Filling the Gap:

The Consequences of Collaborator Loss in Corporate R&D

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ABSTRACT

We examine how collaborator loss affects the individual productivity of knowledge workers in corporate R&D. Specifically, we argue that the effect of such loss depends on whether the lost collaborator was internal or external to the organization, which may have compensatory measures in place to maintain the continuity of R&D efforts. To empirically investigate the effect of internal and external collaborator loss, we leverage 845 unexpected deaths of active inventors. We find a substantial negative effect on inventive productivity for the loss of external collaborators, particularly when the collaborator was of presumably high relevance to the remaining inventor. In contrast, the effect for the loss of internal collaborators is virtually zero. We show that the organization's knowledge management and hiring capabilities are instrumental in explaining the muted effect of internal collaborator loss.

KEYWORDS: Collaboration, innovation, inventors, patents, teams.

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1 Introduction

Knowledge generation is increasingly pursued through collaboration (Wu et al., 2019; Wuchty et al., 2007), where novel insights often arise from the combined inputs of different individuals (Kogut and Zander, 1992). Consequently, a knowledge worker's productivity benefits from collaboration with others (Akcigit et al., 2018). Supporting this, several studies have shown that the loss of a collaborator (e.g., due to death or visa denial) lowers individual productivity, and have examined various characteristics of the lost collaborator and the collaborative relationship that moderate the negative effect on productivity (Azoulay et al., 2010; Bernstein et al., 2022; Choudhury et al., 2024; Jaravel et al., 2018; Khanna, 2021; Mohnen, 2022; Oettl, 2012). However, these studies have not paid much attention to the fact that most knowledge workers (e.g., corporate inventors) are embedded into organizations whose boundaries, delineating internal from external collaborators, and actions may matter for the consequences of collaborator loss.

In this paper, we argue that the effect of collaborator loss on individual productivity depends on whether the lost collaborator is *internal* or *external* to the remaining knowledge worker's organization. Specifically, we suggest that, ceteris paribus, internal collaborator loss has a less negative effect on a remaining knowledge worker's productivity because of organizational measures designed to maintain the continuity of R&D efforts. These measures often involve knowledge management efforts, such as codification and sharing among employees, to counteract knowledge loss (Alavi and Leidner, 2001; Davenport and Prusak, 1998), as well as efforts in hiring and team reconfiguration to "fill the gap" created by the lost collaborator (Lecuona and Reitzig, 2014; Åstebro et al., 2023). While such compensatory measures can help organizations reduce the negative consequences of internal collaborator loss, they remain rather ineffective in the case of external collaborator loss. Consequently, external collaborator loss is likely to have a more substantial negative effect on a remaining knowledge worker's productivity than internal collaborator loss.

We empirically investigate the effects of internal and external collaborator loss among corporate inventors, whose collaborative networks often span organizational boundaries (Agrawal et al., 2006; Fleming et al., 2007). Specifically, we study the impact on inventive productivity, measured in patent output, of inventors who experienced the unexpected death of a prior co-inventor either from the same or a different organization. To precisely delineate collaborations along organizational boundaries, we use the INV-BIO dataset (Dorner et al., 2018). This dataset is based on social security records and tracks the exact employment status as well as patent output of more than 150,000 inventors in Germany from 1980 to 2014. Within this dataset, we identify 845 plausibly exogenous deaths of co-inventors and treat these as instances of collaborator loss for approximately 3,500 inventors who had patented with them at least once in the ten years prior to the inventor's death. As control group, we draw on inventors who had patented with 845 carefully matched 'pseudo-deceased' co-inventors. Using a difference-in-differences design, we investigate the effect of collaborator loss on individual inventive productivity.

In line with prior research, we find a moderate but imprecisely estimated negative effect of collaborator loss on inventive productivity. Over an 8-year period following collaborator loss, the inventive productivity of treated inventors is about 4% lower compared to the control group. This negative effect increases to about 6% when inventive productivity is measured using a quality-weighted patent count.

We find a substantially stronger negative effect on inventive productivity for the loss of external collaborators—with a decrease of 8% in simple patent counts and 14% in quality-weighted patent counts—while the effect for the loss of internal collaborators is virtually zero. These differences become even more pronounced when focusing on collaborators with high relevance for productivity, as argued in the prior literature. Specifically, the loss of an external collaborator has a particularly detrimental effect on inventive productivity if the collaborator held complementary knowledge, had a large network, or the collaboration with the remaining inventor was intensive. In contrast, the loss of internal collaborators with such characteristics still shows no negative effect on inventive productivity.

We present indicative evidence that the muted consequences of internal collaborator loss on inventive productivity are due to compensatory measures by the remaining inventor's organization. First, we find that the impact of internal collaborator loss varies with the organization's knowledge management and hiring capabilities. In organizations with low knowledge management and hiring capabilities, the effect of internal collaborator loss on inventive productivity is negative and sizable, whereas in organizations with high capabilities, the effect of internal collaborator loss turns even positive. This effect heterogeneity by organizational capabilities does not exist for external collaborator loss, suggesting that knowledge management and "filling the gap" efforts are less effective in addressing collaborator loss beyond organizational boundaries. Second, taking a closer look at the remaining inventor's patent output following internal collaborator loss, we find that the organization's compensatory measures appear to help sustain the remaining inventor's inventive productivity by providing access to internal knowledge and new collaborators. In organizations with high knowledge management capabilities, the loss of an internal collaborator increases the remaining inventor's patent output that relies on internal knowledge. Likewise, in organizations with high hiring capabilities, the loss of an internal collaborator increases the remaining inventor's patent output that involves new or newly hired internal collaborators.

Notably, further results suggest that an organization's compensatory measures can reach their limits when tasked with filling the substantial gaps left by highly productive collaborators. The effect of internal collaborator loss varies with the lost collaborator's prior performance. While the loss of a low-performing internal collaborator can even enhance inventive productivity, the loss of a high-performing internal collaborator has a significant negative effect.

Our study contributes to the literature in several ways. First, we extend previous research on collaborator loss among knowledge workers by highlighting the importance of organizational boundaries. This distinction is critical for understanding the consequences of collaborator loss; especially given that knowledge worker networks frequently include internal as well as external collaborators (Agrawal et al., 2006; Breschi and Lissoni, 2004; Fleming et al., 2007).

Second, our study contributes to the literature on peer effects in the workplace. So far, this literature does not agree on whether peer effects affect the productivity of co-workers (Marshall, 1890; Mas and Moretti, 2009; Waldinger, 2012; Cornelissen et al., 2017). Following this literature, one might infer from a null effect of collaborator loss within an organization that direct colleagues do not matter for a knowledge worker's productivity. However, our findings suggest that this can be an oversimplification. The muted effects of internal collaborator loss likely reflect compensating measures taken by the organization.

Third, our study adds to the literature on knowledge production in firms (Aggarwal et al., 2020; Argyres et al., 2020; Kapoor and Adner, 2012; Chang, 2023) by emphasizing the organization's role in managing collaborations. Our findings suggest that organizations' proactive and reactive strategies, such as knowledge management and "filling the gap," can effectively mitigate the impacts of collaborator loss on individual productivity—an important insight given that the most productive knowledge workers, who are also the most mobile, often depart sooner than the organization would prefer (Ng et al., 2007). However, our findings also reveal limitations in these strategies when it comes to external knowledge workers, whose contribution can be crucial for a firm's R&D efforts.

2 Conceptual framework

2.1 Collaborator loss and knowledge worker productivity

The prior literature provides ample evidence for the negative effect of collaborator loss on knowledge worker productivity, typically assessed through publication output for scientists and patent output for inventors. While collaborator loss can manifest in multiple ways, the death of a collaborator is most frequently analyzed in the prior literature, as other forms of loss introduce greater complexity from an econometric perspective.

The loss of a collaborator can have a long-lasting detrimental effect on productivity, particularly when the collaborator held complementary knowledge that is difficult to replace from other sources and where the collaborator was particularly productive. For example, Azoulay et al. (2010) find that the death of star scientists decreases the coauthors' productivity in the long run, attributing this decline to the permanent loss of knowledge the co-authors do not hold themselves or can access otherwise. Oettl (2012) shows that the death of a star scientist who contributed "helpful" knowledge significantly reduces productivity. Bernstein et al. (2022) observe that the death of inventors with a diverse (i.e., foreign) knowledge base disproportionately affects their colleagues' productivity. Similarly, the loss of a collaborator can severely affect productivity if the collaborator's network provided unique access to complementary knowledge. Mohnen (2022) investigates how the death of biomedical scientists affects productivity in their co-author network. She discovers that the effect on co-author productivity is particularly detrimental when the deceased scientist provided connections to otherwise inaccessible scientists and their knowledge, i.e., when the deceased scientist was part of a large otherwise inaccessible network.

Moreover, the collaboration intensity between the knowledge worker and the collaborator can moderate the effect of collaborator loss on productivity. Jaravel et al. (2018) observe that collaborator loss has a particularly severe negative effect on inventor productivity when prior collaborations were frequent, suggesting that substantial investments in the collaborative relationship enhance its effectiveness. Similarly, Choudhury et al. (2024) demonstrate that productivity (proxied through performance ratings) suffers most when the lost collaborator and the knowledge worker share a common language and culture, facilitating communication and understanding.

However, the literature to date has not fully taken into account the role of the boundaries of the organization for the consequences of collaborator loss. A knowledge worker's collaborative network often extends beyond organizational boundaries, including both internal and external collaborators. Internal collaborators may include colleagues from the same or different divisions within the organization (Argyres et al., 2020; Aggarwal et al., 2020). External collaborators typically work in different organizations such as (other) subsidiaries, industry partners, competitors, or academic institutions. Often, these external collaborators are former colleagues with whom the knowledge worker has stayed in contact. The distinction between internal and external collaborator loss is relevant because, as we argue below, organizations can better compensate for the loss of an internal than an external collaborator.

2.2 How organizations compensate for collaborator loss and the role of organizational boundaries

Knowledge workers are valuable assets of organizations whose ability to generate new insights is crucial for a firm's R&D efforts and for maintaining competitive advantage (Grant, 1996). To address this, organizations implement ex-ante and ex-post measures designed to compensate for the loss of collaborators, such as employee mobility or the death of an employee.

Ex-ante, organizations can mitigate the knowledge loss associated with collaborator loss by promoting knowledge management. Active knowledge management encompasses processes and mechanisms such as documentation, databases, and knowledge repositories that disseminate and codify employee knowledge. This ensures that valuable information remains within the organization even after individuals leave (Kogut and Zander, 1992; Davenport and Prusak, 1998; Alavi and Leidner, 2001; Renzl, 2008). By codifying knowledge and creating redundancy, knowledge management efforts help preserve knowledge (Mårtensson, 2000; Heaton and Taylor, 2002; Lecuona and Reitzig, 2014), thereby minimizing the negative impact of collaborator loss on the productivity of remaining knowledge workers.

Ex-post, organizations can fill the gap created by collaborator loss through hiring and internal reconfiguration (Åstebro et al., 2023). By actively recruiting and onboarding a new knowledge worker with a similar profile, organizations can replenish lost knowledge and maintain the diversity needed for effective knowledge generation (Mercan and Schoefer, 2020). Alternatively, organizations may reassign a current employee to affected R&D projects to replace a lost collaborator (Hatch and Dyer, 2004). Either approach ensures that filling the gap with a suitable replacement mitigates the impact of collaborator loss on the productivity of remaining knowledge workers.

While organizations can mitigate the negative consequences of internal collaborator loss through compensatory measures, they fall short when it comes to external collaborator loss. Knowledge management efforts typically focus on maintaining knowledge generated within the organization, i.e., by internal collaborators (Cohen and Levinthal, 1990; López-Sáez et al., 2010). Moreover, finding a suitable replacement to fill the gap often depends on the (internal) labor market conditions and budget constraints specific to the organization of the lost collaborator (Campbell et al., 2012; Mawdsley and Somaya, 2016). Vice versa, knowledge workers do not necessarily benefit from the compensatory measures of the external collaborator's organization. Knowledge workers can hardly draw on the knowledge management of other organizations or immediately build a tie to the individual filling the gap created by the lost collaborator (Burt, 1992; Droege and Hoobler, 2003).

2.3 Summary and empirical roadmap

To summarize, we expect that collaborator loss negatively affects knowledge worker productivity at the individual level, where the effect's magnitude differs between internal and external collaborator loss. More specifically, we expect that internal collaborator loss *ceteris paribus* has a less negative effect on knowledge worker productivity than external collaborator loss. This is because, within organizational boundaries, organizations can compensate for collaborator loss through internal measures. However, these measures are hardly effective in mitigating the effect on a knowledge worker's productivity if the lost collaborator is from a different organization.

In the empirical part of this study, we will examine the effect of internal and external collaborator loss on knowledge worker productivity within a corporate R&D setting. We will specifically examine how an inventor's productivity changes following the death of a co-inventor, who may have been either an internal or external collaborator at the time of death. To better understand these results, we will analyze variations in these effects by focusing on collaborators with presumably higher relevance for the inventor's productivity, such as those with high knowledge complementarity, a large network, and intense collaboration. Moreover, we will investigate organizational compensatory measures—knowledge management and filling the gap—to determine their role in the presumed effect differences between internal and external collaborator loss.

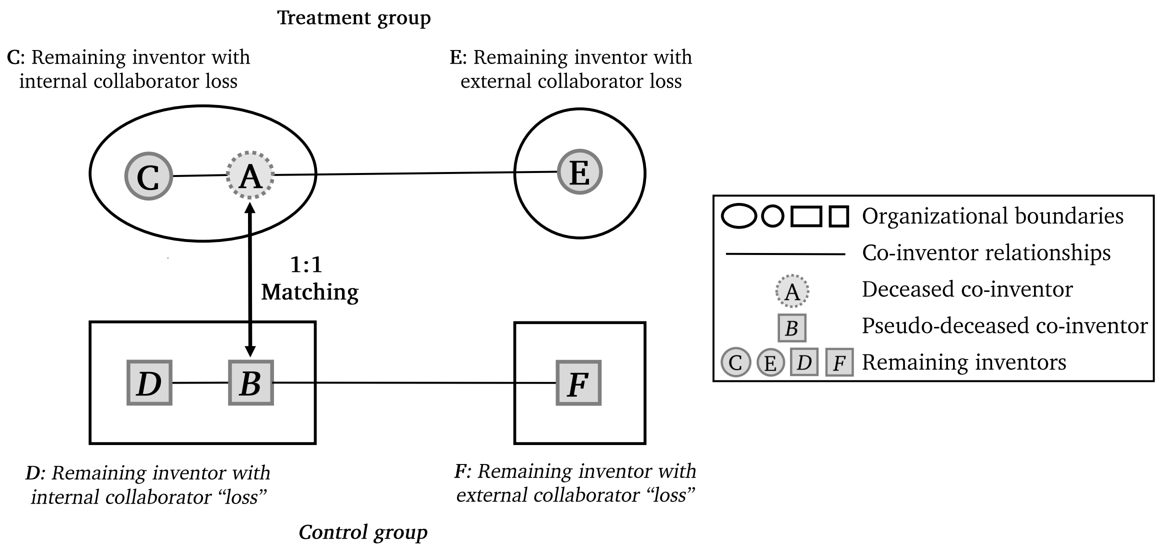
3 Data and empirical strategy

3.1 Outline

We focus our empirical analysis on corporate inventors, as they provide a suitable setting for examining the effect of internal and external collaborator loss on knowledge worker productivity. This focus stems primarily from the fact that both inventive productivity and collaborations are readily observable among corporate inventors. Specifically, we use patent information to measure their inventive productivity through patent counts and to construct their collaborative networks from the co-inventors listed on these patents. To differentiate co-inventors as either internal or external collaborators, we use detailed employment information from administrative data. Section 3.2 provides details on data sources and key variables.

Following the prior literature, we use the death of a previous co-inventor as a proxy for collaborator loss. The main challenge in estimating the effect of collaborator loss on the inventive productivity of the remaining inventors 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) and Bernstein et al. (2022). First, we leverage the natural experiment of unexpected (i.e., exogenous) deaths among inventors. While collaborator losses may take various forms in real life, we focus on unexpected deaths to ensure that the loss of a collaborator is not driven by factors that may also explain changes in inventive productivity.[1] Second, we employ a matching approach where we assign each deceased co-inventor to one pseudo-deceased co-inventor. To guarantee comparability between the deceased and pseudo-deceased co-inventors in terms of inventive productivity, career stage, and available resources, we base this match on a rich set of inventor and employer characteristics, detailed in Section 3.3. Figure 1 provides an overview of our research design.

Figure 1: Overview of research design



We analyze how a remaining inventor's productivity is affected by the co-inventor death in a difference-in-differences (DiD) framework. More specifically, we examine inventive productivity differences between remaining inventors with a deceased co-inventor (the "treatment group") and remaining inventors with a pseudo-deceased co-inventor (the "control group") before and after the (pseudo-)death. With this framework, we obtain average treatment effects of co-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. Section 3.4 discusses details.

3.2 Data and variables

Data sources

We use a linked employer-employee panel dataset (INV-BIO ADIAB 1980-2014), which combines labor market biographies and patenting information of 152,350 German inventors from 1980 until

[1] In this way, we can also exclude the possibility that the inventor can still access the knowledge of the "lost" co-inventor (e.g., the inventors stay in touch) or expect that the knowledge becomes accessible again (e.g., the "lost" co-inventor returns).

2014. These inventors represent the de facto population of individuals 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 obtain patent records between 1980 and 2014 from the EPO and the German Patent and Trademark Office (DPMA).[2]

The dataset comprises a rich set of variables concerning inventors' sociodemographic characteristics, patents, and employment records based on social security data. We use this combination of administrative labor market data and patent data, as both contain complementary information that we leverage in our empirical analysis.[3] 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, which we use to define organizational boundaries.[4] We further observe day-specific changes in inventors' employment status (e.g., due to death, retirement, or mobility), whereas the patent data inform us about the inventors' productivity, knowledge base, and co-inventors (i.e., the inventors' collaborators).

Inventive productivity

Inventor productivity can be assessed using various metrics, such as work output, peer evaluations, salary, and promotions. We focus on inventive productivity because it likely provides the most direct measure for assessing the impact of changes in collaborative input.

Patents. In line with the literature, we use the inventor's simple and citation-weighted annual patent counts as a proxy for inventive productivity (Jaravel et al., 2018; Lanjouw and Schankerman, 2004). To this end, we consider the inventor's European (EP) and national (DE) patents deduplicated at the patent family level.[5] 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

[2]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).

[3]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, 2022).

[4]Two establishments are distinct in at least one of the following characteristics: location (municipality), industry (3-digit NACE), or firm. To illustrate, two bakeries operated by the same firm in the same city would be reported as one establishment. In contrast, a bakery and a mill operated by the same firm would be classified as different establishments even when they are located in the same city. Crucially, it is the establishment's economic activity that determines the distinction, not the employed inventor's industry or technology focus.

[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, patent family members all have 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.

patent counts, we consider all EP citations the focal patent has received in the first five years after the earliest filing date.[6] In our default linear specification, we winsorize all count variables at the 95th percentile to reduce the inefficiency in the estimator introduced due to extreme values.[7]

Patents with new collaborators. We use subsets of patent counts to delineate the contribution of new collaborators to inventive productivity. Specifically, we consider patents with at least one new co-inventor—individuals with whom the remaining inventor had not previously collaborated—to capture the importance of new collaborations. We further narrow down the set of patents to those with at least one co-inventor who was recently hired (within the last two years).

Patents relying on organization knowledge. Finally, we analyze patents that include backward citations to earlier patents by inventors in the same organization at the time of filing. Although the use of patent citations as indicators of knowledge inputs can be contentious (Alcacer and Gittelman, 2006), citations to patents from the same organization likely indicate that the focal patent relies on pre-existing knowledge within the organization.

Collaborator loss

Co-inventor death. 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, 2022). We only consider the deaths of co-inventors who died aged 60 or younger.[8] The average deceased co-inventor in our sample died at the age of 49, with fewer than 2% of co-inventors dying before their 30th birthday.[9]

Characteristics of the lost collaborator

In our empirical analysis, we leverage several characteristics of the lost collaborator, outlined below. Appendix A2 offers a detailed account of these and additional variables.

[6] We consider alternative patent quality measures, specifically the patent family size, the number of granted patents, and the number of "breakthrough" patents, which are in the top 10% of their technology-year cohort in terms of citations. We also consider alternative patent count measures that focus on the inventor's contribution, by counting each patent fractionally according to the number of inventors listed on the patent. Similarly, we isolate the subset of patents that are not joint work with the lost collaborator.

[7] Without winsorizing, the point estimates become larger but lose precision (see Figure A5.1). Our results are robust to higher winsorization thresholds and to a binary dependent variable. With this, we follow the advice of Chen and Roth (2024) for right-skewed variables with many zero values and separate the intensive from the extensive margin.

[8] In our population of inventors, a large fraction is still employed after reaching 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). We also focus on deaths occurring in 2013 or earlier to guarantee at least two years of treatment in our analysis. The results are robust to various subsets of deaths, see Section 5.1 and Table A5.8.

[9] Figure A3.1 shows the distribution of ages at death for the sample of deceased co-inventors. Two reasons explain why the frequency of deaths increases with inventor age. First, some causes of unexpected death (e.g., heart attacks) become more likely with age. Second, the likelihood that an individual has filed at least one patent before death (and thus enters our data) increases with career length.

Internal vs external collaborator. We distinguish between internal and external collaborator losses depending on whether the deceased co-inventor worked within the inventor's organization at the time of death. We delineate organizational boundaries at the establishment level as defined in employment records, where establishments are defined by administrative procedures and delineate "regionally and economically delimited unit[s] in which employees work" (Ganzer et al., 2023, p. 12). An external collaborator may thus work either for a different firm or for a different organizational unit within the same multi-establishment firm.[10] There are two ways a collaborator may be classified as external: either the inventor and the deceased co-inventor previously collaborated within the same organization, but at least one has since moved to a different one (approximately 60%), or they collaborated on an R&D project that involved inventors from different organizations (approximately 40%). Slightly more than 50% of the inventors in our sample experienced the (pseudo-)death of an internal collaborator.

Knowledge complementarity. We measure the knowledge complementarity of the collaborator and the remaining inventor at the time of death by the inverse similarity between their patent portfolios. To this end, we compute the cosine similarity between the 4-digit technology classes (IPC) of their patents (Jaffe, 1986).[11]

Collaborator network size. We measure the collaborator network size by counting the number of co-inventors listed on the same patent documents as the deceased co-inventor, excluding any co-inventors shared with the remaining inventor. This approach is based on the premise that the most relevant network ties are those to which the remaining inventor does not have direct access (Mohnen, 2022).[12]

Collaboration intensity. We operationalize collaboration intensity using the recency of co-patenting, measured by the years since the last joint patent between the lost collaborator and the remaining inventor. We thereby assume that more recent or renewed collaborations indicate a higher intensity of collaboration (Jaravel et al., 2018).[13]

Collaborator inventive productivity. We measure the inventive productivity of the deceased

[10] Inventor dyads who worked in different establishments at the time of death events typically worked in different locations and distinct industries: 21% worked in the same district, and 25% worked in the same 3-digit industry, 61% at the 1-digit level.

[11] In robustness checks, we measure knowledge complementarity not by the inverse similarity but the inverse overlap between the technology class shares in the respective portfolios.

[12] In robustness checks, we first consider the total number of co-inventors of the deceased, and second the number of inventors with similar specializations (same modal 4-digit IPC class) as the lost co-inventor in the co-inventor's organization—individuals with whom the lost co-inventor was likely in contact, even if no direct collaborations occurred.

[13] In robustness checks, we also use the number of joint patents and the joint job tenure (for internal collaborator loss) as alternative measures.

co-inventor by the number of lifetime patents at the time of death.[14]

Characteristics of the inventor's organization

We further consider the characteristics of the remaining inventor's organization, specifically its capabilities related to knowledge management and hiring practices.[15]

Knowledge management capabilities. Effective knowledge management is essential for facilitating knowledge transfer within organizations, particularly across space and time where personal interaction may not be possible. Organizations achieve this through codification routines and knowledge-sharing practices (Zander and Kogut, 1995). However, directly capturing the diverse ways organizations foster knowledge management internally is challenging without traditional survey-based measures. Instead, we rely on an output-oriented measure to gauge knowledge management capabilities. Specifically, we posit that citations to patents from the same organization (self-citations) *without* inventor overlap are an indicative measure of the organization's ability to transmit or utilize knowledge without direct personal connections.[16]

$$Knowledge\ management_{ft} = \frac{Patents\ w/\ selfcites_{ft} - Patents\ w/\ selfcites\ \&\ inventor\ overlap_{ft}}{Patents\ w/\ selfcites_{ft}}$$

The sets of patents in the formula for codification are cumulative, i.e., all patents of the organization f until year t. In our analysis, we use codification from the pre-death year. The measure is undefined for organizations without any self-citations.

Hiring capabilities. Finding, hiring, and training new inventors is typically challenging, costly, and time-consuming (Campbell et al., 2012; Mawdsley and Somaya, 2016; Siegel and Simons, 2010). However, despite these challenges, the mobility rates of inventors vary across markets, and certain organizations excel at drawing in and retaining new talent, either due to their inherent attractiveness or through deliberate actions (Chatterji and Patro, 2014; Bhaskarabhatla et al., 2021). Given the difficulty in directly observing these aspects, we proxy an organization's hiring capabilities by their rate of new inventor hires. Specifically, we measure the hiring capabilities of an organization by the inflow of new inventors in the last pre-treatment year relative to the total number of inventors in the organization at that time. The rationale for our measure of hiring capabilities is

[14] Alternatively, we consider the collaborator's residualized number of lifetime patents, which is the deviation of realized from the expected number of lifetime patents according to a regression including age, year, firm size, and modal main technological area.

[15] It is important to note that by "capabilities," we refer to the organization's existing skills and resources, not to "dynamic capabilities," which involve adapting to changing environments.

[16] This measure rests on two reasonable premises. First, self-citations are a meaningful proxy for an organization's use of internal knowledge in the invention process. Second, the lack of inventor overlap indicates that the inventor team behind the cited patent was not directly involved in the subsequent invention. Accordingly, our measure should capture an organization's ability to utilize internal knowledge without needing the direct involvement of its original creators. We believe organizations are more likely to achieve such transfer if they have knowledge management capabilities, such as codification routines and knowledge-sharing practices, in place.

that organizations with extensive recent hiring relative to their total inventor workforce are likely to have well-developed recruitment processes and experience.

$$Hiring\ capabilities_{ft} = \frac{Inventors\ hired_{ft}}{All\ inventors_{ft}}$$

Control variables

We control for the inventors' age fixed effects to account for life-cycle patterns in inventive productivity. The inventors in our sample are 46 years old on average. We further include inventor fixed effects to control for time-invariant characteristics. Finally, we control for time-specific shocks and time trends across match groups by including deceased co-inventor times relative year fixed effects.

3.3 Co-inventor matching

We match each deceased co-inventor to a pseudo-deceased co-inventor drawn from the 150,000 inventors in our dataset. We do so iteratively and draw pseudo-deceased co-inventors without replacement by death year cohort in chronological order. To minimize violations of the stable unit treatment value assumption, we exclude from the matching pool all inventors in the same organization and all inventors who also collaborated with the deceased co-inventor.[17]

In line with the prior literature (Cohen et al., 2000; Rosenkopf and Almeida, 2003; Nakajima et al., 2010), we select pseudo-deceased co-inventors based on the following matching variables[18] 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) organization size group (the coarsened number of full-time employees an establishment employs). In case of multiple matches per deceased co-inventor, we select the match most similar to the deceased co-inventor in terms of tenure (years of employment), years since last patenting (the time since the inventor filed her last patent), and the uncoarsened number of patent applications, in that order.[19] We assign the death date of the corresponding deceased co-inventor to each matched pseudo-deceased co-inventor.

We successfully match 845 of the 866 deceased co-inventors in our data to pseudo-deceased co-inventors with similar characteristics. Both matched and unmatched characteristics are well-

[17]Our key findings hold in a robustness check where only inventors from the same organization as the deceased co-inventor are considered as matching candidates (Table A5.7, columns 5-6). To minimize contamination, we ensure that the matched pseudo-deceased co-inventor is not part of the deceased co-inventor's collaborative network despite being from the same organization.

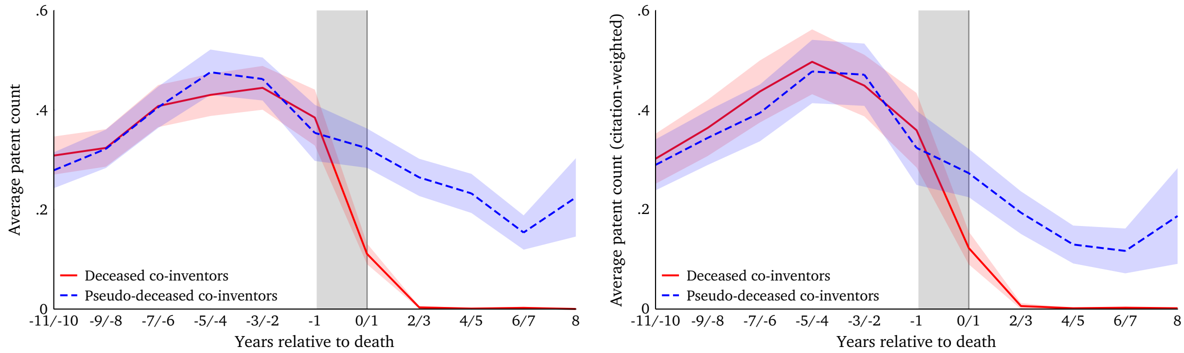
[18]A more detailed description of these variables is included in Table A2.1.

[19]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 and weak matching variables results from a manual optimization of the matching. Our key findings remain robust when we select either a random match among candidates with strict matching variables, or the match with the smallest Mahalanobis distance based on strict and weak matching criteria (Table A5.7, columns 1-4).

balanced between deceased and pseudo-deceased co-inventors. In particular, the levels and trends of productivity are similar between deceased and pseudo-deceased co-inventors. Figure 2 shows that pre-death levels and trends are comparable between the two groups of co-inventors, both for simple patent counts and citation-weighted patent counts. However, as expected, the inventive productivity of the deceased co-inventors drops to practically zero in the year after their death. This drop corroborates that the deaths were unexpected and unrelated to inventive productivity.

Figure 2: Average inventive productivity of deceased and pseudo-deceased co-inventors

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



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

We are interested in how a remaining inventor's productivity is affected by the death of a co-inventor. To this end, we consider as the unit of observation inventors who co-patented with a (pseudo-)deceased co-inventor in the last ten years prior to the (pseudo-)death.[20] In total, there are 3,471 (3,215) inventors with a deceased (pseudo-deceased) co-inventor.[21] Note that our regressions are based on a slightly smaller sample due to singleton observations, which represent remaining inventors who perfectly correlate with some of the included fixed effects.

Overall, inventors with a deceased co-inventor have similar characteristics as inventors with a pseudo-deceased co-inventor (see Table A3.2). The small relative differences in means (and medians) provide strong support for the quality of our match.[22]

[20] The results are robust to focusing on co-inventors with a joint patent in the last four years (Table A5.7, columns 3-4).

[21] We thereby exclude inventors who died themselves during the sample period, which applies to 23 (19) units of observation. We further restrict our sample to remaining inventors with only one (pseudo-)deceased co-inventor. This excludes 195 (146) units of observation. Another 175 inventors have both deceased and pseudo-deceased co-inventors. We drop these from both pools as well. Overall, we exclude approximately 11% of the observations.

[22] We further provide a balancing of inventors with internal and external collaborator loss separately (see Tables A3.3 and A3.4).

3.4 Econometric models

We employ a DiD framework for our empirical analyses. For each remaining inventor i, we consider years $t=-11$ to $t=8$ around the year of death—denoted by k. In line with the literature (Jaravel et al., 2018; Bernstein et al., 2022), we account for the full set of leads and lags around the death year. For remaining inventors with a deceased co-inventor, we denote leads and lags with L_{it}^{real}. For the full sample—remaining inventors with a deceased co-inventor or with a pseudo-deceased co-inventor—we denote leads and lags with L_{it}^{all}. Full-sample leads and lags are specific to the match group s, which contains all remaining inventors linked to the same deceased co-inventor as well as all remaining inventors linked to the corresponding pseudo-deceased co-inventor.

The DiD specification is given as follows:

$$Y_{it} = \alpha_i + \beta^{real} \mathbb{1}_{L_{it}^{real} \geq 0} + \sum_{k=-11}^{8} \beta_{sk}^{all} \mathbb{1}_{L_{it}^{all}=k} + \sum_{j} \gamma_j \mathbb{1}_{age_{it}=j} + \varepsilon_{it}. \tag{Eq. 1}$$

In other words, we add deceased co-inventor times relative year fixed effects, allowing for flexible trends within each set s of inventors in a matched pair of deceased and pseudo-deceased co-inventors.[23] As this set of fixed effects is colinear with year fixed effects, the latter are omitted. In contrast, β^{real} captures the treatment effect for inventors with a (real) deceased co-inventor relative to inventors with a pseudo-deceased co-inventor, within their match group. We further include individual fixed effects α_i and age fixed effects γ_j. We cluster standard errors at the level of the employer of the (pseudo-)deceased co-inventor, but results are robust to alternative choices (see Table A5.6).

The validity of this analysis rests on the common trend assumption: absent co-inventor death, the inventive productivity of the treated inventors would have followed the same path as the productivity of the control inventors in the treatment period.

Most of our analysis focuses on the treatment effect in various subsamples. We estimate full-sample models with interactions of $\mathbb{1}_{L_{it}^{real} \geq 0}$ (equivalent to *death* × *post*) and $\mathbb{1}_{L_{it}^{all} \geq 0}$ (equivalent to *post*), interacted with a binary variable, C_i, indicating observations with a given collaborator or organization characteristic.

$$\begin{aligned} Y_{it} = \alpha_i &+ \beta_{C_i=0}^{real} \mathbb{1}_{L_{it}^{real} \geq 0 \cap C_i=0} + \beta_{C_i=0}^{all} \mathbb{1}_{L_{it}^{all} \geq 0 \cap C_i=0} \\ &+ \beta_{C_i=1}^{real} \mathbb{1}_{L_{it}^{real} \geq 0 \cap C_i=1} + \beta_{C_i=1}^{all} \mathbb{1}_{L_{it}^{all} \geq 0 \cap C_i=1} + \sum_{k=-11}^{8} \beta_{sk}^{all} \mathbb{1}_{L_{it}^{all}=k} + \sum_{j} \gamma_j \mathbb{1}_{age_{it}=j} + \varepsilon_{it}. \end{aligned} \tag{Eq. 2}$$

[23]The reasons to include these fixed effects are twofold. First, β_{sk}^{all} capture trends of specific match groups s, which may arise from the data generation and matching process. Second, as discussed in Bernstein et al. (2022), this additional set of fixed effects rectifies the issues with two-way fixed effects estimators highlighted by the recent literature on DiD estimators (Roth et al., 2023). We show estimation results without this set of fixed effects in Table A5.7.

To simplify exposition, we report the treatment effect for the subsamples $\beta^{real}_{C_i=j}$. For subsamples defined by multiple variables (e.g., internal loss and high organizational capabilities), the same logic applies, but for the full set of variable combinations.

In the event study specification, we normalize the dynamic effects to pre-treatment period $t-1$. This setup then expands to the following equation:

$$Y_{it} = \alpha_i + \sum_{\substack{k=-11 \\ k\neq -1}}^{8} \beta^{real}_{k} \mathbb{1}_{L^{real}_{it}=k} + \sum_{k=-11}^{8} \beta^{all}_{sk} \mathbb{1}_{L^{all}_{it}=k} + \sum_{j} \gamma_j \mathbb{1}_{age_{it}=j} + \varepsilon_{it}. \qquad \text{(Eq. 3)}$$

As the baseline specification, we report a linear dependent variable, winsorized at the 95% level. With this, we accommodate the features of our dependent variable, which is characterized by many zeros and a highly right-skewed distribution. We show the robustness of our main results to alternative specifications, such as a binary, differently winsorized, Poisson, or $\log(1+X)$/inverse hyperbolic sine transformations, in the Appendix.

4 Descriptive statistics

We briefly describe our empirical setting of corporate inventors in Germany, followed by summary statistics of the key variables in our analysis.

4.1 Context description

In our sample, nearly 80% of the inventors work in the manufacturing sector, particularly in electrical engineering (24%), chemicals and plastics (22%), mechanical engineering (14%), and car manufacturing (11%). This sectoral distribution is reflected in the patents' technology areas, with 35% in mechanical engineering being the most prevalent, followed by chemistry (33%), electrical engineering (17%), and instruments (11%). About 60% of the inventors are employed by large organizations with at least 1,000 employees. On average, inventors in our sample have worked for 3.7 different organizations during their careers. The average patent lists three inventors from 1.3 different organizations.

4.2 Summary statistics

Table 1 presents the descriptive statistics for the variables utilized in our analysis.[24] Consistent with our DiD framework, we measure annual inventive productivity from 11 years prior to 8 years after the (pseudo-)death year. On average, the remaining inventors in our sample have 0.65 patents and receive 0.68 citations annually. Moreover, 0.42 patents are filed with at least one new collaborator, and 0.27 patents rely on knowledge originating from within the same organization.

[24]For an overview of all variables and their pairwise correlations, see Table A3.1.

Table 1: Summary statistics

Variable	Mean	Std. Dev.	10%	50%	90%
Characteristics of the inventor					
Patents (simple counts)	0.65	1.18	0.00	0.00	3.00
Patents (citation-weighted counts)	0.68	1.65	0.00	0.00	3.00
Patents with at least one new collaborator	0.42	0.93	0.00	0.00	2.00
Patents relying on organization knowledge	0.27	0.78	0.00	0.00	1.00
Age	44.03	10.65	31.00	43.00	59.00
Characteristics of the lost collaborator					
Internal collaborator	0.52	0.50	0.00	1.00	1.00
Knowledge similarity	0.70	0.29	0.23	0.79	0.99
Collaborator network size	11.29	15.75	0.00	5.00	32.00
Collaboration intensity (recency)	4.61	2.81	1.00	4.00	9.00
Collaborator inventive productivity	8.24	4.75	1.00	9.00	13.00
Characteristics of the inventor's organization					
Knowledge management capabilities	0.86	0.18	0.67	0.92	1.00
Hiring capabilities	0.11	0.20	0.00	0.05	0.18

Notes: Summary statistics in the estimation dataset (N=70,308) for 3,574 remaining inventors and 3,409 remaining inventors of pseudo-deceased co-inventors. Detailed summary statistics for all variables are listed in Table A3.1.

We distinguish between two sets of variables characterizing the context of the collaborator loss. The first set refers to the characteristics of the collaborator, serving as moderator variables to investigate potential heterogeneity in the effect of collaborator loss. Most importantly, we differentiate between whether the collaborator was employed by the same organization as the remaining inventor at the time of death (internal collaborator) or a different organization (external collaborator). About 52% of the lost collaborators are internal ones. We further consider three characteristics the prior literature highlights as relevant to the impact of collaborator loss: knowledge complementarity, network size, and collaboration intensity. On average, the lost collaborator's knowledge complementarity (as the inverse of knowledge similarity) is 0.7, and network size is 11.29 inventors. The last patent between a lost collaborator and the remaining inventors is filed on average 4.61 years prior to death. We also measure the lifetime productivity of the lost collaborator. The average lost collaborator has 8.24 lifetime patents.

The second set of variables relates to the characteristics of the inventor's organization. Knowledge management capabilities average 0.82, (in other words, 82% of self-citations do not relate to the inventor's own patents), and range from 0.67 (10th percentile) to 1 (90th percentile). The hiring capabilities of organizations are on average 0.11 (in other words, 11% of the employed inventors joined the organization in that year), ranging from 0 (10th percentile) to 0.18 (90th percentile).

Internal and external collaborators exhibit distinct differences in their characteristics (Table 2). Internal collaborators show a higher knowledge similarity (inverse of knowledge complementarity, 0.74 vs. 0.73, $p<0.01$) and possess a similar, if slightly smaller, network of non-common co-inventors

(11.29 vs. 11.76, p=0.22), with a statistically insignificant difference. They exhibit a higher collaboration intensity in terms of recency (4.17 vs. 5.26 years ago, p<0.01) but a similar lifetime productivity (17.90 vs. 18.63, p=0.22). These findings align with the expectation that inventors within the same organization are more likely to hold similar knowledge (Jaffe et al., 1993; Grimpe and Kaiser, 2010), have more cohesive networks (Guler and Nerkar, 2012), and engage in more frequent interactions (Audretsch and Feldman, 2004). These findings further suggest that R&D collaborations across organizational boundaries are not random but result from selective processes.[25] We examine the relevance of these differences for the consequences of collaborator loss in Section 5.2.

Table 2: Internal and external collaborator characteristics

Characteristics of the lost collaborator	Internal collaborators			External collaborators				
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Diff.	p-value
Knowledge similarity	0.74	0.83	0.26	0.65	0.73	0.30	0.10	0.000***
Collaborator network size	11.29	5.00	16.67	11.76	6.00	15.12	−0.47	0.222
Collaboration intensity (recency)	4.17	4.00	2.78	5.26	5.00	2.74	−1.09	0.000***
Collaborator inventive productivity (pre-death)	17.90	8.00	24.69	18.63	9.00	24.91	−0.73	0.221

Notes: This table presents summary statistics of pre-death characteristics of inventors experiencing internal collaborator loss (N=3387) and inventors experiencing external collaborator loss (N=3596). The unit of observation is at the remaining inventor level. Reported p-values based on an unpaired t-test. For an extended version, see Table A3.5. For a balancing table between deceased and pseudo-deceased co-inventors and the respective remaining inventors, see Table A3.2. For balancing tables within the subgroups of external and internal inventors, see Table A3.3 and A3.4. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

5 Results

In this section, we examine the effects of internal and external collaborator loss on inventive productivity, investigate heterogeneity in these effects based on collaborator characteristics, and explore organizational measures that may compensate for the loss of internal collaborators. We conclude with a discussion of alternative mechanisms.

5.1 Internal and external collaborator loss

We find that collaborator loss has a moderate but imprecisely estimated negative effect on overall inventive productivity. Table 3 presents the DiD results of collaborator loss, proxied by co-inventor death, on inventive productivity, measured by (citation-weighted) patent counts. Collaborator loss has a negative effect of approximately −0.03 (−0.05) on inventive productivity over an 8-year period (Table 3, Columns 1 and 3). These estimates correspond to a 4% (8%) reduction of the average inventive productivity compared to inventors with a pseudo-deceased co-inventor. The event study results depicted in Figure 3a illustrate the effect dynamics over time and are informative in two ways.

[25] For instance, given that external collaborators hold, on average, less similar knowledge than internal collaborators, they may be more likely to be selected for exploratory research projects.

First, the absence of significant pretrends solidifies the validity of our research design. Second, the negative effect, which gradually intensifies and reaches conventional thresholds of statistical significance, peaks around five years after the co-inventor death. These results suggest that collaborator loss leads, on average, to a decline in inventive productivity—which replicates the negative (albeit considerably larger) effect found in the prior literature for corporate inventors in the US (Bernstein et al., 2022; Jaravel et al., 2018).[26]

Table 3: Impact of collaborator loss on inventive productivity - simple and citation-weighted patent counts (DiD estimates)

	Patents (simple counts)		Patents (citation-weighted)	
	(1)	(2)	(3)	(4)
Collaborator loss	−0.027		−0.054*	
	(0.022)		(0.030)	
Internal collaborator loss		0.022		0.026
		(0.029)		(0.038)
External collaborator loss		−0.079**		−0.139***
		(0.034)		(0.044)
Δ Internal loss − External loss		0.101**		0.165***
		(0.045)		(0.057)
Inventor FE	Yes	Yes	Yes	Yes
Inventor age FE	Yes	Yes	Yes	Yes
Match group×rel. year FE	Yes	Yes	Yes	Yes
Clusters	856	856	856	856
Observations	124168	124168	124168	124168
Adj. R2	0.37	0.37	0.30	0.30
DV mean	0.65	0.65	0.69	0.69

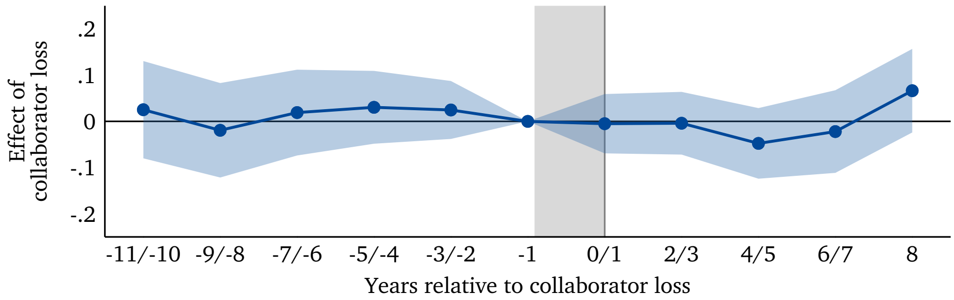
Notes: This table reports the estimates for β^{real} from a linear regression with inventor, inventor age, and deceased co-inventor times relative year fixed effects. The dependent variables (simple and citation-weighted patent counts) are winsorized at the 95% level. The unit of observation is at the inventor-year level. Standard errors clustered at the level of the (pseudo-)deceased co-inventor's organization are in parentheses. Each reported estimate stands for the treatment effect for the relevant subgroup (e.g., $\beta^{real}_{C_i=1}$) or their difference (row Δ Internal loss − External loss reports $\beta^{real}_{C_i=1} - \beta^{real}_{C_i=0}$). * p<0.1, ** p<0.05, *** p<0.01.

We observe a substantial difference in the effect on inventive productivity when distinguishing between internal and external collaborator losses. In Table 3, Column 2, we provide the distinct coefficients of internal and external collaborator loss obtained from a triple DiD regression. We find no negative effect of internal collaborator loss on inventive productivity; with a coefficient of 0.02, the effect is even slightly positive, albeit statistically indistinguishable from zero. Conversely, we find a negative and statistically significant effect of external collaborator loss on inventive productivity. The coefficient is about −0.08 (or −12%), and thus almost three times as large as the one for

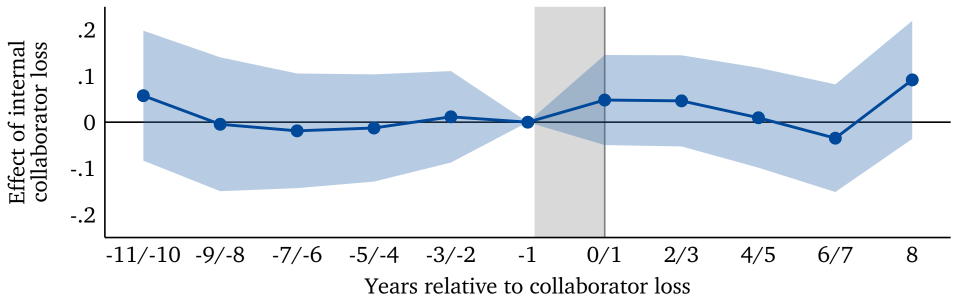
[26]Compared to Jaravel et al. (2018), our analysis faces reduced statistical power due to a smaller sample size and the inclusion of more stringent fixed effects. The smaller magnitude of our estimates relative to those reported by Jaravel et al. (2018) may stem from differences in sample construction, matching approach, regression specification, or the institutional context. For example, our study focuses on German inventors, whereas Jaravel et al. (2018) analyze data from the United States. Institutional differences between these countries—such as labor market regulations, R&D investment levels, and collaboration practices—could influence the effect of collaborator loss on inventive productivity.

Figure 3: Impact of collaborator loss on inventive productivity (event study estimates)

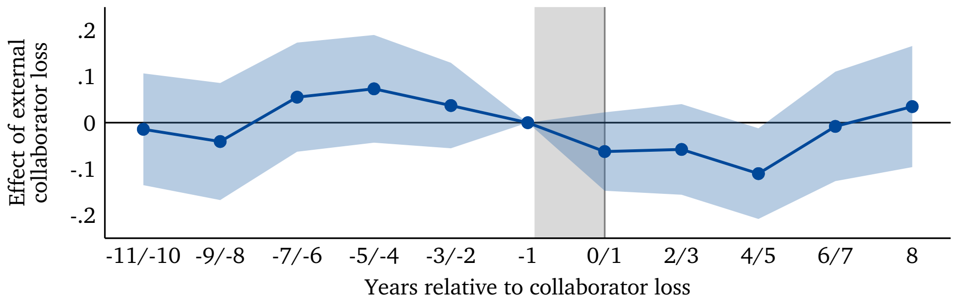
(a) Collaborator loss overall



(b) Internal collaborator loss



(c) External collaborator loss



Notes: The graph presents point estimates and 95% confidence intervals for β_k^{real} for the full sample (Panel a) and from a regression covering subgroups of inventors with internal (Panel b) and external (Panel c) collaborator loss, following Eq. 3. The dependent variable is the simple patent count. It includes inventor fixed effects, inventor age fixed effects, and deceased co-inventor times relative year fixed effects. The unit of observation is at the inventor-year level. Standard errors are clustered at the level of the (pseudo-)deceased co-inventor's organization. The baseline year is $t = -1$, and the remaining coefficients, except t=8, group two years. The graph corresponds to the coefficients reported in Table A4.1.

collaborator loss overall, and statistically significantly different from the one for internal collaborator loss. Figures 3b and 3c present the event study results for internal and external collaborator loss separately. We observe no significant pretrends for either kind of collaborator loss. Moreover, while internal collaborator loss does not reduce inventive productivity in any year of the treatment period, external collaborator loss affects inventive productivity in a pattern similar to, but more pronounced than, that of collaborator loss in general. Altogether, these results indicate that the overall effect on inventive productivity is almost exclusively driven by the loss of external collaborators.

The observed differences in the effects of internal and external collaborator loss on inventive productivity are robust to a large set of methodological choices (see Appendix A5). First, we find the same pattern of results with different measures of inventive productivity, including granted patent counts, family-weighted patent counts, breakthrough patent counts, fractional patent counts, and patent counts excluding those with the respective collaborator. Likewise, the results are consistent when choosing alternative variable transformations (binary, different winsorization, inverse hyperbolic sine, and log transformation). Second, we find the results unchanged when narrowing the sample to collaborator losses that are more likely to be truly exogenous (e.g., co-inventors with full-time employment until death and co-inventors aged 55 or younger at the time of death). Third, we can corroborate the effect pattern using a different estimator (Poisson instead of OLS), alternative model specifications (i.e., fewer fixed effects), and alternative clustering of standard errors (e.g., at either the (pseudo-)deceased co-inventor level or alternative organizational levels). Fourth, we find a very similar effect pattern when using different control groups, either by applying alternative matching approaches or by changing the matching pool to inventors from the same organization as the deceased co-inventor. Finally, we find that the effects remain robust after applying inverse probability weighting to the estimation sample to balance the pre-death characteristics of treated and control inventors.

We can further confirm that the difference in the effects of internal and external collaborator loss is independent of the size of the inventor's organization and whether the external collaborator previously worked in the inventor's organization. Inventors in small organizations may be more likely to engage in external collaborations due to fewer colleagues. A positive correlation between organization size and inventive productivity may thus explain the observed effect pattern. However, we find, across organizations of varying sizes, consistently more negative point estimates for external than for internal collaborator loss (Table A5.9). Furthermore, an inventor's collaborative network may include more external collaborators if former colleagues have left the inventor's organization. If these departures were triggered by a downward trend in the inventor's productivity, this could also explain the observed pattern. Reassuringly, we find that the negative effect of external collaborator loss is practically identical irrespective of whether the deceased co-inventor never worked in the inventor's organization or worked there but subsequently moved on (Table A5.1).[27]

[27] Interestingly, we observe no significant effect on inventive productivity for the subset of external collaborator losses involving inventors who had moved organizations. This null effect is plausible, anticipating our findings in subsequent sections, as these inventors likely maintain multiple connections to their former organizations and benefit from the compensatory measures of those organizations.

To summarize, internal collaborator loss has a substantially less negative effect on inventive productivity than external collaborator loss. This pattern is robust to various methodological choices and does not appear to be driven by other factors that might positively correlate with external collaborator loss and negatively with inventive productivity.

5.2 Heterogeneity by collaborator characteristics

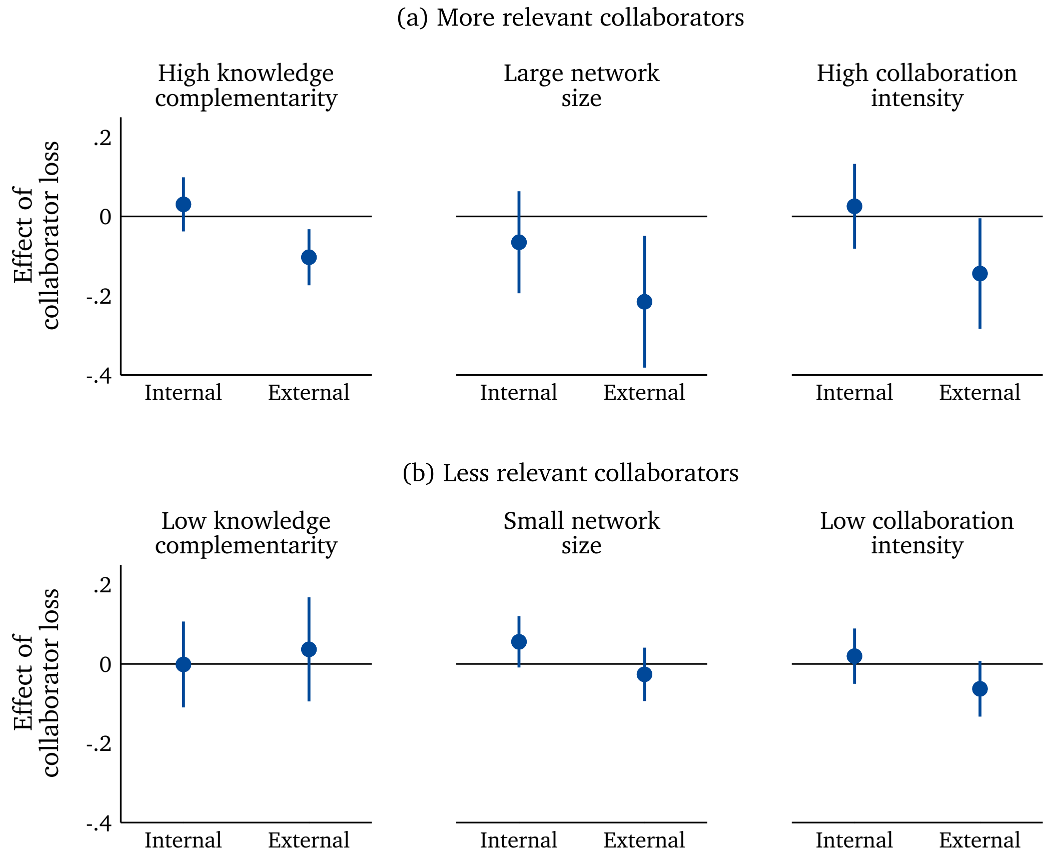
In this section, we investigate whether our finding that internal collaborator loss has a substantially less negative effect on inventive productivity could be due to inherent differences between external and internal collaborators. Indeed, the prior literature has shown that the loss of presumably more relevant collaborators results in a larger negative effect on productivity. Key characteristics that indicate such higher relevance are a high knowledge complementarity, a large network size, and a high collaboration intensity. Our descriptive findings in Section 4 suggest that some of these characteristics are less frequent among internal than external collaborators, underscoring the need for a more thorough examination.

By focusing on the loss of collaborators with presumably higher relevance, we can assess potential effect differences on inventive productivity more clearly. We interact both internal and external collaborator loss with another binary variable, which indicates more relevant collaborators, characterized by a high knowledge complementarity, a large network size, or a high collaboration intensity. If the estimates for internal collaborator loss within this more relevant subset become more negative—thus approximating those for external collaborator loss—we could infer that the aforementioned null effect is due to a large share of internal collaborators with little relevance for inventive productivity in our sample. While this approach does not equate to a true ceteris paribus analysis, observing changes in the relative size of the estimates can still be informative.

We find the difference in effects between internal and external collaborator loss confirmed when focusing on presumably more relevant collaborators. Figure 4a reports the estimates of internal and external collaborator loss on inventive productivity among collaborators with characteristics indicating a high relevance for the remaining inventors.[28] The effect of internal collaborator loss remains statistically insignificant and near zero, regardless of whether the focus is on collaborators characterized by a high knowledge complementarity, large network size, or high collaboration in-

[28] In this section, we discuss estimation results following our main operationalization of the heterogeneity variables. In the Appendix (Table A4.2), we present estimation results using alternative proxies. Specifically, we use i) patent class overlap instead of patent class similarity, ii) the full network size of the lost collaborator and the number of inventors in the same organization, and narrow technology instead of the network size excluding common inventors with the remaining inventor, and iii) the number of joint patents, the number of recent joint patents, and joint tenure instead of collaboration recency. Similar to the main results, we find null effects for internal collaborator loss and negative effects for external collaborator loss.

Figure 4: Impact of internal and external collaborator loss on inventive productivity by collaborator relevance (DiD estimates)



Notes: The graph presents point estimates and 95% confidence intervals for β^{real} in the relevant subgroups. We proxy knowledge complementarity with (the inverse of) patent class similarity and split at the 75th percentile of similarity. More relevant collaborators are such with higher complementarity, i.e. lower similarity. We proxy network size with the number of co-inventors of the lost collaborator, excluding those common with the remaining inventor. We split at the 75th percentile. More relevant collaborators are such with larger network size. We proxy collaboration intensity with the years since the last joint patent between the lost collaborator and the remaining inventor. We split at the 25th percentile, and more relevant collaborators are such with fewer years. For estimation results and alternative proxies, see Table A4.2.

tensity. In contrast, the negative effects of external collaborator loss become more pronounced for collaborators with such characteristics, which aligns well with the findings in the prior literature (Bernstein et al., 2022; Mohnen, 2022; Jaravel et al., 2018). Taken together, we find the difference in effects between internal and external collaborator loss to be even larger among presumably more relevant collaborators than in the full sample. Figure 4b reports corresponding estimates for collaborators presumed to have lower relevance, characterized by low knowledge complementarity, small network size, and low collaboration intensity. Here, the impact of external collaborator loss is significantly less pronounced, leading to a much smaller difference in the effects between internal and external collaborator loss, which loses its statistical significance.

These findings are supported by an additional robustness check, in which we apply inverse probability weighting to balance differences in observable characteristics between internal and external collaborators. If such differences were driving the heterogeneity in the effects of collaborator loss, the estimated effects should converge once the characteristics between the two groups are balanced. However, the results remain highly consistent regardless of whether we use weighted or unweighted samples (Table A6.4).

Taken together, these results speak against inherent differences between internal and external collaborators in driving the substantially smaller effect observed for internal collaborator loss. Other factors must be at play. Against this backdrop, we next turn to our analysis of organizational capabilities as the proposed mechanism. According to our theoretical framework, organizations can mitigate the negative consequences of internal collaborator loss through ex-ante and ex-post compensatory measures, which may explain the muted effect on inventive productivity. We will explore this explanation in the subsequent section.

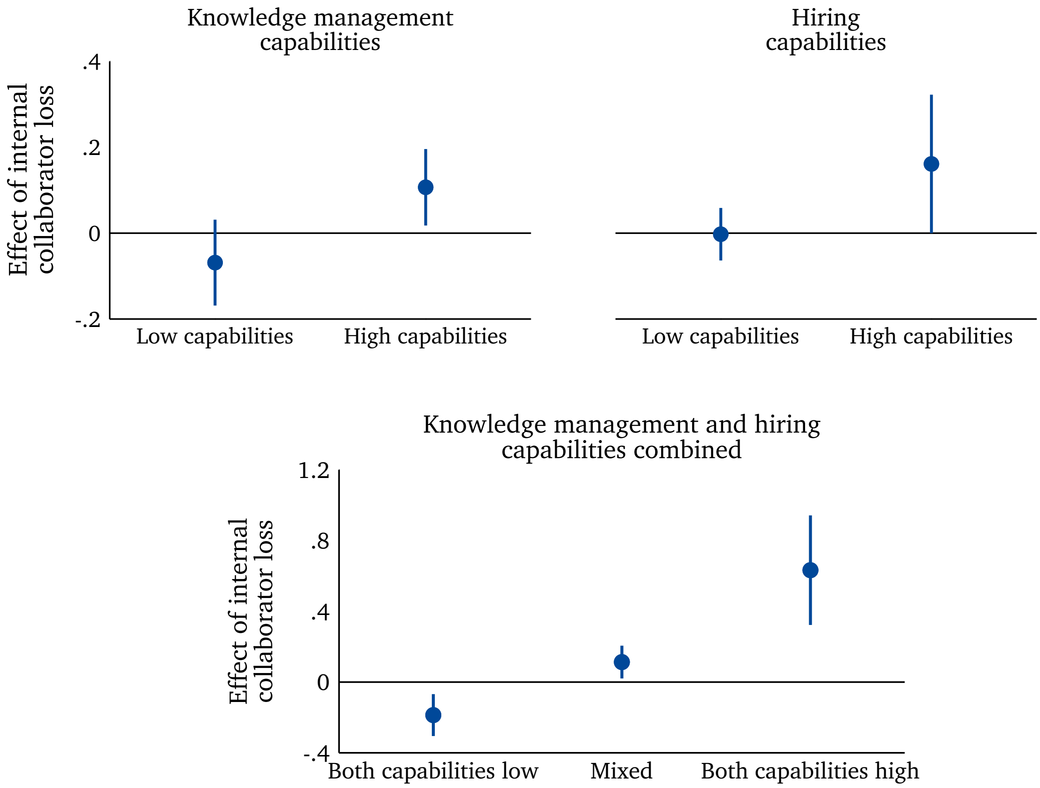
5.3 Compensating measures by the organization

In what follows, we investigate whether organizational measures designed to maintain the continuity of R&D efforts mitigate the negative consequences of internal collaborator loss for the remaining inventors. Specifically, we focus on two key measures: knowledge management, aimed at preventing knowledge loss through codification and sharing among employees, and hiring efforts to "fill the gap" created by the lost collaborator. We argue that organizations vary in their capabilities to implement these measures effectively—a variation we can measure and leverage in our analysis as moderators of the effect. Ultimately, this analysis aims to demonstrate how organizational measures can explain the observed effects of internal collaborator loss on inventive productivity.

The effect of internal collaborator loss on the inventive productivity of the remaining inventors varies with the organization's knowledge management and hiring capabilities. Figure 5 reports the estimates of internal collaborator loss on inventive productivity in organizations with varying knowledge management or hiring capabilities. In organizations with low capabilities overall, internal collaborator loss has a sizable and statistically significant negative effect on inventive productivity. In contrast, organizations with high capabilities experience a substantial positive effect from internal collaborator loss. This effect order aligns with our argument that effective organizational strategies can mitigate—or even reverse—the negative consequences of losing internal collaborators by preventing knowledge loss in the first place and efficiently filling the gap created by the lost collaborator.[29]

[29] Notably, we do not observe this pattern of organizational capabilities moderating the effects of *external* collaborator loss (Tables A4.3 and A4.4).

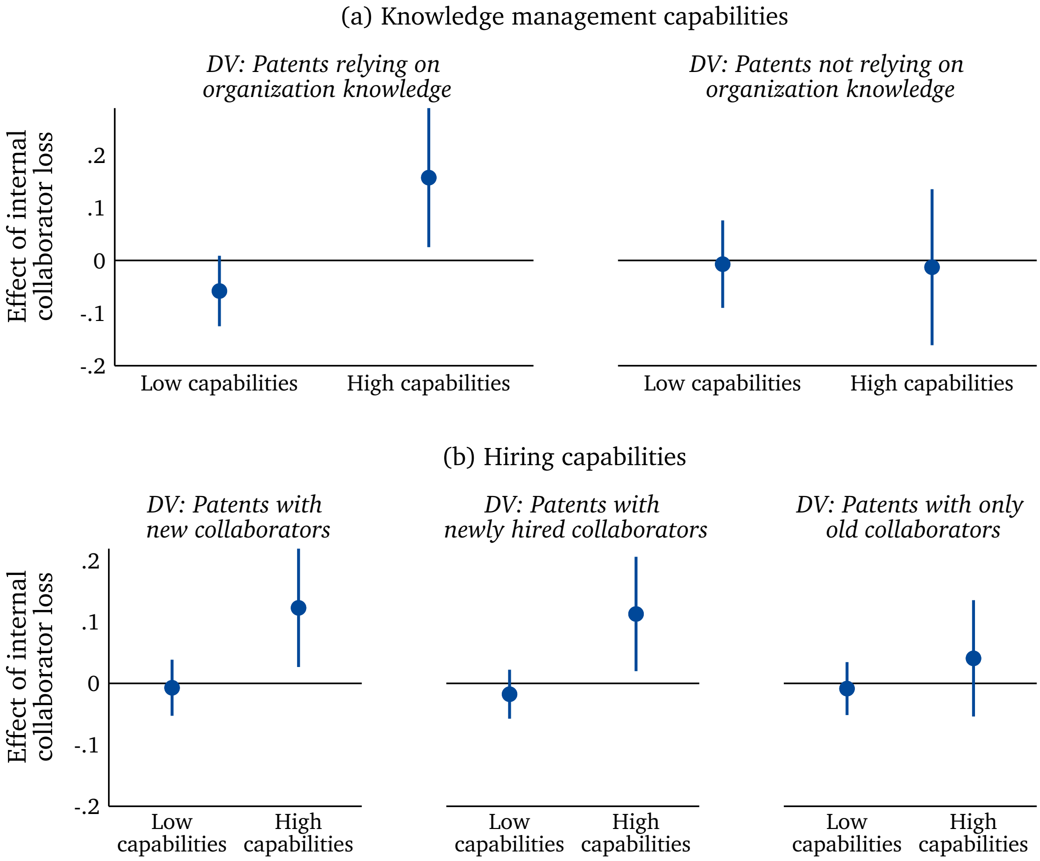
Figure 5: Impact of internal collaborator loss on inventive productivity – organizational capabilities (DiD estimates)



Notes: The graph presents point estimates and 95% confidence intervals for β^{real} in the relevant subgroups. We distinguish between remaining inventors by their organization's knowledge management and hiring capabilities. Subsamples are split at the median (knowledge management capabilities) and the 75th percentile (hiring capabilities). "Combined capabilities" refers to organizations with both high knowledge management and hiring capabilities, both low knowledge management and hiring capabilities, compared to the remainder. For estimation results, including for external collaborator loss, see Tables A4.3 (column 1), A4.4 (column 1), and A4.5.

To establish a closer link between the organization's capabilities and the benefits from compensatory measures, we repeat the previous analysis based on modified versions of the patent count as the dependent variable. First, we consider only patents that rely on knowledge from within the organization. If knowledge management constitutes a relevant mechanism, we expect to see that, after internal collaborator loss, the remaining inventor's inventive productivity increasingly benefits from knowledge from within the organization. This expectation is confirmed (Figure 6a). In organizations with high knowledge management capabilities, the loss of an internal collaborator increases the remaining inventor's patents that rely on internal knowledge. Second, we consider only patents involving new collaborators. If hiring capabilities allow the organization to effectively fill the gap created by the lost internal collaborator, we expect to see that the remaining inventor's inventive productivity relies increasingly on new collaborations within the organization. Indeed, we find this to be the case (Figure 6b): in organizations with high hiring capabilities, the loss of an internal collaborator increases the remaining inventor's patents that involve new or newly hired internal collaborators.

Figure 6: Impact of internal collaborator loss on inventive productivity – knowledge input and new collaborations (DiD estimates)



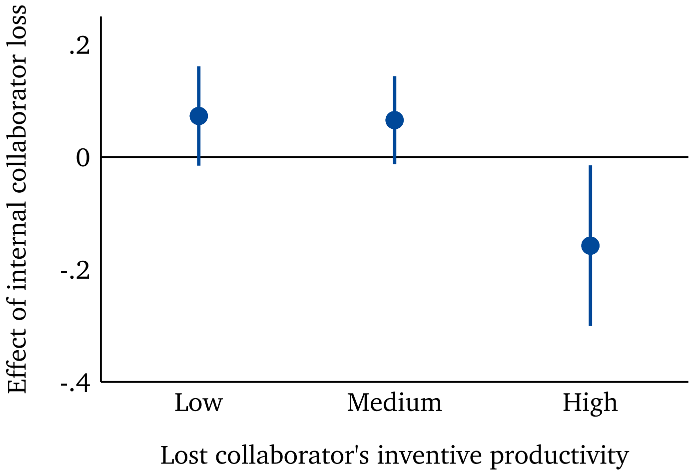
Notes: The graph presents point estimates and 95% confidence intervals for β^{real} in the relevant subgroups. We distinguish between remaining inventors by their organization's knowledge management and hiring capabilities. Subsamples are split at the median (knowledge management capabilities) and the 75th percentile (hiring capabilities—but excluding values of one, which are more likely cases of ID changes or other organizational reconfiguration). Results are comparable for higher thresholds. For estimation results, including for external collaborator loss, see Tables A4.3 (columns 6 and 7) and A4.4 (columns 2, 4, and 5).

5.4 Limits to "filling the gap"

If the organization takes compensatory measures to mitigate the negative effect of internal collaborator loss, why do we find also statistically significant *positive* effects on inventive productivity? One explanation for this may be that the organization fills the gap with a new collaborator who turns out to be more conducive to inventive productivity than the lost collaborator. To explore this, we leverage variation in a so far unused collaborator characteristic: their productivity before death. If inventors indeed benefit from new collaborators filling the gap, we would expect this benefit to be particularly pronounced if the lost collaborator had a low inventive productivity ("low-performing collaborator"). Conversely, we would expect the positive effect of internal collaborator loss to diminish or reverse if the lost collaborator had a high inventive productivity ("high-performing collaborator").

We find negative effects on inventive productivity when high-performing internal collaborators are lost, and positive effects when low-performing internal collaborators are lost (see Figure 7). This pattern of results is informative in two important ways. First, it supports the idea that filling the gap with a relatively more productive new collaborator can explain why the loss of low-performing internal collaborators increases inventive productivity. Second, it highlights the limits of the organization's compensatory measures. The gaps left by high-performing internal collaborators are not easily filled, resulting in a substantial negative effect on inventive productivity, which is otherwise only found for the loss of collaborators beyond the organizational boundaries.

Figure 7: Impact of internal collaborator loss on inventive productivity – collaborator productivity (DiD estimates)



Notes: The graph presents point estimates and 95% confidence intervals for β^{real} in the relevant subgroups. Subsamples are the first, second through fourth, and fifth quintile of lifetime patenting at the death of the (pseudo-)deceased co-inventor and the remainder. Results are comparable for alternative thresholds. For estimation results, including for external collaborator loss and for life cycle-adjusted inventive productivity, see Table A4.6.

Do these findings imply that organizations have a dominant strategy in systematically removing low-performing inventors from their workforce? We strongly caution against this interpretation for several reasons. First, investing in relevant capabilities is costly, and uncertainty remains about whether an organization can successfully fill the gaps created by laid-off employees. Second, low-performing inventors may still be valuable to the organization in ways that remain unaccounted for in our analysis. Finally, inventors might be deterred from joining or fully engaging with an organization if they perceive a high risk of being sidelined or made redundant.

5.5 Alternative explanations

In the following, we briefly discuss the merits of three alternative explanations for the observed effect pattern of collaborator loss on inventive productivity: changes in bargaining power, career effects, and emotional stress relief.

Inventors who lost an internal collaborator may experience a less negative productivity effect than those who lost an external collaborator due to increased bargaining power over their employer, resulting in improved working conditions and a more favorable allocation of internal resources (Sevcenko et al., 2022; Dencker, 2009). This alternative explanation rests on two assumptions: i) labor market frictions increase the employer's dependence on the remaining inventors to fill the gap, increasing the latter ones' bargaining power, and ii) the increase in bargaining power materializes in productivity-increasing resource allocation. To test the first assumption, we examine differences in the effect of internal collaborator loss on inventive productivity depending on the availability of other suitable inventors in the local labor market who could fill the gap (Table A6.1). We find weak evidence that internal collaborator loss has a more negative effect when there are other suitable inventors in the local labor market, which should make the employer less dependent on the focal inventor. However, a similar pattern is observed for external collaborator loss, which is inconsistent with the argument that changes in bargaining power should primarily concern the employer specifically needing to fill the gap. To test the second assumption, we investigate whether internal collaborator loss leads to an increase in the remaining inventor's team size; we do not find this to be the case (Table A6.2). Taken together, these findings suggest that a pure bargaining power explanation is unlikely.

Inventors may also benefit from internal collaborator loss in terms of career changes with a positive effect on their inventive productivity. For instance, recent research has shown that collaborator loss increases the likelihood of vacancy-driven promotions (Anderson, 2024) and mobility (Liu et al., 2023). If these career changes come with access to more attractive projects and research autonomy, this could explain why remaining inventors with internal collaborator loss fare better than those with external collaborator loss. To assess the relevance of such career events, we examine how the effects of internal and external collaborator loss change when excluding remaining inventors that moved or were promoted during the treatment period (Table A6.3). We confirm the differential effects of internal and external collaborator loss on inventive productivity based on subsamples excluding inventors with career changes. This renders career changes an unlikely explanation of our findings.

Finally, emotional stress following the death of an internal collaborator may be managed more effectively by the organization than in the case of an external collaborator, potentially explaining the less negative impact on inventive productivity. However, if emotional stress were the primary explanation behind the productivity effects observed after collaborator loss, we would expect an immediate impact. Contrarily, the negative effect of external collaborator loss peaks after several years, suggesting that emotional stress alone can hardly account for the long-term trends observed.

This discussion highlights that, although alternative explanations cannot be entirely dismissed, organizational compensatory measures align most consistently with our findings. We believe these measures are the most plausible explanation for the observed effects on productivity.

6 Discussion and conclusion

We argue that the loss of an internal collaborator carries less detrimental consequences for the remaining knowledge workers than the loss of an external collaborator, given that the directly affected organization has a vested interest in maintaining R&D continuity and accordingly implements ex-ante and ex-post compensatory measures. Leveraging a comprehensive employer-employee dataset linked to patent data, we examine the effects of internal and external collaborator loss, operationalized as co-inventor death, on the inventive productivity of the remaining inventors.

We find that the loss of a collaborator leads to a moderate decline in the inventive productivity of the remaining inventors, supporting findings from previous studies (Bernstein et al., 2022; Jaravel et al., 2018). The effect is markedly stronger for the loss of external collaborators, particularly when the collaborator was of presumably high relevance to the remaining inventor. In contrast, the loss of internal collaborators shows virtually no negative effect, which we attribute to compensatory measures implemented by the inventor's organization. Indeed, our findings suggest that remaining inventors in organizations with high knowledge management and hiring capabilities increasingly rely on internal knowledge sources and new collaborators, sustaining their productivity despite collaborator loss. However, the loss of a high-performing internal collaborator results in a substantial decline in inventive productivity, suggesting that organizational compensatory measures have their limits.

These findings enhance our understanding of collaborator loss among knowledge workers, a topic that was initially concentrated on academic scientists (Azoulay et al., 2010; Khanna, 2021; Mohnen, 2022; Oettl, 2012). More recently, this focus has expanded to include corporate inventors (Bernstein et al., 2022; Jaravel et al., 2018). Notably, these studies have, for various reasons, not paid much attention to the significance of organizational boundaries, which delineate internal from external collaborators within an inventor's collaborative network. We demonstrate that the impact of collaborator loss on inventive productivity strongly depends on whether the loss occurs within or outside these organizational boundaries. That said, our findings on the distinct effects across organizational boundaries might also apply within firms. Given localized knowledge spillovers (Audretsch and Feldman, 2004; Zucker et al., 1998; Balsmeier et al., 2022), the effects observed for external collaborators could similarly manifest within large organizations, where R&D activities are increasingly decentralized into autonomous units across different locations (Lerner and Wulf, 2007; Argyres and Silverman, 2004).

Furthermore, our study contributes to the ongoing discourse on peer effects in the workplace. The literature is divided on whether peer effects significantly influence coworker productivity (Marshall, 1890; Mas and Moretti, 2009; Waldinger, 2012; Cornelissen et al., 2017). Empirical studies in this literature often rely on negative shocks (i.e., collaborator losses) to quantify the contribution of peers to productivity (e.g., Waldinger, 2012). Following this literature, one might conclude that muted effects of internal collaborator loss imply a negligible contribution of direct colleagues on a knowledge worker's productivity. However, our results suggest that such effects are likely masked by the organization's endogenous response to mitigate potential productivity losses.

Finally, our research contributes to the literature on knowledge production within firms (Aggarwal et al., 2020; Argyres et al., 2020; Kapoor and Adner, 2012) by emphasizing the role that organizations play in managing collaborative relationships. Although the existing literature acknowledges the organization's role, we provide a deeper understanding of how this role manifests in situations of actual or potential knowledge loss. This insight likely extends beyond the specific case of unexpected deaths. Although an employee's departure to another organization does not necessarily sever all ties, it does create a vacancy and often implies loss of tacit knowledge for the focal organization (Sharoni, 2023; Kaiser et al., 2015). As a matter of fact, organizational compensatory measures, such as knowledge management and filling the gap, are more likely designed for the frequent event of employee mobility than for the rare incidence of unexpected deaths.

Our study is not without limitations. First, our research design allows for a causal interpretation of collaborator loss but does not provide exogenous variation in the organizational boundaries. In other words, whether a lost collaborator is internal or external to the knowledge worker's organization is not random. Based on the literature, we address relevant factors distinguishing internal and external collaborators, but there may still be additional nuances beyond the scope of our analysis. Relatedly, our data do not contain precise information on collaborative relationships. Future research based on other data could shed more light on the collaborations themselves. Second, we rely on proxies of the organization's ability to engage in effective knowledge management and hiring practices instead of directly measuring such activities. A worthwhile path for future research could be a more granular examination of what specific actions organizations undertake and which of these are most effective in sustaining productivity in the face of collaborator loss. Finally, we use data on corporate inventors in contemporary Germany. Future research could seek to replicate our findings for knowledge workers in other countries and time windows.

Our findings suggest the following managerial implications. First, our results indicate that organizations with capabilities that help maintain the continuity of R&D processes can buffer and compensate for unanticipated disruptions. In particular, managers should systematically invest in knowledge management, hiring, and related capabilities, and avoid creating points of failure through overly extensive specialization and division of labor. Second, our results show that organizations fail to compensate for the loss of external collaborators, which can play a critical role in knowledge worker productivity. Managers should not only encourage their knowledge workers to foster and expand their external ties but also develop robust contingency plans. These plans should consider to what extent employees rely on external knowledge sources, and support knowledge workers who encounter unforeseen changes in their collaborative network.

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Online Appendix

Content

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[30], 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 misspellings of the names and addresses. Hence, we are

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

confident that we identified the population of inventors except for the inventors not covered by social security data.

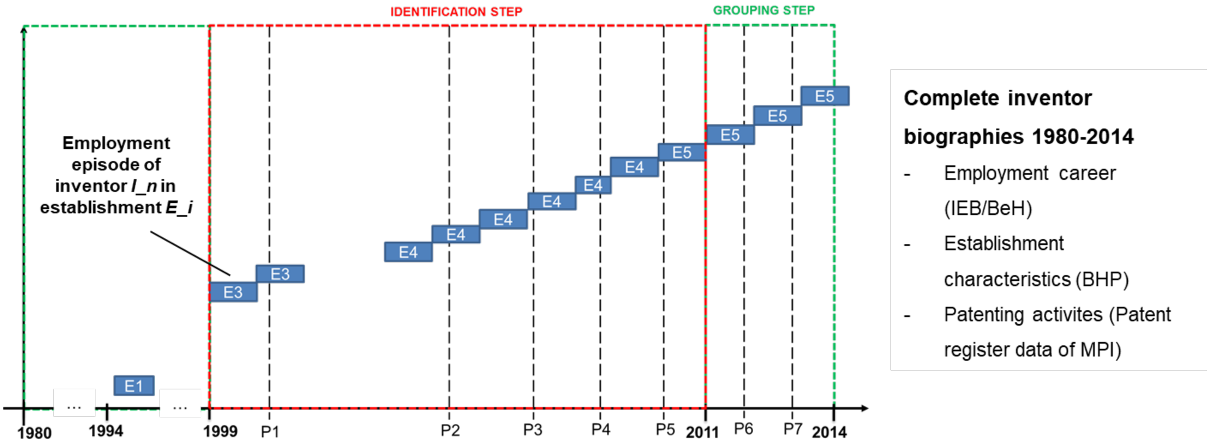
The INV-BIO dataset only contains inventors who were at least listed on one European (EP) patent during the time window 1999-2011 (see identification step in figure A1.1). Individuals who made inventions for which no patent was filed because the inventors or their employers preferred secrecy over patenting 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	Source
	Inventive productivity variables	
Patents	Short-hand for Patents (simple counts)	
Patents (simple counts)	Number of patent families with earliest filing year in the current year.	Inv
Patents (fractional counts)	Number of patent families, counting fractional shares by the number of inventors on a patent	Inv
Patents (simple counts excluding lost collaborator)	Patents (simple counts), but excluding patents with the (pseudo-)deceased co-inventor	Inv, Own
Patents (Lifetime)	Patents, cumulative until the current year. For matching, we coarsen the patent count to groups of 10-14, 15-19, 10s between 20 and 100, 50s between 100 and 300, and 400+ (for the dyadic variable, see below)	Inv
Patents (citation-weighted counts)	Patents, weighted by the number of EP citations received within 5 years	Inv
Patents (breakthrough patent counts)	Number of patent families which are in the top 10% of their technology-year cohort in terms of citations	Inv, Own
Patents (family size-weighted counts)	Number of patent families, weighted by the size of the global DOCDB patent family. For details, see footnote 4 in the main text.	Inv, Own
Patents (granted patent counts)	Number of patent families which comprise at least one granted patent (EP/DE)	Inv, Own
Patents with (only) new collaborator(s)	Number of patent families with at least one (alternatively, only) new co-inventor(s), i.e., inventors whom the remaining inventor had not worked with previously	Inv, Own
Patents with only old collaborators	Number of patent families without new co-inventors, i.e., only with inventors whom the remaining inventor had worked with previously	Inv, Own
Patents with newly hired collaborator(s)	Number of patent families with inventors who, at the time of filing, were recently (within two years) hired at their organization	Inv, Own
Patents (not) relying on organization knowledge	Number of patent families which cite any (none) earlier patent created by inventors who were employed by the remaining inventor's organization when the earlier patent was filed	Inv, Own
Patents with small (large) team	Patents (Simple), separated by patents with few (≤ 3) or many (> 4) inventors	Inv, Own
Team size (average)	Average number of inventors per patent of all patents filed in a given year/period	Inv, Own
	Inventor-level characteristics	
Death (date)	Exit date from the social security data with reason death	Base
Age	Age of the inventor in the current year	Base
Male	Gender of the inventor (Male=1)	Base
Science & engineering worker	Occupation classification and education level indicate high-skilled worker in science and engineering	Base
Organization tenure	Number of years of employment at current organization	Base
Organization size	Number of full-time employees of an organization. While matching, organization size is coarsened in groups of <50, 50-249, 250-999, and 1,000+ employees.	Base
Organization age	Age in years of the organization in the social security data, censored in 1975	Base
Technological focus	Inventor's modal technology field (chemistry, instruments, electrical engineering, mechanical engineering, other)	Inv
	Continued on the next page ...	

Table A2.1: Short variable descriptions

Variable	Description	Source
Years since last patenting	Years between the latest earliest filing date of a patent application and the current time	Inv
Labor market density (narrow, wide)	Number of inventors in the year, geographic region (district or regional labor market) and technology (wide: 34 technology areas, or narrow: IPC4) as the inventor	Inv, Own
	Inventor-collaborator-level characteristics	
Internal loss	Whether a (pseudo-)deceased co-inventor and remaining inventor worked in the same organization at the time of the (pseudo-)death	Own
Knowledge compementarity: Patent class similarity	Cosine similarity between the IPC4-level patenting shares of remaining and (pseudo-)deceased co-inventor. Complementarity is indicated by low values of similarity.	Inv, Own
Knowledge compementarity: Patent class overlap	Overlap between the IPC4-level patenting shares of the remaining and (pseudo-)deceased co-inventors by summing the minimum values of their respective shares across all classes. Specifically, for each class, we identify the lesser share between the two inventors, then sum these minimum values to determine the overall overlap. Complementarity is indicated by low values of overlap.	Inv, Own
Collaborator network size (excluding common inventors)	Number of unique inventors that the (pseudo-)deceased co-inventor filed a patent with, that the remaining inventor had not filed a patent with	Own
Collaborator network size (including common inventors)	Number of unique inventors that the (pseudo-)deceased co-inventor filed a patent with	Own
Collaborator network size (same technology specialization)	Number of unique inventors in the organization of the (pseudo-)deceased co-inventor with the same modal lifetime IPC4 technology	Own
Collaboration intensity (recency)	Years since the last joint patent of remaining inventor and (pseudo-)deceased co-inventor	Base, Own
Collaboration intensity (joint patents)	Number of patents two inventors jointly applied for	Inv, Own
Collaboration intensity (recent joint patents)	Number of patents two inventors jointly applied for in the last four years	Inv, Own
Collaboration intensity (joint tenure)	Number of years two inventors worked in the same establishment	Base, Own
Collaborator inventive productivity	Cumulative patent count of the (pseudo-)deceased co-inventor at the time of death.	Inv, Own
Collaborator inventive productivity (residualized)	Residual of collaborative inventive productivity in a regression with age, year, firm size, and technology area fixed effects	Inv, Own
	Organizational capabilities	
Knowledge management capabilities	Share of patents with self-citations to same organization without an overlap in the inventor team relative to all patents with self-citations	Inv, Own
Hiring capabilities	Share of inventors in the organization who joined in the year before the co-inventor death relative to all inventors in the organization	Inv, Own
	Robustness variables	
Promotion	Promotion event caused by a change in occupation from non-senior to senior (i.e., managerial occupation), by default excluding moves across employers.	Base, Own
Leave	Mobility event caused by a change in the establishment to unemployment or to another employer	Base, Own

Notes: Data source: Base = IAB base data; Inv = INV-BIO ADIAB 8014; Own = Own calculation. In own calculations, we draw on additional data from PATSTAT (citation links, ...).

A3 Descriptive tables and figures

Table A3.1: Summary statistics and pair-wise correlations

Remaining inventors	Summary		Pairwise correlations							
Variable	Mean	SD	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Patents (simple counts)	0.65	1.18	1.00							
(2) Patents (lifetime)	7.46	4.75	0.39	1.00						
(3) Patents (citation-weighted counts)	0.68	1.65	0.75	0.30	1.00					
(4) Patents with at least one new collaborator	0.42	0.93	0.83	0.30	0.70	1.00				
(5) Patents relying on organization knowledge	0.27	0.78	0.69	0.28	0.57	0.59	1.00			
(6) Age	44.03	10.65	-0.05	0.16	-0.06	-0.07	-0.02	1.00		
(7) Male	0.93	0.26	0.05	0.11	0.01	0.02	0.02	0.14	1.00	
(8) Science & engin. worker	0.50	0.50	0.08	0.16	0.06	0.07	0.07	-0.05	0.07	1.00
(9) Organization tenure	10.02	8.08	0.03	0.10	0.01	0.01	0.11	0.40	0.06	-0.09
(10) Organization size (000)	5.05	9.61	0.07	0.13	0.05	0.07	0.09	-0.03	-0.00	0.07
(11) Years since last patenting	2.71	3.35	-0.50	-0.33	-0.37	-0.41	-0.31	0.33	-0.05	-0.08
(12) Internal collaborator	0.52	0.50	0.04	0.01	0.03	0.03	0.11	-0.05	-0.01	0.02
(13) Knowledge similarity	0.70	0.29	-0.02	-0.09	-0.01	-0.02	0.01	-0.04	-0.02	-0.06
(14) Knowledge overlap	0.54	0.26	-0.04	-0.13	-0.02	-0.03	-0.00	-0.04	-0.03	-0.07
(15) Collaborator network size (excl. common inv.)	11.29	15.75	0.07	0.16	0.07	0.08	0.07	-0.06	-0.09	0.06
(16) Collaborator network size (incl. common inv.)	17.30	18.17	0.10	0.21	0.10	0.11	0.10	-0.06	-0.09	0.04
(17) Collaborator network size (same tech. Spec.)	28.88	52.96	0.11	0.16	0.09	0.10	0.12	-0.05	-0.03	0.08
(18) Collaboration intensity (recency)	4.61	2.81	-0.04	0.06	-0.03	-0.03	-0.07	0.21	0.00	-0.01
(19) Collaboration intensity (joint patents)	2.29	3.52	0.16	0.27	0.13	0.11	0.13	0.03	0.03	0.04
(20) Collaboration intensity (joint tenure)	5.23	6.89	0.03	0.04	0.02	0.02	0.11	0.10	0.01	-0.02
(21) Collaborator inventive productivity	8.24	4.75	0.13	0.26	0.10	0.10	0.10	-0.02	-0.02	0.07
(22) Collaborator inventive productivity (resid.)	10.45	23.49	0.13	0.23	0.10	0.11	0.10	-0.05	-0.04	0.06
(23) Knowledge management capabilities	0.86	0.18	0.07	0.14	0.07	0.07	0.11	-0.01	-0.02	0.05
(24) Hiring capabilities	0.11	0.20	-0.02	-0.03	-0.01	-0.01	-0.03	-0.04	0.01	-0.03

	Pairwise correlations (continued)															
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
(9)	1.00															
(10)	0.14	1.00														
(11)	0.01	-0.04	1.00													
(12)	0.21	0.11	-0.09	1.00												
(13)	0.00	-0.12	0.03	0.17	1.00											
(14)	-0.00	-0.12	0.06	0.17	0.92	1.00										
(15)	-0.02	0.20	-0.04	-0.02	-0.18	-0.21	1.00									
(16)	-0.02	0.19	-0.05	0.00	-0.11	-0.14	0.95	1.00								
(17)	0.05	0.29	-0.09	0.15	0.06	0.03	0.26	0.28	1.00							
(18)	0.10	-0.00	0.20	-0.20	-0.07	-0.08	0.08	0.05	-0.03	1.00						
(19)	0.01	0.02	-0.09	0.09	0.19	0.19	0.07	0.17	0.03	-0.10	1.00					
(20)	0.55	0.13	-0.04	0.73	0.13	0.12	0.00	0.01	0.16	-0.04	0.08	1.00				
(21)	-0.01	0.09	-0.10	-0.01	-0.16	-0.23	0.57	0.56	0.20	0.01	0.25	-0.01	1.00			
(22)	-0.04	0.06	-0.08	-0.02	-0.08	-0.11	0.75	0.74	0.23	0.05	0.31	-0.01	0.61	1.00		
(23)	0.09	0.09	-0.06	0.18	0.02	0.00	0.13	0.14	0.12	0.02	0.06	0.13	0.13	0.10	1.00	
(24)	-0.13	-0.06	0.01	-0.11	0.02	0.01	-0.02	0.01	-0.12	-0.05	-0.02	-0.19	-0.05	-0.04	-0.03	1.00

Notes: Full estimation sample. For variable descriptions, see Table A2.1.

Table A3.2: Pre-death characteristics of deceased and remaining inventors (Full sample)

Lost collaborator	Deceased (N = 845)			Pseudo-deceased (N = 845)				
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Diff.	p-value
Patents (Lifetime)	6.04	3.00	7.57	5.95	3.00	7.33	0.09	0.804
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
Organization tenure	12.03	10.00	9.18	11.89	10.00	8.91	0.14	0.755
Organization size	4041.19	777.50	9229.49	3504.52	790.00	7961.90	536.67	0.204
Organization 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
Science & engin. worker	0.39	0.00	0.49	0.41	0.00	0.49	−0.02	0.333

Inventors	Deceased (N = 3574)			Pseudo-deceased (N = 3409)				
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Diff.	p-value
Patents (Lifetime)	11.44	7.00	10.34	10.94	7.00	10.17	0.51	0.039**
Age	45.62	45.00	9.15	45.40	44.00	9.35	0.22	0.312
Male	0.93	1.00	0.25	0.92	1.00	0.27	0.01	0.043**
Organization tenure	10.22	8.00	8.15	9.96	8.00	8.01	0.26	0.195
Organization size	5088.44	1394.00	9634.85	4898.03	1388.00	9401.36	190.41	0.424
Organization age	22.52	27.00	11.82	22.87	28.00	11.91	−0.35	0.242
Years since last patenting	2.01	1.00	2.37	2.03	1.00	2.30	−0.02	0.659

Characteristics of the lost collaborator	Deceased (N = 3574)			Pseudo-deceased (N = 3409)				
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Diff.	p-value
Internal collaborator	0.50	1.00	0.50	0.53	1.00	0.50	−0.02	0.037**
Knowledge similarity	0.70	0.78	0.28	0.69	0.79	0.29	0.01	0.180
Knowledge overlap	0.54	0.53	0.26	0.53	0.53	0.26	0.01	0.245
Collab. network size (excl. common inv.)	12.25	5.00	17.85	10.75	6.00	13.61	1.50	0.000***
Collab. network size (incl. common inv.)	18.08	11.00	20.13	16.92	11.00	16.25	1.16	0.008***
Collab. intensity (recency)	4.73	4.00	2.82	4.66	4.00	2.80	0.07	0.277
Collab. intensity (joint patents)	2.27	1.00	3.45	2.29	1.00	3.51	−0.02	0.807
Collab. intensity (joint tenure)	5.53	1.00	7.30	5.65	3.00	7.01	−0.13	0.455
Collab. inventive productivity (pre-death)	19.92	9.00	27.11	16.51	9.00	21.99	3.40	0.000***

Organizational characteristics	Deceased (N = 3574)			Pseudo-deceased (N = 3409)				
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Diff.	p-value
Knowledge management capabilities	0.86	0.92	0.18	0.86	0.91	0.18	0.00	0.371
Hiring capabilities	0.11	0.05	0.22	0.09	0.05	0.18	0.02	0.000***

Notes: This table presents summary statistics of pre-death characteristics of deceased co-inventors and their matched control group. The unit of observation is at the deceased co-inventor (first part) or remaining inventor (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.

Table A3.3: Pre-death characteristics of remaining inventors with internal collaborator loss

Inventors	Deceased (N = 1797)			Pseudo-deceased (N = 1799)				
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Diff.	p-value
Patents (Lifetime)	11.25	7.00	10.15	11.16	7.00	10.26	0.09	0.788
Age	45.23	45.00	8.18	44.66	44.00	8.40	0.57	0.039**
Male	0.93	1.00	0.25	0.91	1.00	0.28	0.02	0.048**
Organization tenure	11.86	10.00	8.20	11.43	10.00	8.08	0.42	0.119
Organization size	6043.82	1760.00	10 801.87	5854.92	1627.00	10 548.68	188.90	0.596
Organization age	23.72	28.00	11.34	23.99	29.00	11.46	−0.27	0.478
Years since last patenting	1.68	1.00	2.24	1.63	1.00	2.02	0.06	0.419
Characteristics of the lost collaborator	**Deceased (N = 1797)**			**Pseudo-deceased (N = 1799)**				
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Diff.	p-value
Internal collaborator	1.00	1.00	0.00	1.00	1.00	0.00	0.00	
Knowledge similarity	0.74	0.83	0.26	0.74	0.84	0.26	0.00	0.997
Knowledge overlap	0.58	0.58	0.25	0.58	0.59	0.24	0.00	0.551
Collab. network size (excl. common inv.)	12.27	5.00	19.70	10.32	6.00	12.89	1.95	0.000***
Collab. network size (incl. common inv.)	18.13	10.00	22.32	17.06	11.00	16.10	1.07	0.100
Collab. intensity (recency)	4.20	4.00	2.78	4.13	4.00	2.77	0.06	0.485
Collab. intensity (joint patents)	2.52	1.00	4.08	2.61	1.00	4.05	−0.09	0.517
Collab. intensity (joint tenure)	10.88	9.94	6.86	10.56	9.25	6.39	0.32	0.152
Collab. inventive productivity (pre-death)	19.94	9.00	28.36	15.88	8.00	20.17	4.06	0.000***
Organizational characteristics	**Deceased (N = 1797)**			**Pseudo-deceased (N = 1799)**				
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Diff.	p-value
Knowledge management capabilities	0.89	0.92	0.13	0.88	0.92	0.15	0.01	0.071*
Hiring capabilities	0.08	0.05	0.17	0.08	0.05	0.16	0.00	0.654

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

Table A3.4: Pre-death characteristics of remaining inventors with external collaborator loss

Inventors	Deceased (N = 1777)			Pseudo-deceased (N = 1610)				
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Diff.	p-value
Patents (Lifetime)	11.64	7.00	10.52	10.69	7.00	10.07	0.95	0.007***
Age	46.01	44.00	10.03	46.22	45.00	10.25	−0.21	0.555
Male	0.93	1.00	0.25	0.93	1.00	0.26	0.01	0.428
Organization tenure	8.27	6.00	7.65	7.96	6.00	7.48	0.31	0.282
Organization size	3945.80	1075.00	7871.82	3598.77	1059.00	7377.96	347.03	0.229
Organization age	21.09	26.00	12.23	21.34	25.00	12.33	−0.26	0.579
Years since last patenting	2.33	2.00	2.46	2.48	2.00	2.50	−0.15	0.078*

Characteristics of the lost collaborator	Deceased (N = 1777)			Pseudo-deceased (N = 1610)				
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Diff.	p-value
Internal collaborator	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Knowledge similarity	0.66	0.74	0.30	0.63	0.71	0.31	0.02	0.022**
Knowledge overlap	0.50	0.49	0.26	0.48	0.48	0.27	0.01	0.121
Collab. network size (excl. common inv.)	12.23	6.00	15.77	11.24	6.00	14.35	0.99	0.057*
Collab. network size (incl. common inv.)	18.04	11.00	17.65	16.77	11.00	16.43	1.27	0.031**
Collab. intensity (recency)	5.27	5.00	2.76	5.24	5.00	2.72	0.03	0.781
Collab. intensity (joint patents)	2.01	1.00	2.64	1.93	1.00	2.75	0.08	0.377
Collab. intensity (joint tenure)	0.11	0.00	1.08	0.17	0.00	1.19	−0.06	0.143
Collab. inventive productivity (pre-death)	19.90	10.00	25.78	17.23	9.00	23.84	2.68	0.002***

Organizational characteristics	Deceased (N = 1777)			Pseudo-deceased (N = 1610)				
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Diff.	p-value
Knowledge management capabilities	0.82	0.91	0.23	0.82	0.89	0.22	0.00	0.707
Hiring capabilities	0.14	0.05	0.26	0.10	0.05	0.19	0.04	0.000***

Notes: This table presents summary statistics of pre-death characteristics of deceased co-inventors and their matched control group. The unit of observation is at the deceased co-inventor (first part) or remaining inventor (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.

Table A3.5: Pre-death characteristics of remaining inventors (Internal vs external collaborator loss)

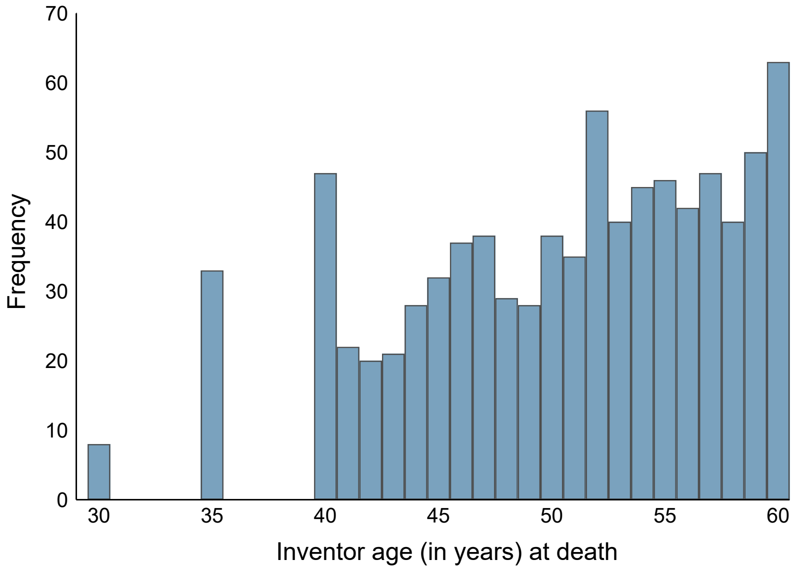
Inventors	Internal collaborators			External collaborators				
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Diff.	p-value
Patents (Lifetime)	11.21	7.00	10.20	11.18	7.00	10.32	0.02	0.923
Age	44.94	44.00	8.30	46.11	45.00	10.13	−1.17	0.000***
Male	0.92	1.00	0.27	0.93	1.00	0.26	−0.01	0.265
Organization tenure	11.64	10.00	8.14	8.12	6.00	7.57	3.52	0.000***
Organization size	5949.34	1664.00	10 674.92	3783.23	1059.00	7645.06	2166.12	0.000***
Organization age	23.86	28.00	11.40	21.21	26.00	12.27	2.65	0.000***
Years since last patenting	1.66	1.00	2.13	2.40	2.00	2.48	−0.75	0.000***

Characteristics of the lost collaborator	Internal collaborators			External collaborators				
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Diff.	p-value
Internal collaborator	1.00	1.00	0.00	0.00	0.00	0.00	1.00	
Knowledge similarity	0.74	0.83	0.26	0.65	0.73	0.30	0.10	0.000***
Knowledge overlap	0.58	0.58	0.24	0.49	0.49	0.26	0.09	0.000***
Collab. network size (excl. common inv.)	11.29	5.00	16.67	11.76	6.00	15.12	−0.47	0.222
Collab. network size (incl. common inv.)	17.59	11.00	19.46	17.44	11.00	17.09	0.16	0.720
Collab. intensity (recency)	4.17	4.00	2.78	5.26	5.00	2.74	−1.09	0.000***
Collab. intensity (joint patents)	2.57	1.00	4.06	1.97	1.00	2.69	0.59	0.000***
Collab. intensity (joint tenure)	10.72	9.58	6.63	0.14	0.00	1.13	10.58	0.000***
Collab. inventive productivity (pre-death)	17.90	8.00	24.69	18.63	9.00	24.91	−0.73	0.221

Organizational characteristics	Internal collaborators			External collaborators				
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Diff.	p-value
Knowledge management capabilities	0.89	0.92	0.14	0.82	0.90	0.23	0.07	0.000***
Hiring capabilities	0.08	0.05	0.16	0.12	0.05	0.23	−0.04	0.000***

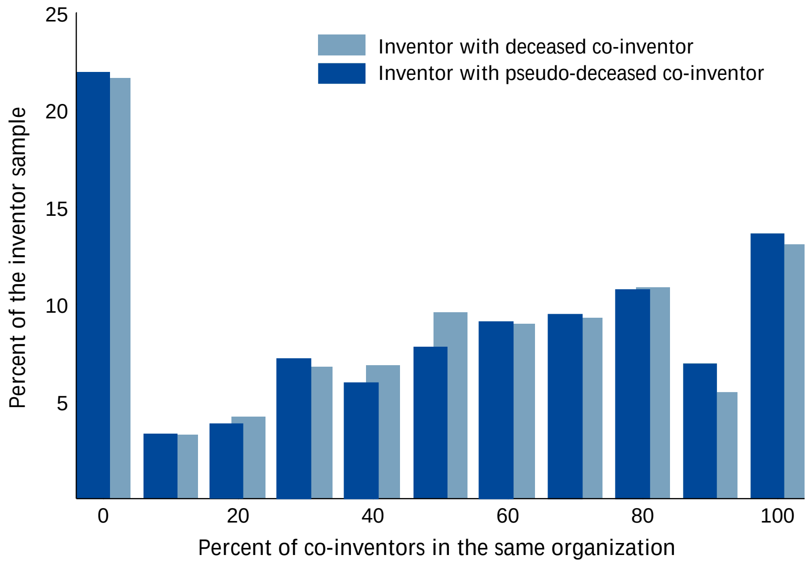
Notes: This table presents summary statistics of pre-death characteristics of inventors experiencing internal collaborator loss (N=3387) and inventors experiencing external collaborator loss (N=3596). The unit of observation is at the remaining inventor level. Reported p-values based on an unpaired t-test. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Figure A3.1: Age of deceased co-inventors



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

Figure A3.2: Co-inventors in the same organization



Notes: For the remaining inventors in the estimation sample, the graph plots the percent of their co-inventors employed in the same establishment in the year prior to the death event. Only co-inventors on patents prior to the death are considered. Inventor-level shares are rounded to the closest 10% to adhere to data confidentiality regulations of the IAB.

A4 Main results

Table A4.1: Impact of internal and external collaborator loss on inventive productivity – simple and citation-weighted patent counts (Event study estimates)

	Patents (simple counts)			Patents (citation-weighted)		
	(1)	(2)		(3)	(4)	
Death year	All	External	Internal	All	External	Internal
$-11/-10$	0.025	-0.014	0.057	-0.034	-0.088	0.012
	(0.054)	(0.062)	(0.072)	(0.069)	(0.087)	(0.083)
$-9/-8$	-0.019	-0.041	-0.005	-0.086	-0.111	-0.066
	(0.052)	(0.065)	(0.074)	(0.069)	(0.091)	(0.087)
$-7/-6$	0.019	0.055	-0.019	0.021	0.085	-0.041
	(0.047)	(0.060)	(0.063)	(0.058)	(0.080)	(0.082)
$-5/-4$	0.030	0.073	-0.013	0.012	0.057	-0.031
	(0.040)	(0.059)	(0.059)	(0.053)	(0.070)	(0.074)
$-3/-2$	0.025	0.037	0.012	0.000	0.000	0.000
	(0.032)	(0.047)	(0.051)	(.)	(.)	(.)
-1	0.000	0.000	0.000	-0.106^{*}	-0.129	-0.082
	(.)	(.)	(.)	(0.055)	(0.081)	(0.078)
0/1	-0.005	-0.062	0.048	-0.098^{**}	-0.193^{***}	-0.010
	(0.033)	(0.043)	(0.050)	(0.049)	(0.073)	(0.071)
2/3	-0.004	-0.058	0.046	-0.049	-0.163^{**}	0.057
	(0.035)	(0.050)	(0.050)	(0.053)	(0.076)	(0.075)
4/5	-0.048	-0.110^{**}	0.010	-0.085	-0.151^{*}	-0.025
	(0.039)	(0.050)	(0.055)	(0.062)	(0.081)	(0.083)
6/7	-0.022	-0.008	-0.035	-0.107^{*}	-0.136	-0.080
	(0.046)	(0.060)	(0.060)	(0.065)	(0.086)	(0.086)
8	0.066	0.035	0.092	-0.020	-0.075	0.027
	(0.046)	(0.067)	(0.065)	(0.065)	(0.085)	(0.094)
Inventor FE	Yes	Yes		Yes	Yes	
Inventor age FE	Yes	Yes		Yes	Yes	
Match group×rel. year FE	Yes	Yes		Yes	Yes	
Clusters	856	856		856	856	
Observations	124168	124168		124168	124168	
Adj. R2	0.37	0.37		0.30	0.30	
DV mean	0.65	0.65		0.69	0.69	

Notes: This table reports the estimates for β^{real} from a linear regression with inventor, inventor age, and deceased co-inventor times relative year fixed effects. In regressions (1) and (2), the dependent variable is the simple patent count, and in (3) and (4), patents are weighted by forward citations. The dependent variables are winsorized at the 95th percentile. The unit of observation is at the inventor-year level. Standard errors clustered at the level of the (pseudo-)deceased co-inventor's organization are in parentheses. Estimates are for years relative to the death year of the deceased co-inventor. For citation-weighted outcomes, we normalize effects to the two-year bin $t{-}3/t{-}2$, as they can already be affected in the pre-period if future, citation-generating patents are never filed due to the collaborator death. For patent-related outcomes, such potential contamination is likely less severe. * p<0.1, ** p<0.05, *** p<0.01.

Table A4.2: Impact of collaborator loss on inventive productivity – regression results for Figure 4 (DiD estimates)

	Knowledge complementarity		Collaborator network size			Collaboration intensity			
	(1) Patent class similarity	(2) Patent class overlap	(3) Excluding common inv.	(4) Including common inv.	(5) Same tech. specializ.	(6) Recency	(7) Joint patents	(8) Recent joint pat.	(9) Joint tenure
Internal collaborator loss:	−0.001	0.050	0.056*	0.030	0.018	0.020	0.007	−0.005	0.015
– Less relevant collaborators	(0.055)	(0.054)	(0.033)	(0.032)	(0.033)	(0.036)	(0.034)	(0.045)	(0.046)
Internal collaborator loss:	0.030	0.014	−0.065	−0.063	−0.007	0.026	0.034	0.046	0.028
– More relevant collaborators	(0.035)	(0.036)	(0.066)	(0.066)	(0.071)	(0.055)	(0.050)	(0.039)	(0.039)
External collaborator loss:	0.037	0.030	−0.026	−0.033	−0.064*	−0.063*	−0.088**	−0.070*	−0.078**
– Less relevant collaborators	(0.067)	(0.067)	(0.034)	(0.033)	(0.035)	(0.036)	(0.038)	(0.041)	(0.034)
External collaborator loss:	−0.103***	−0.103***	−0.215**	−0.244***	−0.178*	−0.144**	−0.070	−0.095*	
– More relevant collaborators	(0.036)	(0.037)	(0.085)	(0.090)	(0.094)	(0.071)	(0.056)	(0.051)	
Δ External-Internal	0.038	−0.020	−0.082*	−0.063	−0.082*	−0.082*	−0.095*	−0.065	−0.106**
– Less relevant collaborators	(0.085)	(0.087)	(0.050)	(0.048)	(0.047)	(0.050)	(0.054)	(0.061)	(0.052)
Δ External-Internal	−0.133***	−0.117**	−0.150	−0.181*	−0.171*	−0.170**	−0.104	−0.141**	
– More relevant collaborators	(0.051)	(0.050)	(0.093)	(0.098)	(0.103)	(0.084)	(0.075)	(0.065)	
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Inventor age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Match group×rel. year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	856	856	856	856	851	856	856	856	856
Observations	124168	124168	124168	124168	123692	124168	124168	124168	124168
Adj. R2	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37
DV mean	0.65	0.65	0.65	0.65	0.65	0.65	0.65	0.65	0.65

Notes: This table reports the estimates for β^{real} from a linear regression with inventor, inventor age, and deceased co-inventor times relative year fixed effects. The dependent variable is the simple patent count. The unit of observation is at the inventor-year level. Standard errors clustered at the level of the (pseudo-)deceased co-inventor's organization are in parentheses. Each reported estimate stands for the treatment effect for the relevant subgroup (e.g., $\beta^{real}_{C_i=1}$) or their difference (e.g., row Δ External-Internal – Less relevant collaborators reports $\beta^{real}_{Ext,Less\,rel.} - \beta^{real}_{Int,Less\,rel.}$). More relevant collaborators are such with low patent class similarity or overlap, many (non-common) co-inventors or colleagues, low joint patenting recency, many joint patents or high joint tenure. For external collaborator loss, joint tenure is zero by definition, so the 'more relevant collaborator' estimate is missing. We split the sample at the 75th percentile, except for joint patenting recency, where more relevant collaborators are those at the 25th percentile and below. * p<0.1, ** p<0.05, *** p<0.01.

Table A4.3: Impact of collaborator loss on inventive productivity – knowledge management capabilities (DiD estimates)

	Patents	Patents with ... collaborator(s)				Patents relying on ...	
	(1) All	(2) at least one new	(3) only new	(4) only old	(5) at least one newly hired	(6) organization knowledge	(7) only other knowledge
Internal collaborator loss: – Low capabilities	−0.069 (0.051)	−0.007 (0.033)	0.031 (0.019)	−0.021 (0.029)	−0.016 (0.028)	−0.058* (0.034)	−0.007 (0.042)
Internal collaborator loss: – High capabilities	0.107** (0.045)	0.041 (0.036)	0.037* (0.020)	0.016 (0.040)	0.022 (0.037)	0.157** (0.067)	−0.013 (0.076)
External collaborator loss: – Low capabilities	−0.090 (0.063)	−0.045 (0.038)	−0.009 (0.023)	−0.050 (0.039)	−0.044 (0.033)	−0.053 (0.038)	−0.025 (0.051)
External collaborator loss: – High capabilities	−0.093 (0.060)	−0.030 (0.040)	−0.009 (0.022)	−0.047 (0.035)	0.035 (0.038)	−0.063 (0.047)	−0.037 (0.054)
Δ Internal loss: High–Low	0.175** (0.076)	0.047 (0.054)	0.006 (0.031)	0.037 (0.054)	0.038 (0.051)	0.215** (0.085)	−0.006 (0.099)
Δ External loss: High–Low	−0.003 (0.088)	0.015 (0.053)	0.000 (0.028)	0.002 (0.055)	0.079 (0.051)	−0.010 (0.063)	−0.012 (0.078)
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Inventor age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Match group×rel. year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	695	695	695	695	695	695	695
Observations	100118	100118	100118	100118	100118	100118	100118
Adj. R2	0.37	0.27	0.13	0.27	0.23	0.33	0.31
DV mean	0.72	0.47	0.25	0.22	0.21	0.33	0.47

Notes: This table reports the estimates for β^{real} from a linear regression with inventor, inventor age, and deceased co-inventor times relative year fixed effects. The unit of observation is at the inventor-year level. Standard errors clustered at the level of the (pseudo-)deceased co-inventor's organization are in parentheses. Each reported estimate stands for the treatment effect for the relevant subgroup (e.g., $\beta^{real}_{C_i=1}$) or their difference (e.g., row Δ Internal loss: High–Low reports $\beta^{real}_{Int,High} - \beta^{real}_{Int,Low}$). The table splits the sample by the knowledge management capabilities of the inventor's organization (median splits within the internal/external collaborator loss subsamples). The dependent variables are simple patent counts winsorized at the 95% level. In columns 2-7, the dependent variables are counts of patents of the remaining inventor that were joint with at least one other inventor they had never co-patented with previously (2), exclusively with other inventors they had never co-patented with (3), etc. In column 5, at least one other inventor joined the organization in t or the preceding two years. Column (6) counts patents with at least one backward citation to a previous patent of the inventor's organization, and (7) counts patents without any such backward citation. * p<0.1, ** p<0.05, *** p<0.01.

Table A4.4: Impact of collaborator loss on inventive productivity – hiring capabilities (DiD estimates)

	Patents	Patents with ... collaborator(s)				Patents relying on ...	
	(1) All	(2) at least one new	(3) only new	(4) only old	(5) at least one newly hired	(6) organization knowledge	(7) only other knowledge
Internal collaborator loss: – Low capabilities	−0.002 (0.031)	−0.007 (0.023)	0.023* (0.014)	−0.009 (0.022)	−0.018 (0.020)	0.043 (0.036)	−0.019 (0.041)
Internal collaborator loss: – High capabilities	0.161** (0.082)	0.123** (0.049)	0.079*** (0.031)	0.041 (0.048)	0.113** (0.047)	0.057 (0.055)	0.095 (0.061)
External collaborator loss: – Low capabilities	−0.101** (0.040)	−0.067** (0.030)	−0.034** (0.015)	−0.035 (0.023)	−0.034 (0.026)	−0.046** (0.023)	−0.050 (0.036)
External collaborator loss: – High capabilities	0.013 (0.075)	0.008 (0.054)	0.021 (0.028)	−0.029 (0.038)	0.030 (0.045)	−0.051 (0.048)	0.038 (0.058)
Δ Internal loss: High–Low	0.164* (0.090)	0.130** (0.057)	0.056 (0.036)	0.049 (0.055)	0.131** (0.055)	0.014 (0.071)	0.115 (0.080)
Δ External loss: High–Low	0.115 (0.088)	0.075 (0.067)	0.055* (0.032)	0.005 (0.048)	0.065 (0.057)	−0.005 (0.056)	0.088 (0.073)
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Inventor age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Match group×rel. year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	856	856	856	856	856	856	856
Observations	124168	124168	124168	124168	124168	124168	124168
Adj. R2	0.37	0.27	0.13	0.27	0.23	0.34	0.31
DV mean	0.65	0.42	0.23	0.20	0.19	0.27	0.45

Notes: This table reports the estimates for β^{real} from a linear regression with inventor, inventor age, and deceased co-inventor times relative year fixed effects. The unit of observation is at the inventor-year level. Standard errors clustered at the level of the (pseudo-)deceased co-inventor's organization are in parentheses. Each reported estimate stands for the treatment effect for the relevant subgroup (e.g., $\beta^{real}_{C_i=1}$) or their difference (e.g., row Δ Internal loss: High–Low reports $\beta^{real}_{Int,High} - \beta^{real}_{Int,Low}$). The table splits the sample by the hiring capabilities of the inventor's organization (75th percentile split, but excluding values of one—which are more likely cases of ID changes or other organizational reconfiguration). The dependent variables are simple patent counts winsorized at the 95% level. In columns 2-7, the dependent variables are counts of patents of the remaining inventor that were joint with at least one other inventor they had never co-patented with previously (2), exclusively with other inventors they had never co-patented with (3), etc. In column 5, at least one other inventor joined the organization in t or the preceding two years. Column (6) counts patents with at least one backward citation to a previous patent of the inventor's organization, and (7) counts patents without any such backward citation. * p<0.1, ** p<0.05, *** p<0.01.

Table A4.5: Impact of collaborator loss on inventive productivity with internal collaborator loss – knowledge management and hiring capabilities in combination (DiD estimates)

	(1)	(2)	(3)
Low capabilities knowledge management and hiring	-0.178^{***}		-0.187^{***}
	(0.061)		(0.060)
High capabilities knowledge management and hiring		0.602^{***}	0.633^{***}
		(0.167)	(0.158)
Remainder	0.159^{***}	-0.017	0.113^{**}
	(0.045)	(0.036)	(0.047)
Inventor FE	Yes	Yes	Yes
Inventor age FE	Yes	Yes	Yes
Match group×rel. year FE	Yes	Yes	Yes
Clusters	466	466	466
Observations	59175	59175	59175
Adj. R2	0.39	0.39	0.39
DV mean	0.73	0.73	0.73

Notes: This table reports the estimates for β^{real} from a linear regression with inventor, inventor age, and deceased co-inventor times relative year fixed effects. The dependent variable is the simple patent count. The unit of observation is at the inventor-year level. Standard errors clustered at the level of the (pseudo-)deceased co-inventor's organization are in parentheses. Each reported estimate stands for the treatment effect for the relevant subgroup (e.g., $\beta^{real}_{C_i=1}$). For variable definitions, see notes of Table A4.3 and Table A4.4. * p<0.1, ** p<0.05, *** p<0.01.

Table A4.6: Impact of collaborator loss on inventive productivity – collaborator inventive productivity (DiD estimates)

	(1) By collaborator inventive productivity (pre-death)	(2) By collaborator inventive productivity (pre-d., residualized)
Internal collaborator loss: Low	0.073	0.056
	(0.045)	(0.050)
Middle	0.066	0.075**
	(0.040)	(0.038)
High	−0.158**	−0.172**
	(0.073)	(0.070)
External collaborator loss: Low	0.014	−0.071
	(0.052)	(0.060)
Middle	−0.050	−0.021
	(0.037)	(0.036)
High	−0.237**	−0.241**
	(0.118)	(0.116)
Inventor FE	Yes	Yes
Inventor age FE	Yes	Yes
Match group×rel. year FE	Yes	Yes
Clusters	856	849
Observations	124168	123022
Adj. R2	0.37	0.37
DV mean	0.65	0.65

Notes: This table reports the estimates for β^{real} from a linear regression with inventor, inventor age, and deceased co-inventor times relative year fixed effects. The dependent variable is the simple patent count. The unit of observation is at the inventor-year level. Standard errors clustered at the level of the (pseudo-)deceased co-inventor's organization are in parentheses. Each reported estimate stands for the treatment effect for the relevant subgroup (e.g., $\beta^{real}_{C_i=1}$). Low and high refer to the lowest and highest quintile of collaborator inventive productivity, middle to the remainder. * p<0.1, ** p<0.05, *** p<0.01.

A5 Robustness

Table A5.1: Impact of collaborator loss on inventive productivity – previous co-work / did the lost collaborator move (DiD estimates)

	Patents (simple counts)		
	(1)	(2)	(3)
Internal collaborator loss	0.022	0.023	0.025
	(0.029)	(0.029)	(0.030)
External collaborator loss	−0.079**		
	(0.034)		
Ext: Never coworkers		−0.106**	−0.106**
		(0.048)	(0.048)
Ext: Previously coworkers		−0.054	
		(0.044)	
- Collaborator moved			−0.115*
			(0.061)
- Collaborator stayed			0.000
			(0.059)
Inventor FE	Yes	Yes	Yes
Inventor age FE	Yes	Yes	Yes
Match group×rel. year FE	Yes	Yes	Yes
Clusters	856	856	856
Observations	124168	124168	124168
Adj. R2	0.37	0.37	0.37
DV mean	0.65	0.65	0.65

Notes: This table reports the estimates for β^{real} from a linear regression with inventor, inventor age, and deceased co-inventor times relative year fixed effects. The dependent variable is the simple patent count. The unit of observation is at the inventor-year level. Standard errors clustered at the level of the (pseudo-)deceased co-inventor's organization are in parentheses. Each reported estimate stands for the treatment effect for the relevant subgroup (e.g., $\beta^{real}_{C_i=1}$). We separate external collaborator loss by whether the inventors were previously coworkers (column 2) and, if so, the lost collaborator had moved or stayed with their organization since the last episode of co-working. * p<0.1, ** p<0.05, *** p<0.01.

Table A5.2: Impact of internal and external collaborator loss on inventive productivity – alternative dependent variables (DiD estimates, part 1)

	Patents (simple count)					
	(1) Bin	(2) Bin	(3) W95	(4) W95	(5) W99	(6) PPML-W95
Collaborator loss	−0.012*		−0.027			
	(0.007)		(0.022)			
Internal collaborator loss		0.001		0.022	0.029	−0.006
		(0.010)		(0.029)	(0.047)	(0.052)
External collaborator loss		−0.024**		−0.079**	−0.089*	−0.141**
		(0.011)		(0.034)	(0.053)	(0.071)
Δ Internal loss − External loss		0.025		0.101**	0.118*	0.136
		(0.016)		(0.045)	(0.069)	(0.087)
Clusters	856	856	856	856	856	850
Observations	124168	124168	124168	124168	124168	105331
DV mean	0.31	0.31	0.65	0.65	0.80	0.77
	Patents (citation-weighted counts)					
	(1) Bin	(2) Bin	(3) W95	(4) W95	(5) W99	(6) PPML-W95
Collaborator loss	−0.015**		−0.054*			
	(0.006)		(0.030)			
Internal collaborator loss		−0.001		0.026	0.047	0.052
		(0.008)		(0.038)	(0.080)	(0.081)
External collaborator loss		−0.029***		−0.139***	−0.190**	−0.188*
		(0.009)		(0.044)	(0.092)	(0.109)
Δ Internal loss − External loss		0.028**		0.165***	0.237**	0.239*
		(0.012)		(0.057)	(0.117)	(0.138)
Clusters	856	856	856	856	856	748
Observations	124168	124168	124168	124168	124168	79490
DV mean	0.20	0.20	0.69	0.69	1.03	1.07
	Patents (family size-weighted counts)					
	(1) Bin	(2) Bin	(3) W95	(4) W95	(5) W99	(6) PPML-W95
Collaborator loss	−0.012*		−0.213**			
	(0.007)		(0.101)			
Internal collaborator loss		0.001		0.025	−0.069	−0.043
		(0.010)		(0.134)	(0.245)	(0.062)
External collaborator loss		−0.024**		−0.463***	−0.672**	−0.166**
		(0.011)		(0.163)	(0.299)	(0.085)
Δ Internal loss − External loss		0.025		0.488**	0.603	0.123
		(0.016)		(0.216)	(0.386)	(0.112)
Clusters	856	856	856	856	856	850
Observations	124168	124168	124168	124168	124168	105331
DV mean	0.31	0.31	2.78	2.78	3.72	3.27

Notes: This table reports the estimates for β^{real} from a linear regression with inventor, inventor age, and deceased co-inventor times relative year fixed effects. Each reported estimate stands for the treatment effect for the relevant subgroup (e.g., $\beta^{real}_{C_i=1}$) or their difference (row Δ Internal loss − External loss reports $\beta^{real}_{C_i=1}-\beta^{real}_{C_i=0}$). The dependent variables are simple patent counts (first table segment), citation-weighted patent counts (second table segment), and family size-weighted patent counts (third segment). In each segment, the dependent variables are binarized (columns 1-2), winsorized at the 95th percentile (columns 3-4), the 99th percentile (column 5), and estimated via Poisson regression (column 6). The unit of observation is at the inventor-year level. Standard errors clustered at the level of the (pseudo-)deceased co-inventor's organization are in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table A5.3: Impact of internal and external collaborator loss on inventive productivity – alternative dependent variables (DiD estimates, part 2)

	Patents (breakthrough)					
	(1) Bin	(2) Bin	(3) W95	(4) W95	(5) W99	(6) PPML-W95
Collaborator loss	−0.009*		−0.009*			
	(0.005)		(0.005)			
Internal collaborator loss		0.004		0.004	0.009	0.036
		(0.006)		(0.006)	(0.011)	(0.082)
External collaborator loss		−0.023***		−0.023***	−0.027**	−0.234**
		(0.008)		(0.008)	(0.013)	(0.111)
Δ Internal loss − External loss		0.027**		0.027**	0.037**	0.270**
		(0.011)		(0.011)	(0.018)	(0.136)
Clusters	856	856	856	856	856	587
Observations	124168	124168	124168	124168	124168	51668
DV mean	0.10	0.10	0.10	0.10	0.14	0.23
	Patents (granted)					
	(1) Bin	(2) Bin	(3) W95	(4) W95	(5) W99	(6) PPML-W95
Collaborator loss	−0.010		−0.015			
	(0.007)		(0.012)			
Internal collaborator loss		−0.002		0.000	−0.002	−0.029
		(0.009)		(0.015)	(0.024)	(0.073)
External collaborator loss		−0.018*		−0.030*	−0.029	−0.115
		(0.010)		(0.017)	(0.028)	(0.098)
Δ Internal loss − External loss		0.016		0.029	0.027	0.086
		(0.014)		(0.022)	(0.034)	(0.131)
Clusters	856	856	856	856	856	793
Observations	124168	124168	124168	124168	124168	85272
DV mean	0.21	0.21	0.29	0.29	0.38	0.43

Notes: This table reports the estimates for β^{real} from a linear regression with inventor, inventor age, and deceased co-inventor times relative year fixed effects. Each reported estimate stands for the treatment effect for the relevant subgroup (e.g., $\beta^{real}_{C_i=1}$) or their difference (row Δ Internal loss − External loss reports $\beta^{real}_{C_i=1} - \beta^{real}_{C_i=0}$). The dependent variables are breakthrough patent counts (first table segment), and counts of granted patents (second segment). In each segment, the dependent variables are binarized (columns 1-2), winsorized at the 95th percentile (columns 3-4), the 99th percentile (column 5), and estimated via Poisson regression (column 6). The unit of observation is at the inventor-year level. Standard errors clustered at the level of the (pseudo-)deceased co-inventor's organization are in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table A5.4: Impact of internal and external collaborator loss on inventive productivity – alternative dependent variables (DiD estimates, part 3)

	Patents (simple count, excluding joint with lost coll.)					
	(1) Bin	(2) Bin	(3) W95	(4) W95	(5) W99	(6) PPML-W95
Collaborator loss	−0.003		−0.009			
	(0.008)		(0.022)			
Internal collaborator loss		0.017*		0.055*	0.073	0.088
		(0.011)		(0.030)	(0.050)	(0.060)
External collaborator loss		−0.025**		−0.075**	−0.086	−0.146*
		(0.012)		(0.035)	(0.054)	(0.081)
Δ Internal loss − External loss		0.043**		0.130***	0.159**	0.234**
		(0.017)		(0.046)	(0.072)	(0.099)
Clusters	856	856	856	856	856	727
Observations	124168	124168	124168	124168	124168	90142
DV mean	0.27	0.27	0.56	0.56	0.68	0.76
	Patents (fractional count)					
	(1) Bin	(2) Bin	(3) W95	(4) W95	(5) W99	(6) PPML-W95
Collaborator loss	−0.012*		−0.007			
	(0.007)		(0.008)			
Internal collaborator loss		0.001		0.007	0.008	0.002
		(0.010)		(0.011)	(0.018)	(0.047)
External collaborator loss		−0.024**		−0.022**	−0.026	−0.132*
		(0.011)		(0.011)	(0.018)	(0.070)
Δ Internal loss − External loss		0.025		0.028*	0.034	0.134
		(0.016)		(0.015)	(0.025)	(0.084)
Clusters	856	856	856	856	856	850
Observations	124168	124168	124168	124168	124168	105331
DV mean	0.31	0.31	0.20	0.20	0.26	0.24

Notes: This table reports the estimates for β^{real} from a linear regression with inventor, inventor age, and deceased co-inventor times relative year fixed effects. Each reported estimate stands for the treatment effect for the relevant subgroup (e.g., $\beta^{real}_{C_i=1}$) or their difference (row Δ Internal loss − External loss reports $\beta^{real}_{C_i=1} - \beta^{real}_{C_i=0}$). The dependent variables are simple patent counts excluding patents joint with the lost collaborator (first table segment) and fractional patent counts (second table segment). In each segment, the dependent variables are binarized (columns 1-2), winsorized at the 95th percentile (columns 3-4), the 99th percentile (column 5), and estimated via Poisson regression (column 6). The unit of observation is at the inventor-year level. Standard errors clustered at the level of the (pseudo-)deceased co-inventor's organization are in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table A5.5: Impact of internal and external collaborator loss on inventive productivity – alternative transformations (DiD estimates)

	log(1+Patents)		ihs(Patents)		log(1+Cit-w. pat)		ihs(Cit-w. pat)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Collaborator loss	−0.014		−0.018		-0.022^{*}		-0.029^{*}	
	(0.012)		(0.015)		(0.013)		(0.017)	
Internal collaborator loss		0.006		0.009		0.008		0.010
		(0.016)		(0.020)		(0.017)		(0.021)
External collaborator loss		-0.035^{*}		-0.046^{**}		-0.054^{***}		-0.069^{***}
		(0.018)		(0.023)		(0.020)		(0.024)
Δ Internal loss − External loss		0.041^{*}		0.054^{*}		0.062^{**}		0.079^{**}
		(0.024)		(0.031)		(0.025)		(0.031)
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Inventor age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Match group×rel. year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	856	856	856	856	856	856	856	856
Observations	124168	124168	124168	124168	124168	124168	124168	124168
Adj. R2	0.38	0.39	0.38	0.38	0.32	0.32	0.32	0.32
DV mean	0.36	0.36	0.46	0.46	0.31	0.31	0.40	0.40

Notes: This table reports the estimates for β^{real} from a linear regression with inventor, inventor age, and deceased co-inventor times relative year fixed effects. The dependent variable is the simple patent count. The unit of observation is at the inventor-year level. Standard errors clustered at the level of the (pseudo-)deceased co-inventor's organization are in parentheses. Each reported estimate stands for the treatment effect for the relevant subgroup (e.g., $\beta^{real}_{C_i=1}$) or their difference (row Δ Internal loss − External loss reports $\beta^{real}_{C_i=1} - \beta^{real}_{C_i=0}$). * p<0.1, ** p<0.05, *** p<0.01.

Table A5.6: Impact of internal and external collaborator loss on inventive productivity – alternative cluster levels (DiD estimates)

Cluster level	(1) (Remaining) Inventor	(2) (Pseudo)-deceased co-inventor	(3) Deceased co-inventor	(4) Rem. inv.'s organization	(5) (P.-)dec. co-inv.'s organization	(6) Dec. co-inv.'s organization
Internal collaborator loss	0.022	0.022	0.022	0.022	0.022	0.022
	(0.029)	(0.030)	(0.034)	(0.030)	(0.029)	(0.035)
External collaborator loss	−0.079***	−0.079**	−0.079**	−0.079**	−0.079**	−0.079**
	(0.029)	(0.033)	(0.038)	(0.033)	(0.034)	(0.040)
Δ Internal loss − External loss	0.101**	0.101**	0.101**	0.101**	0.101**	0.101**
	(0.040)	(0.045)	(0.045)	(0.045)	(0.045)	(0.047)
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes
Inventor age FE	Yes	Yes	Yes	Yes	Yes	Yes
Match group×rel. year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster count	6912	1278	713	1633	856	544
Observations	124168	124168	124168	124168	124168	124168
Adj. R2	0.37	0.37	0.37	0.37	0.37	0.37
DV mean	0.65	0.65	0.65	0.65	0.65	0.65

Notes: This table reports the estimates for β^{real} from a linear regression with inventor, inventor age, and deceased co-inventor times relative year fixed effects. The unit of observation is at the inventor-year level. The dependent variable is the simple patent count. Each reported estimate stands for the treatment effect for the relevant subgroup (e.g., $\beta^{real}_{C_i=1}$) or their difference (row Δ Internal loss − External loss reports $\beta^{real}_{C_i=1}-\beta^{real}_{C_i=0}$). Column 5 shows the default clustering level, the (pseudo)-deceased co-inventor's organization (both for external and internal remaining inventors). For comparison, in column 1, clustering is at the (remaining) inventor level. In column 2, clustering is at the (pseudo)-deceased co-inventor (collaborator) level. In column 3, clustering is at the deceased co-inventor level, which is equivalent to the match group. In column 4, clustering is at the level of the organization of the (remaining) inventor. In column 6, clustering is at the organization of the deceased co-inventor. Cluster counts deviate from observation numbers reported in other parts of the paper due to singleton observations with respect to match group × year FE. * p<0.1, ** p<0.05, *** p<0.01.

Table A5.7: Impact of internal and external collaborator loss on inventive productivity – alternative FE, subsamples, and matching (DiD estimates)

	Match group×rel. year FE omitted		Recent joint patenting only		Within-organization matching		No soft match		Mahalanobis distance	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Collaborator loss	−0.032		−0.048		−0.066**		−0.012		−0.063***	
	(0.033)		(0.034)		(0.028)		(0.025)		(0.024)	
Internal collaborator loss		0.030		−0.009		−0.018		0.054*		−0.009
		(0.042)		(0.038)		(0.044)		(0.031)		(0.030)
External collaborator loss		−0.091**		−0.102*		−0.141***		−0.080**		−0.123***
		(0.039)		(0.053)		(0.029)		(0.037)		(0.039)
Δ Internal loss − External loss		0.122**		0.093		0.123**		0.134***		0.114**
		(0.049)		(0.062)		(0.052)		(0.045)		(0.051)
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Inventor age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Relative year FE	Yes	Yes	No	No	No	No	No	No	No	No
Match group×rel. year FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	909	909	602	602	861	861	853	853	909	909
Observations	125443	125443	77681	77681	132657	132657	124270	124270	130350	130350
Adj. R2	0.32	0.32	0.39	0.40	0.35	0.35	0.37	0.37	0.38	0.38
DV mean	0.65	0.65	0.68	0.68	0.68	0.68	0.66	0.66	0.68	0.68

Notes: This table reports the estimates for β^{real} from a linear regression with inventor, inventor age, and deceased co-inventor times relative year fixed effects. The dependent variable is the simple patent count. The unit of observation is at the inventor-year level. Standard errors clustered at the level of the (pseudo-)deceased co-inventor's organization are in parentheses. Each reported estimate stands for the treatment effect for the relevant subgroup (e.g., $\beta^{real}_{C_i=1}$) or their difference (row Δ Internal loss − External loss reports $\beta^{real}_{C_i=1} - \beta^{real}_{C_i=0}$). Columns 1-2 omit the match group × relative year fixed effects. Columns 3-4 restrict the sample to inventors that had a joint patent with the lost collaborator in the last 4 years, the median of the full sample. Columns 5-6 apply an alternative matching strategy, where pseudo-deceased co-inventors are selected only within the same organization as the deceased co-inventor. In the default specification, the pseudo-deceased co-inventors are selected only outside of the deceased co-inventor's organization to avoid contamination. The same matching criteria are used, but as a series of soft matching criteria to allow for the much reduced number of matching candidates. Columns 7-8 apply an alternative matching strategy, where instead of the soft matching criteria (see Section 3.3), we randomly retain one pseudo-deceased co-inventor among all candidates. Columns 9-10 apply an alternative matching strategy, where the matching is based on coarsened matching only of gender, technology and organization size group, and the Mahalanobis distance of all remaining characteristics otherwise. See Section 3.3 for details. * p<0.1, ** p<0.05, *** p<0.01.

Table A5.8: Impact of internal and external collaborator loss on inventive productivity – alternative selection of deceased co-inventors (DiD estimates)

	Patents						
	(1) Base	(2) Work (1y)	(3) Work (3y)	(4) Non-zero Salary	(5) All (2)-(4)	(6) All, died ≤ 2010	(7) All, died age ≤ 55
Internal collaborator loss	0.022	0.027	0.025	0.003	0.014	0.022	0.002
	(0.029)	(0.032)	(0.032)	(0.036)	(0.037)	(0.043)	(0.043)
External collaborator loss	−0.079**	−0.101***	−0.120***	−0.098**	−0.131***	−0.126***	−0.095*
	(0.034)	(0.038)	(0.038)	(0.038)	(0.042)	(0.046)	(0.049)
Δ Internal loss − External loss	0.101**	0.127***	0.145***	0.101*	0.145***	0.148**	0.097
	(0.045)	(0.049)	(0.049)	(0.054)	(0.056)	(0.060)	(0.063)
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Inventor age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Match group×rel. year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	856	738	724	631	580	439	440
Observations	124168	102610	101601	86863	77893	60261	58154
Adj. R2	0.37	0.36	0.37	0.36	0.36	0.36	0.36
DV mean	0.65	0.65	0.66	0.65	0.65	0.63	0.66

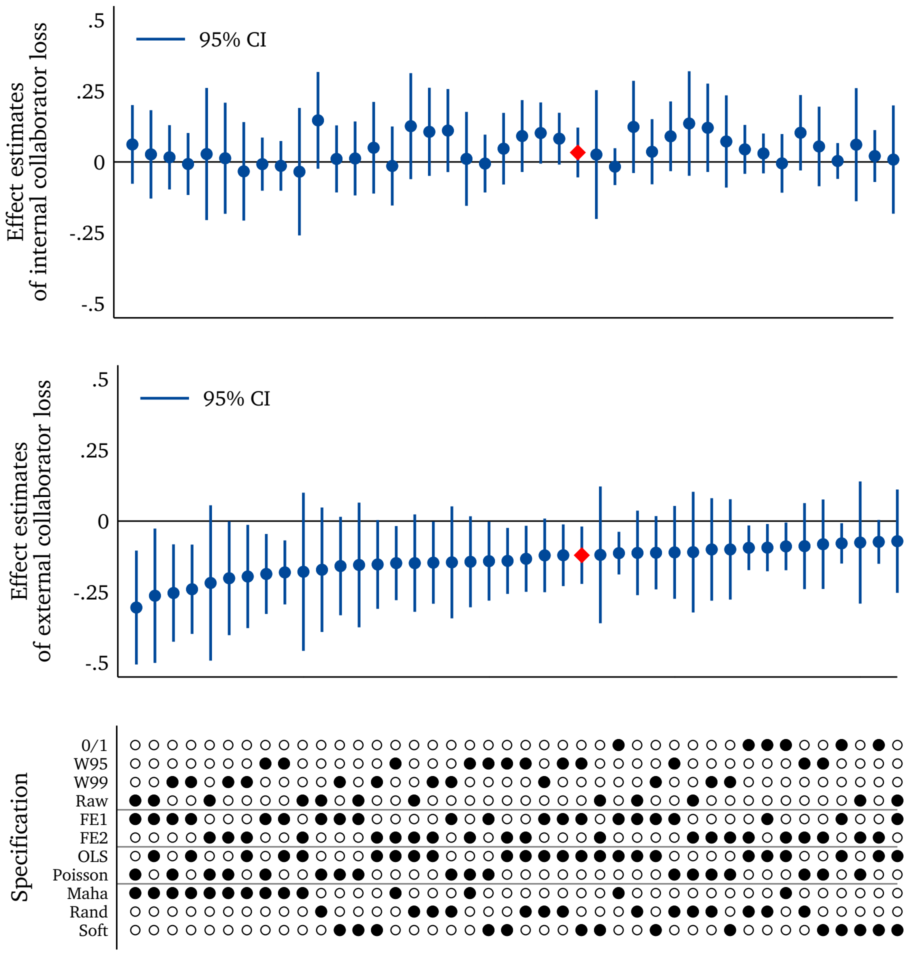
Notes: This table reports the estimates for β^{real} from a linear regression with inventor, inventor age, and deceased co-inventor times relative year fixed effects. The dependent variable is the simple patent count. The unit of observation is at the inventor-year level. Standard errors clustered at the level of the (pseudo-)deceased co-inventor's organization are in parentheses. Each reported estimate stands for the treatment effect for the relevant subgroup (e.g., $\beta^{real}_{C_i=1}$) or their difference (row Δ Internal loss − External loss reports $\beta^{real}_{C_i=1} - \beta^{real}_{C_i=0}$). Column 1 reports the baseline, with lost collaborators who died aged 60 or younger and in 2013 or earlier. Columns 2 and 3 further omit cases where the deceased co-inventor was not regularly employed on 30 among the last 365 days or 60 out of the last 1095 days, respectively. Column 4 omits cases with any zero-salary employment in the last three years, which can, for example, arise due to sick leave. Column 5 combines the restrictions of columns 2-4. Column 6 further restricts to deaths up to 2010, which guarantees a longer post-treatment without sample attrition. Column 7 restricts to deaths of inventors aged 55 and below. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table A5.9: Impact of collaborator loss on inventive productivity – size of the inventor's organization (DiD estimates)

	(1)	(2)		
	Base	Internal	External	Difference
<50 employees	−0.017	0.228	−0.084	−0.312
	(0.110)	(0.195)	(0.115)	(0.208)
50-249 employees	−0.037	0.028	−0.066	−0.094
	(0.052)	(0.075)	(0.063)	(0.094)
250-999 employees	−0.004	0.084	−0.103	−0.187**
	(0.042)	(0.056)	(0.067)	(0.093)
≥1000 employees	−0.035	−0.009	−0.090*	−0.081
	(0.032)	(0.038)	(0.053)	(0.062)
Inventor FE	Yes		Yes	
Inventor age FE	Yes		Yes	
Match group×rel. year FE	Yes		Yes	
Clusters	823		823	
Observations	114057		114057	
Adj. R2	0.37		0.37	
DV mean	0.67		0.67	

Notes: This table reports the estimates for β^{real} from a linear regression with inventor, inventor age, and deceased co-inventor times relative year fixed effects. The dependent variable is the simple patent count. The unit of observation is at the inventor-year level. Standard errors clustered at the level of the (pseudo-)deceased co-inventor's organization are in parentheses. Each reported estimate stands for the treatment effect for the relevant subgroup (e.g., $\beta^{real}_{C_i=1}$). Column 1 reports the treatment effect of *Death* by firm size. The three columns under (2) report estimates from a regression that separates the treatment effect of *Death* by organization size and whether the loss occurred internally or externally. The third column reports differences between internal and external loss estimates. * p<0.1, ** p<0.05, *** p<0.01.

Figure A5.1: Specification curve for the effect estimates of internal and external collaborator loss



Notes: The figure plots effect estimates from various regression specifications in the form of a specification curve (Simonsohn et al., 2020).. 95% confidence intervals. To ease comparison, coefficients are presented as semi-elasticities, i.e., for OLS estimates, we divide the coefficient by the dependent variable mean. The default specification is marked by a red (diamond) point estimate. 0/1 refers to a binarized DV, W95 and W99 to different winsorization levels, and raw to the unwinsorized patent count. FE1 are the default specification following Bernstein et al. (2022), with inventor, age, and deceased co-inventor × relative year fixed effects. FE2 include inventor, relative year, and age fixed effects. Maha, Rand and Soft refer to different matching approaches, see Section 3.3.

A6 Alternative mechanisms

Table A6.1: Impact of collaborator loss on inventive productivity – labor market density (DiD estimates)

	Regional labor market		District	
	(1) Wide	(2) Narrow	(3) Wide	(4) Narrow
Internal collaborator loss: – Low values	0.049	0.122**	0.090	0.060
	(0.056)	(0.056)	(0.065)	(0.055)
Internal collaborator loss: – High values	0.011	−0.004	0.002	0.012
	(0.035)	(0.035)	(0.035)	(0.035)
External collaborator loss: – Low values	0.003	−0.010	−0.031	−0.055
	(0.057)	(0.063)	(0.058)	(0.055)
External collaborator loss: – High values	−0.126***	−0.117***	−0.107**	−0.094*
	(0.046)	(0.045)	(0.046)	(0.048)
Δ Internal loss: High–Low	−0.038	−0.125*	−0.088	−0.048
	(0.070)	(0.071)	(0.079)	(0.069)
Δ External loss: High–Low	−0.129*	−0.107	−0.076	−0.040
	(0.075)	(0.079)	(0.076)	(0.075)
Inventor FE	Yes	Yes	Yes	Yes
Inventor age FE	Yes	Yes	Yes	Yes
Match group×rel. year FE	Yes	Yes	Yes	Yes
Clusters	824	824	824	824
Observations	114135	114135	114135	114135
Adj. R2	0.37	0.37	0.37	0.37
DV mean	0.67	0.67	0.67	0.67

Notes: This table reports the estimates for β^{real} from a linear regression with inventor, inventor age, and deceased co-inventor times relative year fixed effects. The dependent variable is the simple patent count. The unit of observation is at the inventor-year level. Standard errors clustered at the level of the (pseudo-)deceased co-inventor's organization are in parentheses. Each reported estimate stands for the treatment effect for the relevant subgroup (e.g., $\beta^{real}_{C_i=1}$) or their difference (e.g., row Δ Internal loss: High–Low reports $\beta^{real}_{Int,High}-\beta^{real}_{Int,Low}$). We split by the labor market density of inventors. We count the number of inventors by year and geographic region in the same technological area (wide) or IPC4 category (narrow), with narrow categories indicating the highest replacement suitability. There are 402 districts ("Kreis", 331 in our data), which are grouped into 141 regional labor markets ("Regionale Arbeitsmärkte", 127 in our data). We separate out low values (bottom 25%). * p<0.1, ** p<0.05, *** p<0.01.

Table A6.2: Impact of collaborator loss on inventor resources – team size (DiD estimates)

	Full sample		Years with patents	Collapsed panel
	(1) Patents w. small team	(2) Patents w. large team	(3) Team size (avg)	(4) Team size (avg)
Internal collaborator loss	0.017	0.010	−0.039	−0.050
	(0.023)	(0.022)	(0.093)	(0.111)
External collaborator loss	−0.045*	−0.050**	0.092	0.067
	(0.024)	(0.025)	(0.117)	(0.128)
Δ Internal loss − External loss	0.062*	0.061*	−0.131	−0.117
	(0.032)	(0.033)	(0.159)	(0.162)
Inventor FE	Yes	Yes	Yes	Yes
Inventor age FE	Yes	Yes	Yes	No
Match group×rel. year FE	Yes	Yes	Yes	No
Match group FE	No	No	No	Yes
Clusters	856	856	674	648
Observations	124168	124168	34472	6960
Adj. R2	0.32	0.32	0.48	0.37
DV mean	0.33	0.39	4.22	4.12

Notes: This table reports the estimates for β^{real} from a linear regression with inventor, inventor age, and deceased co-inventor times relative year fixed effects. Each reported estimate stands for the treatment effect for the relevant subgroup (e.g., $\beta^{real}_{C_i=1}$) or their difference (row Δ Internal loss − External loss reports $\beta^{real}_{C_i=1} - \beta^{real}_{C_i=0}$). In columns 1 and 2, the dependent variable is the simple patent count separated by patents with few (3 or less) or many (4 or more) inventors, winsorized at the 95th percentile. In columns 3 and 4, the dependent variable is the patents' average inventor team. In column 3, only observations with non-zero patenting are considered, as the averages are undefined otherwise. In columns 1-4, the unit of observation is at the inventor-year level. The collapsed panel regression in column 4 only retains one pre- and one post-treatment observation for each inventor that patented before or after the treatment, respectively. Standard errors clustered at the level of the (pseudo-)deceased co-inventor's organization are in parentheses. Each reported estimate stands for the treatment effect for the relevant subgroup (e.g., $\beta^{real}_{C_i=1}$) or their difference (rows Δ – e.g., $\beta^{real}_{C_i=1} - \beta^{real}_{C_i=0}$). * p<0.1, ** p<0.05, *** p<0.01.

Table A6.3: Impact of collaborator loss on inventive productivity – excluding promotion/leave events (DiD estimates)

	Baseline	Excl. Promotions		Excl. leavers	
	(1)	(2) Post-Death	(3) Post Death-2	(4) Post Death	(5) Post Death-2
Internal collaborator loss	0.022	0.019	0.015	0.008	0.023
	(0.029)	(0.028)	(0.029)	(0.039)	(0.042)
External collaborator loss	-0.079^{**}	-0.067^{*}	-0.076^{**}	-0.108^{***}	-0.112^{**}
	(0.034)	(0.035)	(0.036)	(0.040)	(0.047)
Δ Internal loss − External loss	0.101^{**}	0.085^{*}	0.091^{**}	0.117^{**}	0.135^{**}
	(0.045)	(0.044)	(0.044)	(0.059)	(0.063)
Inventor FE	Yes	Yes	Yes	Yes	Yes
Inventor age FE	Yes	Yes	Yes	Yes	Yes
Match group×rel. year FE	Yes	Yes	Yes	Yes	Yes
Clusters	856	808	795	672	631
Observations	124168	101739	96070	75802	66486
Adj. R2	0.37	0.37	0.36	0.37	0.37
DV mean	0.65	0.63	0.62	0.69	0.70

Notes: This table reports the estimates for β^{real} from a linear regression with inventor, inventor age, and deceased co-inventor times relative year fixed effects. The dependent variable is the simple patent count. The unit of observation is at the inventor-year level. Standard errors clustered at the level of the (pseudo-)deceased co-inventor's organization are in parentheses. Each reported estimate stands for the treatment effect for the relevant subgroup (e.g., $\beta^{real}_{C_i=1}$) or their difference (row Δ Internal loss − External loss reports $\beta^{real}_{C_i=1} - \beta^{real}_{C_i=0}$). In column 2, we exclude all inventors who experienced a promotion event on or after the death year. In column 3, we also exclude inventors who had promotion events in the two years prior to death. Columns 4 and 5 implement the same restrictions but with leave events. * p<0.1, ** p<0.05, *** p<0.01.

Table A6.4: Impact of collaborator loss on inventive productivity – inverse probability weighting (DiD estimates)

DV	Patents							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Internal collaborator loss	0.022	0.006			0.099**	0.053		
	(0.029)	(0.031)			(0.046)	(0.044)		
External collaborator loss	−0.079**	−0.099**	−0.205***	−0.169***			−0.246***	−0.182***
	(0.034)	(0.044)	(0.046)	(0.047)			(0.046)	(0.047)
Δ Internal loss − External loss	0.101**	0.105**						
	(0.045)	(0.052)						
Subsample 1	All treated inv.		External treated		Internal treated		External treated	
Subsample 2	All control inv.		Internal control		External control		Internal treated	
Weighting	–	IPW	–	IPW	–	IPW	–	IPW
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Inventor age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Match group×rel. year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster count	856	695	448	448	441	441	348	348
Observations	124168	100118	49611	49611	47098	47098	50431	50431
Adj. R2	0.37	0.37	0.38	0.40	0.38	0.39	0.40	0.41
DV mean	0.65	0.72	0.74	0.74	0.73	0.73	0.75	0.75

Notes: This table shows estimates adjusted for inverse probability weighting (IPW) estimated using the characteristics in footnote 2, compared with unweighted estimates. Otherwise, the specifications follow Table 3. Each reported estimate stands for the treatment effect for the relevant subgroup (e.g., $\beta^{real}_{C_i=1}$) or their difference (row Δ Internal loss − External loss reports $\beta^{real}_{C_i=1} - \beta^{real}_{C_i=0}$). Column 1 shows the default specification from the paper, and in columns 2, we adjust the estimation sample for probability weights. The remaining columns differ in the considered samples, where columns 3, 5 and 7 use unweighted estimates and columns 4, 6 and 8 show IPW-adjusted estimates. Columns 3 and 4 retain treated inventors with external collaborator loss and control inventors with (pseudo) internal collaborator loss. Columns 5 and 6 retain treated inventors with internal collaborator loss and control inventors with (pseudo) external collaborator loss. Columns 7 and 8 retain only treated inventors and compare those with external against those with internal collaborator loss. In columns 2, 4 and 6, IPW balances for treatment (death) vs control, whereas in column 8, IPW balances for internal vs external collaborator loss within the treatment (death) sample. Table A6.5 shows balancing after IPW.
* p<0.1, ** p<0.05, *** p<0.01.

Table A6.5: Difference in pre-death characteristics (samples with inverse probability weighting)

Comparison:	All treated vs all control inv.			Ext. treated vs. int. control			Int. treated vs. ext. control			Ext. treated vs. int. treated		
Variable	Diff.	Std. Err	p-value	Diff.	Std. Err	p-value	Diff.	Std. Err	p-value	Diff.	Std. Err	p-value
Patents (Lifetime)	0.008	(0.281)	0.976	−0.053	(0.460)	0.908	0.181	(0.470)	0.701	0.003	(0.450)	0.994
Age	−0.003	(0.225)	0.991	0.213	(0.402)	0.597	−0.448	(0.472)	0.343	−0.274	(0.382)	0.473
Male	0.000	(0.007)	0.996	0.001	(0.012)	0.906	0.005	(0.013)	0.712	0.003	(0.012)	0.823
Organization tenure	−0.011	(0.218)	0.961	0.459	(0.415)	0.270	−0.546	(0.548)	0.319	−0.616	(0.435)	0.157
Organization size	−0.005	(0.268)	0.985	0.646	(0.594)	0.277	−0.109	(0.573)	0.849	−0.560	(0.564)	0.321
Organization age	−0.019	(0.303)	0.949	−0.080	(0.471)	0.865	−0.468	(0.536)	0.382	−0.549	(0.533)	0.303
Years since last patenting	0.001	(0.064)	0.987	0.000	(0.098)	1.000	−0.026	(0.120)	0.830	0.042	(0.107)	0.694
Knowledge similarity	0.000	(0.008)	0.995	0.006	(0.013)	0.608	−0.003	(0.013)	0.841	−0.007	(0.012)	0.593
Knowledge overlap	0.005	(0.007)	0.477	0.003	(0.011)	0.780	0.010	(0.011)	0.395	0.003	(0.011)	0.790
Collab. network size (excl. common inv.)	0.062	(0.440)	0.888	−0.332	(0.636)	0.601	0.014	(0.787)	0.986	0.589	(0.725)	0.417
Collab. network size (incl. common inv.)	−0.572	(0.500)	0.252	−1.082	(0.717)	0.132	−0.584	(0.890)	0.511	0.311	(0.818)	0.704
Collab. intensity (recency)	0.012	(0.075)	0.873	−0.004	(0.119)	0.973	0.035	(0.133)	0.793	0.035	(0.120)	0.770
Collab. intensity (joint patents)	0.002	(0.101)	0.984	−0.052	(0.162)	0.746	0.118	(0.147)	0.421	0.030	(0.146)	0.836
Collab. inventive productivity (pre-death)	0.098	(0.704)	0.890	−0.477	(1.056)	0.651	−0.071	(1.306)	0.957	0.588	(1.069)	0.582
Knowledge management capabilities	0.000	(0.005)	0.993	−0.001	(0.008)	0.889	0.003	(0.008)	0.675	−0.003	(0.009)	0.704
Hiring capabilities	0.001	(0.005)	0.830	−0.001	(0.011)	0.916	0.004	(0.010)	0.679	0.024	(0.015)	0.111

Notes: Differences between subsample 1 and subsample 2 for each of the columns in Table A6.4.

References in Online Appendix

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