinants of innovation output. First, we include the variable *ln(# of R&D workers)* which is the natural logarithm of the total number of R&D workers. Second, we include *ln(capital)* expressed as the natural logarithm of capital stock measured as the book value of physical capital. Third, we include a set of sector dummies defined according to the two-digit NACE Rev.1 industry classification, and control for regional effects and time-fixed effects using dummy variables. Fourth, we account for unobserved permanent firm heterogeneity and state dependence — as described below. Fifth, we include a variable *PhD employee dummy*, reflecting the employment of at least one R&D worker with a PhD degree.

Model specification and estimation

The patent production function. We employ a Cobb-Douglas knowledge production function (Hausman, Hall, and Griliches, 1984; Blundell *et al.*, 1995) in which quality-adjusted innovation output depends on the R&D labor and capital inputs. A key feature of our model is that we treat R&D labor as a differentiated input. We split the firm's R&D labor force into hires from university research, L_U, recent graduates, L_G, hires from firms, L_F, other hires, L_O, stayers, L_S, and support workers, L_P. At this level of disaggregation, many firms will have zero hires of some particular R&D labor type in any given year. To properly accommodate this important feature of our data, we construct a composite measure of R&D labor which combines the different R&D labor inputs in a linear way (Griliches, 1967; Hellerstein, Neumark, and Troske, 1999; Galindo-Rueda and Haskel, 2005; Kaiser *et al.*, 2015). Each labor type k adds to the composite with a separate coefficient θ_k which measures its impact relative to stayers (for whom the coefficient is normalized at 1). Embedding this composite into the Cobb-Douglas knowledge production function and using natural logarithms, we then obtain the approximate relationship:

$$lnP = \ln A + \delta \ln K + \rho \ln L + \beta_F s_F + \beta_U s_U + \beta_G s_G + \beta_O s_O + \beta_P s_P, \tag{1}$$

where P denotes quality-adjusted innovation output, $L = L_F + L_U + L_G + L_O + L_S + L_P$ is the simple count of R&D workers of any type, and s_k denotes the share of labor type k, L_k/L. All firms in our sample employ at least one R&D worker. Hence, all observations on L are positive so the actual formation of the labor shares s_k does not present a problem. The labor shares add to 1, thus, we need to exclude one worker share from the estimation to avoid the model being perfectly collinear. The term A denotes additional control variables such as industry and time dummies. The β_k parameters relate to the relative impacts θ_k of labor type k via the relationship $\beta_k = \rho(\theta_k - 1)$. Equation (1) allows us to compare the impacts of different labor types on innovation output, and hence, to infer the validity of our theoretical hypotheses.

Note that Equation (1) is not a standard log-linear specification due to the introduction of the linear R&D labor composite. The many zeros introduced by the differentiated nature of our measure of R&D labor inputs essentially precludes such a specification. Hence, the β_k parameters do not translate directly into elasticities. They are best interpreted by referring back to the relative impacts of labor type k via the relationship $\beta_k = \rho(\theta_k - 1)$. Basically, a positive β_k coefficient implies that an additional unit of labor type k provides higher returns with respect to innovative output than would one additional stayer, the excluded category. This is also the basis for assessing the *effect size* of the estimated differences (effect size is arguably of critical importance, see Bettis *et al.*, 2016). It is based on the marginal effect of adding a further unit of a specific R&D labor type on innovative output. We derive their precise expression and present graphs of the marginal effects in the Online Appendix.

Count data models. The dependent variable is discrete and takes the value zero or a positive integer, making a count data model appropriate. The most popular count data model is a Poisson regression (Cameron and Trivedi, 1986; Winkelmann, 2008) with an exponential mean function similar to its application to patent data in Hausman, Hall, and Griliches (1984). However, the Poisson model assumes equality between the conditional mean and conditional variance, i.e., equi-dispersion. This assumption is often violated when using patent data (Blundell *et al.*, 1995; Cincera, 1997). Therefore, we use the negative binomial (NegBin) model which allows for a more flexible relationship between the mean and variance, and for over-dispersion in the data. Tests for equality of mean and variance favor the NegBin model over the Poisson model in our case also.

Unobserved heterogeneity. Our specification controls for firm-specific permanent heterogeneity in innovation output, e.g., due to differences in R&D management, different R&D investment appropriability conditions, or different technological opportunities. Random effects are inappropriate in our setting since unobserved permanent heterogeneity is likely to be correlated with the regressors. Blundell *et al*. (1995, 1999) suggest a correlated effects approach using a proxy for unobserved permanent heterogeneity. Their 'pre-sample mean estimator' is developed for count data models where the information on the dependent variable is longer than on the explanatory variables. This applies to our data: Patent data start in 1978, firm-level data (allowing for lags) start in 2000. The estimator uses the average of the dependent variable over the pre-sample period as a proxy for the correlated effects (for each firm). Hence, the main assumption here is that the source of unobserved permanent heterogeneity in innovation output is reflected mostly in the firm's pre-sample patent history.

The pre-sample mean estimator relies on the stationarity of the dependent variable. Since there is a strong upward trend in the number of patent applications, we apply a trend adjustment to the proxy variable as suggested by Kaiser *et al*. (2015). In our practical implementation of the correlated effects proxy variable, we follow Blundell *et al*. (1995, 1999, 2002) and include the variable *ln(# of pre-sample patents)* expressed as the natural logarithm of the pre-sample mean number of patent applications per firm. Because 87 percent of our observations relate to firms with no pre-sample patent applications, we substitute an arbitrary small constant to allow logarithmic transformation, and account for this substitution by including a dummy variable which is coded 1 if the firm has at least one pre-sample patent and 0 otherwise (*# of pre-sample patents > 0 dummy*).

State dependence. We control for possible state dependence in innovation output. Blundell *et al*. (1995) include firm *i*'s discounted patent stock as an explanatory variable. However, we follow the approach in Crépon and Duguet (1997) and introduce state dependence by including a variable, *Lagged patent dummy*, reflecting patent output in *t-1* since this emphasizes recent patent output and circumvents collinearity problems when using fixed effects proxy variables.

RESULTS

Table 1 presents the firm-year level descriptive statistics for the dependent and explanatory variables as well as a correlation matrix of our key explanatory variables. Stayers (63.9%) constitute by far the largest group of R&D workers among current R&D employment, followed by support workers (16.2%), and private sector hires (jointly 11.2%) the majority of whom are not from a patenting firm nor do they have university research experience. Other hires and recent graduates account for about 4 percent each of the R&D workforce, while hires from university research constitute the smallest employment category at 0.8 percent of all R&D workers. In our data, the average firm employs 6.8 R&D workers. The correlation matrix shows that the correlations among variables generally are low, confirmed by mean variance inflation factors ranging between 1.97 and 2.1 depending on the model, which is well below the critical value of 10 suggested by Belsley, Kuh, and Welsch (1980).

[Insert Table 1 about here]

Table 2 presents our main estimation results. We estimate three different models that correspond to Hypotheses 1 to 3. Note that the estimated coefficients corresponding to R&D worker shares do not translate directly into marginal effects. The estimated coefficients should be interpreted relative to the base category, stayers. For example, the estimated coefficient of hires from universities, β_U, in Table 3 Model I is 1.496 which implies that workers of that type have a $1 + \frac{\beta_U}{\rho} = 7.53$ times higher impact on firm quality adjusted innovation output than the impact of R&D stayers. This is similar to the estimates for other knowledge-intensive worker groups in Kaiser *et al*. (2015).

[Insert Table 2 about here]

We derive exact marginal effects and corresponding standard errors in the Online Appendix. The marginal effect on quality-adjusted innovation output of adding one worker of type *k* in Model I depends on (i) the share of type *k* workers, (ii) the initial innovative output (number of patents applied for by the firm plus citations), and (iii) the initial number of R&D workers of all different skill types. To provide meaningful and interpretable marginal effects we set the number of patents per worker applied for by the employing firm equal to the sample average, and set the number of workers of any mobile skill type other than *k* to zero. The marginal effect of hiring one additional worker of type *k* then depends on the share of type *k* workers in total R&D employment. Note that all marginal effects are downward-sloping (see Online Appendix), implying that if a firm already has a high share of a certain type of researchers, hiring additional researchers of this type will yield relatively low marginal innovation output. Our estimates are depicted in the Online Appendix Figures 2 to 4 which map the marginal effect of worker type *k* to the respective employment share.

Table 2 Model I tests Hypothesis 1 which predicts that workers with university research experience from either firms or universities should provide higher positive returns with respect to firms' quality-adjusted innovation output than firm hires with no university research experience. This hypothesis is strongly supported by our estimation results (p=0.014). The coefficient of hires from firms with university experience is as high as the coefficient of hires from university, with no statistically significant differences. In contrast, both coefficients are around 2.6 times larger than the coefficient of hires from firms with no university experience. The overall significant result seems to be driven mainly by firm hires with university research experience whereas the difference between university hires and firm hires without university experience is only marginally significant (p=0.080).

The related marginal effects and the associated confidence bands are depicted in the Online Appendix (Figure 2) and show that adding one hire with university experience is associated to 0.061 additional patents if the receiving firm hires workers of this type only. The marginal effect decreases with the increasing initial share of hires from firms with university experience. To properly gauge the economic significance of this result, we can compare the marginal effect of 0.061 to the sample average of quality-adjusted innovative output of 0.306. Hence, the effect of hiring another worker with university experience amounts to 20 percent of the overall sample average. We note that the change results from the addition of one worker which is a fairly large change given that the sample average of the overall number of R&D workers employed is about 8. The marginal effect of university hires is around 0.059 at the maximum, more than twice as large as the largest marginal effect for firm hires with no university experience. It is of similar economic significance to the effect of hiring researchers from universities. For hires from firms, adding one additional worker with no university experience results in a marginal effect of 10 percent of the average innovative output.

Hypotheses 2a/b/c combine the two dimensions of worker experience and are tested in Table

2 Model II. They predict that hiring individuals with both types of experience (Figure 1 Panel (4)) boosts quality-adjusted innovation output more than hires with the types of experiences depicted in Figure 1 Panels 1, 2, and 3. Note that hires of individuals with university experience but no experience of working in a patenting firm (Figure 1 Panel 2) may be from universities or from firms with no patenting experience. For transparency, we estimate two separate coefficients to capture this kind of experience (coefficients (4) and (7) in Table 2). Hence, to test Hypotheses 2a/b/c we consider a total of five coefficients. In line with our expectations, firm hires with both past patenting and university experience has the highest estimated coefficient followed by university hires, and then firm hires with no patenting experience but with university experience. The estimated coefficient of hires with no university experience from patenting firms, is smaller than the coefficient of hires with university experience from non-patenting firms but larger than the coefficient of hires with university experience from patenting firms. The lowest estimated coefficient is for individuals with neither type of experience, hired from firms is not significantly different from the base category of stayers.

However, the positive differences between the size of the parameters for hires with university experience from patenting firms, and each of the other types of firm hires show varying degrees of statistical significance (see lower part of Table 2). We find support for Hypotheses 2b and 2c since the coefficient of hires with university experience from patenting firms is larger than the coefficient of hires without university experience (marginally significant, p=0.058) and hires with neither type of experience (p=0.003) from similar firms. We find no support for Hypothesis 2a. There is no statistically significant difference between the size of the coefficient of hires with university experience recruited from patent active firms on the one hand, and the coefficients of hires with university experience from non-patenting firms (p=0. 314), or hires from universities (p=0. 486) on the other. In sum, while either type of experience clearly matters on its own, we find no strong support for the idea of complementarity between individual-level experience from patenting firms and from university research employment. What seems to matter strongly for the effect on quality-adjusted innovation performance is whether or not the focal hire has university research experience. The Online Appendix Figure 3 depicts these differences as the related marginal effects. They are largest for hires with university experience from patenting firms, and smallest and statistically insignificant for firm hires with neither university nor patenting firm experience.

Hypothesis 3 predicts that a research-friendly organizational culture increases the impact of both hires of firm employees with university experience and hires from universities. To test this hypothesis, we interact (1) the shares of firm hires with university experience, and (2) hires directly from university respectively, with a dummy variable for a TMT with at least one scientist member. We include the TMT dummy interacted with the share of R&D hires with no university experience, in order to control for any additional impact of a research-friendly organizational culture in the focal firm on the effect of hiring an employee with general (non-university) experience. Hence, our base case which assumes no additional impact of scientific culture consists of hires with unknown experience, graduates straight from university, support workers, and workers who choose not to move. Table 2 Model III presents the corresponding estimation results. It shows that the interactions involving the *Researcher on TMT dummy* are positive and of a similar magnitude for both worker types with university experience. The interactions are statistically significant both on their own and jointly (p=0.018) which is in line with Hypothesis 3. Also interesting is that the presence of a scientist on the TMT seems not to matter for the effect on innovation output of hires without university experience recruited from other firms. The interaction term for this group is estimated very imprecisely which makes inference vis-à-vis the effects of the university experience groups similarly very imprecise (the joint test of differences between all three groups yields an insignificant *p*-value of 0.29). In line with our argument, the (precisely estimated) additional effects of hires of workers with university experience show that an academic research-friendly culture is important for integrating individuals with university research experience.

Online Appendix Figure 4 shows the related marginal effects and confidence bands. It distinguishes between a TMT with and without a member with R&D experience. The marginal effects for the two types of hires with university experience, and a scientist member on the TMT are highly significant both economically and statistically. For shares of workers of either type close to 0, the marginal effects are around 0.13, and more than twice as large as for the same type of worker if the TMT does not have a researcher member. The difference is economically significant; it amounts to approximately 20 percent of the innovative output of an average firm in the sample.

ALTERNATIVE EXPLANATIONS AND ROBUSTNESS CHECKS

In this section we discuss the possibility that other factors are driving our estimation results, and run alternative models to check whether our results hold in different settings. These checks are presented in the Online Appendix. A potential alternative explanation for our main result that hires with university experience increase quality-adjusted innovation output more than any other skill group, might be that university hires and firm hires with university experience are more experienced and/or older than other types of R&D workers, and particularly individuals without university experience hired from other firms. Our data show that both hires with university experience recruited from firms, and university hires are *younger* on average than hires without university experience. Firm hires with university experience have the same number of years of work experience as firm hires without university experience while hires from universities have fewer accumulated years of work experience.

Of course, individuals with university experience compared to any of the other groups are more likely to hold a doctoral degree. To test whether years of employment in a university setting might be affecting our results, we use the empirical setup used to test Hypothesis 1 (Table 2, Model I). We split research workers hired from universities, and university research experienced hires from firms, into low and high university tenure categories split at the median (3 years of university employment). Although the coefficient of university hires with above-median tenure is larger, a *t*-test does not reveal significant differences across tenure categories in the effect of university hires. For recruitment from firms of individuals with university experience there are very few observations with three or more years of working in a university so the test is not feasible for this group.

An alternative explanation of our finding for organizational culture might be that the match between TMT scientific expertise and the expertise of the hired scientist matters more than the organizational culture in the recruiting firm for the new recruit's innovation output. However, if the specific expertise match drives the effect of hiring academic scientists, we should observe more frequent matches between TMT member's and recruited scientist's educational fields in recruitments of scientists with academic research experience, compared to recruitments of scientists without such experience. However, a *t*-test reveals no significant difference (p=0.20) between the mean percentages of TMT and research scientist educational field match, for hires with university experience and hires with no university experience. We interpret this as evidence that any match between TMT and research scientist expertise is not driving the observed differences in terms of impact of innovation output.

We conducted several robustness checks. First, we examined whether not adjusting for citation quality changed the results. The results of Model I the baseline model are supported without applying citation adjustments to the dependent variable, although the corresponding estimated coefficients and marginal effects are slightly smaller compared to the specification adjusted for citation quality. We also analyzed the extent to which a few particularly patent active firms (defined as owning more than 100 patents), or firms in the chemicals sector (which includes biotechnology) matters for the results. We found that excluding either one or other of these groups does not affect our estimation results for the baseline model substantially. However, again the corresponding estimated coefficients and marginal effects are smaller than when using the full data.

Although our main results are robust, and alternative explanations seem not to hold, it is possible that our results are driven by unobserved time-varying factors which affect both patenting and the hiring of workers with university experience. For example, firms that want to increase their innovation output will make various types of R&D investment including hiring university researchers, or workers with university experience from other firms. These investments might jointly be determining innovation output and hiring. This type of unobserved time-varying heterogeneity is not accounted for in our main estimates. Therefore, as a further robustness check we ran a general method of moments (GMM) regression where we instrument all labor shares. GMM estimation is used widely in strategic management research (see for instance, Milanov and Shepherd, 2013 for use of this method in a strategic management context).

We use the estimator derived by Blundell *et al*. (2002) which accounts for both fixed effects and the lagged dependent variables. The estimator is comparable to to the popular linear regression dynamic panel data models (Arellano and Bond, 1991; Arellano and Bover, 1995). Following Kim and Marschke (2005), and as suggested by Wooldridge (1991), we apply a quasidifferencing transformation to correct for fixed effects similar to the standard 'within transformation' of linear models, and use longer lags of the dependent and independent variables as instruments. In addition to these lags, we use the share of each worker type in other firms within the same industry and region as instruments (for an account of the properties of instrumental variables and how they help alleviate endogeneity concerns, see Hamilton and Nickerson, 2003; Semadeni, Withers, and Trevis Certo, 2014), based on the idea that labor supply shocks affect the hiring strategies of all firms in the same industry and the same region, without being correlated to the error term in the count data model.

The GMM estimator is extremely data-demanding since it does not allow for gaps in panel data, and needs at least three consecutive observations per firm. The data available for the GMM estimation consists of 9,416 observations for 2,864 unique firms, a substantially reduced sample size. In addition to the low shares of hires from patenting firms, and of firms with a scientist TMT member, it is not feasible to use this estimator to test Hypotheses 2 and 3. However, the GMM results related to Hypothesis 1 are qualitatively very similar to our initial estimates although the coefficient estimates for the various worker groups are much larger for the GMM. This might partly reflect the fact that the GMM estimator can be poorly identified in short samples such as ours. However, Hypothesis 1 is strongly supported at the conventional significance levels.

While the GMM estimation results support our baseline results, it could be argued that having a TMT member with a R&D background might be endogenously determined — having a TMT member with an R&D education might simply reflect the firms' efforts to promote innovation output. One way to resolve this identification problem is to identify the instrumental variables and re-apply the GMM estimation. Since we do not have appropriate instrumental variables to identify the causal effects of a TMT with a scientist member, we employ coarsened exact matching (CEM, Iacus, King, Porro, and Katz, 2012) and propensity score matching (PSM, Rosenbaum and Rubin, 1983), and run a NegBin count data estimation on the matched data. The identifying assumption here is that having a TMT member with an R&D education — i.e., being 'treated' — is random conditional on the observable variables that affect both treatment and patenting.

Consistent with Hypothesis 3, our interest is in the difference derived from TMT with at least one member with a science background in the effect of firm hires with university experience, and hires direct from a university. Our treatment group comprises all firms with both a science trained TMT member and at least one firm hire with university experience, or a university hire. The corresponding control group consists of firms with a university hire or a firm hire with university experience but no scientist TMT member. The first step in the PSM estimation is to estimate probit models for treatment, run on our treatment and control group firms, using essentially the same set of explanatory variables as for our main estimation. Our probit model is a good predictor of selection into treatment. We use nearest neighbor PSM with replacement. The log number of R&D workers, two year dummies, and three sector dummies are not well matched; the respective means of the treatment and control group firms are statistically significantly different. Therefore, we use these variables as additional control variables in our NegBin regression for patent counts on the treatment dummy variable.

For the CEM, the matching is exact within a set of strata, subsets of the explanatory variables. While this is an advantage over PSM, the downside is that CEM discards observations that cannot be matched (43% of our treated observations). Finally, using the matched treatment and control observations, we estimate NegBin models for the number of patent applications. We use the dummy variable for treatment. The estimated coefficient of the treatment dummy is 3.0 for the CEM-based regression, and 3.6 for the PSM-based approach. Both coefficients are statistically highly significant. These figures are qualitatively and quantitatively in line with our main results (Table 2, Model III).

CONCLUDING DISCUSSION

This paper started from the proposition that hiring researchers with university experience can provide the firm with science-based problem-solving capabilities which in turn, should lead to more firm-level quality adjusted innovation output since individuals with this type of experience increase innovation output more than hires of researchers with other types of experience. We found support for the general idea that inward mobility of researchers has a positive effect on the level of innovation output in private business firms. More specifically, we showed that newly hired researchers with university experience have a greater effect on innovation than other types of inward mobility. This difference is economically significant and amounts to 20 percent of the innovative output of the average firm in our sample.

We observed also that hiring a scientist with a mix of employment experience — as a university scientist and as an employee in a patenting firm — has a stronger effect than the other three possible types of individual-level experience combined. However, these differences are driven largely by the hired individual's university researcher experience. The hypothesis that there are no differences between having these types of experience compared to university research experience only, cannot be rejected (Hypothesis 2a). Accordingly, we found no support for the hypothesis of complementarity. In contrast, we found strong support for the idea that hiring organizations need to have a university research friendly culture to benefit from hiring individuals with university research experience — reflected by the presence of a scientist on the TMT (in line with Hypothesis 3), and that this effect appears to be present regardless of whether the individual with university experience was recruited directly from a university, or from another firm.

We make an empirical contribution to the learning-by-hiring literature by accounting explicitly for important heterogeneity in experience among individual hires in affecting the innovation output of private firms. However, when viewed jointly, the results related to Hypotheses 2 and 3 indicate that hiring individuals with experience additional to university research experience does not reduce the incentive and coordination problems because of the different nature of academic and industrial research. However, our results indicate the presence of an 'organizational advantage' (Ghoshal and Moran, 1996). It seems that organizations with appropriate organizational cultures are able (very) productively to integrate individuals with academic research experience into their innovation activities.

A focus on creating and managing a university research friendly culture may mean that such organizations are able to incentivize individuals with academic research experience, and to coordinate their activities with those of workers with different experience, to the benefit of innovation output. In other words, these organizations become better at evaluating technological information (Arora and Gambardella, 1994) when hiring academic scientists, because of their ability to integrate these scientists in their innovation processes. Our findings are in line also with the idea in Cohen and Levinthal (1990) and Rosenberg (1990) in the context of private firms' absorptive capacity; knowledge is not a public good, and its absorption requires substantial and specific investment in the form of an appropriate organizational culture in the context of academic scientists' productive integration in for-profit firms.

Our arguments and findings contribute also by highlighting the existence in some researchers of a taste for science (Stern, 2004; Roach and Sauermann, 2010; Agarwal and Ohyama, 2013). We show that the benefits to the hiring firm of recruiting individuals with university research experience who also have experience of working in industry, seem to persist. That is, the advantages of academic research experience do not appear to be eroded by later industry experience.

The findings from this study have implications for managerial practice. For example, the impact of R&D stayers is small in both absolute and relative terms which suggests that firms need to devise strategies to keep their worker stock up to date with science and engineering developments. This could be achieved by implementing initiatives to facilitate exchanges of knowledge between academia and industry. Of course, hiring from academia should reduce the adverse effects of knowledge decay, prompting the question of why industry does not recruit more often from universities, especially given our finding that the direct impact on innovation output of stayers is much lower than the impact made by mobile workers. We believe that the answer to this question is related to the firm's organizational culture with respect to how academic research is supported (Cockburn and Henderson, 1998). Certainly, our results suggest that organizational culture is crucial in this context: Firms with little or no experience related to creating and managing a university research friendly culture can find it difficult to integrate academic researchers into their knowledge production.

This study has some limitations. As already noted, we use a proxy only for organizational culture: A scientist member of the TMT. While this is advantageous for our study, future research could model organizational culture in a more direct way. An emerging stream of literature (Corredoira and Rosenkopf, 2010; Godart, Shipilov, and Claes, 2014; Kaiser *et al.*, 2015) argues that workers who leave one organization and move to another may continue to contribute to the previous organization's innovation output based on individual social ties. We do not account for this effect in this paper. Future research could explore heterogeneity in experience but in the context of the effect on the previous employer's innovation related benefits. Finally, Fleming and Sorenson (2004) suggest that scientific thinking in relation to technological problem solving is more important if technologies are tightly coupled. We need to investigate whether hiring university scientists is more beneficial for firm-level innovation output for companies working with very similar technologies compared to less similar technologies.

In conclusion, among firm hires, individuals with university research experience are particularly valuable for firms' innovation output. However, the returns from hiring individuals with such experience depend critically on whether the hiring firm has a research-friendly culture. Indeed, a research-friendly culture is needed regardless of whether the researcher with university research experience is hired from a university or from a private firm. We hope that our findings will prompt further research on R&D worker recruitment, and the types of workers and organizations that bring the most benefits.

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Table 1. Summary statistics and correlation table (n=15,964)

	Mean	Std.dev.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
# of citation-weighted patents in *t* (dependent variable)	0.306	4.452										
(1) # of pre-sample patents	0.000	0.002	1									
(2) # of pre-sample patents > 0 dummy	0.128	0.334	0.225	1								
(3) Lagged patent dummy	0.041	0.198	0.283	0.462	1							
(4) Hires from patenting firms w/ university exp.	0.003	0.044	0.015	0.036	0.033	1						
(5) Hires from non-patenting firms w/ university exp.	0.011	0.081	0.002	0.003	0.009	-0.005	1					
(6) Hires from patenting firms w/o university exp.	0.018	0.103	0.017	0.058	0.056	0.024	-0.007	1				
(7) Hires from non-patenting firms w/o university exp.	0.080	0.225	-0.015	-0.048	-0.023	-0.020	-0.017	-0.032	1			
(8) Hires from universities	0.008	0.072	0.009	0.046	0.027	0.008	-0.008	-0.004	-0.024	1		
(9) Other hires	0.041	0.169	-0.008	-0.031	-0.020	-0.012	-0.020	-0.029	-0.059	-0.019	1	
(10) University graduates	0.039	0.153	0.002	0.000	0.012	-0.010	-0.012	-0.024	-0.055	0.001	-0.034	1
(11) R&D support workers	0.162	0.330	-0.015	0.023	-0.003	-0.027	-0.044	-0.055	-0.138	-0.045	-0.098	-0.102
(12) Researcher on TMT dummy	0.041	0.199	0.195	0.214	0.226	0.003	-0.008	0.025	-0.032	0.001	-0.029	-0.008
(13) Researcher on TMT dummy × hires from patenting firms w/ university experience	0.000	0.003	0.149	0.079	0.136	0.075	0.005	0.030	-0.004	0.004	-0.005	0.007
(14) Researcher on TMT dummy × hires from non-patenting firms w/ university experience	0.000	0.009	0.038	0.041	0.042	0.005	0.110	0.006	-0.003	-0.001	-0.006	0.000
(15) Researcher on TMT dummy × hires from patenting firms w/o university experience	0.001	0.020	0.084	0.085	0.099	0.011	-0.001	0.180	-0.013	0.000	-0.010	-0.002
(16) Researcher on TMT dummy × hires from non-patenting firms w/o university experience	0.002	0.023	0.050	0.049	0.067	0.003	0.000	0.003	0.075	-0.004	-0.013	0.002
(17) Researcher on TMT dummy × hires from university	0.000	0.008	0.067	0.064	0.073	0.004	-0.003	0.004	-0.011	0.105	-0.006	0.026
(18) # of R&D workers	6.826	33.646	0.740	0.157	0.216	0.008	-0.002	0.008	-0.020	0.001	-0.016	0.002
(19) Capital stock/1000000	173.636	2073.755	0.170	0.074	0.065	0.000	-0.005	-0.003	-0.011	-0.004	0.002	-0.006
(20) PhD employee dummy	0.139	0.346	0.147	0.283	0.254	0.056	0.033	0.031	-0.037	0.054	-0.035	0.015

	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
(11) R&D support workers	1									
(12) Researcher on TMT dummy	-0.007	1								
(13) Researcher on TMT dummy × hires from patenting firms w/ university experience	-0.005	0.228	1							
(14) Researcher on TMT dummy × hires from non-patenting firms w/ university experience	-0.008	0.163	0.098	1						
(15) Researcher on TMT dummy × hires from patenting firms w/o university experience	-0.014	0.305	0.199	0.059	1					
(16) Researcher on TMT dummy × hires from non-patenting firms w/o university experience	-0.011	0.385	0.117	0.086	0.085	1				
(17) Researcher on TMT dummy × hires from university	-0.013	0.217	0.087	0.025	0.061	0.042	1			
(18) # of R&D workers	-0.024	0.246	0.136	0.042	0.083	0.076	0.067	1		
(19) Capital stock/1000000	0.003	0.122	0.036	0.012	0.021	0.031	0.019	0.233	1	
(20) PhD employee dummy	-0.032	0.250	0.114	0.058	0.076	0.096	0.094	0.290	0.107	1

Table 2. The effect of inward mobility of researchers on the innovation output of firms

	Model I			Model II			Model III		
	Coeff.	***p*-val.**	**Std.err.**	**Coeff.**	***p*-val.**	**Std.err.**	**Coeff.**	***p*-val.**	**Std.err.**
Employment shares									
(1) Hires from firms w/ university experience	1.559	0.000	0.341				1.462	0.000	0.359
(2) Hires from firms w/o university experience	0.580	0.006	0.213				0.503	0.027	0.228
(3) Hires from patenting firms w/ university experience				1.963	0.000	0.499			
(4) Hires from non-patenting firms w/ university experience				1.268	0.011	0.498			
(5) Hires from patenting firms w/o university experience				0.908	0.001	0.282			
(6) Hires from non-patenting firms w/o university experience				0.338	0.256	0.298			
(7) Hires from universities	1.496	0.003	0.501	1.476	0.003	0.503	1.361	0.011	0.533
Other hires	0.234	0.593	0.438	0.230	0.599	0.437	0.231	0.588	0.427
University graduates	0.784	0.019	0.334	0.771	0.021	0.334	0.707	0.041	0.345
R&D support workers	0.342	0.143	0.233	0.330	0.155	0.233	0.338	0.155	0.238
TMT interactions with various emplyment shares									
(8) Researcher on TMT dummy							0.143	0.379	0.163
(9) Researcher on TMT dummy × hires from universities							2.405	0.036	1.146
(10) Researcher on TMT dummy × hires from firms w/ university experience							2.357	0.045	1.176
(11) Researcher on TMT dummy × hires from firms w/o university experience							0.470	0.575	0.840
Control variables									
ln(# of R&D workers)	0.229	0.001	0.071	0.230	0.001	0.071	0.202	0.004	0.070
ln(capital)	0.140	0.000	0.033	0.141	0.000	0.033	0.139	0.000	0.033
PhD employee dummy	0.077	0.577	0.138	0.073	0.596	0.138	0.062	0.650	0.137
Lagged patent dummy	1.112	0.000	0.137	1.111	0.000	0.137	1.123	0.000	0.137
ln(# of pre-sample patents)	0.524	0.000	0.071	0.520	0.000	0.071	0.519	0.000	0.071
# of pre-sample patents > 0 dummy	0.178	0.590	0.331	0.180	0.585	0.330	0.203	0.534	0.327
Hypotheses tests									
	Chi^2		*p*-val.	Chi^2		*p*-val.	Chi^2		*p*-val.
Hypothesis 1									
(1) = (2)	6.61		0.010						
(7) = (2)	3.06		0.080						
Joint	8.50		0.014						
Hypothesis 2									
(3) = (4)				1.01		0.314			
(3) = (5)				3.61		0.058			
(3) = (6)				8.86		0.003			
(3) = (7)				0.49		0.486			
Joint				*11.49*		*0.022*			
Hypothesis 3									
(9) = 0							4.02		0.045
(10) = 0							4.41		0.036
Joint							*9.15*		*0.018*
Observations	15,964			15,964			15,964		
Firms	5,385			5,385			5,385		

Note: Robust t-values are clustered by firms. All explanatory variables are lagged by one period. Time dummies and sector dummies are included.

		Recruit with academic research experience	
		No	Yes
Recruit with experience from technology active firm	No	Baseline (1)	Added strength in *evaluating* technological information (2)
	Yes	Added strength in *utilizing* technological information (3)	Added strength in *evaluating* and *utilizing* technological information (4)

Figure 1. Heterogeneity in the innovation-related benefits to firms from experiences among R&D worker recruits

ONLINE APPENDIX

Marginal effects

The conditional mean function of our most general estimation model, Model III in Table 2, is:

$$\hat{P} = E[\hat{Y} \mid x] = \exp\left(\hat{\kappa} D(P_{-1} > 0) + \sum_{j=1}^{6} \hat{\beta}_j s_j + D(TMT = 1)\left(\sum_{m=1}^{3} \hat{\gamma}_k s_j\right) + \hat{\phi} D(TMT_{it} = 1) + \hat{\rho} \ln(L) + \hat{\gamma} W\right), \quad \text{(A.1)}$$

where $\hat{P}$ denotes the predicted number of patents of a firm within the current year. The term $D(Y_{it-1} > 0)$ is a dummy variable that is coded 1 if the firm patented during the previous year and 0 otherwise. Worker shares are $s_j = \frac{\mathrm{L_j}}{\mathrm{L}}$ where L_j denotes the number of R&D workers of type *j* in the firm, while L denotes the total number of R&D workers in the firm, $L = \sum_{j=1}^{7} L_j$. The latter summation goes over all worker types we consider: hires from firms with university experience, hires from firms without university experience, hires from university, other hires, recent graduates, support workers and stayers. Stayers constitute the base category in the summation $\sum_{j=1}^{6} \hat{\beta}_j s_j$ which is why the first sum in Equation (A.1) is from 1 to 6 only. The term $D(TMT = 1)$ denotes a dummy variable that is coded one if there is at least one TMT member with an R&D education in the firm. The second sum in Equation (A.1), $\sum_{m=1}^{3} \hat{\gamma}_m s_m$, is, following Hypothesis 3, over the three worker groups hires from university, firm hires with university experience and firm hires without university experience. The term W denotes additional control variables.

The marginal effect of worker type k on the number of patents is:

$$\frac{\partial \hat{P}}{\partial L_k} = \frac{\hat{P}}{L}\left(\hat{\beta}_k + \hat{\gamma}_k D(TMT_{it} = 1) - \sum_{j=1}^{6} \hat{\beta}_j s_j - D(TMT_{it} = 1)\left(\sum_{m=1}^{3} \hat{\gamma}_m s_m\right) + \hat{\rho}\right). \quad \text{(A.2)}$$

The marginal effect hence depends upon the number of patents per worker, the TMT dummy variable and the worker shares. To simplify the analysis and to be able to present interpretable and meaningful marginal effects we set $\hat{P} / L$ to the sample mean. We additionally set the number of workers except for skill group *k* and stayers to 0. Equation (A.2) then reduces to:

$$\frac{\partial \hat{P}}{\partial L_k} = \frac{\hat{P}}{L}\left(\hat{\beta}_k (1 - s_k) + \hat{\gamma}_k D(TMT_{it} = 1)(1 - s_k) + \hat{\rho}\right)$$

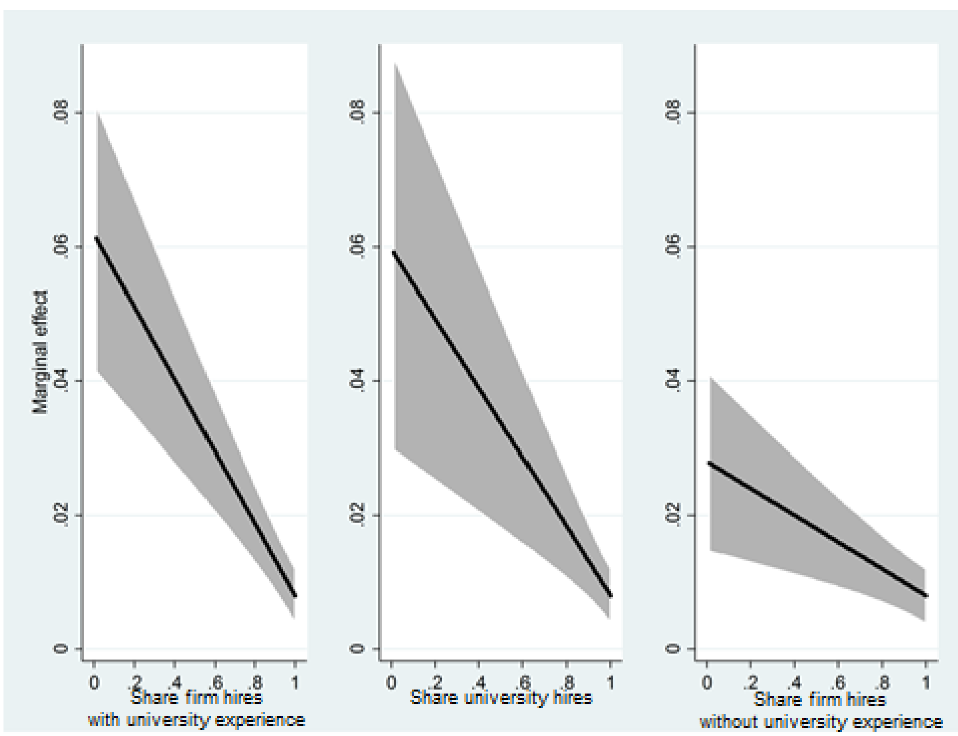
which is positive and linearly decreasing in s_k and decreasing if $\hat{\beta}_k$, $\hat{\gamma}_k$ and $\hat{\rho}$ are positive.

We calculate the corresponding standard errors using the "Delta-method" (Greene 2003, p. 913-914). Let θ denote a vector of parameters with $\theta = \left(\hat{\beta}_k, \hat{\gamma}_k, \hat{\rho}\right)$ and let Ψ_k denote the corresponding variance-covariance matrix. The variance of the marginal effect of skill group k is then given by

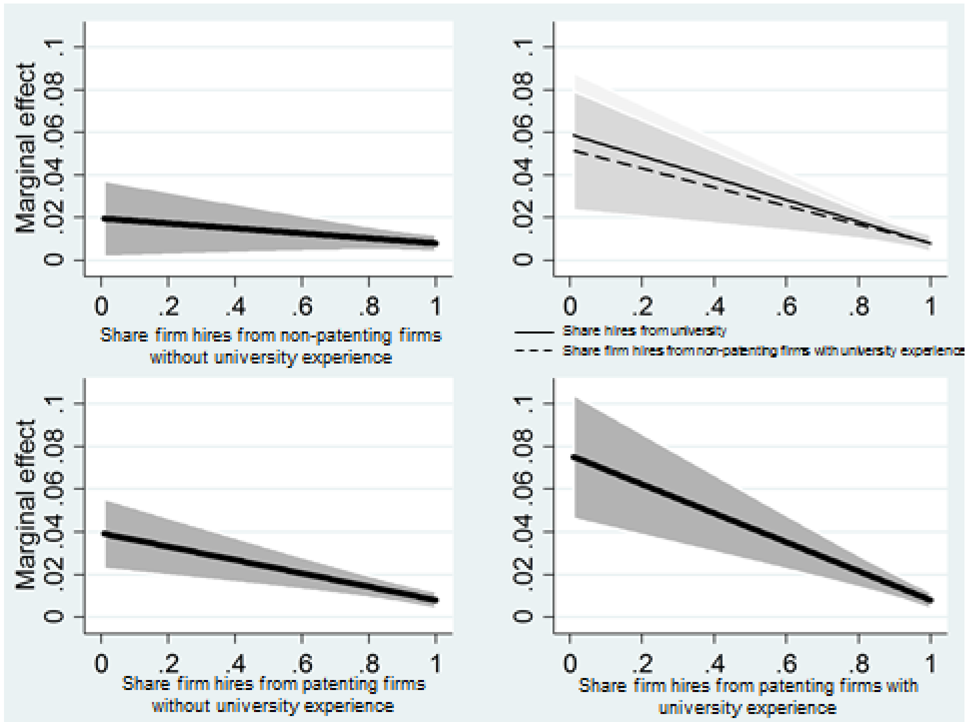
$$V\left[\partial \hat{P} / \partial L_k\right] = C(\theta)' \psi_k C(\theta),$$

where $C(\theta)$ denotes the vector of partial derivatives of the marginal effect with respect to each parameter in θ:

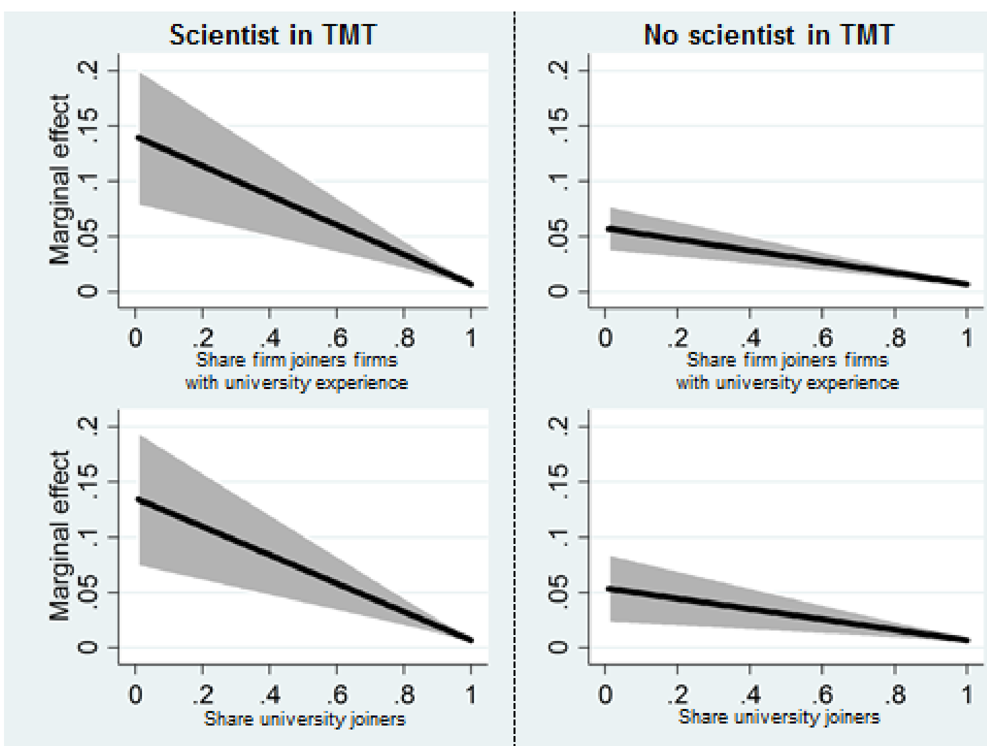
$$C(\theta) = \begin{pmatrix} \dfrac{\partial(\partial \hat{P} \;/ \partial L_k)}{\partial \beta_k} \\ \dfrac{\partial(\partial \hat{P} \;/ \partial L_k)}{\partial \gamma_k} \\ \dfrac{\partial(\partial \hat{P}_{it} / \partial L_k)}{\partial \rho} \end{pmatrix} = \frac{\hat{P}}{L} \begin{pmatrix} 1 - \dfrac{L_k}{L} \\ D(TMT \;=1) - D(TMT \;=1)\dfrac{L_k}{L} \\ 1 \end{pmatrix}.$$



Online Appendix Figure 2. Marginal effects for Model I (90 percent confidence bands)



Online Appendix Figure 3. Marginal effects for Model II (90 percent confidence bands)



Online Appendix Figure 4. Marginal effects for Model III (90 percent confidence bands)

Online Appendix Table 1. Worker characteristics

	Firm Hires w/ uni. exp.	Firm Hires w/o uni exp.	University Hires
Age	37.3	39.17	35.1
Years of working experience	13.7	13.6	11.7
PhD dummy	26.4%	4.2%	34.5%

Online Appendix Table 2. Extra robustness checks for Model I

	No citation weights			**No chemical sector**			**No major patenters**		
	Coeff.	***p*-value**	**Std.err.**	**Coeff.**	***p*-value**	**Std.err.**	**Coeff.**	***p*-value**	**Std.err.**
Employment shares									
(3) Hires from firms w/ university experience	1.456	0.000	0.391	1.480	0.000	0.348	1.207	0.000	0.334
(4) Hires from firms w/o university experience	0.484	0.029	0.221	0.577	0.007	0.213	0.465	0.021	0.201
(9) Hires from universities	1.261	0.014	0.512	1.485	0.004	0.521	1.239	0.013	0.501
Other hires	0.171	0.697	0.438	0.244	0.573	0.433	0.030	0.945	0.439
University graduates	0.711	0.028	0.323	0.733	0.031	0.340	0.565	0.085	0.329
R&D support workers	0.383	0.126	0.251	0.339	0.146	0.233	0.141	0.464	0.192
Control variables									
ln(# of R&D workers)	0.215	0.009	0.082	0.218	0.003	0.073	0.094	0.125	0.061
ln(capital)	0.139	0.000	0.038	0.145	0.000	0.033	0.131	0.000	0.034
PhD employee dummy	0.155	0.235	0.131	0.098	0.499	0.145	0.363	0.010	0.142
Lagged patent dummy	1.148	0.000	0.136	1.108	0.000	0.142	1.229	0.000	0.143
ln(# of pre-sample patents)	0.509	0.000	0.068	0.502	0.000	0.077	0.310	0.000	0.062
# of pre-sample patents > 0 dummy	0.244	0.423	0.304	0.295	0.400	0.350	1.138	0.000	0.289
Hypotheses tests									
	Chi^2	*p*-value		Chi^2	*p*-value		Chi^2	*p*-value	
Hypothesis 2									
(3) = (4)	4.42	0.036		5.63	0.018		4.39	0.036	
(9) = (4)	2.14	0.144		2.85	0.092		2.24	0.134	
Joint	*5.79*	*0.055*		*7.57*	*0.023*		*6.09*	*0.048*	
Observations	15,964			15,715			15,964		

Note: Robust *t*-values are clustered by firms. All explanatory variables are lagged by one period. Time dummies and sector dummies are included.

Online Appendix Table 3. Dynamic fixed effect Poisson GMM estimation results

	Model I		
	Coeff.	*p* -value	Std.err.
(1) Hires from firms w/ university experience	2.265	0.000	0.287
(2) Hires from firms w/o university experience	1.849	0.000	0.180
(3) Hires from universities	5.048	0.000	0.727
Other hires	5.048	0.000	0.831
University graduates	3.590	0.000	0.624
R&D support workers	1.105	0.000	0.271
ln(# of R&D workers)	0.228	0.000	0.063
ln(capital)	0.769	0.000	0.049
Lagged patent dummy	0.253	0.001	0.073
Twice lagged patent dummy	0.961	0.000	0.076
Hypotheses tests	Chi^2		*p* -value
Hypothesis 1			
(1) = (2)	0.726		0.394
(3) = (2)	7.705		0.006
Joint	79.213		0.000
Specification tests			
	Chi^2		*p* -value
AR(1)	-2.532		0.011
AR(2)	-0.994		0.320
Sargan	95.023		0.286
Observations	9416		
Firms	2864		

Note: All explanatory variables are lagged by one period. Specification includes a set of time dummies.

Online Appendix Table 4. NegBin estimates based on matched control observations

			Unmatched raw difference		**Matched raw difference**		**Coarsened exact matching**		**Propensity score matching**	
	# treated	**# controls**	**Mean**	**Std. dev.**	**Mean**	**Std. dev.**	**Coeff.**	**Std. err.**	**Coeff.**	**Std. err.**
H3	195	1174	13.197	1.079	5.697	3.090	3.007	0.933	3.557	1.454

CEM matches 58.5% of the treated observations.
Additional control variables in PSM-based NegBin regression:
ln(R&D workers), year 2002, year 2004; sectors:
plastic & glass, medical devices, patent intensive