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ABSTRACT

Filling the Gap: The Consequences of Collaborator Loss in Corporate R&D*

We examine how collaborator loss affects knowledge workers in corporate R&D. We argue that such a loss affects the remaining collaborators not only by reducing their team-specific capital (as argued in the prior literature) but also by increasing their bargaining power over the employer, who is in need of filling the gap left by the lost collaborator to ensure the continuation of R&D projects. This shift in bargaining power may, in turn, lead to benefits, such as additional resources or more attractive working conditions. These benefits can partially compensate for the negative effect of reduced team-specific capital on productivity and influence the career trajectories of the remaining collaborators. We empirically investigate the consequences of collaborator loss by exploiting 845 unexpected deaths of active inventors. We find that inventor death has a moderate negative effect on the productivity of the remaining collaborators. This negative effect disappears when we focus on the remaining collaborators who work for the same employer as the deceased inventor. Moreover, this group is more likely to be promoted and less likely to leave their current employer.

JEL Classification: J62, O32, J24

Keywords: collaboration, mobility, innovation, inventors, patents, teams

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1 Introduction

Knowledge generation is increasingly pursued in collaboration (Akcigit et al., 2018; Wu et al., 2019; Wuchty et al., 2007). The success of such collaborative efforts is grounded in the joint use of "team-specific capital" (Jaravel et al., 2018).[1] In this, collaborators combine explicit and tacit knowledge—human capital—and resources rooted in their relationships with each other—social capital. Mainly in the context of science, previous studies have shown that the loss of a researcher (e.g., due to death) leads to a reduction in team-specific capital among collaborators, which in turn decreases their long-term productivity (Azoulay et al., 2010; Mohnen, 2022; Khanna, 2021). However, this literature has overlooked an aspect with particular relevance in the corporate context. That is, the loss of a knowledge worker affects not only collaborators but also the employer, who seeks the continuation of current operations by filling the gap.

In this paper, we argue that the employer's need to fill the gap following the loss[2] of a knowledge worker increases the remaining collaborators' bargaining power, with consequences for their productivity and careers. Given labor market frictions (Alchian and Demsetz, 1972; Campbell et al., 2012; Mawdsley and Somaya, 2016), the employer is likely to prefer filling the gap with an internal candidate suitable to replace the lost knowledge worker. A loss thus increases the employer's dependence on the remaining collaborators, enhancing their bargaining power (Sevcenko et al., 2022). With higher bargaining power, the remaining collaborators can negotiate benefits that are conducive to their productivity, such as additional resources or more attractive working conditions (Becker, 1964; Chang and Wang, 1996; Greenwald, 1986; Dencker, 2009; Bloom and Van Reenen, 2011). This potentially counteracts the negative effect of the collaborator loss on productivity due to the reduction in team-specific capital. In addition to its effect on productivity, the increase in bargaining power may also change career trajectories. First, the remaining collaborators are more likely to advance within the firm, as promotions may be among the benefits offered by the current employer. Second, moving to a new employer likely becomes less attractive for the remaining collaborators because of the benefits offered by the current employer.

We empirically investigate the consequences of collaborator loss among inventors in cor-

[1] Like Jaravel et al. (2018), we understand this term to mean that the "capital" is acquired while working in the team. If a team is dissolved, the capital is not lost, it continues to exist. Therefore, even if we use the term commonly used in the literature, "team-specific capital" should be understood in the sense of "collaborator-specific capital".

[2] We define collaborator loss as the irreversible unavailability of a knowledge worker for her current or former collaborators—which consequently also implies the unavailability of her knowledge. Collaborator loss can occur for various reasons, such as retirement, exit from the inventive profession, and death. Arguably, moves between employers may also be considered as collaborator loss. However, as prior research has shown, knowledge flows between former collaborators across organizational boundaries can be substantial (Agrawal et al., 2006). This makes it less clear to what extent such moves reduce the remaining collaborators' team-specific capital.

porate R&D and show that bargaining power explains important heterogeneity in the effect on productivity and career trajectories of the remaining inventors. For firms, inventors are key to successful innovation (Bhaskarabhatla et al., 2021), and their mobility is central to knowledge flows (Kaiser et al., 2015; Tzabbar et al., 2022). To establish causal relationships in this setting, we follow the empirical strategy introduced by Azoulay et al. (2010) in the context of biomedical scientists and recently expanded by Jaravel et al. (2018) to the context of inventors. That is, we exploit the unexpected deaths of active inventors as plausibly exogenous collaborator losses to their coinventors.

We draw on a novel and unique employer-employee dataset, the INV-BIO dataset (Dorner et al., 2018), which records complete biographies of more than 150,000 inventors in Germany between 1980 and 2014. This dataset tracks each inventor's employment status and inventive output over time with high precision. In this dataset, we identify 845 unexpected deaths of inventors. These deaths are plausibly exogenous because the deceased inventors were not older than 60 at the time of death and had worked full-time in the preceding months. As remaining collaborators, we consider all inventors that have patented at least once with the respective deceased inventor in the ten years prior to death. As a comparison group, we use the collaborators of 845 carefully matched 'pseudo-deceased' inventors. We use difference-in-differences designs and hazard models to investigate the effect of the unexpected death of an inventor on the productivity (patented inventions) and the career trajectories (promotion and job mobility) of the remaining collaborators.

We first replicate the main finding of previous studies and confirm that—in line with the notion of reduced team-specific capital—collaborator loss has a lasting negative effect on inventor productivity. Our argument that the loss of a collaborator may also lead to a gain in the bargaining power of the remaining collaborators due to the employer's need to fill the gap motivates the next step. We separately analyze the productivity effect for the group of inventors with the same employer as the deceased inventor. Here, we find no negative effect of collaborator loss on productivity. This result is hard to explain if the reduction of team-specific capital was the only consequence of collaborator loss. Instead, our results are consistent with a countervailing effect on productivity resulting from a more favorable allocation of internal resources and more attractive working conditions for the remaining collaborators with the same employer.

We further test whether the loss of a collaborator directly affects the remaining collaborators' career trajectories. First, we show that the remaining collaborators with the same employer are likelier to receive a promotion. Second, these inventors are less likely to leave their current employers. Finally, we find that the career effects occur instantly and phase out before productivity effects materialize. Given this chronological order, we can rule out that the career effects simply result from changes in the remaining collaborators' productivity.

We conduct additional tests to strengthen the plausibility of our explanation. First, we show that a promotion after collaborator loss is more likely if the deceased inventor held a senior position. Second, we show that the negative mobility effect is strongest where the remaining collaborator is a suitable replacement for the deceased inventor in terms of human and social capital (cf. Melero and Palomeras, 2015). These heterogeneity results provide additional support for our "filling the gap" thesis.

Our study contributes to several strands of literature. First, it adds to the literature on collaborations and the careers of knowledge workers by investigating the effects of collaborator loss on the career trajectories of knowledge workers. Our study extends the existing research that has only focused on (decreases in) productivity but has ignored the role of the employer interested in filling the gap resulting from collaborator loss. Additionally, we highlight the role of substitutability among inventors for their individual careers, whereas the literature emphasizes complementarity as foundational for the joint performance of inventors. Second, our study improves our understanding of employment relationships in knowledge-intensive jobs. In particular, it introduces bargaining power as an important aspect of such relationships, which determine the productivity and careers of knowledge workers.

2 Theory

2.1 Collaborator loss and team-specific capital

With the loss of a collaborator, the remaining collaborators experience a reduction of team-specific capital, which has a human and a social capital component. A reduction in team human capital implies that the remaining collaborators lose access to knowledge held by the lost collaborator (cf. Azoulay et al., 2010; Balsmeier et al., 2022). The lost collaborator's tacit knowledge, i.e., conscious and unconscious knowledge stored in the heads of an individual (Grant, 1996; Howells, 2002), is particularly difficult to access from other sources. The team may have partially shared tacit knowledge through exposure and personal interaction (Jaffe et al., 1993; Singh and Agrawal, 2011). Other tacit knowledge, such as intuition or gut feeling of the lost collaborator, remains virtually impossible for others to acquire (Leonard and Sensiper, 1998; Spender, 1993).

In addition to the reduction of team human capital, the loss of a collaborator also leads to a reduction in team social capital, i.e., 'a set of resources rooted in relationships' (Nahapiet and Ghoshal, 1998, 243). Social capital is a complex construct (Leana and Van Buren III, 1999; Seibert et al., 2001). It ties different individuals in networks together (Burt, R. S., 1992), induces trust and reciprocity, and enables cooperation, collective action, and shared representation (Kale et al., 2000; Jacobs, 1961; Mawdsley and Somaya, 2016). Social capital is partly reduced as the loss of a collaborator disrupts the collaboration network. The reduction in social capital lowers the amount and value of information shared between ties (Burt, R. S., 1992), complicating coordination and communication among the remaining collaborators. As a result, their efficiency and effectiveness decline (Srikanth and Puranam, 2011; Reagans et al., 2005).

The reduction in team-specific capital extends beyond the individuals with whom the lost collaborator is currently working at the same employer. The acquired team-specific capital connects former collaborators after the completion of a joint project, even if they moved to a different employer. There are at least two reasons for the persistence of team-specific capital. First, collaborators, in our context, inventors, typically stay in contact and exchange ideas even years after collaborating on a joint invention (Breschi and Lissoni, 2004; Singh, 2005). Indeed, the related literature has shown that former coinventors continue to be an important knowledge source (Fleming et al., 2007) and a key determinant for an inventor's productivity (Jaravel et al., 2018).[3] Second, knowledge transfer frequently occurs between inventors working for different employers (Agrawal et al., 2006). Across-firm R&D collaboration is well established and usually aims to compensate for a lack of resources such as knowledge (Hagedoorn, 2002).

2.2 Collaborator loss and bargaining power

A loss of a collaborator will also affect the employer. This is because the employer needs to quickly fill the gap left by the lost collaborator to ensure the continuation of ongoing or planned operations. Hence, in addition to a reduction in team-specific capital, the collaborator loss may also lead to a gain in bargaining power for the remaining collaborators.

Generally, when one party is more dependent on the other to obtain resources than vice versa, it has less bargaining power and, therefore, less control over the relationship (Emerson, 1962; Pfeffer and Salancik, 1977; Blau, 2017). The literature typically assumes that the employer has greater bargaining power than the employee (e.g., Phillips, 2001). However, this asymmetry in bargaining power can change if, for instance, the employee controls key resources. An inventor can, for example, have substantial bargaining power if the employer needs the inventor's knowledge and cannot easily obtain it from other sources (Kehoe et al., 2018).

[3] Although our focus lies on collaborators and not networks, the results of this literature transfer to our context. Social capital, for instance, is embedded in collaborators' awareness of who knows what and how this knowledge of current and former collaborators can be accessed (Srikanth and Puranam, 2011; Reagans et al., 2005).

Transferred to our context, the loss of a collaborator increases the employer's dependence on the remaining collaborators, which in turn shifts bargaining power to them (Sevcenko et al., 2022; Dencker, 2009). To ensure the continuation of ongoing R&D projects and research lines or to keep deadlines, the employer may need to quickly fill the gap left by the lost collaborator. The employer can seek to fill this gap by hiring a new inventor from outside of the organization. However, external inventors are unlikely to hold knowledge sufficiently similar to the lost inventor to render them suitable substitutes (Leonard and Sensiper, 1998; Taylor and Greve, 2006). Even if external inventors with similar knowledge exist, they are—in light of labor market frictions—typically hard to find, costly to hire, or time-consuming to train (Campbell et al., 2012; Mawdsley and Somaya, 2016; Siegel and Simons, 2010).

In contrast, the remaining collaborators are more readily available, which allows the employer to fill the gap faster and with lower costs. Moreover, the remaining collaborators are more likely to hold knowledge similar to that of the lost collaborator. Similar knowledge includes collective tacit knowledge, which they have generated together with the lost collaborator, and individual tacit knowledge, which they acquired through close interaction with the lost collaborator. In addition, social capital may be easier to (re)build when inventors work for the same employer. This may be partly because they have already worked together in the past or because they share the same values (corporate culture). Consequently, it is more effective and efficient for the employer to rely on the remaining collaborators to fill the gap. This increases the demand for these collaborators. However, it becomes clear that any gain in bargaining power is almost exclusively for the remaining collaborators with the same employer as the lost collaborator.

2.3 The effect of collaborator loss on productivity and career trajectories

To date, the relevant literature has associated collaborator loss only with a reduction in team-specific capital (e.g., Azoulay et al., 2010; Jaravel et al., 2018). However, as argued above, collaborator loss can also increase the remaining collaborators' bargaining power over their employer. The remaining collaborators can leverage their gained bargaining power to demand more resources and better working conditions, such as increased autonomy or managerial attention (Becker, 1964; Chang and Wang, 1996; Greenwald, 1986; Dencker, 2009; Bloom and Van Reenen, 2011). This, in turn, can positively impact their productivity, partially compensating for the productivity decrease due to the reduction in team-specific capital. Hence, losing a collaborator may have two opposing effects on the remaining collaborators. On the one hand, the reduction of team-specific capital may lower productivity (Jaravel et al., 2018). On the other hand, the increase in bargaining power may partially offset this negative productivity effect or even lead to a net increase in productivity.

Following our arguments above, we expect productivity effects to differ depending on whether the remaining collaborators and the lost one worked for the same or a different employer. The reduction of team-specific capital affects both groups. In contrast, the effect of the expected shift in bargaining power predominantly concerns the group of remaining collaborators with the same employer as the lost collaborator. We use the differences in the two opposing effects to detect the contribution of the gain in bargaining power to the net impact on productivity.

In addition to productivity, collaborator loss can also affect the career trajectories of the remaining collaborators with the same employer, particularly promotion and mobility. In our context, collaborator loss can increase the likelihood of a promotion among the remaining collaborators for three reasons. First, a promotion may follow from the remaining collaborator's increase in bargaining power. In this case, the promotion would be primarily a benefit offered by the employer to the employees (Becker, 1964; Chang and Wang, 1996; Greenwald, 1986; Dencker, 2009; Bloom and Van Reenen, 2011). Second, a promotion may be required to fill the gap because the lost collaborator leaves a senior position. Filling the gap with one of the remaining collaborators may still be a more effective and efficient option than hiring an external inventor—even if the vacant position is at a higher hierarchical level. For leadership positions in particular, demand-side imperfections in the labor market should make hiring a new (senior) inventor particularly difficult (Mawdsley and Somaya, 2016). Third, a promotion may be possible because the lost collaborator left resources that the remaining collaborators can now salvage. The second and third reasons are linked to each other, and the second reason is only true conditional on the lost collaborator holding a senior position. In summary, we argue that losing a collaborator increases the likelihood of the remaining collaborators receiving a promotion. This leads to our first hypothesis:

Hypothesis 1: Collaborator loss increases the probability of a promotion of the remaining collaborators with the same employer.

In addition to promotion, we expect that the increase in bargaining power among the remaining collaborators with the same employer will also affect their mobility. In general, employees leave a firm if they think that they can plausibly expect a better match with (and more benefits from) a new employer (Jovanovic, 1979; Topel and Ward, 1992). Because the remaining collaborators with the same employer as the lost collaborator have more bargaining power over their current employer, they enjoy benefits that increase the quality of their current employer-employee match (i.e., additional resources or better working conditions). This, in turn, lowers the expected likelihood of a better match with another employer, which should make changing the employer less attractive. Following these arguments, we expect the probability of mobility to decrease for the remaining collaborators, which leads to our second hypothesis:

Hypothesis 2: Collaborator loss decreases the probability of a move of the remaining collaborators with the same employer.

3 Data Sources and variables

3.1 Data sources

To analyze the effect of collaborator loss on the productivity and career trajectory of the remaining collaborators, we use a linked employer-employee panel dataset (INV-BIO ADIAB 1980-2014), which combines labor market biographies and patenting information. Overall, the INV-BIO dataset contains complete biographies of 152,350 inventors from 1980 until 2014. Inventors are individuals who are listed in the administrative labor market data and who filed at least one patent application with the European Patent Office (EPO) between 1999 and 2011 and resided in Germany at the time of the patent filing. For these inventors, we obtained patent records between 1980 and 2014 from the EPO and the German Patent and Trademark Office (GPTO). The labor market biographies are based on social security data obtained from the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB). The dataset comprises a rich set of variables concerning inventors' sociodemographic characteristics, patents, and employment records. Appendix A1 contains a description of the different steps leading to our dataset and extensive checks of the data quality. For a detailed account of the dataset construction, see Dorner et al. (2018).

We use this combination of administrative labor market data and patent data, as both contain complementary information that we leverage in our empirical analysis.[4] The labor market data allow us to track the inventors' careers more precisely than possible with patent data. In particular, we have information on the inventors' employer at the fine-grained establishment level and observe day-specific changes in their employment status (e.g., due to

[4]Social security data on labor market careers in Germany have been used extensively in research on productivity and human capital of workers and firms (Card et al., 2013; Dustmann et al., 2009, 2017; Bender et al., 2018; Fuest et al., 2018; Jaeger and Heining, 2019).

death, mobility or promotion). The patent data inform us about the inventors' productivity, technology focus, and coinventors (i.e., the inventor's collaborators).

3.2 Variables

In the following section, we will describe the variables used in our regression analyses. An overview of all variables, including those only used in the sample construction, is included in Appendix A2, Table A2-1.

Dependent variables

Productivity – In line with the literature, we use the inventor's simple and citation-weighted annual patent counts as a proxy for productivity (Jaravel et al., 2018; Lanjouw and Schankerman, 2004). To this end, we consider the inventor's EP patents deduplicated at the patent family[5] level. We take the earliest filing (priority) date within the patent family as the reference point, which is closest to the actual date of invention. For the citation-weighted patent counts, we consider all EP citations the focal patent has received in the first five years after the earliest filing date.

Promotion – We obtain information on promotion events from the labor market data. We only consider the first within-employer promotion to a senior position during the analysis period. The operationalization of this variable makes use of the fact that the occupational classification in the labor market data distinguishes senior positions, such as heads of departments and company branches.[6]

Mobility – This variable captures the inventor's first move from their current employer during the analysis period. The labor market data record inventors' employment status changes and provide the reported cause of the change (e.g., job-to-job transitions, retirement, or unemployment). We consider all employment changes that result in the inventor leaving her current employer except changes into (premature) retirement. The predominant share of these changes is job-to-job transitions. In robustness checks, we further exclude moves into unemployment.

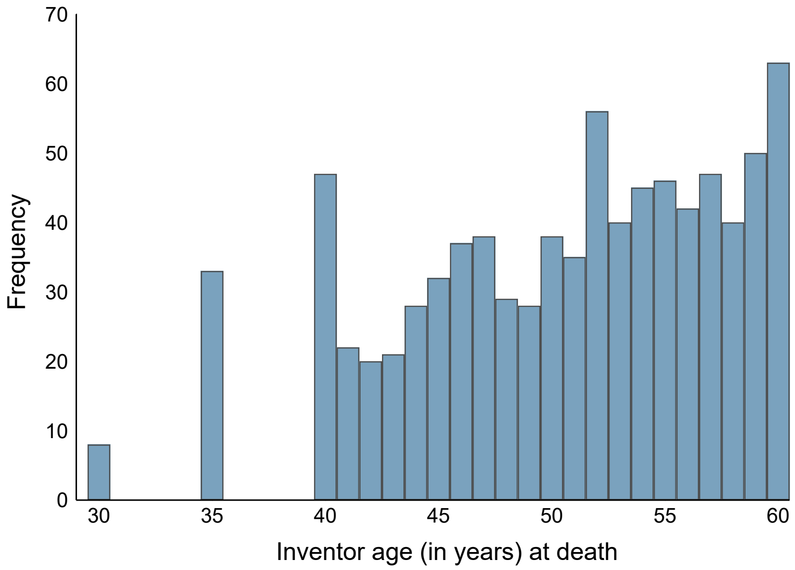
[5]Patent families refer to different patent documents that protect a single invention, i.e., the identical technical content. According to the DOCDB family definition, members of a patent family all have exactly the same priority date (date of first application). A patent family typically contains patent documents protecting an identical invention in different jurisdictions, i.e., countries (see https://www.epo.org/searching-for-patents/helpful-resources/first-time-here/patent-families/docdb.html, accessed on September 17, 2022). We extracted the citations received by all members of a patent family and removed the duplicates. The resulting number of citations corresponds to the number of unique patent documents that refer to the inventions in our sample as prior art.

[6]This classification follows the Bundesagentur fuer Arbeit (2011, p. 42f)

Covariates

Death of an inventor – In our empirical strategy, we use unexpected deaths as plausibly exogenous collaborator losses. The labor market data report inventor deaths accurate to the day based on a specific notification in the underlying social security data. These death notifications are mandatory and appear unrelated to employer and employee characteristics (Jaeger and Heining, 2019). We only consider the deaths of inventors who died aged 60 or younger.[7] Figure 1 shows the distribution of ages at death for the sample of deceased inventors. The frequency of deaths increases with inventor age for two main reasons. First, some causes of unexpected death (e.g., heart attacks) become more likely with age. Second, the likelihood that an inventor has filed at least one patent before death (and thus becomes part of our data) increases with career length. The average deceased inventor died at age 49.

Figure 1: Age of deceased inventors



Notes: The graph plots the age of the deceased inventors at the time of death. Inventor age below 40 is coarsened in this graph to adhere to data confidentiality regulations of the IAB.

Same employer – We distinguish between the remaining collaborators depending on whether they worked for the same employer as the deceased inventor at the time of death. For this binary variable, we leverage employment information about the inventors at the establishment level. Two establishments are distinct in at least one of the following characteristics: location, industry, or firm. Thus, inventors in different establishments may work

[7]In our population of inventors, a large fraction is still employed after reaching the age of 60 and contributes to patents. The retirement age in the period in question slowly rises from 65 years (cohort of 1946 and earlier) to 67 years (cohort of 1964 and later).

in the same firm but not in the same organizational unit, that is, for the same employer. Slightly more than 50% of the remaining collaborators worked in the same establishment as the deceased inventor.[8]

Deceased inventor in a senior position – This binary variable indicates whether the deceased inventor held a senior position prior to her death.

Replacement suitability – We also measure whether a remaining collaborator is particularly suitable to replace the deceased inventor. We operationalize the replacement suitability as the share of patented coinventions relative to all patented inventions of the remaining and deceased inventors. The rationale behind this measure is that inventors working on the same project have the necessary, ergo usually similar, human capital, learn from each other through collaboration, and can build up social capital through direct interaction. In robustness checks, we also employ two alternative operationalizations based on technological expertise (the overlap of technology classes at the IPC4 level between the remaining collaborators and the deceased inventor) and work history (joint tenure of the remaining collaborators and the deceased inventor).

Other control variables – We control for the inventors' age to account for lifecycle patterns in inventor productivity. The remaining collaborators in our sample are 46 years old on average. We further include inventor fixed effects to control for time-invariant characteristics and calendar year fixed effects to control for time-specific shocks.

4 Empirical strategy

4.1 Outline

The main challenge in estimating the effect of collaborator loss on productivity and career trajectories of the remaining collaborators is that the effect may be confounded by other factors, such as the employer's R&D strategy. To isolate the effect of collaborator loss from confounders, we follow a twofold strategy that mirrors Jaravel et al. (2018).

First, we leverage the natural experiment of unexpected deaths among inventors. While collaborator losses may take various forms in real life, we focus on unexpected (i.e., exogenous) deaths to ensure that the loss of a collaborator is not driven by factors that may also explain the productivity of the remaining collaborators. In this way, we can also exclude the possibility that the remaining collaborators can still access the knowledge of the lost

[8]In the other cases, the two inventors were not working in the same establishment at the time of death. There can be two reasons for this: either the two inventors used to work in the same establishment, but at least one of them moved to another establishment since then (approximately 60%) or the two inventors were part of a team that involved inventors from different establishments (approximately 40%) at the time of making the invention.

collaborator (e.g., the inventors stay in touch) or expect that the knowledge becomes accessible again (e.g., the lost inventor returns). Second, we employ a matching approach where we assign each deceased inventor to one pseudo-deceased inventor. To guarantee comparability between the deceased and pseudo-deceased inventors in terms of productivity, career stage, and available resources, we base this match on a rich set of inventor and employer characteristics, which we will explain in more detail below.

We analyze the consequences of an inventor's unexpected death on the productivity of the remaining collaborators in a difference-in-differences (DiD) framework. More specifically, we compare the remaining collaborators of the deceased inventors (the "treated collaborators") with the remaining collaborators of the pseudo-deceased inventors (the "control collaborators") before and after the unexpected (pseudo-)death. With this framework, we obtain average treatment effects of inventor death that allow a causal interpretation. We further provide event study estimates to investigate effect dynamics and to examine the validity of the common trend assumption.

We study the consequences of an inventor's unexpected death on the career trajectory of the remaining collaborators through survival analysis. We do so to account for the different nature of the career-related outcome variables, i.e., the time until the first occurrence of promotion or mobility after the inventor death. Again, we compare treated with control collaborators and estimate the probability of promotion or mobility in the first two years after the unexpected death of the inventor.

4.2 Inventor matching

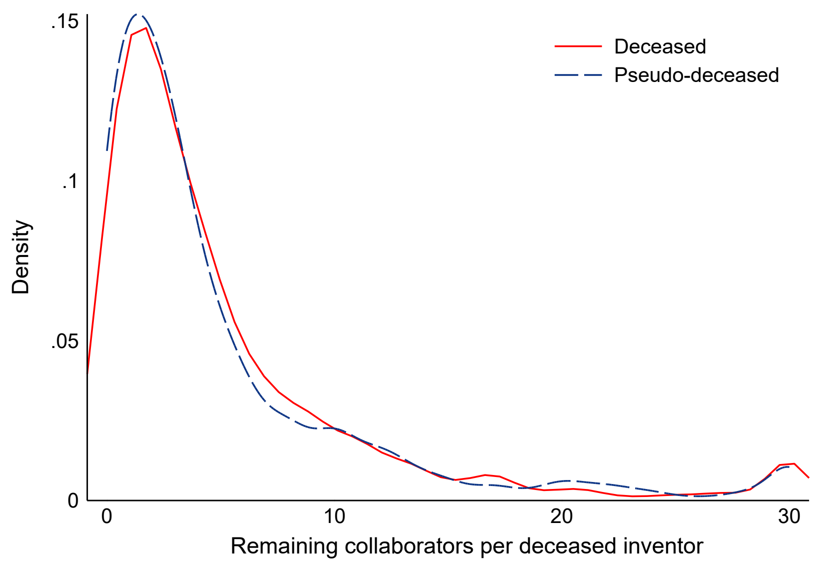
We match each deceased inventor to a pseudo-deceased inventor drawn from the 150,000 inventors in our dataset. We do so iteratively and draw pseudo-deceased inventors without replacement by death year cohort in chronological order. To minimize violations of the stable unit treatment value assumption, we exclude colleagues and coinventors of the deceased inventor as matching candidates. In line with the prior literature (Cohen et al., 2000; Rosenkopf and Almeida, 2003; Nakajima et al., 2010), we select pseudo-deceased inventors based on the following matching variables[9] observed at the time of death: (1) gender, (2) age, (3) lifetime patent count (the coarsened number of patent applications the inventors produced since starting their careers), (4) technology focus (inventor's modal technology field), and (5) employer size group (the coarsened number of full-time employees an establishment employs). In case of multiple matches per deceased inventor, we select the inventor who is most similar to the deceased inventor in terms of tenure (the number of years the inventor had been employed with a particular employer), years since

[9]A more detailed description of these variables is included in Appendix A2, Table A2-1.

last patenting (the time since the inventor filed her last patent), and the uncoarsened number of patent applications, in that order.[10] We assign the death date of the corresponding deceased inventor to each matched pseudo-deceased inventor.

We are interested in how the death of inventors affects the remaining collaborators. We define the remaining collaborators as those who copatented with the (pseudo-)deceased inventor in the last ten years prior to the (pseudo-)death. Figure 2 displays the distribution of the number of remaining collaborators of the deceased inventors. The distribution is right-skewed, with most deceased inventors having up to five remaining collaborators. The following analysis excludes deceased inventors with zero remaining collaborators.[11]

Figure 2: Number of remaining collaborators per deceased inventor



Notes: The graph plots the number of remaining collaborators of deceased and pseudo-deceased inventors. The number of collaborators censored at 30.

We successfully match 845 out of 866 deceased inventors in our data to pseudo-deceased inventors with similar characteristics. Both matched and unmatched characteristics are well balanced between deceased and pseudo-deceased inventors and between the two groups of remaining collaborators (see Table A2-3 in the Appendix). The small relative differences in means (and medians) provide strong support for the quality of our match.

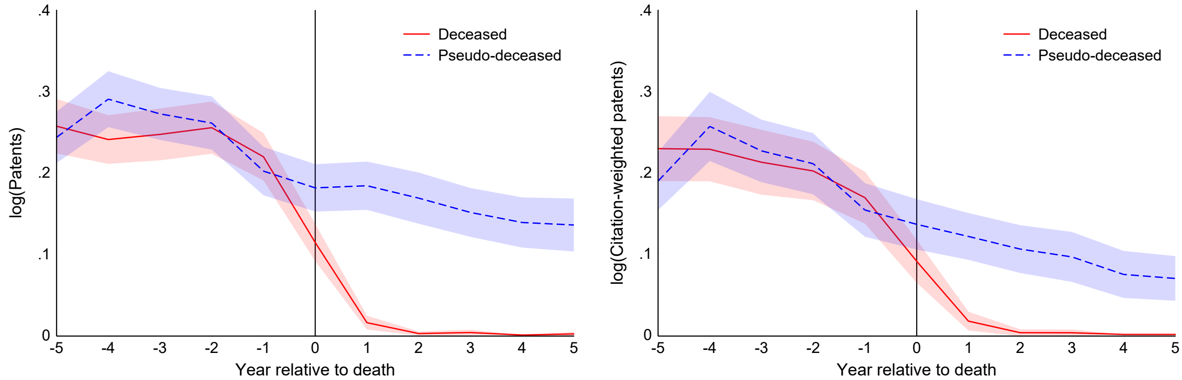
[10]The reason for the additional weak matching criteria is to strike a balance between stable matching and retaining a high number of successful matches. The classification into strict matching variables and weak matching variables are the result of a manual optimization of the matching.

[11]In total, there are 3,471 (3,215) remaining collaborators of deceased (pseudo-deceased) inventors. We exclude the remaining collaborators who themselves died during the sample period, which applies to 23 (19) units of observation. We further restrict our sample to the remaining collaborators who are linked to only one (pseudo-)deceased inventor. This excludes 195 (146) units of observation. Another 175 remaining collaborators are linked to both a deceased and a pseudo-deceased inventor. We drop these from both pools as well. Overall, we exclude approximately 11% of the observations.

The levels and trends of productivity are similar between deceased and pseudo-deceased inventors. Figure 3 shows that predeath levels and trends are comparable between the two groups of inventors, both for simple patent counts (Panel a) and citation-weighted patent counts (Panel b). However, as expected, the productivity of the deceased inventors drops to practically zero in the year after their death. This drop corroborates that the deaths were unexpected and unrelated to the inventors' productivity.

Figure 3: Average productivity by deceased and pseudo-deceased inventors

(a) Patents (simple count) (b) Patents (citation-weighted)



Notes: The two graphs show the yearly average for deceased inventors' patent family counts (left) and citation-weighted patent counts (right). Shaded areas reflect 95% confidence bands around the yearly means. Inventor lifecycle effects and right-hand truncation explain the general downward trends over time.

4.3 Econometric models

In the first part of our analysis, we estimate the effect of inventor death on the productivity of the remaining collaborators in a DiD framework. For each remaining collaborator, we consider years $t = -5$ to $t = 5$ around the year of death. The validity of this analysis rests on the common trend assumption; that is, absent death, the productivity of the treated collaborators would have followed the same path as the productivity of the control collaborators in the treatment period. The DiD specification is given as follows:

$$\log(1 + Y_{it}) = \alpha_i + death_i \times \beta_{t \geq d(i)} + \gamma_{t-d(i)} + \delta' Z_{it} + \mu_t + \epsilon_{it}. \qquad \text{(Eq. 1)}$$

In all DiD specifications, we use individual fixed effects and year fixed effects. We further include relative period fixed effects. The matrix Z contains additional, time-varying control variables at the collaborator level, particularly age fixed effects.[12] We cluster standard errors at the collaborator level.

[12] As full inventor, year and age fixed effects are collinear, we omit additional fixed effect levels. The results are robust to using age and age-squared fixed effects instead.

In the event study specification (with the year prior to death as the baseline period), this expands to:

$$\log(1 + Y_{it}) = \alpha_i + \sum_{k=-5;k\neq-1}^{5} (death_i \times \beta_k + \gamma_k) + \delta' Z_{it} + \mu_t + \epsilon_{it}. \quad \text{(Eq. 2)}$$

In the second part of our analysis, we estimate the effect of inventor death on the career trajectories of the remaining collaborators through survival analysis. More specifically, we examine whether the remaining collaborators' likelihood of mobility and promotion changes in the first two years after death. To this end, we use a Cox proportional hazard rate model with time-invariant regressors, specified as a continuous-time hazard rate function. The model consists of a nonparametric baseline hazard rate and a multiplicative term allowing the regressors to have a proportional impact relative to the baseline. We let h_{change} denote the hazard rate of mobility or promotion, stratified by the remaining collaborator's modal technology area l. We include collaborator characteristics, z, and death year fixed effects, $year_i$, as control variables. The model is then specified as follows:

$$h_{change}\,(t \mid death_i, l_i, z_i) = h^{l_i}(t)\,\exp(\alpha + \beta\; death_i + \gamma z_i), \quad \text{(Eq. 3)}$$

where β represents the effect of an inventor death on the change hazard rate. We assume that death is exogenous given our matching procedure, the stratification and control variables such as age and death year. That is, we assume that the mobility and promotion rates of treated and control collaborators would follow the same path without death. We capture the influence of life cycles and macroeconomic events on the baseline hazard rate of change with controls for age, age squared, and the death year, all part of the vector z_i. For heterogeneity analysis, we include interactions between the death variable and the heterogeneity variable of interest in the regression. Since Kaplan–Meier estimates indicate heterogeneous effects depending on the time frame, we truncate the event data at different time spans: half a year, one year, and two years.

4.4 Summary statistics

Table 1 summarizes the descriptive statistics of the variables used in our analysis.[13] We distinguish between two sets of dependent variables related to the remaining collaborators' productivity and career trajectory. In line with our DiD framework, we measure the annual productivity from five years before to five years after the (pseudo-)death year. On average, the remaining collaborators file 0.9 patents and receive 1.3 citations annually. To capture changes in their career trajectory, we observe promotion and mobility events within two years after (pseudo-)death. Approximately 16% of the remaining collaborators received a promotion to a senior position within two years after their coinventors' (pseudo)death. Approximately 40% of the remaining collaborators move at least once in the same period.

Table 1: Summary statistics

Variable	Type	Mean	Std. Dev.	10%	50%	90%
Productivity						
Patents (Simple)	DV	0.90	2.28	0.00	0.00	3.00
Patents (Citation-weighted)	DV	1.31	6.69	0.00	0.00	3.00
Career trajectory						
Promotion	DV	0.16	0.36	0.00	0.00	1.00
Move	DV	0.40	0.49	0.00	0.00	1.00
Individual and dyad variables						
Age	IndV	46.06	9.72	34.00	45.00	60.00
Same employer	IndV	0.54	0.50	0.00	1.00	1.00
Deceased inventor senior	IndV	0.13	0.33	0.00	0.00	1.00
Replacement suitability	IndV	0.28	0.45	0.00	0.00	1.00

Notes: Summary statistics in the estimation dataset (N=70,308) for 3,574 remaining collaborators and 3,409 collaborators of pseudo-deceased inventors. Detailed summary statistics for all variables are listed in Table A2-2 in the Appendix.

We leverage several characteristics of the remaining collaborators as moderator variables to explore potential heterogeneity in the effect of inventor death. In particular, we distinguish among the remaining collaborators by whether they had the same employer as the (pseudo-)deceased inventor at the time of death, whether the (pseudo-)deceased inventor had a senior position, and whether the (pseudo-)deceased inventor was particularly suitable to replace the deceased inventor.

[13] For an overview of all variables and their pairwise correlations, see Table A2-2 in the Appendix.

5 Results

5.1 Productivity

We first replicate the analyses of previous studies (Bernstein et al., 2019; Jaravel et al., 2018) to confirm the findings from the US in the German context, i.e., that collaborator loss has an overall lasting negative effect on productivity. Table 2 presents the DiD results of inventor death on the productivity of the remaining collaborators. In the full sample, inventor death has a statistically significant negative effect of approximately -2% on the annual patent count in the treatment period (Table 2, Column 1). This effect is approximately one-third as large as the effect observed by Jaravel et al. (2018) within the same time window. To study the dynamics of the effect, we plot the event study results in Figure 4. We can infer two important findings from the event study. First, there are no significant pretrends, which solidifies the validity of our research design. Second, the negative effect on productivity increases in magnitude over time, reaching statistical significance from the third year onward—a pattern also observed by Jaravel et al. (2018).

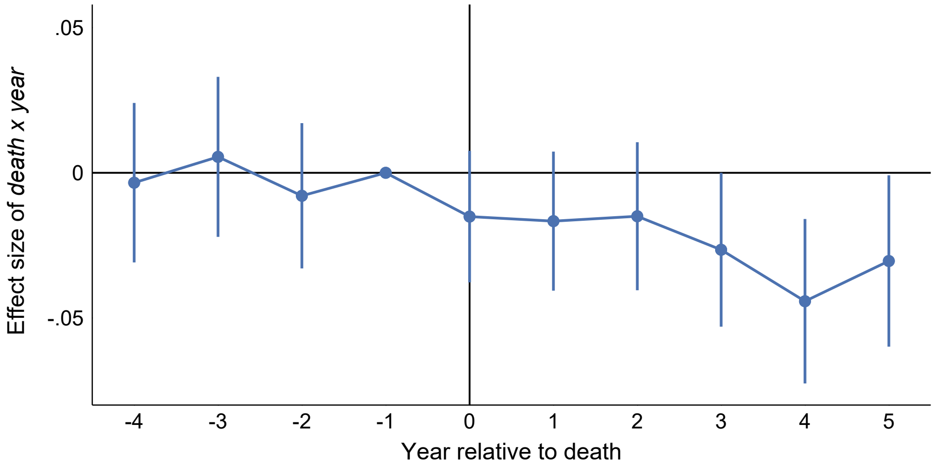
Table 2: Impact of inventor death on the productivity for the remaining collaborators - simple and citation-weighted patent counts (DiD estimates)

	(1)	(2)	(3)	(4)	(5)	(6)
DV: log		Patents			Patents (citation-weighted)	
	All	Same employer	Different employer	All	Same employer	Different employer
Death × Post	-0.020^{**}	0.002	-0.047^{***}	-0.024^{*}	0.005	-0.060^{***}
	(0.010)	(0.014)	(0.014)	(0.012)	(0.018)	(0.017)
Collaborator FE	Yes	Yes	Yes	Yes	Yes	Yes
Collaborator age	Yes	Yes	Yes	Yes	Yes	Yes
Calendar year FE	Yes	Yes	Yes	Yes	Yes	Yes
Collaborators	6983	3797	3186	6983	3797	3186
Observations	70308	38281	32027	70308	38281	32027
Adj. R2	0.07	0.07	0.08	0.07	0.08	0.07

Notes: This table reports the estimates from a linear regression with remaining collaborator, collaborator age, and year fixed effects. The dependent variables (simple and citation-weighted patent counts) are log-transformed. The coefficients can thus be interpreted as semi-elasticities. The unit of observation is at the remaining collaborator level. Robust standard errors clustered at the collaborator level in parentheses.
* p<0.1, ** p<0.05, *** p<0.01.

Next, we split the sample and distinguish between the remaining collaborators based on whether they had the same employer as the deceased inventor. This sample split follows from our argument that collaborator loss may also lead to a gain in the bargaining power of the remaining collaborators working for the same employer. For the remaining collaborators with the same employer, we find no negative effect of inventor death on productivity (Table 2, Column 2). For the remaining collaborators with a different employer, we find a negative and statistically significant effect on productivity (Table 2, Column 3). With a magnitude of approximately -5%, this estimate is more than twice as large as the one for the full sample and similar to what Jaravel et al. (2018) found for US inventors. We see the same pattern when using a quality-weighted patent count based on patent citations (Table 2, Columns 4-6). This finding is robust to alternative operationalizations of the dependent variables (fractional patent counts, inverse hyperbolic sine instead of the log transformation), different model specifications (inventor age fixed effects), and a broader clustering of standard errors (see Table A3-2 in the Appendix for all robustness checks).

Figure 4: Impact of inventor death on productivity for the remaining collaborators - patent counts (event study estimates)



Notes: The graph presents plotted point estimates of the variable *death* interacted with event year dummies. The dependent variable is the annual patent count. The unit of observation is at the remaining collaborator level. The baseline year is $t-1$, coefficient $t-4$ groups two years. The graph corresponds to the coefficients reported in Table A3-1 in the Appendix. Confidence intervals are at the 90% level.

The heterogeneous effects on productivity depending on whether the remaining and deceased collaborators share the same employer are consistent with our theoretical arguments. We find that the remaining collaborators who work for a different employer than the deceased inventor experience a reduction in team-specific capital due to the death of their collaborator. However, as their employer does not have a gap to fill, these inventors experience no gain in bargaining power. Consequently, the observed productivity effect is unlikely to contain a countervailing effect of bargaining power, and it is thus strictly negative. In contrast, remaining collaborators of the same employer experience a gain in bargaining power over their employer, which compensates for the reduction in team-specific capital that would otherwise have led to a decline in productivity. Since the observed net effect of inventor death on productivity includes this countervailing effect of bargaining power, we no longer find a significant negative effect for this group of inventors.

5.2 Promotions

In the following, we examine the effect of collaborator loss on the remaining collaborators' career trajectories. We first examine whether the remaining collaborators are more likely to receive a promotion after the death of an inventor relative to the control group. We estimate the probability of an inventor's promotion to a senior position through Cox proportional hazard models. Again, we distinguish between remaining collaborators with the same or with a different employer (Table 3), assuming that the mechanism we are interested in—an increase in bargaining power—is only at play for inventors who work for the same employer. We find that the remaining collaborators with the same employer are more likely to receive a promotion compared to the control group. They have a significantly higher probability of a promotion within the first year after the death of the collaborator. In contrast, the remaining collaborators with a different employer have no significantly higher probability of a promotion.[14] These results support our first hypothesis that collaborator loss increases the probability of a promotion of the remaining collaborators with the same employer.

Table 3: Impact of inventor death on promotion to a senior position for the remaining collaborators (Cox hazard estimates)

	(1)	(2)	(3)	(4)	(5)	(6)
	Same employer			Different employer		
DV: Promotion	<0.5 years	<1 year	<2 years	<0.5 years	<1 year	<2 years
Deceased	0.604*	0.544**	0.231	0.239	0.106	0.020
	(0.314)	(0.238)	(0.158)	(0.417)	(0.259)	(0.173)
Collaborator age	Yes	Yes	Yes	Yes	Yes	Yes
Death year FE	Yes	Yes	Yes	Yes	Yes	Yes
Events	40	71	174	22	59	134
Collaborators	3797	3797	3797	3186	3186	3186

Notes: Hazard ratio estimates from a Cox regression with death year fixed effects and age, age squared covariates. Robust standard errors in parentheses. Stratified by modal main technology area. For Kaplan-Meier estimates, see Figure A6-1 in the Appendix. * p<0.1, ** p<0.05, *** p<0.01.

Since we cannot directly observe our mechanism, i.e., an increase in bargaining power, we explore the origin of the positive effect on promotion among the remaining collaborators with the same employer. In particular, we investigate whether the effect is likely to be a

[14]The probability of promotion to a management position is unchanged when the deceased and remaining collaborator worked in a different establishment, irrespective of whether the deceased inventor was a manager herself. Corresponding estimates are in presented in Figure A6-2 in the Appendix.

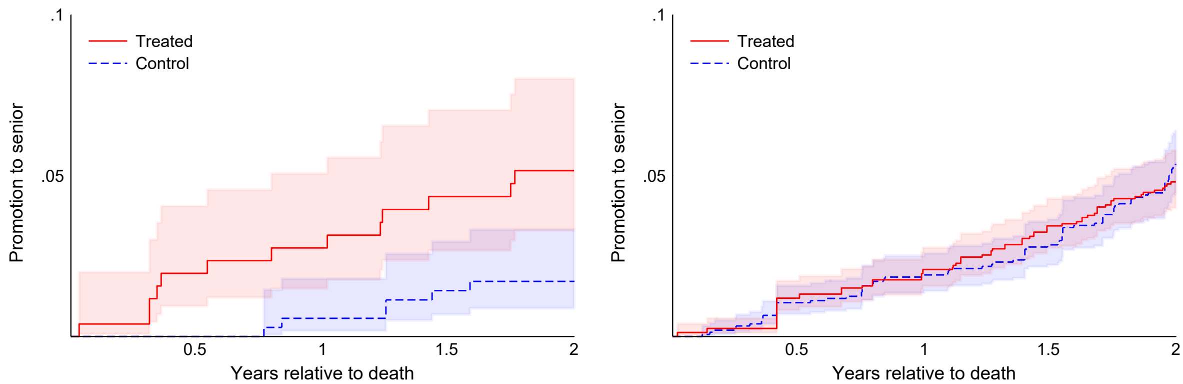
replacement effect. To this end, we split the group of remaining collaborators with the same employer depending on whether the deceased inventor held a senior position and estimate separate Kaplan–Meier curves for the event of promotion. We find that the effect is driven by promotions of the remaining collaborators where the deceased inventor vacated a senior position. The divergence of promotion rates is strong and persistent for this group of inventors relative to the control group (Figure 5a). In contrast, the promotion rates are statistically indistinguishable between treated and control collaborators when the inventor death did not vacate a senior position (Figure 5b).

These results do not provide direct evidence of a shift in the bargaining power of the remaining inventors, but they support our argument that the lost collaborators leave a gap that the employer needs to fill. As mentioned above, collaborators working for the same employer are the best alternative due to the costs of hiring a new inventor (e.g., agency costs, onboarding costs). Thus, their bargaining power toward the employer is likely to increase. Moreover, the observation that promotions following inventor death accrue only if the lost collaborator had a senior position is in line with our first hypothesis.

Figure 5: Impact of inventor death on promotion to a senior position for the remaining collaborators with the same employer by position of the deceased inventor (Kaplan–Meier estimates)

(a) Deceased inventor held senior position

(b) Deceased inventor held no senior position



Notes: This figure presents Kaplan-Meier estimates for promotion events for the remaining collaborators working for the same employer up to two years after the inventor's death. The unit of observation is at the remaining collaborator level. Confidence intervals are at the 90% level. Corresponding Cox hazard estimates can be found in Table A4-1 in the Appendix.

5.3 Mobility

We further examine whether the remaining collaborators are less likely to leave the current employer after the death of a collaborator relative to the control group. We estimate the probability of an inventor's move through Cox proportional hazard models, again distinguishing between remaining collaborators with the same or a different employer (Table 4). For the remaining collaborators with the same employer, the average probability of a move is approximately 50% lower in the first six months compared to those without a deceased inventor, but this initial significant difference levels off over time. The hazard rates fully converge within two years. For the remaining collaborators with a different employer, the probability of a move is not significantly different from the control group, i.e., collaborators without a deceased inventor.

Table 4: Impact of inventor death on mobility for the remaining collaborators by employer (Cox hazard estimates)

	(1)	(2)	(3)	(4)	(5)	(6)
	Same employer			Different employer		
DV: Move	<0.5 years	<1 year	<2 years	<0.5 years	<1 year	<2 years
Deceased	-0.529^{***}	-0.147	0.064	-0.081	-0.104	-0.021
	(0.162)	(0.110)	(0.084)	(0.144)	(0.106)	(0.082)
Collaborator age	Yes	Yes	Yes	Yes	Yes	Yes
Death year FE	Yes	Yes	Yes	Yes	Yes	Yes
Events	168	335	569	193	354	605
Collaborators	3797	3797	3797	3186	3186	3186

Notes: Mobility captures job separations, mostly direct job-to-job transitions. Hazard ratio estimates from a Cox regression with death year fixed effects, age, and age squared covariates. Robust standard errors in parentheses. Stratified by modal main technology area. For Kaplan-Meier estimates, see Figure A6-3 in the Appendix. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

These results align with our explanation that the remaining collaborators with the same employer gain bargaining power, which may result in benefits that make their current employer more attractive relative to outside options. Our results also indicate that career effects occur instantly and phase out within two years, i.e., before productivity effects become visible. Hence, these results support our second hypothesis that collaborator loss reduces the probability of a move of the remaining collaborators with the same employer.

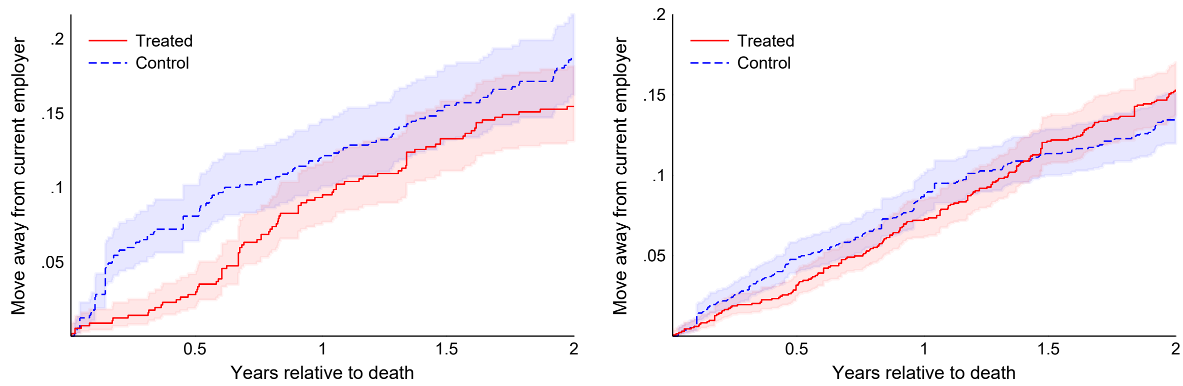
To further support our argument that the previous results reflect an increase in bargaining power over the employer, we explore whether the effect of a deceased inventor on the mobility of the remaining collaborators with the same employer depends on the remaining collaborators' suitability to replace the deceased inventor. As argued above, remaining collaborators should be more suitable if they hold similar human capital (i.e., knowledge) to the deceased inventor and have been working with the deceased inventor to build up social capital. Consequently, we examine differential effects on mobility depending on the actual replacement suitability of the remaining collaborators (i.e., the share of patented coinventions relative to all patented inventions of the remaining and the lost collaborator).

We illustrate the heterogeneity in the effect on mobility by replacement suitability by comparing the Kaplan–Meier estimates for the two subsamples of the remaining collaborators with a high (above the 75th percentile) versus a low (below the 75th percentile) replacement suitability. We find that, statistically, the effect of inventor death on the likelihood that the remaining collaborators move to a new employer is confined to cases with high replacement suitability (Figure 6a). In the other case, the hazard rates between treated and control collaborators are statistically indistinguishable (Figure 6b). Overall, employers seem to retain remaining collaborators (or those collaborators do not move to a new employer) that provide an adequate replacement for the deceased inventor. In contrast, employers appear less prone to retain inadequate remaining collaborators (or such inventors are more likely to move). We again interpret these results as supporting evidence that the bargaining power of (suitable) remaining collaborators over the employer increases.

Figure 6: Impact of inventor death on the mobility of the remaining collaborators with the same employer by replacement suitability (Kaplan–Meier estimates)

(a) High replacement suitability

(b) Small replacement suitability



Notes: This figure presents Kaplan–Meier estimates for move events of the remaining collaborators up to two years after the deceased inventor's death. The unit of observation is at the remaining collaborator level. Confidence intervals are at the 90% level. Corresponding Cox hazard estimates can be found in Table A5-2 in the Appendix. For the different employer subsample, see Figure A6-4 in the Appendix.

5.4 Robustness

We can corroborate the findings concerning the effect of inventor death on the remaining collaborators' career trajectory in several robustness checks. Concerning the effect on promotion, we show that the results are robust to alternative specifications. First, we vary the dependent variable by including or excluding promotions that come with a move to another employer. The corresponding results in Table A4-2 in the Appendix remain qualitatively unchanged. Consistent with the reduction in mobility, promotion events across employers become less likely after the death of a collaborator. Furthermore, the results are robust to different choices of stratification.

We provide additional robustness checks for the mobility regressions. We restrict mobility events to exclude moves to unemployment, so the mobility event is only the subsequent move to a new employer. The Cox regression results in Table A5-1 in the Appendix remain unchanged. In the same table, we also present results with different choices of stratification.

Our primary measure of replacement suitability isolates the remaining collaborators with a high intensity of copatenting with the deceased (Table A5-2 in the Appendix). This variable captures both a loss in human and social capital caused by the death of a collaborator. To show robustness, we create two additional variables to measure replacement suitability: tenure-based replacement suitability, i.e., the number of years both inventors have worked together for the same employer, and technology-based replacement suitability, i.e., the overlap of technological specialization between both inventors based on the distribution of patent technology classes (IPC). While the former primarily (but not exclusively) captures the loss of social capital, the latter is primarily (but not exclusively) a proxy for the loss of human capital. Both continuous variables are split at the 75th percentile, resulting in subsamples of similar size as those based on our primary measure of replacement suitability. We find consistent results when distinguishing the remaining collaborators by their joint tenure with the deceased inventor (Table A5-3 in the Appendix) and a technological focus similar to that of the deceased inventor (Table A5-4 in the Appendix).

5.5 Alternative mechanisms

We argue that the remaining collaborators not only lose part of the team-specific capital due to the loss of a collaborator but may also gain bargaining power. More specifically, we argue that the remaining collaborators, working for the same employer as the lost inventor, experience a less negative productivity effect due to improved working conditions and a more favorable allocation of internal resources. A gain in bargaining power also affects their career trajectories: they are more likely to be promoted and less likely to leave the firm than inventors who did not lose a collaborator.

The mechanism, i.e., the gain in bargaining power, remains unobserved in our empirical analysis. Empirically, we can show that our results are more pronounced in cases where the remaining collaborators are a suitable replacement for the lost collaborator and, thus, can fill the gap left behind. However, this leaves room for alternative explanations of our findings. Below, we list the most relevant ones and provide arguments why bargaining power remains—in our view—the most plausible explanation for our findings.

The first set of alternative explanations concerns unaccounted heterogeneity in team characteristics. First, highly connected collaborators may be better able to compensate for collaborator loss than less connected collaborators due to the strength of redundant ties

(Hardy et al., 2005). However, the literature has consistently found negative effects of collaborator loss on the productivity of the remaining collaborators (e.g., Mohnen, 2022, in medical science), suggesting that compensation is nontrivial. If collaborator loss was easy to compensate for, employers would not immediately seek to fill the gap, and we would not observe career trajectory effects. Second, collaborators may be redundant, so collaborator loss leads to more efficient collaboration. For example, team literature has shown that increasing team size could reduce individual productivity (Brooks Jr, 1975). If collaborator loss indeed leads to individual efficiency gains, the productivity increase could impact career trajectories. However, we observe an immediate and transitory effect on career trajectories confined to the first year at a time when the productivity increase is unlikely to have fully materialized. Third, collaborator loss may affect power dynamics within collaborations. Collaborator loss may free up resources for less influential inventors who were previously unable to implement their ideas. We are not aware of direct evidence of this in the literature.[15] Moreover, we do not find that the remaining collaborators are less influential than the (pseudo-)deceased inventors. In the descriptive statistics, the remaining collaborators even show above-average productivity (number of lifetime patents) compared to the (pseudo-)deceased inventors.

The second set of alternative explanations focuses on different strategies by the employers. First, employers may successfully fill the gap through external hiring, despite our argument that relying on internal inventors should be more efficient and effective. If the externally hired inventor is a suitable replacement, the remaining collaborators may not experience a substantial reduction in team-specific capital (particularly human capital). However, if this was true, there would be no reason to believe that the likelihood of mobility or promotion for the remaining collaborators would change relative to the control inventors. Second, employers may increase the project-specific R&D budget to compensate for the loss. In addition to the productivity results, this could also explain our negative mobility results, as an increase in the R&D budget could make work (temporarily) more attractive for the remaining collaborators. However, an increase in the R&D budget would not explain why, in particular, inventors similar to the lost inventor are less likely to move to a new employer. Given our results on heterogeneity by replacement suitability, a general increase in budget is unlikely to explain our results.

The third set of alternative explanations considers the reactions of other employers and behavioral factors. Changes in career trajectories may be due to reduced labor market opportunities because of other employers' reactions to information about expected productivity. This implies a signaling story. However, verifiable labor market signals such as

[15] Although Azoulay et al. (2010) find crowding-in following the death of star scientists, the primary mechanism is inflow into the field, and it is unclear whether this finding translates to intraorganizational power struggles.

observable productivity develop only over time, both in our setting and in the literature (Jaravel et al., 2018). Even if expectations about future productivity become public, e.g., because connected communities are well informed about the inventor's death, the effects do not overlap with our empirical results. Productivity effects and labor market events should coincide as inventors become less attractive to outside hires. Instead, we find that productivity and career effects occur at different temporal levels and for different groups of remaining collaborators. Finally, emotional distress following the death of a collaborator may be more emphatically managed by the same employer than by a different employer, which seems to be consistent with our results. However, the negative effect of emotional distress on productivity should be immediate and transitory, whereas the observed effect on productivity is delayed and permanent. Moreover, emotional distress would not explain the promotions we observe after the death of an inventor.

This overview shows that other explanations may explain part of our results. However, an increase in the bargaining power of the remaining collaborators working for the same employer seems to be the only mechanism that aligns with all our results. While we do not claim that an increase in bargaining power is the only mechanism underlying our results, based on the literature and our analyses, we think it provides the most convincing explanation for the empirical findings.

6 Discussion and concluding remarks

Relying on a novel and unique employer-employee dataset, our paper exploits the unexpected deaths of active inventors to investigate the impact of collaborator loss on the productivity and career trajectories of the remaining collaborators. We find a moderate negative effect of inventor death on the productivity of all remaining collaborators. However, this negative effect disappears if we focus on the subgroup of inventors working for the same employer as the lost inventor. We also find significant career trajectory effects. Specifically, we find that the remaining collaborators working for the same employer are more likely to be promoted and less likely to leave their current employer than the control group. We explain these results by the fact that the loss of a collaborator affects not only the remaining collaborators but also the employer. Hence, it leads to a reduction in team-specific capital among the remaining collaborators with the same employer, and leads to a gain in bargaining power.

Our study makes several theoretical contributions. First, it contributes to the literature on teamwork and the careers of knowledge workers by investigating the consequences of collaborator loss on the career trajectories of knowledge workers. The literature has mainly focused on the reduction in team-specific capital (Azoulay et al., 2010; Mohnen, 2022;

Khanna, 2021), overlooking the countervailing effect of a shift in bargaining power from the employer to the remaining collaborators within the firm (Sevcenko et al., 2022). This is not surprising since the literature has mainly considered the reduction in team-specific capital in the context of academia. In academia, coauthors primarily invest their own resources (time and research budget), and the outcomes (publications and citations) mainly contribute to the status of the researchers themselves. They benefit the employer, i.e., the university, only as a second-order effect, for instance, through positions of universities or departments in rankings and society through the knowledge generated (Khazragui and Hudson, 2015). In our context, however, the employer has a powerful interest in continuing the project to avoid the loss of R&D expenditure and possibly even of competitive advantage.

Second, this study contributes to our understanding of employment relationships in knowledge-intensive jobs. It provides insights into how changes in bargaining power between knowledge workers and employers affect employment relationships and, consequently, individual productivity and careers (Ekinci and Wehrheim, 2022). Much has been written about bargaining power in an employment relationship. The literature typically assumes that the employer has greater bargaining power than the employee (e.g., Phillips, 2001). Exceptions can be particularly productive employees, so-called stars (Coff, 1999). Stars have been shown to have certain rights and privileges, such as being given more autonomy in spending budgets, choosing their own tasks, and sometimes even the composition of the teams they work with (Gambardella et al., 2020). We show that under exceptional circumstances—in our case, after the unexpected loss of an inventor—even nonstars seem to experience an increase in their bargaining power. The prerequisite for this, however, is that they have human and social capital to replace the lost collaborator since it is precisely their suitability to fill the gap that creates bargaining power.

Moreover, the literature on inventor teams has focused primarily on inventor complementarity rather than substitutability (Melero and Palomeras, 2015). The focus on complementarity is a consequence of the strong interest in knowledge diversity (Tortoriello et al., 2015; Horwitz and Horwitz, 2007) and innovation as an outcome of knowledge recombination (Nelson and Winter, 1982). However, as we show, substitutability in inventor teams is also highly relevant as a determinant of individual productivity and career outcomes. This is not only true for contexts in which an inventor changes his or her employer or dies suddenly. It also applies to situations where labor market frictions prevent hiring suitable inventors or scarce resources make hiring new employees impossible (Mawdsley and Somaya, 2016). Additionally, in the case of mergers and acquisitions, which primarily serve to realize synergy effects (O'Shaughnessy and Flanagan, 1998; Porter, 1985), selected employees may be dismissed. Then, it is essential to know which employees are "disposable"—or better replaceable—and by whom.

Our study is not without limitations. First, our experimental design allows for a causal interpretation of our results. However, we cannot directly observe the mechanisms underlying our results. Although we offer a theoretical framework, several robustness checks, and a conceptual discussion of alternative explanations, future research should seek to observe the allocation of resources among the remaining collaborators to substantiate how bargaining power affects their productivity. Future work should also investigate mechanisms other than bargaining power for a positive productivity effect, such as changes in the organization's strategy. Second, although our dataset contains detailed information about inventors, we do not observe the motives of the inventors or their roles within teams. Hence, we cannot exclude the possibility that these variables explain part of our findings. Our understanding of team dynamics would thus benefit from future research looking at who is on the team. Furthermore, we cannot rule out that the bargaining power mechanism is specific to particular (labor) market conditions. Prior research has shown that markets for inventors show variation in mobility rates, which implies, among other things, different degrees of labor market frictions (Mawdsley and Somaya, 2016). We use data on inventors across all industries with patenting activities in contemporary Germany. Future research may want to estimate the bargaining power mechanism in other countries, time windows, or selected industries (such as industries that are more or less dependent on tacit knowledge).

Despite these limitations, our work also has several practical implications. First, our results show that inventors with a similar profile are more likely to replace the lost collaborator. Hence, employing inventors with overlapping knowledge can benefit organizations in certain circumstances, such as when an inventor unexpectedly leaves the organization. This finding speaks against an extensive specialization and division of labor, which has been suggested in the economics literature (Brusoni et al., 2001). In a similar vein, Lecuona and Reitzig (2014) show, for Mexican plant workers, that an excess of human capital resources increases firm performance when the firms operate in sectors with high competitive pressure. While overlapping knowledge between team members can serve as a bridge to allow knowledge recombination in the first place (Dougherty, 1992; Hambrick et al., 1996), our study suggests that it may also help compensate for the unexpected and permanent loss of collaborators. Second, hiring former collaborators of currently employed inventors, in the literature referred to as comobility (see, e.g., Marx and Timmermans, 2017) or lift-outs (see, e.g., Groysberg and Abrahams, 2006), might be an option to acquire social capital. Third, companies collaborate to access resources such as knowledge they do not have in-house. When these resources are lost, companies seem to struggle to compensate for the loss. Collaboration can be beneficial. However, firms should be careful that collaboration does not lead them to unlearn how to invent themselves (Hsuan and Mahnke, 2011).

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Appendix

A1 Description of the data construction

We created a novel, linked inventor biography dataset - INV-BIO ADIAB 1980-2014, in the following: INV-BIO - which is based on inventor and patent information obtained from patent register data that is linked to administrative labor market career data on individuals and their employing establishments (for a detailed description, see Dorner et al. (2018)).

The INV-BIO data set records complete biographies of 152,350 inventors from 1980 until 2014. For this period, inventor track records based on patent registers of the European Patent Office (EPO) and the German Patent and Trademark Office (DPMA), and labor market biographies originating from social security data obtained from the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB) were combined in a research data set.

A1.1 Creation of the dataset

The sampling frame of the INV-BIO data is the population of inventors who are listed on patent applications filed with the EPO between 1999 and 2011 and resided in Germany at the time of the patent filing. The data were obtained from PATSTAT[16], the Worldwide Statistical Database offered by the EPO, which contains bibliographical and legal status patent data from leading industrialized and developing countries.

To identify unique inventors, a name disambiguation approach was needed. We used a methodological approach combining record linkage and techniques from machine learning. This approach enabled us to create disambiguated inventor IDs. The inventor names and residential addresses extracted from the patent records were used to identify inventors in the social security data between 1999 and 2011. In a subsequent step, we created consistent patent track records for the period between 1980 and 2014. To evaluate the data linkages, we used predictive methods from a machine learning toolkit.

Cases of inventors identified in the patent data, but not matched with the labor market data, arise mainly because they belong to a group of individuals that are not covered by general social security. In the IAB employment data, self-employed inventors, freelancers, civil servants, retirees, or students are not covered. Data quality issues are another reason. The latter are, however, not a major concern since the probabilistic record linkage algorithms that we used for the data generation enable fuzzy matchings and account for

[16] See https://www.epo.org/searching-for-patents/business/patstat.html, accessed on January 1, 2022.

misspellings of the names and addresses. Hence, we are confident that we identified the population of inventors except for the inventors not covered by social security data.

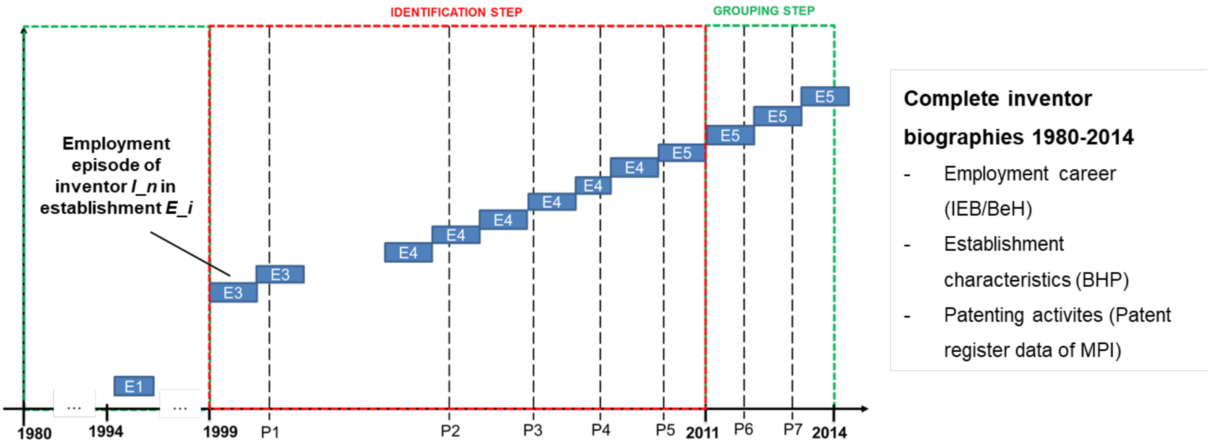
The INV-BIO dataset only contains inventors who were at least listed on one European (EP) patent during the time window 1999-2011 (see identification step in Figure A1-1). Individuals who made inventions for which no patent was filed because the inventors or their employers preferred secrecy over patenting are not included in our data. To get an understanding of the share of inventors we cover in our data, we use the average number of individuals with an academic degree that are reported as employees in research and development in the period 1999-2011. The number of reported individuals amounts to 637,308 individuals. The inventors in our dataset, hence, equal nearly 25% of the potentially patenting population of employees. These figures show that there is still a large number of potential inventors we do not cover in our data that observes inventors conditional on one EP patent filed between 1999 and 2011. We further conducted extensive checks of the quality of the data matches. Part of these checks is documented in the Appendix of Dorner et al. (2018).

The linked-employer-employee data liked with patent data contain socio-demographic characteristics of the individuals, information on employment, benefit receipts, job search activities, and variables describing the residential location. It also contains structural information about the German establishments the inventors in our data had been employed with throughout their careers as well as a comprehensive set of indicators describing the workforce of these establishments (e.g., number of employees, the share of workers by the level of education, occupation, wage level, demography), the precise location of the site, and the industrial classification of economic activities in the NACE scheme.

In the next step, we added the patent histories of the inventors comprising all patents filed between 1980 and 2014 with the EPO, the DPMA, or the World Intellectual Property Office (WIPO) (see grouping step in Figure A1-1). The matching was done based on inventor names, as well as on applicant/employer data recorded in the patent register and the labor market data. To ensure high-quality matches, we conducted various checks, including a manual check of a randomly drawn subsample of the data. The INV-BIO data include 643,856 patent families, as represented by patent documents covering a single invention and having exactly the same priority rights (leading to an identical date of first filing). This represents approximately 71.4% of the inventions for which an EP patent was filed by at least one inventor residing in Germany during the time window from 1999 until 2011. The patent data were supplemented with bibliographic and procedural data on the respective patents, including filing and grant dates, the technology classes assigned to the invention, the countries in which patent protection was requested by the applicant(s), and the forward citations the patents received from subsequent patents.

The structure of the dataset is displayed in Figure A1-1 below.

Figure A1-1: Structure of the linked inventor biography dataset INV-BIO



A1.2 Quality checks

To check the representativeness of our data for the population of all EP and all DE (German) patents, we conducted two tests. First, we compared the number of DOCDB patent families (each patent family consists of all patent documents that cover a single invention and that all have exactly the same first filing date) linked to unique inventors in our data with the total number of DE patent applications that included at least one German inventor. Our sample represents about 71.4% (yearly average) of this population of patent families between 1999 and 2011. The maximum coverage of almost 80% is realized in 2008. As a result of the cohort approach adopted, the representativeness drops outside of the 1999-2011 time window to a level of about 30%.

Second, we calculated the ratio of German patents by five technology main areas (mechanical engineering, process engineering, chemicals/pharma, instruments, and other areas) that are represented in the inventor-patent data of the INV-BIO dataset. We find some variation in the representativeness of our data across main technical areas. The best representation of patents in the 1999-2011 time window is achieved in chemistry. In some filing years, even more than 90% of the DE patent applications protecting inventions that were classified as chemistry by the patent examiners are in our dataset. On average, the representation remains very high at a level of above 80%. Also, the population of electrical engineering patents is largely represented in the INV-BIO data. Fields such as instruments and mechanical engineering show similar coverage rates of about 70% on average in the 1999-2011 time window. However, the coverage of patents assigned to the main area ‘other’ field is lower. One reason for the lower representation rate is that a large part of these patents is filed in civil engineering, an industrial segment in which public sector civil servants, researchers, and self-employed architects presumably play an important role. Both groups are not recorded in the social security data.

Given the large size of the sample in the 1999-2011 time window, we argue that estimates obtained from the data will yield a good approximation to population estimates. However, due to the lack of information on the actual inventor population, no inventor-level weights can be provided for statistical projection to the population level.

A1.3 Data availability

The linked inventor data (INV-BIO ADIAB 1980-2014) was made available to third parties in February 2019. The data can be used for non-commercial research projects via the FDZ of the BA at the IAB. The data access is carried out via an obligatory initial guest stay in Nuremberg (or one of the other FDZ locations) and the option of remote data access via JoSuA (see https://fdz.iab.de/en/FDZ_Individual_Data/INV-BIO-ADIAB/INV-BIO-ADIAB8014.aspx, accessed on January 1, 2022).

To protect the privacy of the individuals and establishments in the data and to limit the threat of potential de-anonymization, some information from the original register has been classified as sensitive. For instance, the information on work and residential location of the employee is only available at the level of cities and districts (NUTS 3 level). Furthermore, the technology and industry classifications are grouped, and patent characteristics, such as forward citations, are right-tail coarsened. For our work, we had access to un-grouped and un-coarsened data.

A2 Description of the variables

Table A2-1: Short variable descriptions

Variable	Description	Usage	Source
	Productivity		
Patents	Short-hand for Patents (Simple)		
Patents (Simple)	Number of EPO patent families with earliest filing year in the current year.	H	Inv
Patents (Lifetime)	Patents, cumulative until the current year. We coarsen the patent count to groups of 10-14, 15-19, 10s between 20 and 100, 50s between 100 and 300, and 400+	M	Inv
Patents (Citation-weighted)	Patents, weighted by the number of EP citations received within 5 years	H	Inv
Patents (Fractional)	Patents, but counting fractional shares by the number of inventors on a patent	H	Inv
	Career trajectory		
Promotion	Promotion event caused by a change in occupation from non-senior to senior (see below), by default excluding moves across employers. Some variants restrict to promotions that incorporate such a move.	H	Base, Own
Move	Mobility event caused by a change in the establishment to unemployment or another employer	H	Base, Own
	Individual variables		
Death (date)	Exit date from the social security data with reason death	H, M	Base
Age	Age of the inventor in the current year	M, C	Base
Male	Gender of the inventor (Male=1)	M	Base
Science & engineering worker	Occupation classification and education level indicate high-skilled worker in science and engineering	B	Base
Inventor senior	Occupation of the inventor in the current year is a senior, i.e., management occupation.	B, H	Base
Employer tenure	Number of years of employment at current establishment	M, B	Base
Employer size	Number of full-time employees of an establishment. Establishment size is coarsened in groups of <50, 50-249, 250-999, and 1,000+ employees while matching.	M, B	Base
Employer age	Age in years of the establishment in the social security data, censored in 1975	B	Base
Technological focus	Inventor's modal technology field (chemistry, instruments, electrical engineering, mechanical engineering, other)	M	Inv
	Continued on the next page ...		

Table A2-1: Short variable descriptions

Variable	Description	Usage	Source
Years since last patenting	Years between the latest earliest filing date of a patent application and the current time	M	Inv
Network size	Number of collaborators (co-inventors) of an inventor	B	Inv, Own
	Dyad variables		
Same employer	Whether a (pseudo-)deceased and remaining collaborator worked in the same establishment at the time of the (pseudo-)death	B, H	Own
Collaborator senior	Occupation of the (pseudo-)deceased inventor in the death year is a senior, i.e., management occupation.	B, H	Base
Joint tenure	Number of years two inventors worked in the same establishment	B, H	Base, Own
Joint patenting duration	Years between the first and the last joint patent of two inventors	B	Inv, Own
Joint patents	Number of patents two inventors jointly applied for	B	Inv, Own
Joint knowledge base	Overlap in technology between two inventors, operationalized with IPC4 technology class overlap.	B	Inv, Own
Replacement suitability	Short-hand for replacement suitability (patent-based)		
Replacement suitability (patent-based)	Similarity between deceased and remaining collaborator in terms of joint patents. Implemented as the intensity of joint patents of two inventors relative to their individual patenting. Patent-based similarity is high if the joint patent intensity has above-median importance for both deceased and remaining collaborator, which approaches a split at the 75th percentile.	H	Inv, Own
Replacement suitability (technology-based)	Similarity between deceased and remaining collaborator in terms of technology (joint knowledge base). Implemented as split at the 75th percentile.	H	Inv, Own
Replacement suitability (tenure-based)	Overlap between deceased and remaining collaborator in terms of tenure. Implemented as a split of the 'joint tenure' variable at the 75th percentile.	H	Inv, Own

Notes: M stands for Matching, C for control variable, B for variables used in balancing tests, H for hypothesis test. Data source: Base = IAB base data; Inv = INV-BIO ADIAB 8014; Own = Own calculation.

A2.1 Descriptive Tables

Table A2-2: Summary statistics and pair-wise correlations

Remaining collaborators		Summary		Pair-wise correlations							
Variable	Type	Mean	SD	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Patents (Simple)	DV	0.90	2.28	1.00							
(2) Patents (Lifetime)	M	7.31	4.89	0.30	1.00						
(3) Patents (Citation-weighted)	DV	1.31	6.69	0.56	0.15	1.00					
(4) Patents (Fractional)	DV	0.30	0.86	0.87	0.28	0.39	1.00				
(5) Promotion	DV	0.16	0.36	0.06	0.08	0.04	0.04	1.00			
(6) Move	DV	0.40	0.49	-0.01	-0.08	-0.00	-0.01	-0.00	1.00		
(7) Age	IndV	46.06	9.72	-0.09	0.23	-0.05	-0.06	-0.11	-0.16	1.00	
(8) Male	M	0.93	0.26	0.03	0.11	-0.00	0.05	0.04	-0.05	0.15	1.00
(9) Science & engin. worker	B	0.48	0.50	0.09	0.14	0.05	0.06	0.09	-0.01	-0.08	0.06
(10) Collaborator senior	IndV	0.10	0.30	0.01	0.09	0.00	0.01	-0.04	0.00	0.12	0.04
(11) Employer tenure	M	10.16	8.24	-0.02	0.12	-0.03	-0.00	0.01	-0.25	0.47	0.06
(12) Employer size (000)	M	5.07	9.70	0.07	0.12	0.03	0.05	0.13	-0.11	-0.04	-0.00
(13) Employer age	B	22.71	11.97	0.01	0.06	-0.03	0.01	0.07	-0.15	0.04	-0.00
(14) Years since last patenting	M	2.64	3.03	-0.35	-0.33	-0.17	-0.31	-0.08	0.01	0.27	-0.05
(15) Network size	B	13.04	14.97	0.24	0.56	0.18	0.16	0.08	-0.06	0.14	0.01
(16) Same employer	IndV	0.54	0.50	0.05	0.01	0.04	0.04	0.05	-0.06	-0.06	-0.01
(17) Deceased inventor senior	IndV	0.13	0.33	0.01	0.02	0.00	0.00	0.02	0.00	-0.02	0.01
(18) Joint tenure	B	5.47	6.89	0.01	0.05	-0.00	0.01	0.01	-0.11	0.15	0.01
(19) Joint patenting duration	M	2.00	2.42	0.07	0.25	0.04	0.06	-0.00	-0.02	0.13	0.05
(20) Joint patents	B	2.29	3.50	0.14	0.26	0.10	0.08	-0.01	0.01	0.03	0.03
(21) Joint knowledge base	IndV	0.54	0.26	-0.02	-0.12	0.02	-0.04	-0.01	0.03	-0.04	-0.03
(22) Replacement suitability	IndV	0.28	0.45	-0.10	-0.36	-0.05	-0.11	-0.04	0.06	-0.05	-0.03

	Pair-wise correlations (continued)													
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
(9)	1.00													
(10)	-0.31	1.00												
(11)	-0.09	0.01	1.00											
(12)	0.07	-0.00	0.15	1.00										
(13)	-0.02	0.00	0.49	0.27	1.00									
(14)	-0.12	0.00	0.05	-0.05	0.01	1.00								
(15)	0.08	0.05	0.08	0.16	0.04	-0.20	1.00							
(16)	0.04	-0.04	0.18	0.10	0.08	-0.13	0.01	1.00						
(17)	-0.05	0.11	-0.01	0.02	0.04	-0.02	0.02	-0.05	1.00					
(18)	-0.02	-0.02	0.52	0.13	0.26	-0.04	0.03	0.71	-0.04	1.00				
(19)	0.04	0.05	0.10	-0.02	0.01	-0.09	0.13	0.11	0.04	0.17	1.00			
(20)	0.05	0.03	0.01	0.02	-0.01	-0.09	0.18	0.09	0.08	0.08	0.55	1.00		
(21)	-0.05	-0.03	-0.01	-0.11	-0.03	0.06	-0.03	0.15	-0.05	0.10	0.15	0.19	1.00	
(22)	-0.08	-0.03	-0.03	-0.08	-0.04	0.16	-0.23	0.07	-0.06	0.04	0.13	0.23	0.41	1.00

Notes: Variable types are dependent variable (DV), independent variable (IndV), match variable (M) and balancing test variable (B).

Table A2-3: Pre-death characteristics of deceased inventors and the remaining collaborators

Deceased inventors	Deceased (N = 845)			Pseudo-deceased (N = 845)				
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Diff.	p-value
Patents (Lifetime)	6.08	3.00	7.69	5.98	3.00	7.43	0.10	0.792
Age	49.25	51.00	7.34	49.25	51.00	7.34	0.00	1.000
Male	0.96	1.00	0.20	0.96	1.00	0.20	0.00	1.000
Science & engin. worker	0.39	0.00	0.49	0.41	0.00	0.49	−0.02	0.333
Not senior inventor	0.91	1.00	0.29	0.89	1.00	0.31	0.01	0.370
Employer tenure	12.03	10.00	9.18	11.89	10.00	8.91	0.14	0.755
Employer size	4041.19	777.50	9229.49	3504.52	790.00	7961.90	536.67	0.204
Employer age	22.38	26.00	11.73	22.29	26.00	11.68	0.08	0.887
Years since last patenting	3.43	2.00	3.43	3.37	2.00	3.30	0.05	0.740
Network size of inventor	5.57	3.00	8.36	5.35	3.00	7.77	0.22	0.569
Remaining collaborators	**Deceased (N = 3574)**			**Pseudo-deceased (N = 3409)**				
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Diff.	p-value
Patents (Lifetime)	11.57	7.00	10.57	11.05	7.00	10.40	0.51	0.041**
Age	45.62	45.00	9.15	45.40	44.00	9.35	0.22	0.325
Male	0.93	1.00	0.25	0.92	1.00	0.27	0.01	0.043**
Science & engin. worker	0.49	0.00	0.50	0.50	0.00	0.50	0.00	0.725
Not senior inventor	0.90	1.00	0.31	0.91	1.00	0.29	−0.01	0.144
Employer tenure	10.22	8.00	8.15	9.96	8.00	8.02	0.26	0.203
Employer size	5086.72	1394.00	9635.34	4900.01	1388.00	9400.82	186.71	0.433
Employer age	22.53	27.00	11.83	22.86	28.00	11.91	−0.33	0.265
Years since last patenting	2.01	1.00	2.37	2.03	1.00	2.30	−0.03	0.641
Remaining collaborators	**Deceased (N = 3574)**			**Pseudo-deceased (N = 3409)**				
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Diff.	p-value
Same employer	0.53	1.00	0.50	0.56	1.00	0.50	−0.02	0.059*
Joint tenure	5.57	2.25	7.14	5.47	3.00	6.72	0.10	0.560
Joint patenting duration	2.01	1.00	2.47	2.00	1.00	2.41	0.01	0.849
Collaborator not senior	0.89	1.00	0.32	0.87	1.00	0.34	0.01	0.078*
Joint patents	2.27	1.00	3.45	2.29	1.00	3.51	−0.02	0.807
Joint knowledge base	0.54	0.54	0.26	0.53	0.54	0.27	0.01	0.105

Notes: This table presents summary statistics of pre-death characteristics of deceased inventors and their matched control group. The unit of observation is at the deceased inventor (first part) or remaining collaborator (second and third part) level. Reported p-values based on an unpaired t-test. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

A3 Productivity estimates

Table A3-1: Impact of inventor death on the productivity for the remaining collaborators – simple and citation-weighted patent counts (Event study estimates)

DV: log	(1)	(2)	(3)	(4)	(5)	(6)
	Patents			Patents (citation-weighted)		
	All	Same employer	Different employer	All	Same employer	Different employer
Death −4/−5	−0.003	−0.032	0.023	0.011	−0.022	0.042
	(0.017)	(0.023)	(0.024)	(0.021)	(0.030)	(0.029)
Death year−3	0.005	−0.026	0.039*	0.026	−0.011	0.066**
	(0.017)	(0.024)	(0.024)	(0.022)	(0.031)	(0.030)
Death year−2	−0.008	−0.014	−0.001	0.000	0.000	0.000
	(0.015)	(0.022)	(0.021)	(.)	(.)	(.)
Death year−1	0.000	0.000	0.000	−0.015	−0.007	−0.026
	(.)	(.)	(.)	(0.021)	(0.030)	(0.028)
Death year	−0.015	−0.018	−0.013	−0.020	−0.023	−0.019
	(0.014)	(0.020)	(0.019)	(0.020)	(0.030)	(0.027)
Death year+1	−0.017	−0.003	−0.034*	−0.015	0.004	−0.042
	(0.015)	(0.021)	(0.020)	(0.020)	(0.029)	(0.028)
Death year+2	−0.015	−0.017	−0.015	0.005	0.022	−0.025
	(0.015)	(0.022)	(0.021)	(0.021)	(0.030)	(0.029)
Death year+3	−0.027*	−0.023	−0.035	−0.039*	−0.034	−0.055*
	(0.016)	(0.023)	(0.022)	(0.022)	(0.031)	(0.030)
Death year+4	−0.044**	−0.028	−0.070***	−0.030	−0.015	−0.059*
	(0.017)	(0.024)	(0.024)	(0.023)	(0.033)	(0.031)
Death year+5	−0.030*	−0.038	−0.031	−0.006	−0.006	−0.021
	(0.018)	(0.025)	(0.025)	(0.023)	(0.034)	(0.032)
Collaborator FE	Yes	Yes	Yes	Yes	Yes	Yes
Collaborator age	Yes	Yes	Yes	Yes	Yes	Yes
Calendar year FE	Yes	Yes	Yes	Yes	Yes	Yes
Collaborators	6983	3797	3186	6983	3797	3186
Observations	70308	38281	32027	70308	38281	32027
Adj. R2	0.08	0.08	0.09	0.08	0.08	0.08

Notes: This table reports the estimates from a linear regression with collaborator, collaborator age, and year fixed effects. The dependent variables (simple and citation-weighted patent counts) is log-transformed. The coefficients can thus be interpreted as semi-elasticities. The unit of observation is at the remaining collaborator level. Robust standard errors clustered at the collaborator level in parentheses. * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table A3-2: Impact of inventor death on the productivity for the remaining collaborators – simple and citation-weighted patent counts (DiD estimates)

DV: IHS	(1)	(2)	(3)	(4)	(5)	(6)
	Patents			Patents (citation-weighted)		
	All	Same employer	Different employer	All	Same employer	Different employer
Death × Post	−0.027**	0.002	−0.062***	−0.031**	0.006	−0.078***
	(0.013)	(0.018)	(0.018)	(0.015)	(0.022)	(0.021)
Collaborator FE	Yes	Yes	Yes	Yes	Yes	Yes
Collaborator age FE	Yes	Yes	Yes	Yes	Yes	Yes
Calendar year FE	Yes	Yes	Yes	Yes	Yes	Yes
Collaborators	6983	3797	3186	6983	3797	3186
Observations	70308	38281	32027	70308	38281	32027
Adj. R2	0.08	0.08	0.09	0.08	0.08	0.08

DV: log	(7)	(8)	(9)	(10)	(11)	(12)
	Patents (fractional)			Patents		
	All	Same employer	Different employer	All	Same employer	Different employer
Death × Post	−0.012**	−0.002	−0.023***	−0.020**	0.003	−0.048***
	(0.006)	(0.008)	(0.008)	(0.010)	(0.014)	(0.014)
Collaborator FE	Yes	Yes	Yes	Yes	Yes	Yes
Collaborator age FE	Yes	Yes	Yes			
Inventor age				Yes	Yes	Yes
Calendar year FE	Yes	Yes	Yes	Yes	Yes	Yes
Collaborators	6983	3797	3186	6983	3797	3186
Observations	70308	38281	32027	70308	38281	32027
Adj. R2	0.05	0.05	0.06	0.08	0.07	0.08

DV: log	(13)	(14)	(15)	(16)	(17)	(18)
	Patents (Pseudo/Deceased cluster)			Patents (Deceased cluster)		
	All	Same employer	Different employer	All	Same employer	Different employer
Death × Post	−0.020	0.003	−0.048**	−0.020	0.003	−0.048**
	(0.017)	(0.024)	(0.019)	(0.015)	(0.021)	(0.019)
Collaborator FE	Yes	Yes	Yes	Yes	Yes	Yes
Collaborator age FE	Yes	Yes	Yes	Yes	Yes	Yes
Calendar year FE	Yes	Yes	Yes	Yes	Yes	Yes
Collaborators	6983	3797	3186	6983	3797	3186
Clusters	1349	1007	920	784	659	637
Observations	70308	38281	32027	70308	38281	32027
Adj. R2	0.08	0.07	0.08	0.08	0.07	0.08

Notes: This table reports the estimates from a linear regression with collaborator, collaborator age, and year fixed effects. The dependent variables (simple and citation-weighted patent counts) is log-transformed. The coefficients can thus be interpreted as semi-elasticities. The unit of observation is at the remaining collaborator level. Robust standard errors clustered at the collaborator level in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

A4 Promotion estimates

Table A4-1: Impact of death on promotion events for the remaining collaborators (Cox hazard estimates)

	(1)	(2)	(3)	(4)	(5)	(6)
	Same employer			Different employer		
DV: Promotion	<0.5 years	<1 year	<2 years	<0.5 years	<1 year	<2 years
Deceased	0.185	0.258	0.127	0.281	0.119	−0.071
	(0.307)	(0.245)	(0.166)	(0.443)	(0.294)	(0.204)
Deceased senior	−22.090***	−1.643**	−1.072**	−0.048	0.345	0.362
	(0.541)	(0.761)	(0.443)	(0.804)	(0.408)	(0.288)
Deceased × Deceased senior	22.814	1.982**	0.921*	−0.424	0.074	0.286
	(.)	(0.882)	(0.544)	(1.364)	(0.569)	(0.391)
Collaborator age	Yes	Yes	Yes	Yes	Yes	Yes
Death year FE	Yes	Yes	Yes	Yes	Yes	Yes
Events	40	71	174	22	59	134
Collaborators	3742	3742	3742	3161	3161	3161

Notes: Hazard ratio estimates from a Cox regression with death year fixed effects and age, age squared covariates. Robust standard errors in parentheses. Stratified by modal main technology area. The standard error of the interaction coefficient in column one could not be estimated because, until this point, no promotion events occurred in the group of remaining collaborators connected to pseudo-deceased inventors. This is also visible in the Kaplan-Meier estimates of Figure 5. * p<0.1, ** p<0.05, *** p<0.01.

Table A4-2: Robustness: Impact of death on promotion events for the remaining collaborators (Cox hazard estimates)

Promotion type	(1) Exclude moves	(2) Allow moves	(3) Only moves
Deceased	0.258	0.274	0.201
	(0.245)	(0.228)	(0.597)
Deceased senior	-1.643^{**}	-1.065^{*}	0.192
	(0.761)	(0.563)	(0.860)
Deceased × Deceased senior	1.982^{**}	1.222^{*}	−44.462
	(0.882)	(0.714)	(.)
Collaborator age	Yes	Yes	Yes
Death year FE	Yes	Yes	Yes
Events	71	86	15
Collaborators	3742	3742	3742

Stratification	(4) Technology	(5) Death year	(6) Without
Deceased	0.258	0.313	0.313
	(0.245)	(0.251)	(0.251)
Deceased senior	-1.643^{**}	-1.339^{*}	-1.338^{*}
	(0.761)	(0.733)	(0.734)
Deceased × Deceased senior	1.982^{**}	1.549^{*}	1.556^{*}
	(0.882)	(0.851)	(0.858)
Collaborator age	Yes	Yes	Yes
Death year FE	Yes	Yes	Yes
Events	71	71	71
Collaborators	3742	3742	3742

Notes: Hazard ratio estimates from a Cox regression with death year fixed effects and age, age squared covariates. Robust standard errors in parentheses. Stratified by modal main technology area (columns 1-4), alternatively by death year (column 5), and without stratification (column 6). * p<0.1, ** p<0.05, *** p<0.01.

A5 Mobility estimates

Table A5-1: Robustness: Mobility for the remaining collaborators (Cox hazard estimates)

	Move, by stratification, <0.5 years			Job-to-job, same employer		
	(1) Technology	(2) Death year	(3) Without	(4) <0.5 years	(5) <1 year	(6) <2 years
Deceased	−0.529***	−0.529***	−0.560***	−0.612***	−0.188	0.045
	(0.162)	(0.162)	(0.163)	(0.178)	(0.122)	(0.093)
Collaborator age	Yes	Yes	Yes	Yes	Yes	Yes
Death year FE	Yes	Yes	Yes	Yes	Yes	Yes
Events	168	168	168	134	267	455
Collaborators	3797	3797	3797	3797	3797	3797

Notes: Hazard ratio estimates from a Cox regression with death year fixed effects and age, age squared covariates. Robust standard errors in parentheses. Stratified by modal main technology area. * p<0.1, ** p<0.05, *** p<0.01.

Table A5-2: Impact of death on the mobility for the remaining collaborators by patenting-based replacement suitability (Cox hazard estimates)

	(1)	(2)	(3)	(4)	(5)	(6)
Same employer	High replacement suitability			Small replacement suitability		
DV: Move	<0.5 years	<1 year	<2 years	<0.5 years	<1 year	<2 years
Deceased	−0.846***	−0.105	−0.063	−0.375*	−0.162	0.133
	(0.273)	(0.175)	(0.144)	(0.205)	(0.142)	(0.105)
Collaborator age	Yes	Yes	Yes	Yes	Yes	Yes
Death year FE	Yes	Yes	Yes	Yes	Yes	Yes
Events	62	123	193	106	212	376
Collaborators	1142	1142	1142	2655	2655	2655
	(7)	(8)	(9)	(10)	(11)	(12)
Different employer	High replacement suitability			Small replacement suitability		
DV: Move	<0.5 years	<1 year	<2 years	<0.5 years	<1 year	<2 years
Deceased	−0.318	−0.101	0.044	0.015	−0.091	−0.020
	(0.283)	(0.202)	(0.156)	(0.167)	(0.124)	(0.096)
Collaborator age	Yes	Yes	Yes	Yes	Yes	Yes
Death year FE	Yes	Yes	Yes	Yes	Yes	Yes
Events	48	94	157	145	260	448
Collaborators	756	756	756	2430	2430	2430

Notes: Hazard ratio estimates from a Cox regression with death year fixed effects and age, age squared covariates. Robust standard errors in parentheses. Replacement suitability is defined according to the joint patenting of deceased and remaining collaborator, see Table A2-1. Stratified by modal main technology area. * p<0.1, ** p<0.05, *** p<0.01.

Table A5-3: Impact of death on the mobility for the remaining collaborators by tenure-based replacement suitability (Cox hazard estimates)

	(1)	(2)	(3)	(4)	(5)	(6)
Same employer	High replacement suitability			Small replacement suitability		
DV: Move	<0.5 years	<1 year	<2 years	<0.5 years	<1 year	<2 years
Deceased	−0.621**	−0.222	0.012	−0.459**	−0.089	0.100
	(0.292)	(0.184)	(0.142)	(0.195)	(0.137)	(0.105)
Collaborator age	Yes	Yes	Yes	Yes	Yes	Yes
Death year FE	Yes	Yes	Yes	Yes	Yes	Yes
Events	48	115	194	120	220	375
Collaborators	1731	1731	1731	2066	2066	2066

	(7)	(8)	(9)	(10)	(11)	(12)
Different employer	High replacement suitability			Small replacement suitability		
DV: Move	<0.5 years	<1 year	<2 years	<0.5 years	<1 year	<2 years
Deceased	0.000	36.152***	48.669***	−0.082	−0.129	−0.031
	(.)	(0.665)	(1.022)	(0.145)	(0.107)	(0.083)
Collaborator age	Yes	Yes	Yes	Yes	Yes	Yes
Death year FE	Yes	Yes	Yes	Yes	Yes	Yes
Events	2	6	7	191	348	598
Collaborators	11	11	11	3175	3175	3175

Notes: Hazard ratio estimates from a Cox regression with death year fixed effects and age, age squared covariates. Robust standard errors in parentheses. Replacement suitability is defined according to the tenure of deceased and remaining collaborator, see Table A2-1. Stratified by modal main technology area. * p<0.1, ** p<0.05, *** p<0.01.

Table A5-4: Impact of death on the mobility for the remaining collaborators by technology-based replacement suitability (Cox hazard estimates)

	(1)	(2)	(3)	(4)	(5)	(6)
Same employer	High replacement suitability			Small replacement suitability		
DV: Move	<0.5 years	<1 year	<2 years	<0.5 years	<1 year	<2 years
Deceased	−0.689**	0.047	0.081	−0.455**	−0.218	0.040
	(0.345)	(0.204)	(0.158)	(0.189)	(0.133)	(0.100)
Collaborator age	Yes	Yes	Yes	Yes	Yes	Yes
Death year FE	Yes	Yes	Yes	Yes	Yes	Yes
Events	42	96	162	126	239	407
Collaborators	1104	1104	1104	2693	2693	2693
	(7)	(8)	(9)	(10)	(11)	(12)
Different employer	High replacement suitability			Small replacement suitability		
DV: Move	<0.5 years	<1 year	<2 years	<0.5 years	<1 year	<2 years
Deceased	−0.256	−0.127	0.073	−0.032	−0.089	−0.040
	(0.348)	(0.234)	(0.190)	(0.160)	(0.120)	(0.091)
Collaborator age	Yes	Yes	Yes	Yes	Yes	Yes
Death year FE	Yes	Yes	Yes	Yes	Yes	Yes
Events	36	76	118	157	278	487
Collaborators	641	641	641	2545	2545	2545

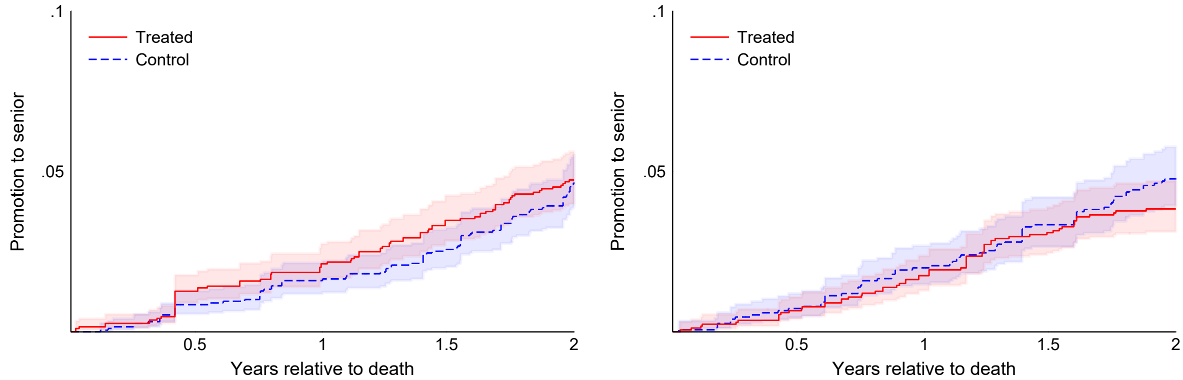
Notes: Hazard ratio estimates from a Cox regression with death year fixed effects and age, age squared covariates. Robust standard errors in parentheses. Technology-based replacement suitability is defined according to the joint knowledge base of deceased and remaining collaborator, see Table A2-1. Stratified by modal main technology area. * p<0.1, ** p<0.05, *** p<0.01.

A6 Figures

Figure A6-1: Impact of inventor death on promotion to a senior position for all remaining collaborators (Kaplan–Meier estimates)

(a) Same employer

(b) Different employer

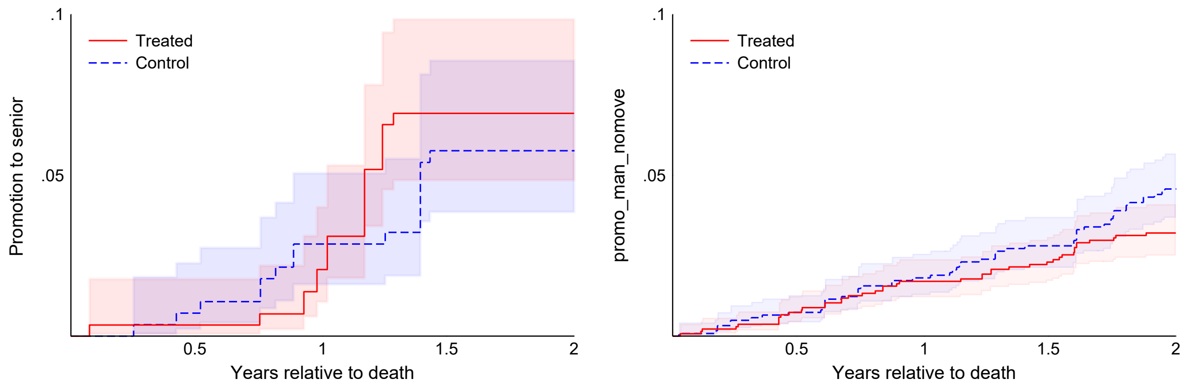


Notes: This figure presents plotted Kaplan-Meier estimates for promotion events for the remaining collaborators after the deceased inventor's death. The unit of observation is at the collaborator level. Confidence intervals are at the 90% level. Corresponding Cox hazard estimates can be found in Table 3.

Figure A6-2: Impact of inventor death on promotion to a senior position for the remaining collaborators working for a different employer (Kaplan-Meier estimates)

(a) Deceased inventor held senior position

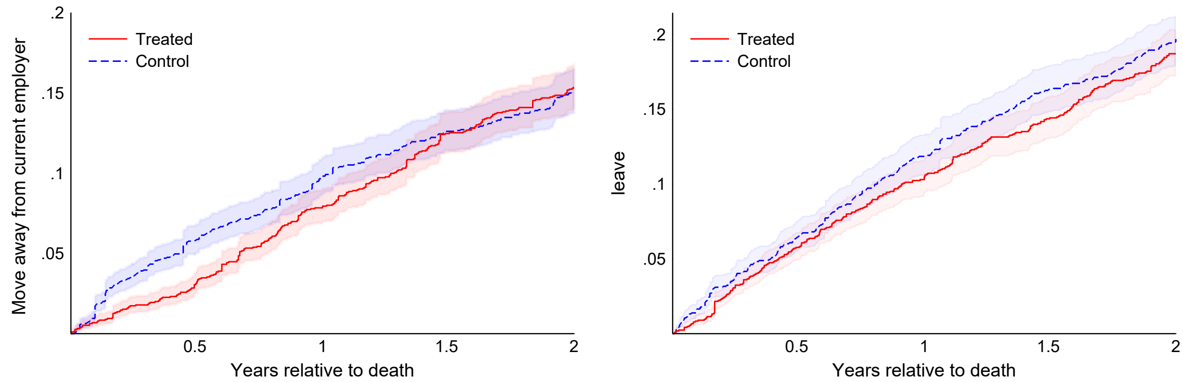
(b) Deceased inventor held no senior position



Notes: This figure presents plotted Kaplan-Meier estimates for promotion events for the remaining collaborators after the deceased inventor's death. The unit of observation is at the collaborator level. Confidence intervals are at the 90% level. Corresponding Cox hazard estimates can be found in Table A4-1.

Figure A6-3: Impact of inventor death on the mobility of the remaining collaborators (Kaplan-Meier estimates)

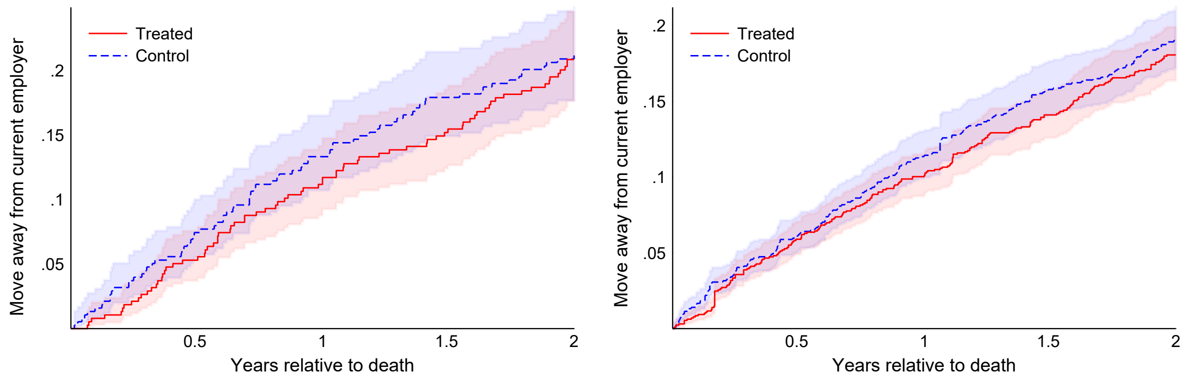
(a) Same employer (b) Different employer



Notes: This figure presents plotted Kaplan-Meier estimates for move events for the remaining collaborators after the deceased inventor's death. The unit of observation is at the collaborator level. Confidence intervals are at the 90% level. Corresponding Cox hazard estimates can be found in Table 4.

Figure A6-4: Impact of inventor death on the mobility of the remaining collaborators working for a different employer, by patenting-based replacement suitability (Kaplan-Meier estimates)

(a) High replacement suitability (b) Small replacement suitability



Notes: This figure presents plotted Kaplan-Meier estimates for move events for the remaining collaborators after the deceased inventor's death. Replacement suitability is defined according to the joint patenting of deceased and remaining collaborator, see Table A2-1. The unit of observation is at the collaborator level. Confidence intervals are at the 90% level. Corresponding Cox hazard estimates can be found in Table A5-2. For the same employer subsample, see Figure 6 in the main text.