# Death and Turmoil in R&D Teams *

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**Abstract**

We use a novel method to define the R&D team and use the unexpected death of an R&D worker to study its effect on the organization of R&D teams in profit-making firms. Average treatment effects on exit probability, entry probability, wages of stayers, and characteristics of leavers are null. Hires are slightly younger in treatment than control. Treatment effects do not vary by the size of the R&D team but vary in interesting ways by the characteristics of the deceased and with job market liquidity. Results suggest weak complementarity of personnel and almost perfect substitution of talent in business R&D. Management appears able to quickly adjust the team to the shock.

*Keywords:* innovation, knowledge spillovers, managerial response, organizational economics, peer effects, R&D teams

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# 1 Introduction

Both economists and management scholars appear to agree that one of the most complex functions to manage is research and development (R&D), while simultaneously being central to productivity improvements at both the aggregate and firm level (e.g. Bloom et al., 2020; Doraszelski & Jaumandreu, 2013). Grant (1996) expresses this fundamental management challenge, stating that knowledge acquisition requires specialization, hence requiring coordinated efforts across specialists who possesses many different types of knowledge. Yet, Grant (1996) continues to argue that as organizations must depend on individuals in this knowledge accumulation, there is no substitute to the efforts of the individuals. The organization then coordinates among these individuals in various ways.

It is therefore no surprise that when examining the unexpected departure of scientists, Azoulay et al. (2010) and Jaravel et al. (2018) find that it leads to reduced research and inventive output and wages for their co-workers. Such a reduction of productivity at the individual level suggests that management should try to adjust to the sudden loss of an R&D team member one way or another. The ability to adjust, or the lack of it, is likely instrumental not only for firm-level development of productivity but also for aggregate productivity growth, given that some 60% (OECD, 2022) of R&D takes place at private firms. We study how management in a profit-making firm reacts to such unexpected losses of an R&D worker.

First, to give some color to what might happen when a close collaborator in a team unexpectedly dies, we use an analogy. In some instances, such as the death of a strong leader of a musical band, the remaining members might flounder or even disperse. Well-known examples include the Doors and Nirvana. The loss of Jim Morrison led to the decline of the Doors as a musical force. Nirvana similarly ceased to produce new songs after the death of Kurt Cobain, yet Dave Grohl went on to achieve a successful career as a lead singer and guitar player with the Foo Fighters, after having been a drummer for Nirvana.

However, the death of a creative collaborator may not always cause such shocks to creative output. In some cases, a band has continued to deliver good musical performances even after a key member of the team passes away. AC/DC is a good example. It maintained success after the lead singer, Bon Scott, died of acute alcohol poisoning. AC/DC replaced Bon Scott with the new lead singer, Brian Johnson, within a matter of months, and produced the acclaimed album "Back in Black." Another example is Joy Division, which had a strong leader in Ian Curtis, who sadly committed suicide just when the band had reached its apex. Despite the loss of Curtis, the group's remaining members added a keyboardist and came back strong as New Order. These examples of musical groups suggest that the impact of the shock may be conditioned on the creativity of the departed, the additional number of leavers, and perhaps also on the collaborative process of the team.

Musical groups are not for-profit firms, but if they do not sell their music in one way or another, they often cease to play together, and in that sense the popular music analogy carries over and sets the stage for this article. To understand whether such adverse shocks have similar implications for creative teams of much larger size and with significantly more complex coordination of production tasks than those typically examined before, we study how a complete R&D team (as opposed to a group of coauthors or co-inventors on scientific papers and patents) at a for-profit firm reacts to the unexpected loss of a team member.

We ask the following questions: Does the loss of an R&D worker lead to further losses of team members or to further hires? What type of workers are those who were lost and those newly hired following the shock? In other words, do managers adjust the composition of its R&D team? Do managers recalibrate the wages of new workers or the compensation of the workers who remain? Which co-workers within R&D are unaffected, and which are strongly affected? We thus expand on the outcomes previously analyzed (typically, productivity) by examining staff turnover in terms of those who leave and those who are newly hired.

If a firm has an optimally configured team before the shock, the benchmark assumption is that, like AC/DC and Joy Division, it would want the team to readjust quickly. As in one of the examples above, the unexpected loss of a team member, if not addressed, can lead to additional exodus by otherwise productive team members, and a further decline in team productivity by those who remain than if the team had merely lost one member. The question is also whether it is possible to address the unexpected loss through managerial adjustments. For example, the discussion among the remaining members of Nirvana to try to replace Kurt Cobain ended very quickly, and the band simply dissolved.

More precisely, the effect of the death of R&D workers on peers should depend on whether team members are complements or substitutes. In the model by Lucas (1978), for example, skill complementarity in teams has a downward effect on co-worker wages, as they become less productive after the loss of a close collaborator. When task complementarity across co-workers is greater, so is the negative impact. Strong task complementarity also has implications regarding who leaves the team. If complementarity is strong, productivity among those who decide to leave would have decreased significantly if they had remained. It follows that more productive and more complementary co-workers are more likely to leave. Another model that addresses the problem is the human capital theory by Becker (1964), which states that firms share rents with workers to persuade those with valuable human capital not to quit (Ejermo & Schubert, 2018). Management thus raises the salaries of complementary workers after a negative shock to the team. The above makes clear that outside opportunities might also influence the impact of a sudden loss of a team member. Frictions in the labor market can be substantial (e.g., Ransom 2022) and are thought to affect the ability of firms to maintain their inventive ability in R&D through opportunities to hire replacement workers (Marshall 1890; Moretti 2011).

Another key concept that is relevant to this article concerns the mobility (loss) of R&D personnel. Most work in this area focuses on how employee mobility might cause information spillovers, examining the claim by Arrow (1962) that the "mobility of personnel among firms provides a way of spreading information" (1962, p. 615). Examples are Møen (2005), Kaiser et al. (2015), Maliranta et al. (2009), Song et al. (2003), Tzabbar & Kehoe (2014), and Khanna (2022). To our knowledge, however, few have studied how mobility is affected by the random loss of a co-worker.[1]

We can now speculate on what actions managers might take after a firm suffers the sudden loss of a member of its R&D team. Based on literatur, managers have several levers on which it can pull to restore the team's productivity. However, these types of actions are typically unavailable to an individual faced with the sudden loss of a co-inventor or coauthor, thus separating our study from prior analyses of the death of co-workers. For example, managers can change the working conditions of existing R&D team members to persuade them not to leave, such as raising salaries (Becker 1964). Complementing these actions, managers can seek to hire replacement personnel (Møen 2005), who can often be sourced locally (Marshall 1890). At the same time, team members might leave as a result of the unexpected loss in order to increase their productivity (Hoisl, 2007), potentially diminishing the remaining team members' productivity further. The actions taken by managers in for-profit firms to adjust to the loss are not clear in the prior literature, nor is how co-workers react to the loss and whether their adjustments are affected by frictions in the local labor market. To date, little to no evidence has been produced about the managerial reactions in firms to shocks to R&D teams. Given that R&D workers are highly trained and specialize in particular functions, replacing them and regaining the co-workers' productivity level might be more difficult than is the case after the loss of less specialized workers. But because R&D teams at firms are much larger than pairs of coinventors or coauthors, the firm's internal labor market might resolve most problems of substituting for the loss of the deceased. To date, the net effect is unclear.

We devise a novel approach to identify members of a firm's R&D team. Using detailed occupational and educational information, we go beyond prior work by identifying these co-workers, irrespective of whether they co-invented or copublished in the past. We then apply this method to Swedish registry data, with information on inventors from European Patent Office data. We couple this information on R&D team members with the identification strategy pioneered by Azoulay et al. (2010) and further developed in an innovation context by Jaravel et al. (2018) and in a blue-collar context by Jäger & Heining (2019) and rely on the death of a member of the R&D team to provide exogenous variation in team size and composition. We couple exogenous variation induced by deaths with a conditional difference-in-differences (DID) method to obtain causal estimates.

First, we find that the average probability of an R&D worker's departure is unaffected by the loss of a team member through death. However, there are important conditional effects that are informative on the mechanisms of cooperation within large R&D teams. Second, the characteristics of R&D team members who leave are on average no different than before/without the treatment. However, again there are important conditional effects. Third, the probability that a an R&D

[1]For a review of the management literature on this, see Mawdsley & Somaya (2016). They conclude that "virtually no studies have examined employee mobility as an involuntary event" (p. 106). An interesting approach has been to look at shocks to laws within jurisdictions that either relax or constrain labor mobility across jurisdictions. For a review, see Starr (2019).

member is a hire is not affected on average, but again we find important conditional effects. Fourth, those who are hired to join the R&D team are approximately 1 per cent younger as a results of losing a team member unexpectedly. Greater liquidity of the local labor markets aids in hiring older individuals. Impacts of losing an R&D team member materialize mostly for team members who have the same occupation as the deceased, while the results are much weaker or not at all present for team members with a different occupation as the deceased. Finally, we analyze the wages of the team members who remain. They do not receive higher compensation, as proposed by bargaining theory, nor do wages drop, as found in studies of losses of for example co-patenters (Jaravel et al., 2018), but remain constant.

Combining these results, we conclude that management appears, maybe surprisingly, able to adjust the R&D team to the unexpected loss of a collaborator. These results are in line with earlier results where no effects were found at the firm (Jaravel et al., 2018) or university (Waldinger, 2012) level. We hasten to analyze whether the mostly null main treatment effects are a function of the size of the R&D team, as the average team comprise as many as 148 individuals. We do not, however, observe any robustly different impacts even for the smallest teams. As a partial explanation we note that voluntary worker exits are common, as the annual rate of departures is 10.8%, or 16 individuals, and the annual share of new hires in the teams is 6.5% or 10 individuals. These numbers suggests that an additional unexpected loss of a teammate can be handled within the normal fare of replacements. When we find any externalities on the team from the shock, they mainly appear for R&D workers who work in similar occupational areas as the deceased and for older workers that suffer when a senior colleague dies. These results indicate that there are some complementarities in R&D tasks among close collaborators.

We contribute to several related strands of literature. The cornerstone of our work is our definition of an R&D team. For a long time, researchers have sought to define members of the R&D team at firms (e.g., Møen, 2005; Kaiser et al., 2015; Maliranta et al., 2009). Our novel contribution provides a simple list of three-digit R&D occupations that can easily be used by others and in which staff in these occupations are verified in three different ways as part of the R&D function. Our method of identifying the team is not limited to R&D and could be applied to forms of teams that are new and never studied before, such as those working in marketing, sales, or other functions, as long as one, analogously, can find reasonable definitions of groups of co-workers based on occupational codes that can be calibrated against data.

Second, our work is related to articles that link patent holders to other information (see Giuri et al., 2007; Toivanen & Väänänen, 2012, 2016; Bell et al., 2018; Aghion et al., 2017, 2023; Akcigit et al., 2017; Kerr & Lincoln, 2010; Akcigit et al., 2016, and Akcigit et al., 2018). In contrast to these articles, which concentrate on inventors or their co-workers broadly defined (e.g. Aghion et al., 2023 study both blue- and white-collar co-workers of inventors), we focus on members of R&D teams at for-profit firms.

Third, we consider the larger literature on peer effects in the workplace. The literature on shocks to coauthoring or co-inventing teams has expanded from Azoulay et al. (2010), Jaravel et al. (2018), and Pöge et al. (2022) that study coauthors or co-inventors, to looking at larger teams and small firms. For example, Samila et al. (2021) explore the effects of a third person dying on the scientific collaboration of the remaining two. As patenters represent only 2.1% of all RD workers in our data, our method identifies approximately 50 times more co-workers potentially affected by the death of a colleague than methods restricted to co-patenter. We study the impact on the full R&D team in a firm, exploring conditional treatment effects that depend on team size, team type, and the characteristics of the deceased. For related work outside of the R&D workforce and the impact of death shocks on the firm as a whole see e.g. (Choi et al., 2021; Huber et al., 2021; Åstebro & Serrano, 2015; Becker & Hvide, 2021; Sauvagnat & Schivardi, 2019; Jäger & Heining, 2019).

Finally, we contribute to the broader literature on the internal labor market at a firm (Ichniowski & Shaw, 2009), the bargaining over wages between firms and workers (Stole & Zwiebel, 1996a,b), team effectiveness (for a review, see Cooke et al., 2015), and local labor market agglomeration (Marshall, 1890; Moretti, 2011). We find no evidence that R&D workers extract rents that compensate them for the loss of a co-worker, that teams rebound quickly from the shock, that the local labor market functions to smooth the acquisition of replacement workers, while it offers little impact on the probability and types of departures.

Following this introduction, we devote section 2 to a description of the R&D teams in our data, the validation of our definition of an R&D team and how we identify the exogenous shock, and our protocol for matching treated and control groups. Section 2 also contains a descriptive analysis of mobility, team size, and patenting, and we benchmark these numbers to confirm their accuracy. We provide a descriptive analysis of what happens to the R&D team, leavers, and hires as well as the wages of stayers in section 3. Section 4 contains a causal analysis of the effects of losing an R&D worker. Section 5 concludes.

# 2 Data

## 2.1 Data preliminaries and matching

In this subsection, we detail the data sources, the definition of an R&D team member, our approach to identifying deaths, definitions of the main variables, the protocol for matching treated to nontreated individuals and firms, and, finally, descriptive statistics that demonstrate the success of our matching.

**Data sources.** We use two main data sources: A longitudinal integrated database for health insurance and labor market studies (LISA) and European Patent Office (EPO) patent data. The Swedish register of all people employed in the country is matched by their social security number with register data from their employers in LISA to form the universe of workers at privately owned firms, from which we sample R&D teams. From these data, we extract all individuals working at business enterprises in the private sector in Sweden in 2001 to 2016. The data contain typical information on workers: Age, gender, wage, employment status, and occupational code.

**Definition of an R&D worker.** To define the most innovative occupations, we first extract all Swedish residents listed as inventors on a patent application at the EPO from 1985 to 2010. These data are matched with LISA, as described in Jung & Ejermo (2014).

Leveraging our inventor data, we then use the Swedish ISCO-compatible occupational classification table to identify occupations that are especially inventive.[2] There are two classification structures of occupations in the data. For 2001-2013, we use the ISCO-88 (SSYK96) scheme. For 2014-2016, we use corresponding categories in the ISCO-08 (SSYK2012) scheme. As categories are not identical across the two schemes, we merge some occupations to form related stable groups across the two periods.

Occupations are in rank order, from the highest to the lowest in terms of inventiveness, and we define occupational inventiveness as the number of inventors (of patented inventions) by a given three-digit occupational class. Having defined all innovative R&D occupations, we then identify all R&D workers at each firm. We identify as R&D workers all individuals who at some point between 2001 and 2016 held one of the occupations listed in Table 1, but exclude employees in these occupations who have less than two years of college education.[3] Past patenters represent only 2.1% of all RD workers in our data.

**Identifying deaths.** We identify deaths based on employer notifications to the Social Security system and restrict the analysis to deaths of R&D workers who are under 60 years old in the year of their death. In line with past research (e.g. Jäger & Heining, 2019, and Pöge et al., 2022), we exclude deaths that were preceded by social insurance payments in the prior year. Social insurance payments will indicate sick days and thus advanced health problems, but may also be attributable to parental leave. To rule out deaths due to, for example, industrial accidents, we further exclude deaths at firms with multiple worker deaths in a given year. Since we match deaths to placebo at $k = -4$ (see next paragraph on how) and whilst data starts in 2001, we cannot use deaths occurring before 2005 for analyses. Using these sampling conditions, we identify 683 unexpected deaths during the period 2005 to 2017. Note that deaths among R&D workers are rare. For the population of R&D workers under age 60 at private firms, the probability of death is 0.34% in any given year. In comparison, the average exit rate from R&D teams in our (exit) estimation sample is 10.8%.

**Matching protocol.** We adapt the matching procedure by Jäger & Heining (2019). First,

[2] Because we exclude firms in the public sector, year-observations at universities were excluded even though employees at universities are highly inventive.

[3] In Sweden, many two-year college programs offer terminal degrees that lead to, for example, "technician" status. In Table 1 these programs lead to jobs represented by, for example, SSYK codes 311 and 351, but can be found as well in most of the other occupational codes at the four-digit level. We rely on data constructed from surveys of firms of their employees' occupations. Coverage is better at larger firms, and the smallest firms may avoid the survey altogether and therefore are not included. For further details on the Swedish occupational data, see e.g. Tåg et al. (2016).

we exclude firms in the public sector, firms with less than three R&D workers, and individuals with no firm affiliation or whose wage, age, or education is unknown. Following Jäger & Heining 2019, we draw a deceased R&D worker and match one-to-one without replacement to a surviving ("placebo") R&D worker from a firm that was not treated in the same year. Denoting the calendar year of death by $d$, we use coarsened exact matching (CEM, Iacus et al., 2012) on the characteristics of the deceased individual in year $k = t - d = -4$, measured in treatment time (i.e., four years before death), where $t$ is the calendar year of the observation in question. Our matching vector of individual characteristics consists of: age, wage, gender, year, and occupational group (groups 1-8 in Table 1). We also match the deceased to the placebo on two firm characteristics in $k = -4$: The firm's wage decile and its R&D team size.[4] We follow Jäger & Heining (2019) and allow firms to be sampled more than once but not in the same treatment year. This decision implies that co-workers of the deceased and placebo individuals can be included more than once in the sample if the same firm has multiple deaths (and multiple placebo deaths) in different treatment years. In all, we match the unexpected deceased to placebo individuals on seven characteristics. We succeed in matching 519/683 (76%) of the unexpected deceased with a placebo individual active in 519 firms. The individuals in the treatment and control groups, then, are R&D co-workers of the deceased and placebo deceased R&D workers.

**Descriptive statistics on matching.** Panel A in Table 2 compares the 519 deceased R&D workers to the 519 placebo R&D workers, as well as their R&D co-workers on the individual match criteria. The first column gives descriptive statistics of the deceased R&D workers, whereas the second column shows the corresponding numbers for the placebos. We find that the matching procedure performs well on all matching dimensions. In addition we include two non-match variables, (years of) Education and (years of) Tenure in the firm, and show that the deceased and placebo workers are close to identical also on these variables. The third and fourth columns reveal that the treated R&D co-workers and the control co-workers also match extremely well to each other, both on matching and non-matching variables. Panel B in Table 2 provides evidence on the firm-level match for the 519 treated and 519 control firms. Again, we find that the matching process works well also at the firm level, with differences in R&D team size and wage percentile of the firm between treated and control groups that are very small.

**Dependent Variables.** We employ several dependent variables: An indicator variable taking the value one in the year when leaving the firm, and a similar indicator taking the value one in the year when an individual joins a firm, wage, age and education of the departing, hired, and remaining employees. Annual wages are in log 2012 Swedish krona, divided by 100. Education is an indicator that takes value of one if the individual has an MSc degree or higher. Age is in log years.

[4] For age, wage, and R&D team size, we employ a coarsened binning structure using Sturge's rule. For the other variables, we employ exact matching. Sturge's rule splits the data into $m$ bins of equal size, where $m$ is given by $m = [\log 2n] + 1$ and $n$ is the number of observations. Wage deciles are recalculated for each year.

**Independent Variables.** We use seven variables to examine heterogeneity in the effect from losing an R&D worker: First, whether the deceased was an older employee ($Old$); second, a measure of the density of the local labor market in the same occupation as the deceased worker ($LLM$); third, whether the deceased had a high wage ($High\ wage$); fourth, whether the employee was in the same or different occupation as the deceased (as defined in Table 1); fifth, if the deceased was in a higher occupational category than the employee ($Superior$); sixth, the number of years in which the employee worked together with the deceased at the firm ($Workhist$; in our estimations we, in addition, always control for the employee's own tenure at the firm), and, seventh, the initial size of the team at matching, implemented by a series of team size categories.[5]

## 2.2 Benchmarking the R&D team size measure

In this subsection, we benchmark our new R&D team definition in three different ways in order to verify that it performs as one would expect from a measure of the R&D team.[6] Coming up with a measure of the R&D team is not a trivial exercise, as indicated by prior attempts (Møen, 2005; Kaiser et al., 2015, and Maliranta et al., 2009). There are concerns that one could either seriously overcount or, alternatively, undercount the size of the R&D team. First, we benchmark our R&D team measure to information gleaned from an independently performed survey of R&D personnel conducted every year by Statistics Sweden. We then compare some descriptive statistics on R&D team mobility to those found in the literature. Finally, we investigate whether our R&D team variable is correlated with inventive output in a way that one would assume based on prior research.

**Benchmarking to the R&D survey.** To calibrate our definition of which occupations and individuals to include in R&D, we compare the number of R&D workers at the firm level that our sampling approach yields to the number of R&D workers reported by the same firm in the national representative survey of R&D in 2009. A respondent at each firm reports the R&D worker total firm headcount in that survey. We calibrate the list of qualifying R&D job categories until we reach the maximum correlation between the survey respondents' reported R&D headcount, and our estimated number of R&D workers obtained from the registry data for the same survey responding firms, obtaining $R^2 = 0.96$ between the two figures. The estimated total number of R&D workers counted using our constructed R&D team definition (68,000) is then relatively close to the actual

[5]Some details. $Old_j$ is set at 1 if the age of the deceased $j$ is higher than the average of R&D workers at the same firm; otherwise, 0. The thickness of the local labor market is defined as: $LLM_{jmrd-4} = (RD_{jmrd-4}/RD_{jrd-4})/(RD_{jmd-4}/RD_{jd-4})$, where $d$ denotes the calendar year of death, $RD_{jmrd-4}$ is the count of R&D workers in occupational category $m$ in region $r$ of the deceased $j$ at time $d-4$, $RD_{jrd-4}$ is the count of all R&D workers in $r$, and $(RD_{jmd-4}/RD_{jd-4})$ is the corresponding share at the national level. $High\ wage_j$ is set at 1 if the wage of the deceased $j$ is in the top quartile of the wage distribution of R&D workers at the same firm; otherwise, 0; $Tenure$ is the number of years that the employee has worked at the firm; and $Joint\ work\ history$ is the number of years that deceased $j$ and the employee both worked at the firm before the death of $j$.

[6]We use all R&D team members in our matched sample of 519+519 firms in this benchmarking exercise.

headcount reported for responding firms (55,551).

**Benchmarking to the literature.** To further benchmark our R&D team data, we first calculate R&D hiring as the sum of all external R&D personnel hired by a firm given year, whereas the number of R&D leavers is the sum of all R&D personnel who leave the firm in a given year. We divide these figures by the number of individuals in the same team in the year an individual leaves or is hired and them compute averages across firms. We find a leaver rate of 10.8% and a hiring rate of 6.5%, which translates into approximately 16 (6) leavers and 10 (3) hires per year in a team of average (median) size in the estimation sample.

We benchmark these figures to two prior studies. The first is a cross-country study of wage structures within and across firms in ten countries by Lazear & Shaw (2009), who find that firm-level leaver rates vary substantially across firms and countries. The typical firm's leaver rate varies from "lows of around 15 percent in Norway, Sweden, Finland, and early observations for Germany, to highs of 35 percent in France." The firm-level estimates by Lazear & Shaw (2009) for Sweden appear comparable to those in our study. They find that leaver rates of white-collar employees in Sweden vary between approximately 11% and 14% between 1974 and 1990, and hiring rates that vary similarly.[7]

Another benchmark is Møen (2005), who finds that in Norway, the firm-level separation (leaver) rates of R&D personnel vary between 19% and 22%, depending on the definition of R&D personnel used (using different education levels). Compared to these two studies, our data on leavers and hires seem reasonably well calibrated.

**Benchmarking the relationship between R&D team size and inventive output.** Data on patent productivity are presented in the Appendix, Figure A1. As is typical, the distribution of patents per firm per year is highly skewed, with most firms producing zero patents in a given year. To avoid the zero-patent count from hiding the differences among strictly positive counts, we show the distribution only for non-zero counts.

We next verify that R&D team size is correlated with innovative output, in line with the large literature relating R&D investment to patenting, beginning with Hausman et al. (1984). In the Appendix, Figure A2, we display a scatter plot in which the $x$-axis describes the size of the R&D team and the $y$-axis the number of patents. The figure also displays a linear projection of the number of patents per firm per year on the size of the R&D team. Both the scatter plot and the regression line suggest a positive association between R&D team size and the number of patents.

In the spirit of Hausman et al. (1984), we further verify the relationship between the R&D team size and patenting by using firm-year level data to estimate a (firm-) fixed effects Poisson model in which the dependent variable is the number of patents by firm $i$ in year $t$, and the key explanatory variable is the size of the R&D team of firm $i$ in year $t$, its square (divided by 1,000), and its lags. In line with previous literature, we find that the relationship between contemporaneous R&D team

[7] The authors caution against comparing leaver-rate levels across countries for these data, as the different data sets measure separations over different periods and types of jobs. Therefore, levels are not strictly comparable across countries.

size and the number of patents is positive, and marginally declining.[8] The results are reported in Appendix Table A1. These results suggest that our measurement of the R&D team is meaningful.

**Benchmarking summary.** In sum, the analyses indicate that our novel definition of an R&D team produces plausible statistics on the correlation between estimated and reported R&D team size, levels of annual R&D hiring and departure rates, and the correlation between R&D team size and patenting. The new R&D measure has the significant advantage of measuring the human capital inputs to invention at a firm without conditioning the identification of these inputs on having had observable inventive outcomes. This is in contrast to much of the literature. At the same time, our measure is based on substantially more detailed information than in previous efforts to classify individuals as R&D workers.

# 3 Descriptive analysis

**Estimation samples.** One issue that we need to address before we embark on further analyses is the heterogeneity in R&D team sizes. The $85^{th}$ percentile of the initial R&D team size distribution is 419 R&D workers, quite far off from the mean which is 194 and the median of 55. To avoid undue influence on estimates from a firm with an R&D team that is an outlier, we exclude all firms with initial R&D team sizes above the $85^{th}$ percentile. We choose the $85^{th}$ percentile as the cutoff as a compromise between preserving sample size and reducing extreme heterogeneity in team size: An inspection of the data reveals that, after the $85^{th}$ percentile, the distribution thins out significantly. For example, the $90^{th}$ percentile has close to 600 employees. We also remove R&D teams that initially have less than three workers. The reasoning is that if a team of three experience death, it still remains a team (of two). All sample restrictions are performed on initial team size at $k = -4$, the same year for which matching is performed.

Team size may have an important conditioning effect on the likelihood of death, and may also condition the size of the treatment effect. As described in the estimation section we always control for the size of the R&D team at $k = -1$ (i.e., lagged R&D team size). In our main analyses, we also analyze treatment effects conditional on team size. Finally, in the robustness section, we perform analysis restricting the sample to those firms whose initial R&D team size is at most at the median of the initial distribution.

Some large year-to-year changes in R&D team size are likely the result of mergers of firms, rather than having anything to do with the death of an R&D worker (see e.g. Lockett et al., 2011). Therefore, we exclude from the analysis observations that have large changes in firm size. After inspecting the data, we exclude firms with year-to-year changes in R&D team size above the $98^{th}$ percentile. Imposing these team size and team growth restrictions leads to a total of 699 firms in

[8]The inflection point is at the R&D team size on the order of 700The specification includes calendar-year dummies; in line with Hausman et al. (1984), we find that the lagged values of the R&D team size do not matter.

the estimation sample (339 treatment and 360 control firms).

We restrict the estimation window to 2001-2016 in terms of calendar time and to $k = -3, .., 6$ in terms of treatment time, where $k = 0$ is the year of death. We employ four different samples and subsamples of them. The sample for the probability of leaving and being a hire consists of a panel of all year-observations of all team members until they leave or are censored in 2016. Our sample for the type of leavers and hires is a repeated cross-section consisting of the last (leavers) or first (hires) observations of an individual in a given R&D team, conditional on the individual joining the firm after the first year in our data or leaving the firm before the last year in our data. Our sample for R&D co-workers who remain consists of all individuals who worked on the R&D team at $k = -1$ and did not leave during our observation period.[9] The samples are further split between whether the hires, leavers and stayers have the same or a different occupational group than the focal (deceased or placebo) individual. The occupational groups are defined as in Table 1.

**Distribution descriptives.** The distribution of R&D team size is highly skewed. Distributions for treated and control in $k = -4$ are given in the Appendix, Figure A3. After imposing the team size restrictions discussed above, the average team size in the estimation sample is 148, and the median is 51.[10]

**Pre- and Post-descriptives for Control and Treated.** We examine the probability of departure, the characteristics of those who leave the firm, the characteristics of those hired, and the remuneration of the R&D workers who remain at the firm using simple descriptive data. We ask: Does the loss of a co-worker on the R&D team due to death affect the probability that another member will leave, the type of members who leave the team and are hired to join the team, and the wages of those who remain?

Table 3 panel A shows the means and the standard deviations for the probability of leaving and the probability of being a hire in the pre- and post-periods, displayed separately for the treatment and control groups. The probability to leave increases from 0.05 to 0.11 for the treated, and from 0.04 to 0.11 for the control group, suggesting a null average treatment effect. The probability of being a new hire decreases from 0.12 to 0.00 in the treatment group, and the same change occurs for the control group, also indicating a null average treatment effect.

Panel B shows the means and the standard deviations for the leavers in the pre- and post-periods, displayed separately for the treatment and control groups. The wages of leavers in the treatment group do not change (8.4-8.4), (first row of Panel B, Columns 1 and 3) and that of the leaving individuals in the control group do not change either (Columns 5 and 7) – suggesting a null average treatment effect on wages for leavers. With respect to the age of the leavers, we see no

[9] One could construct the sample of stayers differently. Our results on stayers are robust to the inclusion of all individuals in all years, except in the year that they were hired or left, and to the inclusion of all observations.

[10] Having several estimation samples leads to potential confusion regarding the descriptive statistics on R&D team size. To produce these mean and median R&D team sizes, we use firm-year level observations from the sample covering 2001-2016 and restrict the observations to $k = -3, .., 6$ in terms of treatment time. When we refer to R&D team size descriptive statistics, we mean these numbers unless we state otherwise.

change in their mean age in the treatment group and control groups. Finally, the share of leavers who have at least an MSc is 60% in the treatment group before and 60% after the loss of a co-worker due to death. The respective number in the control group is 70% in both periods, indicating a zero average treatment effect.

For the characteristics of the hires, displayed in Panel C, we find no differences across treated and control individuals and in changes in the two groups over time (pre- versus post-treatment). Finally, among those who remain, Panel D shows the wages of those in the treatment group as well as those in the control group increase by 0.1 log points, i.e., about 11% (in real terms). The simple estimate of the average treatment effect on incumbent wages is thus zero.

These estimates do not take into account other potentially important conditions. Indeed, as will become apparent from the regressions, the conditional treatments effects do vary, sometimes substantially. To analyze these conditional effects we turn to econometric analysis.

# 4 Econometric analysis

## 4.1 Econometric specification

Profit-oriented firms should carefully manage their workforce in general and their R&D team in particular. Similarly, workers seek to choose the employer and employment that best suits them: Good R&D workers may therefore purposely select or may be selected on purpose through assortative matching.Therefore, to study how firms manage their R&D teams, we use an exogenous and observable shock to R&D teams to circumvent what is otherwise an endogenous hiring decision and study the adjustment process by managers in adapting R&D staffing to this shock. Our main regression takes the form

$$Y_{ik} = \delta_0 Treatpost_{ik} + \alpha_1 RD_{ik-1} + \alpha_i + \alpha_k + \alpha_t + \epsilon_{ik}, \tag{1}$$

where $Y_{ik}$ represents different outcome variables for individual $i$ in treatment (as opposed to calendar) year $k$ (described below), and $Treatpost_{ik}$ changes from 0 to 1 in year $k = 0$ for those in the treatment group and remains 1 thereafter. As in Jäger & Heining (2019), we use $k = t - d$ to denote treatment time, i.e., leads ($k < 0$) and lags ($k > 0$) of the event, where $t$ is the calendar year of the observation, and $d$ is the calendar year in which the (placebo) death occurred. $\alpha_i$, $\alpha_k$, and $\alpha_t$ are individual, treatment year, and calendar year fixed effects.

Our outcome variables are (1) an indicator that takes a value of 1 in year $k$ if individual $i$ leaves his or her employer in that year, and is otherwise 0; (2) an indicator that takes a value of 1 in year $k$ if individual $i$ is hired in that year, and is otherwise 0; (3) the natural logarithm of annual wages, $Wage_{ik}$; (4) the natural logarithm of the age of the individual, $Age_{ik}$; and (5) an indicator for whether individual $i$ has a master's degree or higher, $Education_{ik}$.

To deepen our analysis, we introduce interactions between $Treatpost_{ik}$ and observable characteristics of the deceased and individual $i$, as explained in Section 2.1. This approach yields coefficients $\delta_X$ for the interaction terms $Treatpost \times X$, $X \in \{Old,\ LLM,\ High\ wage,\ Superior,\ Workhist\}$. All the variables in $X$ are time invariant. When we introduce these interactions, we also include in the model a measure of tenure of individual $i$ as it is important to separate the effect of own tenure from the joint work history with the (placebo) deceased.[11] We also examine interactions with the initial size of the team at $k = -4$. This measure is also time invariant.

Alternatively, we replace the term $\delta_0 Treatpost$ with $\sum_{k=-2}^{5} \delta_k L_{ik}TE$, i.e., we use six lags (including the treatment year,) and two leads to indicate the time elapsed after (before) death, where the term $L_{ik}TE$ takes a value of 1 if a death was recorded in the firm $k$ years earlier (later).[12] This specification allows us to gauge whether the treatment effect varies over time.

Our DID setup is staggered, i.e., different firms and individuals receive the treatment at different points in calendar time. Recent research suggests various ways for dealing with heterogeneous treatment effects in a staggered setting (see, e.g., Goodman-Bacon, 2021, de Chaisemartin & D'Haultfœuille, 2020 and Callaway & Sant'Anna, 2020). We address this potential issue by having treatment time as our measure of time and including calendar year and treatment year controls. This modeling choice follows e.g. Jäger & Heining (2019) and is partially motivated by the fact that some of our estimations are nonlinear; the solutions in the aforementioned papers are devised for linear models. In the section on robustness analysis, we check whether the treatment effects change over time.

The key identifying assumption is that, conditional on the control variables, the trends in the outcome variable would have been the same in the treatment group as in the control group, in the absence of the treatment. As is standard in this type of setting, we can test this assumption for the pre-period but need to maintain the assumption untested in the post-period.

## 4.2 The probability that a team member will leave the firm

Our first result is that the shock of unexpectedly losing a collaborator does not, on average, cause more individuals to leave than would be the case in the absence of such a loss. As seen in Column (1) in Table 4, the mean effect is not significantly different from zero. The average treatment effect, 0.0022, is also relatively small when compared to the sample mean probability of voluntarily leaving the employer in a given year, which is 0.108. The upper bound of the 95% confidence interval is 0.027. We can thus rule out effects larger than quarter of the average probability to leave.

However, when we condition the treatment effect on several observables (Columns 2, 4, and 6 of Table 4), we observe some subgroup treatment heterogeneity that are of magnitudes larger than the probability of voluntarily leaving the employer. For the baseline subgroup of treated individuals who lost a younger, low-wage, co-worker at the same or lower level in the hierarchy with whom they had no joint work history, in extremely thin local labor markets ($LLM = 0$), the treatment effect

[11] The exception to this are the hire-analyses, as there by definition the joint work history does not exist.

[12] In this specification, we normalize the treatment effect in treatment year $k = -3$ to zero.

is estimated at 0.14 for those with the same occupation than the deceased (Column 4). The same coefficient is estimated to be 0.08 for those with a different occupation as the deceased (Column 6); the former coefficient is significant at the 1% level, the latter is not. The combined treatment effect across the two subgroups with same and different jobs as the deceased is then 0.13 (Column 2).

Examining only those with the same jobs as the deceased (Column 4), The treatment effect is 6.8 per cent lower than this baseline if the deceased was a top earner ($High\ wage = 1$) and is 0.64 per cent points lower for each year of joint work history between the deceased and individual $i$. The latter coefficient will need an economic interpretation. Since the probability to leave in a given year is 0.108, the relative effect of 1 year of working together is a reduction of that probability by 0.0064/0.108, or a 5.9% reduction for every year of joint work history. Since the average number of years of joint work history in this sample is 9, this comes to a sample mean reduction of the probability to leave of 80%, a significant effect. Comparing Columns (4) and (6) further shows that many of the conditional effects are driven by those in the same occupation as the deceased. That is, a conclusion is that the treatment heterogeneity mostly appears for those with the same jobs as the deceased.

At first blush, it might seem strange that the probability of departure decreases when the deceased is a top earner, or if an individual worked with the deceased longer, or worked in a similar occupation as the deceased. However, these results could be explained by a common factor, namely that these conditions increase the likelihood of an opportunity to move up in the hierarchy and receive a higher wage. That is, an employee who has similar skills obtains an opportunity for a better job with higher pay that becomes vacant due to the death of a top-earning colleague. (The negative sign of the coefficient for when the deceased is above individual $i$ in the hierarchy – $Superior$ – further supports this interpretation.)

In addition to these heterogeneous effects, we find that the local labor market has a marginally statistically significant interaction effect with the treatment effect. The coefficient, -0.033 (Column 2), suggests that going from a local labor market which has no R&D workers in the same occupational category as $i$ ($LLM = 0$), to a market in which the share of R&D workers in the same occupational category is at the national average ($LLM = 1$) decreases the probability of departure by three percentage points. It is useful to keep this in mind as we will later discover that the liquidity of the local job market also increases the chances of hiring the right replacement person to the deceased.

When we explore whether the treatment effect on the probability to leave is heterogenous with respect to initial size of the R&D team (see Table 5), we find little evidence of that being the case.

The estimates provide evidence on the extent to which complementarity in R&D extend beyond pairs of inventors in science to all types of R&D workers in businesses. Should there be large complementarities with the deceased in close-knit teams, one would expect larger rates of exits among the smallest teams, and, intuitively, a declining exit rate with increasing team sizes as complementarities decline and the negative effects of losing a colleague also declines. The data on team size, however, do not support such clear-cut conclusions. However, the results on the differences in conditional effects between those with the same and those with different job classifications as the deceased suggest that closer work relationships do imply some stronger treatment effects on co-workers when a person unexpectedly leaves the R&D team.

## 4.3 Characteristics of those who leave the firm

The above analysis establishes that the loss of an R&D team member due to death raises the probability that other team members will leave, but only under certain circumstances. Understanding changes in the composition of those who leave is of potentially equal importance, and we now analyze this.

We next report the impact of the shock on the wage, age and education of the leaving individuals. We find that the shock due to unexpected death has, typically, a zero average treatment effect on the characteristics of the leavers. For wage, we can rule out effects smaller than -1.9% and larger than 5.2%; for age, effects smaller and larger than ±1.9%; and for education, effects smaller than -7.6% and larger than 3.2%. However, some interesting conditional treatment effects emerge. Specifically, there are some subgroup differences in the age of leavers conditional on the characteristics of the deceased and the size of the local labor market. As displayed in Table 6, Column (8), leavers are 4.3% older if the deceased is a superior. Given a mean age of 41 in this sample, this implies that leavers are 1.8 years older if a superior dies ($[\exp(0.043) - 1] \times 41$).

Having worked together with the deceased also changes the composition of the leavers. For all three outcomes, wage, age and education, a longer period of working together reduces the treatment effect. The effect is more than half a percentage point (0.67%) reduction of the wage of leavers for each additional year of joint work history and leavers are also 0.27% younger for every year the person worked together with the deceased colleague. These estimate are, however, not of important magnitudes. For example, the latter implies that leavers are 1 day younger for every year they worked together with the deceased ($[\exp(0.0027) - 1] \times 365$). Finally, we find that leavers in a different occupation from the deceased are less likely to have an MSc degree if their joint work history is longer.

What can explain these effects of having a joint work history with the deceased? The joint work history may capture the degree to which the focal team member and the deceased develop ways in which to specialize, i.e., increase their degree of complementarity. But the loss of this complementarity is quite weak and its importance should probably not be overstated.

Returning to one result, we find that losing a superior has a specific impact on the age and education of leavers: leavers are 4.3% older if the deceased is a superior. In addition, in Column (14) we see that the leavers are also approximately 14% more likely to be highly educated after a superior is lost. The combination of these two results suggests the presence of complementarities between a higher-level member of the R&D team (that suddenly dies) and older or more educated co-workers. In fact, the direction of the effects suggest that the loss of complementarity with a superior more than outweighs the possible promotional opportunities that were identified through the coefficient for joint work history, making older and more educated co-workers more likely to be in the leaver population. On the other hand, results in Table 4 suggested that for younger workers the death of a superior appear to open up promotion possibilities making them more likely to be among the stayers.

In sum, after the unexpected death of a colleague, leavers appear similar, on average, compared to leavers in a normal year. Joint work history and the superiority of the deceased causes interesting effects on the leaver population, opening up internal job opportunities for younger team members, and more likely shutting them down for older and more educated team members.

## 4.4 Probability to be a new hire

We next analyze the probability that an individual is a new hire. The econometric setup is almost identical to that when analyzing the probability of leaving, except the outcome takes the value one when an individual is first observed in the firm and zero otherwise. We cannot include the number of years of joint work history between the deceased and individual $i$, as it is always zero in the year of hire and the analysis sample starts with the year 2002, so that we can see whether the individual is new compared to the first year in the panel, 2001.

Unexpectedly losing a collaborator does not, on average, cause more individuals to be hired for the average treated R&D team, as seen in Columns (1), (2) and (3) of Table 7. For example, in Column (1) we can rule out effects smaller than -1.7% and larger than 1.6%. However, there are interesting conditional effects.

For the baseline subgroup of treated individuals, defined as before, the treatment effect is estimated at -0.071, statistically significant at the 5% level. The effect is rather similar for individuals with the same and different occupations than the deceased (Columns 4 and 6).

Examining only those with the same jobs as the deceased (Column 4), the treatment effect is 6.7 percentage points smaller in absolute value than this baseline if the deceased was a top earner ($High\ wage = 1$). This effect completely offsets the coefficient for the baseline groups probability of being hired (the joint F-test is not significantly different from zero). Comparing Columns (4) and (6) further shows that all the conditional effects are driven by those in the same occupation as the deceased.

In addition, we find that the local labor market has a statistically significant positive interaction effect with the treatment effect. The coefficient, 0.032 (Column 4), suggests that going from a local labor market which has no R&D workers in the same occupational category as $i$ ($LLM = 0$), to a market in which the share of R&D workers in the same occupational category is at the national average ($LLM = 1$) increases the probability of being a new hire by three percentage points. The result suggests that the more electrical engineers there are locally, the more likely it is to find a good substitute for an electrical engineer that just passed away. Other coefficents are not significant at conventional levels.

Further analyzing the heterogeneity in the probability of being a new hire, Table 9 indicates that this probability does not depend on the size of the initial R&D team. Hence the variation in the probability to be a new hire is estimated to be constant across different sized teams.

## 4.5 Characteristics of those who join the firm

We next analyze changes in the types of people who are hired as a result of the shock. As argued above, management will try to reduce the negative impact of the loss of a team member on team productivity by bringing in new hires. If there is imperfect substitution of skills, then we would expect to see imperfect replacement of the skills of the deceased among new hires. As before, odd columns display the results for the main effects, and even columns give the results for interactions with characteristics of the deceased. Estimates for wages and ages of hires are rather noisy, and impacts on the education of hires are very small.

In Table 9, we find that, on average, the wages of new hires are not statistically significantly different from the typical wages of hires by firms in non-shock years, regardless of whether their jobs are the same as those of the deceased or different (Columns 1, 3, and 5). Regarding confidence intervals and referring to results using the all workers sample, we can rule out effects smaller than -3.4% and larger than 4.7% for wage; for age, effects smaller than -3.0% and larger than 0.01%; and for education, effects smaller than -3.2% and larger than 4.2%.

Columns (2), (4) and (6) reveal no significant heterogeneity in the treatment effect on the wages of new hires either.[13]

There are, however, important treatment effects on the age of new hires. Results in Column (7) suggest that new hires are on average approximately 1.4% younger after treatment. The effect is driven by those with the same occupation as the deceased, for whom the effect is -1.7% (Column 9). This means that the age of hires is lowered by approximately 0.6 years ($[\exp(-0.0174) - 1] \times 35$) compared to a normal year, estimated at the (hire) sample average employee age of 35. Column (10) further reports heterogenous effects on the age of hires, where the death of a lower-level, lower-wage and younger co-worker in a shallow local labor market leads to a decrease in the age of hires by 6.2%, representing a reduction in hiring age of this group by over two years, an effect that is quite meaningful.

The matching on age between the deceased and the new hire increases in a deeper local labor market, as could be expected. The estimate for LLM in Column (10) indicates that there is an attenuation of roughly 1% in the age difference between the new hire and the deceased for every one-standard-deviation increase in LLM (= $[\exp(0.0361) - 1] \times 0.0.35$, Column 10, Row 4). On average, management are not fully able to match the age of the deceased with new hires age, tending

[13] We do not include interactions between $Treatpost_{ik}$ and $Superior$ and $Work\ hist$, as both are determined using information on both the deceased and the focal individual and thus are either undefined for new hires ($Superior$) or zero for everybody ($Work\ hist$).

to hire replacement workers about 0.6 years younger than in a normal year.

## 4.6 Wages of stayers

In our final analysis, we focus on whether the firm adjusts the wages of the staying workers in response to the unexpected death of an R&D team member. Results are reported in Table 10, which has the by-now familiar structure. We see no impact overall on the wages of the stayers, either on average (Column 1) or after conditioning on the characteristics of the deceased, the local labor market, and the joint work history of the deceased and the focal individual (Column 2). Furthermore, we do not see much of any hetereogenity between those in the same or different occupations as the deceased (Columns 3 and 4.) To give an idea of the precision of these null results, the 95% confidence interval for the ATT in Column (1) is [-0.027, 0.006].

Furthermore, the effects on wages do not depend on the size of the initial R&D team. The results, shown in Table 11, indicate that the effect on stayers' wages is zero regardless of initial team size. The baseline effect is estimated at 0.026 when using the whole sample, but the standard error is 0.050 and the confidence intervals for the coefficients of the interaction terms overlap with each other.

## 4.7 Putting the pieces together

The prior analyses shed light on important adjustments after the unexpected loss of a member of the R&D team. To piece the different results together we have compiled the statistically significant (at the 5% level) treatment effect coefficients and treatment effect - interaction coefficients into Table 12.

For our discrete outcome variables ($P(leave)$, $P(hire)$, $education$), the coefficients can be interpreted as changes in the probability of the outcome variable taking the value one, i.e., the co-worker leaving, being a hire, or having high education (measured as a dummy for having an MSc). For the logarithmic outcome variables (log(wage), log(age)), the interpretation is the per cent change in the level of the outcome variable, i.e., wage and age.

For most independent variables the interpretation is the marginal change from moving from zero to one for the independent variable. For the interaction with the liquidity of the local labor market (LLM) we report the effect of moving from an LLM with zero liquidity (i.e. no other employed in that profession in the local job market), to one matching the average liquidity of the profession in Sweden ($LLM = 1$). For joint work history we report the effect of one more year of joint work history. The interpretation of the interaction terms' coefficients are changes in the effect of the treatment.

In interpreting the table it is helpful to keep in mind that the base category is the unexpected loss of a young, low wage member of the R&D team who was a subordinate in the hierarchy to the focal coworker, and with whom the treated R&D-team member had no joint work history.

Further, the firm in which this loss takes place is in a location where the job market for the type of individuals that was lost is extremely thin (i.e., $LLM = 0$). We report elasticities for individuals sharing the occupation with the deceased in the upper panel; results in the lower panel pertain to individuals having a different occupation than the deceased. Naturally, these results should be interpreted against the background of us finding (relatively precisely estimated) zero average treatment effects throughout.

With that in mind and starting from individuals in the same occupation as the deceased (i.e., the upper panel), we find that teams that lose an individual in the base category are worst hit: They experience 1) a large increase (13%) in the probability of additional individuals leaving the team (Column 1); 2) the team members they lose are older (i.e., more experienced; Column 3); 3) they struggle replacing the lost and leaving team members as their hiring goes down (Column 5); and 4) they end up hiring less experienced new team members (Column 7). However, the thicker the job market (= the higher the value of $LLM$), the smaller the problems in hiring, since the hiring probability then increases (Column 5) and the age of the new hires increase (Column 7).

Teams that lose a high wage individual react quite differently. They experience a significantly lower increase in the probability of further team members leaving (Column 1). On the hiring side they are not affected. The differences between the effects on losing an individual in the base group and losing a high wage individual can be explained both by management reacting differently - the loss of a high wage individual is plausibly a larger shock to team productivity - and by the team members' different reactions, as discussed above.

Finally, we find that the effect of sharing work history with the deceased attenuates the impact of the treatment (Columns 1-3).

When we compare the results in the lower panel to those in the upper panel, we find that the effects are milder, i.e., there are fewer statistically significant impacts on the base treatment group, but that the results are mostly in line with those estimated for individuals in the same occupation as the deceased. In contrast to the upper panel, 1) the liquidity of the local labor market affects the composition of leavers, with leavers having lower wage the more liquid the local labor market (Column 2); 2) losing an older co-worker leads to more educated individuals leaving (Column 4); 3) LLM increasing the wages of the hires; and 4) losing a high wage individual decreasing the wage of the new hires (Column 6).

## 4.8 Robustness analyses

We perform a number of robustness tests. First, we check whether the treatment effects on wages of stayers and the probability of their departure change over time. We report the results on the probability of departure in the Appendix Figure A4. The differences in the point estimates during the treatment period are not statistically significantly different from one another in any year and the pre-treatment period estimates hugs the zero.

When we estimate the time-varying treatment effects on the wages of the stayers, we find systematically negative but statistically insignificant results using the full sample (Appendix Figure A5). When we focus on the subsample of team members with the same occupation as the deceased, we find a more pronounced negative pattern (Appendix Figure A6). However, none of the first five post-treatment point estimates are statistically significant at the 5% level. That the point estimates are trending down might be a function of the data construction, where firms with longer time series might be those with slightly downward trending relative wages, while younger firms with shorter time series might experience the converse. In any case, the trend cannot be interpreted as having anything to do with the shocks.

We estimated event-study models for all other dependent variables and samples as well, but do not report them because the estimates for them are zero or noisy.

# 5 Discussion and Conclusions

R&D is one of the core functions of companies, yet potentially among the more difficult to manage because the productivity of the R&D team depends on how well its members work together. Existing evidence shows that, for coauthors and co-inventors, research output (Azoulay et al. 2010) and inventiveness (Jaravel et al. 2018) therefore both suffer after the loss of a fellow author or inventor.

However, prior research has not been able to determine the compositional effects of such shocks on teams. Co-workers might or might not leave en masse, and firms may or may not replace those who leave with equally skilled team members. What is critical for profit-driven firms is their ability to compensate for the sudden loss of an R&D worker, and this is the process that we study.

We shed light on how for-profit firms adjust their R&D teams after the unexpected loss of a team member. To do so, we use Swedish matched employer-employee data merged with a death registry and patent data and leverage detailed educational and occupational information to identify R&D team members at a firm that had an employee die unexpectedly before the age of 60. We justify our definition of an R&D team by showing that it is positively correlated with patenting output by the firm and is well calibrated with the reported number of R&D workers at firms that responded to a representative nationwide R&D survey.

Summarizing our main results we find that the average probability to leave and to join the firm remain unchanged, leavers are similar on average, and wages are similar as in a no-shock year and firm, while hires are slightly younger, on average. The deaths occur in a context in which the labor market for R&D workers turns out to be quite fluid. Every year, new hires comprise about 6.5% of the R&D team, and 10.8% of the members of these teams leave the firm. Hence, the accidental death of one worker may not result in anything unusual for the average firm. An alternative way of describing the results is that management efficiently reacts to the problem of substituting the deceased.

Using data on leavers and hirings, we can examine dynamic responses after a team member dies in more detail than before. Our results are consistent with Jäger & Heining (2019), who find that, after a blue-collar worker dies, there is no major loss of other blue-collar workers. Our results reveal a first sign of weak complementarities among R&D workers. As shown by the example of AC/DC, they also suggest that R&D teams are not likely to break down after the death of a fellow team member.

While we find zero or small effects on average, we find important heterogeneity both in terms of the characteristics of the deceased, and the local labor market. Firms that lose an R&D worker who is both young and junior in terms of position in hierarchy and wage are hardest hit. However, the probability of departure declines significantly if the deceased is a top earner and the departure probability declines radically if the focal individual has worked longer with the deceased. The effects are larger for those with the same occupation as the deceased. Under these conditions: same occupation, longer time working together, and a top earner leaving, the opportunity to move up the hierarchy may be more likely.Here, the analogy with musical groups breaks down. Musicians in closely knit bands do not have a large internal market, so it is unlikely that the lost member can be replaced by someone else already in the band.

We also find interesting effects of the death shock on the *types* of team members who leave the firm. Leavers are generally older and more educated if the deceased is a superior. The result suggests the presence of complementarities among senior members of the R&D team. The direction of the effects suggests that the loss of complementarity with a senior member for an older and more educated worker more than outweighs the possible internal promotional opportunities, making older team members more likely to be in the leaver population. For younger workers the death of a senior R&D team member instead appear to open up promotion possibilities making them more likely to be among the stayers. The net effect of these two countervailing forces is zero on the average probability to leave.

The results raise the question of how managers handle the impact of the unexpected loss of an R&D team member. Do they simply replace those who leave, including the dying person, with equivalent workers from the open market? While we find that the loss of a team member has no effect on the average probability of hiring, we find that managers make hires after treatment that are on average approximately 0.6 years younger than the normal hire, suggesting either a forced mismatch or a deliberate attempt at rejuvenating the team, but hires are no different in terms of the wage they receive or their education. We further find that greater liquidity of the local labor markets aids in performing this matching. These conditional effects suggest that management prefer a matched replacement, and that the average differences that occur may be beyond their control, suggesting a somewhat imperfect substitution when hiring replacements in the open market.

Another potential managerial way to address the loss of a teammate due to death is to raise the compensation of remaining teammates (Becker, 1964). However, we find no meaningful change in wages relative to the control group. Jaravel et al. (2018) find a stark wage shock for co-patenters, estimated at -4%, which Pöge et al. (2022) confirm, suggesting that remaining teammates suffer productivity losses when a co-patenter suddenly dies. However, rather than the norm, one might consider the negative wage effect of a co-patenter death on other co-patenters as a potential upper bound in R&D teams, as patenting is rare among R&D workers to begin with (patenters represent only 2.1% of all R&D workers in our data), such collaborations take years to develop, and co-patenters often work together very closely. Therefore, it may not be surprising that co-workers on business R&D teams, with both patenters and non-patenters, experience less negative impacts on their wage trajectory from a colleagues' unexpected death. The studies by Azoulay et al. (2010) and Jaravel et al. (2018) may then be thought of as providing glimpses of the upper distribution of potential treatment effects among different types of R&D teams.

In addition, the typical study has been on teams of two (Azoulay et al., 2010; Jaravel et al., 2018; Pöge et al., 2022), although recently effects on teams of three (Samila et al., 2021), and up to 25 (non-R&D) team members have been studied (Jäger & Heining, 2019). Since the teams we study on average are 148 members large, an immediate question is if the treatment effects are stronger in smaller teams? However, we find no differences in the probability to leave or hire, nor in average wages due to the shock across different sized R&D teams. Rather, what seems to be important is whether the deceased has the same work experience as the focal individual and how long they have been working together.

Altogether, the results lead us to conclude that whatever complementarities in knowledge production that exist among R&D team members in profit making businesses due to the tacit nature of their work, they appear to be limited in scope and losing a team member unexpectedly therefore does not impose large efficiency losses on the average R&D team. Although coauthors and co-inventors are known to suffer after losing a close collaborator, and PhD students appear to suffer greatly from losing their advisor (e.g. Waldinger, 2010), it is not obvious why large R&D teams at for-profit firms should suffer similar productivity losses. We hope that the new method for identifying R&D teams will stimulate broader research on the dynamics, mobility, and productivity of personnel in R&D and lead to further analysis of peer effects in other workplace teams as well.

Our research design creates an opportunity for further research using the newly developed R&D team definition to examine managerial responses to shocks to R&D teams in other countries, or other types of shocks than death, and more precise identification of treatment effects of mobility in R&D labor markets. The method creates a pseudo-team that is more precisely defined than previous attempts at using business population samples to construct R&D teams (Møen, 2005; Kaiser et al., 2015, and Maliranta et al., 2009), and we show that the method accurately represents the total number of R&D workers in firms that report R&D employee counts, and generates reasonable correlations with innovation outputs. Using occupational classification data one can also define smaller teams of closer colleagues than the full contingent of all R&D workers in a firm, and one can study different sized teams as well. It will become more difficult to study even more close-knit R&D teams, for example those working on detailed product categories, as such data to our knowledge are not available in register based employer-employee data. Others have already found ingenious ways of using employer-employee data to study other forms of smaller teams, such as the founding team in startups (e.g., Choi et al., 2021).

Some potential alternative models could be considered. The first alternative idea is that stayers might experience lower utility from staying at the firm after the death of a close coworker. The results on the higher probability of departure for older workers are consistent with this explanation, but since the average effect on the probability of exit is null, and compensation for stayers is not raised, whatever disutility that is perceived from staying, it neither imparts a great exodus, nor any attempts at compensating staying workers by management.

A second alternative theory, and one that is favored by sociologists (e.g. Sørensen & Sharkey 2014), is that workers are perfect substitutes and rise through the ranks based on seniority. The loss of a higher paid or higher ranking R&D team member then might positively affect the opportunity for a younger employee to stay to hope to rise through the ranks, in which case their wages should increase. We do find indications that younger workers are more likely to be among the stayers when senior team members leave. The fact that new hires are likely to be younger further supports this interpretation. And we do find some evidence of positive wage effects on stayers' wages after a high-paid team member dies. Given the tradition of viewing R&D as a task with high degree of complementarity, we cannot credibly interpret these results as favoring perfect substitutability, but results are nevertheless intriguing and invite further research on the topic.

Since we split the analysis of treatment effects on three groups of workers: stayers, leavers, and new hires, it is interesting to reflect on how to interpret the effects given that they are estimates based on choices made by workers, and sometimes by managers as well. The choice to leave is an endogenous decision. However, our study is no different than other studies using death of a coworker as a quasi-experimental treatment. For example, studies of the productivity of scientists/inventors conditional on the death of a collaborator in fact study the change in article or patent production *choices*. Similarly, studies of salaries conditional on the death of a collaborator reflect the change in offers by managers and accepted wages by those choosing to remain. It so happens that in our study, estimates of wages of stayers are not affected by also including those leaving the firm. This is due to two effects. First, leavers are typically no different than stayers, so wages do not change much due to compositional changes in the workforce. Second, leavers are a small fraction of the joint population of leavers and stayers, (the average share of leavers being 10.8%), and therefore would have small effects on estimates if they were included among stayers.

Another issue to reflect on is whether our estimated null average treatment effects are a function of rapid adjustments by management, our favored interpretation, or simply due to low power, biased estimates, or noisy measures, three common explanations for null results. Bias towards null is possible if the shock is not exogenous and managers take action to adjust in advance of the event. We therefore follow tradition in the literature and remove death events that are preceded by indications of health issues. If our method of composing the R&D team is to select coworkers completely at random, a null effect is to be expected. To mitigate this possibility we carefully benchmark our estimate against the total number of R&D personnel in firms responding to a survey, and we show that our R&D team size measure is correlated with innovative output at levels, and with employee turnover numbers reported in prior literature.

Because Sweden is a high-income country and one of the most R&D-intensive countries in the world,[14] our results might provide a benchmark for how, in a stable, well-functioning, and predictable environment with generally high labor fluidity, management can compensate for a negative personnel shock to their R&D team involving one person, even in the smallest teams.

[14] See Appendix A.3 for some country-level comparative statistics.

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# 6 Tables

Table 1: Most Innovative Occupations that Define R&D Workers

| Group | SSYK96 | Name SSYK96 | SSYK2012 | Name SSYK2012 |
|---|---|---|---|---|
| 1 | 211 | Physicists, chemists and related prof. | 211 | Physicists and chemists |
| 2 | 214 | Architects, engineers and related prof. | 214+216 | Engineering professionals (214) |
| | | | | Architects and surveyors (216) |
| 3 | 221 | Life science professionals | 213 | Biolog., pharmacolog. and specialists in agri. & forest. |
| 4 | 311 | Physical and engineering science technicians | 311 | Physical and engineering science techn. |
| 5 | 212 | Mathematicians and statisticians | 212 | Mathematicians, actuaries and statisticians |
| 6 | 222 | Health professionals (except nursing) | 221+225+226 | Medical doctors (221) |
| | | | | Veterinarians (225) |
| | | | | Dentists (226) |
| 7 | 213+312 | Computing professionals (213) | 251+351 | ICT architects, systems analysts and test managers (251) |
| | | Computer associate professionals (312) | | ICT operations and user support technicians (351) |
| 8 | 1237 | R&D manager | 1331+1332 | Research and development managers, level 1 and 2 |

Table 2: Comparison of Match Results - Individuals and firms.

| *Panel A: individuals* | | | | |
|---|---|---|---|---|
| | Deceased and placebo deceased workers | | R&D co-workers | |
| | Deceased group | Placebo group | Treatment group | Control group |
| Age | 44.5 | 44.5 | 44.4 | 44.7 |
| | (8.7) | (8.7) | (9.0) | (9.0) |
| Female | 0.2 | 0.2 | 0.3 | 0.3 |
| | (0.4) | (0.4) | (0.4) | (0.5) |
| Wage | 4532.1 | 4560.6 | 4695.2 | 4675.4 |
| | (1988.0) | (2034.3) | (2202.3) | (2227.6) |
| Years of education | 15.6 | 15.6 | 15.8 | 15.9 |
| | (1.3) | (1.2) | (1.4) | (1.4) |
| Tenure | 6.6 | 6.6 | 5.5 | 5.9 |
| | (3.7) | (3.7) | (3.8) | (3.9) |
| Observations | 519 | 519 | 161,910 | 154,940 |

| *Panel B: firms* | | |
|---|---|---|
| | Deceased group | Placebo group |
| R&D team size | 197.1 | 193.4 |
| | (346.4) | (349.3) |
| Firm wage decile | 74.8 | 74.8 |
| | (12.8) | (12.8) |
| Observations | 519 | 519 |

*Notes:* All variables are measured in $k = -4$. Deceased and placebo deceased workers are sampled without replacement. Multiple deaths in one firm in one year are excluded. Firms may however be sampled more than once since they may experience more than one death during the observation period 2002 - 2016. Both treated and control R&D coworkers can therefore be sampled more than once if they are treated in different years in the same firm. The two leftmost columns describe the deceased and placebo deceased and their firms taken at $k = -4$. The two rightmost columns contain descriptive characteristics of the coworkers to the deceased and placebo deceased. Standard deviations are reported in parentheses. The 519 unique treated firms are distributed by R&D team size as follows: 3-10: 88 cases, 11-25: 91, 26-50: 64 and 51-: 276.

Table 3: Probability to leave, be a new hire, and characteristics of leavers, hires and stayers

| *Panel A: Probability to leave or be a hire* | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Variables | Treated | | | | Control | | | |
| | pre | | post | | pre | | post | |
| | mean | sd | mean | sd | mean | sd | mean | sd |
| P(leave) | 0.05 | 0.22 | 0.11 | 0.31 | 0.04 | 0.20 | 0.11 | 0.32 |
| P(being a hire) | 0.12 | 0.32 | 0.00 | 0.01 | 0.12 | 0.32 | 0.00 | 0.01 |
| Observations | 160,993 | | 165,955 | | 157,833 | | 163,293 | |
| *Panel B: Leavers* | | | | | | | | |
| Variables | Treated | | | | Control | | | |
| | pre | | post | | pre | | post | |
| | mean | sd | mean | sd | mean | sd | mean | sd |
| Ln(wage) | 8.4 | 0.7 | 8.4 | 0.6 | 8.4 | 0.7 | 8.4 | 0.7 |
| Ln(age) | 3.7 | 0.3 | 3.7 | 0.3 | 3.7 | 0.3 | 3.7 | 0.3 |
| Education | 0.6 | 0.5 | 0.6 | 0.5 | 0.7 | 0.5 | 0.7 | 0.5 |
| L3rdteamsize | 445.5 | 316.9 | 391.1 | 314.6 | 484.1 | 330.5 | 426.8 | 322.9 |
| Observations | 21,593 | | 31,281 | | 19,788 | | 30,487 | |
| *Panel C: Hires* | | | | | | | | |
| Variables | Treated | | | | Control | | | |
| | pre | | post | | pre | | post | |
| | mean | sd | mean | sd | mean | sd | mean | sd |
| Ln(wage) | 8.3 | 0.6 | 8.3 | 0.6 | 8.3 | 0.6 | 8.3 | 0.6 |
| Ln(age) | 3.6 | 0.3 | 3.6 | 0.3 | 3.6 | 0.3 | 3.6 | 0.3 |
| Education | 0.6 | 0.5 | 0.6 | 0.5 | 0.6 | 0.5 | 0.6 | 0.5 |
| L3rdteamsize | 409.4 | 329.1 | 430.1 | 328.7 | 443.2 | 332.7 | 427.2 | 317.6 |
| Observations | 21,636 | | 28,021 | | 21,012 | | 27,315 | |
| *Panel D: Incumbent workers* | | | | | | | | |
| Variables | Treated | | | | Control | | | |
| | pre | | post | | pre | | post | |
| | mean | sd | mean | sd | mean | sd | mean | sd |
| Ln(wage) | 8.5 | 0.5 | 8.6 | 0.5 | 8.5 | 0.5 | 8.6 | 0.5 |
| Observations | 9,616 | | 15,385 | | 9,652 | | 15,672 | |

*Notes:* Observations are at the individual-year level. The exit sample consists of all individuals in R&D teams of the included firms; the leaver sample consists of last observations of an individual in a firm (except for the last year of the firm in the data); the hire sample from the first observations of an individual in a firm (except the first year of the firm in the data), and the incumbent worker sample of observations of individuals who stay within the same firm for the length of the observation period 2002 - 2016.

Table 4: Probability to leave

| | All | | Same | | Different | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Treatpost | 0.0022 | 0.1275*** | 0.0010 | 0.1346*** | 0.0097 | 0.0779 |
| | (0.0126) | (0.0372) | (0.0133) | (0.0381) | (0.0186) | (0.0548) |
| Lagged R&D teamsize / 10 | 0.0005 | 0.0007 | 0.0002 | 0.0005 | 0.0023 | 0.0022 |
| | (0.0010) | (0.0009) | (0.0010) | (0.0010) | (0.0017) | (0.0017) |
| x Old | | 0.0173 | | 0.0243 | | 0.0060 |
| | | (0.0247) | | (0.0243) | | (0.0321) |
| x LLM | | -0.0327* | | -0.0297 | | -0.0242 |
| | | (0.0190) | | (0.0216) | | (0.0266) |
| x High wage | | -0.0684*** | | -0.0881*** | | -0.0034 |
| | | (0.0242) | | (0.0257) | | (0.0337) |
| x Superior | | -0.0278 | | -0.0375 | | -0.0064 |
| | | (0.0229) | | (0.0340) | | (0.0296) |
| x Workhist | | -0.0064*** | | -0.0066*** | | -0.0057*** |
| | | (0.0008) | | (0.0009) | | (0.0012) |
| Obs. | 648,074 | 641,311 | 502,841 | 497,626 | 145,233 | 143,685 |
| R-squared | 0.32 | 0.32 | 0.31 | 0.32 | 0.33 | 0.33 |
| Old | | 0.00 | | 0.00 | | 0.03 |
| LLM | | 0.00 | | 0.00 | | 0.25 |
| High wage | | 0.10 | | 0.22 | | 0.18 |
| Superior | | 0.01 | | 0.04 | | 0.13 |

*Notes:* We run an LPM where the dependent variable takes value 1 in the year when individual $i$ leaves the firm and is zero otherwise. The data is an individual-year-level panel where we track each individual either from the first year of employment in the sample firm or from treatment year $k = -4$ until either the end of the sample ($k = 6$; those individuals who do not leave) or the year of exit. The sample in column "All" consists of all employees in R&D in firm $j$ in year $k$. The samples in columns "Same" and "Different" are defined as individuals working in the same / different occupation as the (placebo) deceased in the year of death ($k = 0$). Each individual appears in the sample only in the year before leaving the employer that the individual worked for in $k = -4$. Explanatory variables are defined as in the main text. Coefficients marked $\times\ x$, $x \in \{Old,\ LLM,\ High\,wage,\ Superior,\ Workhist\}$ are coefficients of interactions between $Treatpost$ and $x$. The specification includes also all variables in $x$ as well as their interactions with $Treated$ which takes value 1 if individual $i$ is in the treatment group, 0 otherwise. Below the solid line we report p-values of joint test of $Treatpost$ and $Treatpost \times\ x$. All specifications include a full set of treatment and calendar year dummies and the length of individual $i$'s own tenure as a control. Robust standard errors clustered at the firm level. ***, ** and * indicate statistical significance at 1, 5 and 10% level.

Table 5: Probability to leave - interaction with initial R&D team size

| | All | Same | Different |
|---|---|---|---|
| | (1) | (2) | (3) |
| Treatpost | 0.0230 | 0.0079 | 0.0777 |
| | (0.0241) | (0.0213) | (0.0597) |
| x R&D teamsize 11-25 | 0.0265 | 0.0499 | -0.0551 |
| | (0.0323) | (0.0314) | (0.0655) |
| x R&D teamsize 26-50 | 0.0390 | 0.0635 | -0.0446 |
| | (0.0444) | (0.0504) | (0.0813) |
| x R&D teamsize 51- | 0.0215 | 0.0447 | -0.0607 |
| | (0.0278) | (0.0273) | (0.0617) |
| x R&D teamsize 51- x | -0.0095*** | -0.0105*** | -0.0037 |
| | (0.0020) | (0.0023) | (0.0057) |
| Obs. | 648,074 | 502,841 | 145,233 |
| R-squared | 0.32 | 0.32 | 0.33 |
| team size 11-25 | 0.04 | 0.03 | 0.48 |
| team size 26-50 | 0.11 | 0.13 | 0.57 |
| team size >50 | 0.01 | 0.01 | 0.44 |
| team size >50 x | 0.02 | 0.02 | 0.48 |

*Notes:* The numbers on the "team size..." rows refer to the p-values of the joint significance of the $Treatpost$ and interaction coefficients. The interactions are with dummy variables indicating the size of the initial R&D team. The baseline category are initial teams with at most 10 members. The last interaction is a triple interaction $Treatpost \times D[team\ size > 50] \times team\ size/100$. The p-value for the triple interaction is calculated for an initial team size of 75.

## Table 6: Characteristics of Leavers

| Dependent variable: | Wage | | | | | | Age | | | | | | Education | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | All | | Same | | Different | | All | | Same | | Different | | All | | Same | | Different | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) | (16) | (17) | (18) |
| Treatpost | 0.0167 | 0.0893 | 0.0052 | 0.0638 | 0.0374 | 0.1557 | 0.0006 | 0.0671$^{***}$ | -0.0052 | 0.0777$^{***}$ | 0.0153 | 0.0298 | -0.0219 | -0.0825 | -0.0266 | -0.0617 | -0.0047 | -0.1154 |
| | (0.0182) | (0.0704) | (0.0166) | (0.0697) | (0.0387) | (0.1180) | (0.0096) | (0.0238) | (0.0109) | (0.0243) | (0.0140) | (0.0530) | (0.0276) | (0.0525) | (0.0349) | (0.0575) | (0.0372) | (0.0801) |
| Lagged R&D teamsize / 10 | 0.0011$^{***}$ | 0.0010$^{***}$ | 0.0012$^{***}$ | 0.0012$^{***}$ | -0.0019$^{***}$ | -0.0025$^{***}$ | 0.0010$^{***}$ | 0.0009$^{***}$ | 0.0010$^{***}$ | 0.0009$^{***}$ | 0.0002 | 0.0005 | 0.0046$^{***}$ | 0.0044$^{***}$ | 0.0054$^{***}$ | 0.0046$^{***}$ | 0.0007 | 0.0008 |
| | (0.0002) | (0.0002) | (0.0002) | (0.0002) | (0.0006) | (0.0006) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0003) | (0.0004) | (0.0003) | (0.0004) | (0.0004) | (0.0005) | (0.0007) | (0.0007) |
| x Old | | 0.0459 | | 0.0447 | | 0.0154 | | -0.0209 | | -0.0188 | | -0.0308 | | 0.0703$^{**}$ | | 0.0218 | | 0.0999$^{**}$ |
| | | (0.0335) | | (0.0354) | | (0.0639) | | (0.0147) | | (0.0165) | | (0.0255) | | (0.0322) | | (0.0325) | | (0.0498) |
| x LLM | | -0.0868$^{*}$ | | -0.0596 | | -0.1660$^{**}$ | | -0.0150 | | -0.0230 | | 0.0138 | | 0.0257 | | 0.0185 | | 0.0918$^{*}$ |
| | | (0.0470) | | (0.0466) | | (0.0685) | | (0.0173) | | (0.0175) | | (0.0339) | | (0.0309) | | (0.0315) | | (0.0510) |
| x High wage | | -0.0252 | | -0.0100 | | -0.0204 | | 0.0124 | | 0.0091 | | 0.0360 | | 0.0176 | | 0.0572 | | -0.0470 |
| | | (0.0311) | | (0.0340) | | (0.0616) | | (0.0147) | | (0.0150) | | (0.0269) | | (0.0366) | | (0.0352) | | (0.0523) |
| x Superior | | 0.0144 | | -0.0457 | | 0.0455 | | 0.0432$^{**}$ | | 0.0333 | | 0.0470$^{*}$ | | 0.1372$^{***}$ | | 0.1661$^{***}$ | | 0.0173 |
| | | (0.0407) | | (0.0373) | | (0.0700) | | (0.0188) | | (0.0221) | | (0.0285) | | (0.0483) | | (0.0485) | | (0.0509) |
| x Workhist | | -0.0067$^{***}$ | | -0.0083$^{***}$ | | -0.0008 | | -0.0027$^{***}$ | | -0.0025$^{**}$ | | -0.0040$^{**}$ | | -0.0002 | | 0.0023 | | -0.0134$^{***}$ |
| | | (0.0023) | | (0.0024) | | (0.0048) | | (0.0009) | | (0.0010) | | (0.0018) | | (0.0018) | | (0.0016) | | (0.0039) |
| Obs. | 103,149 | 54,904 | 77,206 | 41,654 | 25,943 | 13,250 | 103,149 | 54,904 | 77,206 | 41,654 | 25,943 | 13,250 | 103,149 | 54,904 | 77,206 | 41,654 | 25,943 | 13,250 |
| R-squared | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.04 | 0.02 | 0.33 | 0.02 | 0.34 | 0.01 | 0.28 | 0.11 | 0.14 | 0.16 | 0.20 | 0.01 | 0.05 |
| Old | | 0.03 | | 0.10 | | 0.10 | | 0.08 | | 0.03 | | 0.98 | | 0.79 | | 0.41 | | 0.85 |
| LLM | | 0.95 | | 0.91 | | 0.90 | | 0.00 | | 0.00 | | 0.21 | | 0.10 | | 0.27 | | 0.68 |
| High wage | | 0.36 | | 0.45 | | 0.19 | | 0.00 | | 0.00 | | 0.20 | | 0.26 | | 0.94 | | 0.04 |
| Superior | | 0.20 | | 0.80 | | 0.17 | | 0.00 | | 0.00 | | 0.14 | | 0.39 | | 0.10 | | 0.23 |
| Workhist | | 0.24 | | 0.43 | | 0.19 | | 0.01 | | 0.00 | | 0.63 | | 0.11 | | 0.30 | | 0.11 |

*Notes:* The dependent variables are (1) ln($wage$), (2) ln($age$) and (3) an indicator taking the value 1 if the individual has an M.Sc. degree or higher, else zero for individual $i$ in year $t$. We run OLS regressions for ln($wage$) and ln($age$), and an LPM for education on repeated cross-sections of individual level data. The sample in column "All" consists of all employees in R&D in firm $j$ in year $k$. The samples in columns "Same" and "Different" are defined as individuals working in the same / different occupation as the (placebo) deceased in the year of death ($k = 0$). Each individual appears in the sample only in the year before leaving the employer that the individual worked for in $k = -4$. Explanatory variables are defined as in the main text. Coefficients marked $\times\ x$, $x \in \{Old,\ LLM,\ High\,wage,\ Superior,\ Workhist\}$ are coefficients of interactions between $Treatpost$ and $x$. The specification includes also all variables in $x$ as well as their interactions with $Treated$ which takes value 1 if individual $i$ is in the treatment group, 0 otherwise. Below the solid line we report p-values of joint test of $Treatpost$ and $Treatpost \times\ x$. All specifications include a full set of treatment and calendar year dummies and the length of individual $i$'s own tenure as a control. Robust standard errors clustered at the firm level. ***, ** and * indicate statistical significance at 1, 5 and 10% level.

## Table 7: Probability to be a hire

| | All | | Same | | Different | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Treatpost | -0.0004 | -0.0705** | 0.0023 | -0.0673** | -0.0061 | -0.0757** |
| | (0.0086) | (0.0280) | (0.0095) | (0.0308) | (0.0120) | (0.0329) |
| Lagged R&D teamsize / 10 | -0.0058*** | -0.0059*** | -0.0060*** | -0.0062*** | -0.0053** | -0.0051** |
| | (0.0014) | (0.0014) | (0.0015) | (0.0015) | (0.0021) | (0.0021) |
| x Old | | -0.0227 | | -0.0239 | | -0.0194 |
| | | (0.0156) | | (0.0184) | | (0.0177) |
| x LLM | | 0.0365*** | | 0.0317** | | 0.0514*** |
| | | (0.0139) | | (0.0148) | | (0.0156) |
| x High wage | | 0.0593*** | | 0.0668*** | | 0.0381 |
| | | (0.0210) | | (0.0243) | | (0.0270) |
| x Superior | | 0.0118 | | 0.0140 | | 0.0022 |
| | | (0.0167) | | (0.0361) | | (0.0198) |
| Obs. | 648,074 | 641,311 | 502,841 | 497,626 | 145,233 | 143,685 |
| R-squared | 0.39 | 0.39 | 0.39 | 0.39 | 0.40 | 0.41 |
| Old | | 0.00 | | 0.00 | | 0.02 |
| LLM | | 0.08 | | 0.11 | | 0.31 |
| High wage | | 0.65 | | 0.99 | | 0.12 |
| Superior | | 0.05 | | 0.22 | | 0.01 |

*Notes:* We run an LPM where the dependent variable takes value 1 in the year when individual $i$ is hired in the firm and is zero otherwise. The data is an individual-year-level panel where we track each individual either from the first year of employment in the sample firm or from treatment year $k = -4$ until either the end of the sample ($k = 6$; those individuals who do not leave) or the year of exit. The sample in column "All" consists of all employees in R&D in firm $j$ in year $k$. The samples in columns "Same" and "Different" are defined as individuals working in the same / different occupation as the (placebo) deceased in the year of death ($k = 0$). Each individual appears in the sample only in the year before leaving the employer that the individual worked for in $k = -4$. Explanatory variables are defined as in the main text. Coefficients marked $\times\ x$, $x \in \{Old, LLM, High\,wage, Superior, Workhist\}$ are coefficients of interactions between $Treatpost$ and $x$. The specification includes also all variables in $x$ as well as their interactions with $Treated$ which takes value 1 if individual $i$ is in the treatment group, 0 otherwise. Below the solid line we report p-values of joint test of $Treatpost$ and $Treatpost \times\ x$. All specifications include a full set of treatment and calendar year dummies and the length of individual $i$'s own tenure as a control. Robust standard errors clustered at the firm level. ***, ** and * indicate statistical significance at 1, 5 and 10% level.

Table 8: Probability to be a hire - interaction with initial R&D team size

| | All | Same | Different |
|---|---|---|---|
| | (1) | (2) | (3) |
| Treatpost | -0.0487 | -0.0249 | -0.1324* |
| | (0.0312) | (0.0245) | (0.0707) |
| x R&D teamsize 11-25 | -0.1298 | -0.1852 | 0.0449 |
| | (0.1034) | (0.1266) | (0.0771) |
| x R&D teamsize 26-50 | 0.0114 | -0.0129 | 0.0942 |
| | (0.0365) | (0.0350) | (0.0728) |
| x R&D teamsize 51- | 0.0330 | 0.0041 | 0.1246* |
| | (0.0343) | (0.0292) | (0.0730) |
| x R&D teamsize 51- x | 0.0035 | 0.0041* | 0.0038 |
| | (0.0022) | (0.0024) | (0.0035) |
| Obs. | 648,074 | 502,841 | 145,233 |
| R-squared | 0.39 | 0.39 | 0.40 |
| team size 11-25 | 0.07 | 0.09 | 0.01 |
| team size 26-50 | 0.07 | 0.15 | 0.05 |
| team size >50 | 0.33 | 0.24 | 0.71 |
| team size >50 x | 0.38 | 0.28 | 0.79 |

*Notes:* The numbers on the "team size..." rows refer to the p-values of the joint significance of the $Treatpost$ and interaction coefficients. The interactions are with dummy variables indicating the size of the initial R&D team. The baseline category are initial teams with at most 10 members. The last interaction is a triple interaction $Treatpost \times D[team\ size > 50] \times team\ size/100$. The p-value for the triple interaction is calculated for an initial team size of 75. See notes in Table 4 for other information.

## Table 9: Characteristics of Hires

| Dependent variable: | Wage | | | | | | Age | | | | | | Education | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | All | | Same | | Different | | All | | Same | | Different | | All | | Same | | Different | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) | (16) | (17) | (18) |
| Treatpost | 0.0066 | -0.0112 | 0.0096 | -0.0175 | 0.0100 | -0.0374 | -0.0144$^{*}$ | -0.0612$^{***}$ | -0.0174$^{**}$ | -0.0621$^{***}$ | -0.0010 | -0.0896$^{***}$ | 0.0051 | -0.0053 | -0.0019 | -0.0343 | 0.0296 | -0.0307 |
| | (0.0208) | (0.0380) | (0.0210) | (0.0382) | (0.0422) | (0.0739) | (0.0079) | (0.0184) | (0.0089) | (0.0197) | (0.0152) | (0.0320) | (0.0189) | (0.0369) | (0.0229) | (0.0392) | (0.0344) | (0.0815) |
| Lagged R&D teamsize / 10 | -0.0009$^{***}$ | -0.0008$^{***}$ | -0.0009$^{***}$ | -0.0007$^{***}$ | -0.0027$^{***}$ | -0.0027$^{***}$ | 0.0000 | 0.0001 | 0.0000 | 0.0001 | -0.0001 | -0.0001 | 0.0047$^{***}$ | 0.0044$^{***}$ | 0.0055$^{***}$ | 0.0049$^{***}$ | 0.0005 | 0.0006 |
| | (0.0002) | (0.0002) | (0.0002) | (0.0002) | (0.0005) | (0.0005) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0001) | (0.0003) | (0.0003) | (0.0003) | (0.0003) | (0.0007) | (0.0006) |
| x Old | | -0.0423 | | -0.0351 | | -0.0367 | | 0.0073 | | 0.0084 | | 0.0165 | | -0.0015 | | 0.0073 | | 0.0170 |
| | | (0.0259) | | (0.0260) | | (0.0404) | | (0.0112) | | (0.0128) | | (0.0175) | | (0.0267) | | (0.0271) | | (0.0539) |
| x LLM | | 0.0439$^{**}$ | | 0.0366$^{*}$ | | 0.1007$^{**}$ | | 0.0376$^{***}$ | | 0.0361$^{***}$ | | 0.0628$^{***}$ | | -0.0011 | | -0.0020 | | 0.0422 |
| | | (0.0219) | | (0.0215) | | (0.0490) | | (0.0121) | | (0.0116) | | (0.0229) | | (0.0248) | | (0.0246) | | (0.0458) |
| x High wage | | -0.0121 | | 0.0114 | | -0.0944$^{**}$ | | -0.0071 | | -0.0103 | | 0.0142 | | 0.0079 | | 0.0236 | | -0.0223 |
| | | (0.0250) | | (0.0267) | | (0.0394) | | (0.0113) | | (0.0134) | | (0.0175) | | (0.0293) | | (0.0330) | | (0.0472) |
| Obs. | 97,984 | 97,984 | 73,587 | 73,587 | 24,397 | 24,397 | 97,984 | 97,984 | 73,587 | 73,587 | 24,397 | 24,397 | 97,984 | 97,984 | 73,587 | 73,587 | 24,397 | 24,397 |
| R-squared | 0.01 | 0.01 | 0.01 | 0.01 | 0.02 | 0.03 | 0.00 | 0.01 | 0.00 | 0.01 | 0.01 | 0.01 | 0.11 | 0.12 | 0.16 | 0.18 | 0.01 | 0.02 |
| Old | | 0.16 | | 0.17 | | 0.33 | | 0.00 | | 0.00 | | 0.02 | | 0.85 | | 0.52 | | 0.85 |
| LLM | | 0.28 | | 0.51 | | 0.22 | | 0.06 | | 0.07 | | 0.18 | | 0.82 | | 0.22 | | 0.84 |
| High wage | | 0.56 | | 0.89 | | 0.07 | | 0.00 | | 0.00 | | 0.02 | | 0.95 | | 0.82 | | 0.53 |

*Notes:* Each individual appears in the sample only in the year the individual starts to work in a treatment or control firm after $k = -4$. See notes in Table 6 for other information. The specifications in this table do not include the length of individual $i$'s own tenure as a control.

Table 10: Wages for Incumbents

| | All | | Same | | Different | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Treatpost | -0.0106 | -0.0088 | -0.0150 | 0.0009 | -0.0033 | -0.0167 |
| | (0.0083) | (0.0289) | (0.0092) | (0.0304) | (0.0130) | (0.0444) |
| Lagged R&D teamsize / 10 | -0.0002 | -0.0004 | -0.0003 | -0.0005 | 0.0002 | 0.0002 |
| | (0.0008) | (0.0008) | (0.0009) | (0.0009) | (0.0010) | (0.0011) |
| x Old | | 0.0011 | | -0.0094 | | 0.0144 |
| | | (0.0140) | | (0.0162) | | (0.0201) |
| x LLM | | -0.0058 | | -0.0162 | | 0.0133 |
| | | (0.0152) | | (0.0151) | | (0.0257) |
| x High wage | | 0.0167 | | 0.0298* | | -0.0087 |
| | | (0.0138) | | (0.0173) | | (0.0187) |
| x Superior | | -0.0076 | | -0.0078 | | -0.0222 |
| | | (0.0131) | | (0.0176) | | (0.0213) |
| x Workhist | | -0.0006 | | -0.0007 | | -0.0002 |
| | | (0.0009) | | (0.0012) | | (0.0015) |
| Obs. | 50,325 | 49,793 | 32,150 | 31,821 | 18,175 | 17,972 |
| R-squared | 0.76 | 0.77 | 0.76 | 0.77 | 0.75 | 0.76 |
| Old | | 0.75 | | 0.75 | | 0.95 |
| LLM | | 0.42 | | 0.45 | | 0.90 |
| High wage | | 0.78 | | 0.31 | | 0.55 |
| Superior | | 0.58 | | 0.79 | | 0.46 |
| Workhist | | 0.74 | | 0.99 | | 0.70 |

*Notes:* The estimation sample consists of individuals who stay with the same firm for the entire duration of the observation period. The sample is a panel with wage observed for each year in employment within the same firm. The models are within-individual linear regressions with individual and firm fixed effects. See notes in Table 6 for other information.

Table 11: Wages for Incumbents - interaction with initial R&D team size

| | All | Same | Different |
|---|---|---|---|
| | (1) | (2) | (3) |
| Treatpost | 0.0262 | -0.0150 | 0.1195 |
| | (0.0495) | (0.0472) | (0.1291) |
| x R&D teamsize 11-25 | 0.0106 | 0.0932 | -0.1528 |
| | (0.0598) | (0.0643) | (0.1359) |
| x R&D teamsize 26-50 | -0.0060 | -0.0084 | -0.0584 |
| | (0.0530) | (0.0526) | (0.1315) |
| x R&D teamsize 51- | -0.0465 | -0.0131 | -0.1289 |
| | (0.0503) | (0.0486) | (0.1296) |
| x R&D teamsize 51- x | 0.0018 | 0.0026 | 0.0007 |
| | (0.0021) | (0.0027) | (0.0030) |
| Obs. | 50,325 | 32,150 | 18,175 |
| R-squared | 0.76 | 0.76 | 0.76 |
| team size 11-25 | 0.29 | 0.08 | 0.44 |
| team size 26-50 | 0.33 | 0.35 | 0.03 |
| team size >50 | 0.10 | 0.06 | 0.61 |
| team size >50 x | 0.09 | 0.05 | 0.60 |

*Notes:* The numbers on the "team size..." rows refer to the p-values of the joint significance of the $Treatpost$ and interaction coefficients. The interactions are with dummy variables indicating the size of the initial R&D team. The baseline category are initial teams with at most 10 members. The last interaction is a triple interaction $Treatpost \times D[team\ size > 50] \times team\ size/100$. The p-value for the triple interaction is calculated for an initial team size of 75. See notes in Table 6 for other information.

Table 12: Summary of Statistically Significant Treatment Effect Coefficients

| Same occupation | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Effect | P(leave) | Leaver characteristics | | | P(hire) | Hire characteristics | | | Stayers |
| | | wage | age | education | | wage | age | education | wage |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Base | 0.13 | | 0.08 | | -0.07 | | -0.06 | | |
| Old | | | | | | | | | |
| LLM | | | | | 0.03 | | 0.04 | | |
| High wage | -0.09 | | | | 0.07 | | | | |
| Superior | | | | 0.17 | | | | | |
| Work history | -0.007 | -0.008 | -0.003 | | | | | | |
| **Different occupation** | | | | | | | | | |
| Effect | P(leave) | Leaver characteristics | | | P(hire) | Hire characteristics | | | Stayers |
| | | wage | age | education | | wage | age | education | wage |
| Base | | | | | -0.08 | | -0.09 | | |
| Old | | | | 0.1 | | | | | |
| LLM | | -0.17 | | | 0.05 | 0.1 | 0.06 | | |
| High wage | | | | | | -0.09 | | | |
| Superior | | | | | | | | | |
| Work history | -0.006 | | -0.004 | -0.01 | | | | | |

*Notes:* The numbers in this table are the (rounded) treatment effect and treatment effect - interaction coefficients from the difference-in-difference analyses that are statistically significant at the 5% level or better.

# A Appendix

In this Appendix we display the results from Poisson regression where the dependent variable is the number of patent by firm $j$ in year $t$ and the explanatory variable is the size of the R&D team in year $t$, its square, and its lagged values. (Appendix A.1) We also display graphs referred to in the main text (Appendix A.2). We also provide some basic information about innovation and R&D in the Swedish private sector in Appendix A.3.

## A.1 Appendix tables

Table A1: Patent count Poisson FE regressions

| Dependent variable: | Number of Patents | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| R&D teamsize | -0.0004 | 0.0096*** | 0.0083*** | 0.0088*** | 0.0095*** |
| | (0.0013) | (0.0019) | (0.0026) | (0.0034) | (0.0036) |
| R&D teamsize sq. / 1000 | | -0.0150*** | -0.0141*** | -0.0145*** | -0.0147** |
| | | (0.0028) | (0.0040) | (0.0053) | (0.0058) |
| L.R&D teamsize | | | 0.0001 | -0.0009 | -0.0017 |
| | | | (0.0018) | (0.0016) | (0.0017) |
| L2.R&D teamsize | | | | -0.0005 | -0.0022 |
| | | | | (0.0016) | (0.0017) |
| L3.R&D teamsize | | | | | 0.0009 |
| | | | | | (0.0017) |
| log likelihood | -1,549.18 | -1,521.28 | -1,223.13 | -959.57 | -738.72 |
| Firms | 221 | 221 | 199 | 174 | 152 |
| Observations | 2,085 | 2,085 | 1,710 | 1,368 | 1,096 |

*Notes:* The sample covers the years 2002 - 2016 and firms that patent at least once during the observation period. The dependent variable is the number of patents for firm $j$ in year $t$. The explanatory variables are the (lags of) R&D team size and its square (divided by 1000). The specification includes firm and calendar year fixed effects. Heteroskedasticity robust standard errors are reported. ***, ** and * indicate statistical significance at 1, 5 and 10% level.

## A.2 Appendix figures

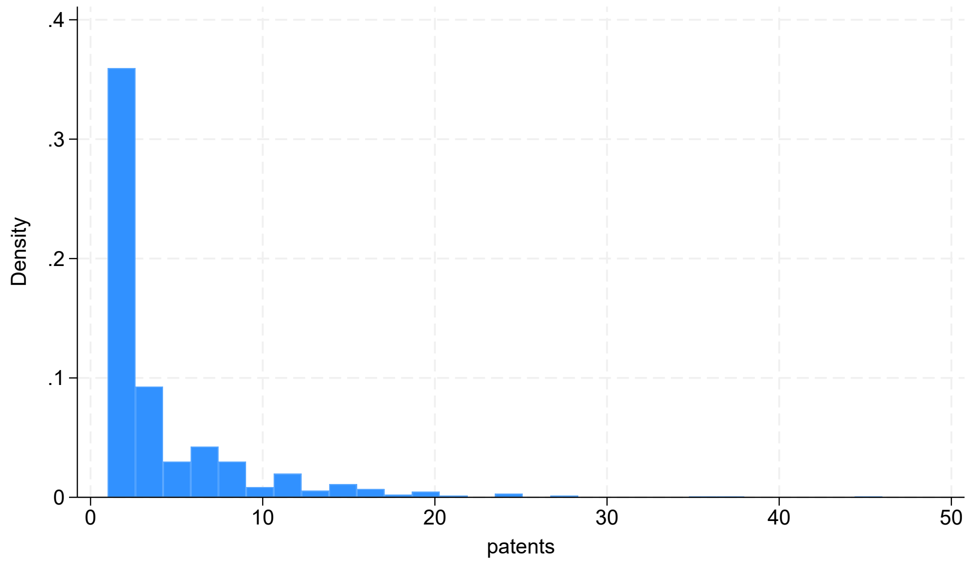


Figure A1: Distribution of Number of Patents by Firm, Zero Counts Excluded.

*Notes:* Observations are firm-year observations. The sample is the estimation sample except that observations with zero patents are excluded.

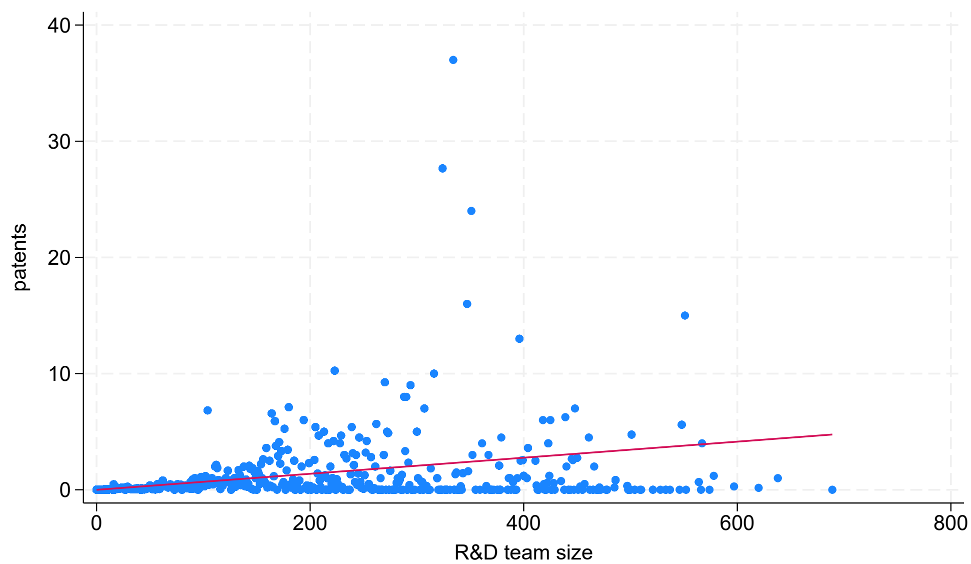


Figure A2: R&D Team Size – Patenting Relationship

*Notes:* Observations are firm-year observations. The sample is the estimation sample.

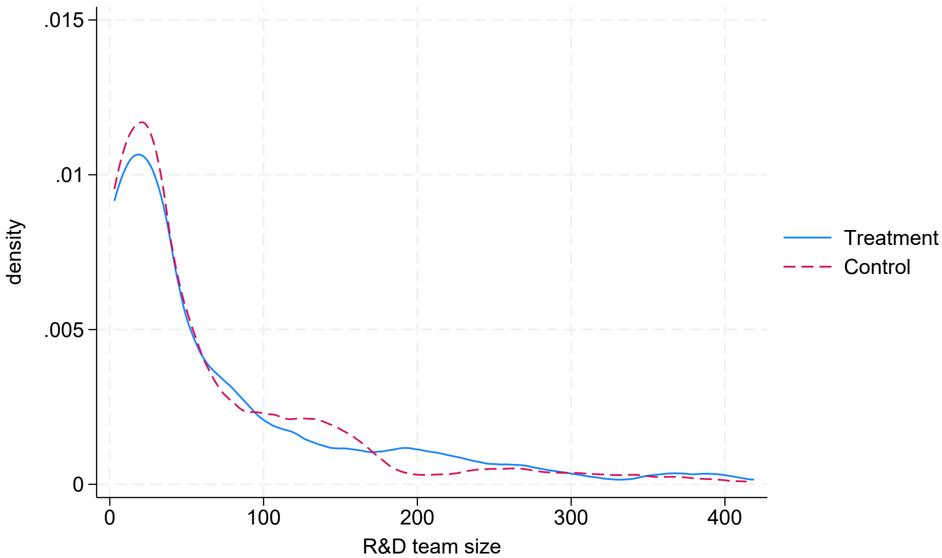


FIGURE A3: DISTRIBUTION OF R&D TEAM SIZE IN $k = -4$

*Notes:* Observations are firm observations 4 years prior to (placebo) death. Only firms in the estimation sample are included.

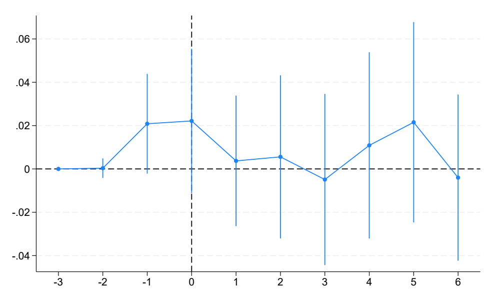


FIGURE A4: EXIT PROBABILITY ESTIMATES - TIME-VARYING TREATMENT EFFECTS, INDIVIDUAL LEVEL DATA.

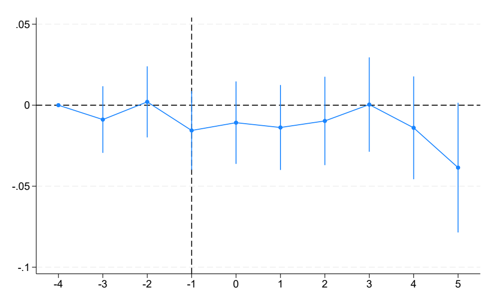


FIGURE A5: *Log wage* ESTIMATES - TIME-VARYING TREATMENT EFFECTS, INDIVIDUAL LEVEL DATA.

## A.3 Innovation and R&D in the Swedish private sector

According to the OECD (2017), Sweden ranks in the top-4 in the number of researchers among employees, and similarly in R&D – to – GDP intensity. Sweden's R&D – to – GDP – ratio in 2011 was 3.25, substantially higher than both OECD (2.31) and EU averages (EU15 2.02, EU28

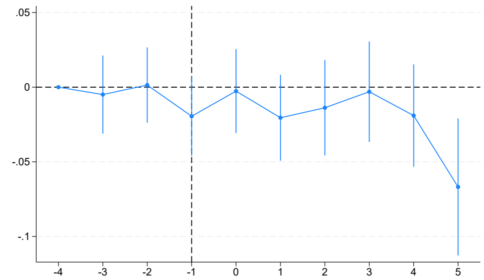


Figure A6: *Log wage* estimates - time-varying treatment effects, individual level data: Same occupation.

1.87). Similarly, in terms of researchers' share in the labor force, Sweden's share (15.64) was clearly higher than the EU averages (EU15 12.12, EU28 10.28). As a rough proxy for R&D productivity, we calculate the number of patent applications per R&D worker. Sweden's innovation rate at 0.036 is more than 50% higher than the EU15 (0.021) and EU28 (0.020) averages. Even though Sweden is not the leading OECD country by any of these measures, it is apparently both intensive and productive in its R&D.

The private sector is quite important for aggregate Swedish R&D. According to 2011 OECD figures, the share of business R&D of all R&D investments was almost 70% in Sweden. This compares to the EU averages of 52-55%. Thus, private R&D is important in Sweden both relative to all R&D, and in comparison to other OECD countries.

The OECD provides statistics from 2011 on the breakdown of R&D personnel in Sweden. Supporting our argument that not all R&D team members necessarily patent, 62.1% of R&D personnel in 2011 were researchers, but another 24.5% were technicians, and 13.4% were other support staff. Importantly for us, some 70% of all R&D personnel were employed by business enterprises. In the business sector, the share of researchers was somewhat lower than in general (53.5%), 30.6% were technicians and the remaining 15.9% were employed as other support staff.