Inventor Teams, Invention Quality, and Occupational Contexts

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ABSTRACT

This paper explores how the premature death of an inventor affects the productivity and career trajectories of co-inventors. To this end, we develop and analyze a dataset covering the careers of 152,350 German inventors. The data combines highly precise employer-employee data from official social security registers with patent office information covering the period from 1980-2014. Departing from about 799 registered premature deaths of inventors and the same number of matched inventors, we study how co-inventors were affected by the death of their peers. Using a difference-in-differences and an event study design, we investigate the reaction of the co-inventors' patenting activities, career advancement and job mobility. Using a number of measures and robustness checks, our results show that the premature death of a co-inventor reduces the productivity of the surviving co-inventors. The effect sets in immediately and survivors do not seem to recover from the shock in the five years following. We argue that employers will seek to retain co-inventors under certain conditions in order to continue lines of research and invention. The empirical results confirm our expectations: surviving inventors are significantly less likely to move to a different employer and are more likely to be promoted compared to inventors in the control group. These effects seem to diminish after about two years. (212 words)

KEYWORDS: Innovation, inventors, mobility, teams, patents.

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1 Introduction

Teams are groups of individuals working together towards a common objective. They can be understood as social communities that can realize efficiency gains (Kogut and Zander, 1996). An important mechanism through which these gains can be realized is social capital, a set of resources rooted in relationships between team members. These relationships form the foundation of trust, cooperation, and collective action (Jacobs, 1961; Nahapiet and Ghoshal, 1998; Mawdsley and Somaya, 2016). But what happens if these relationships are destroyed, i.e., if part of the social capital is unexpectedly and irretrievably lost? For firms, this question is relevant, since teams play an essential role in the creation and sharing of knowledge necessary for coming up with innovation (Akcigit et al., 2018; Azoulay et al., 2010; Jaravel et al., 2018; Wu et al., 2019; Wuchty et al., 2007). For individuals, this question is important, since an unexpected death of a co-inventor may radically change the future career prospects of the survivors.

Earlier studies have shown that an unexpected and permanent loss of team social capital, e.g., by losing one of the team members, decreases the productivity of the remaining members of the team (Azoulay et al., 2010; Jaravel et al., 2018; Jones, 2009). We are interested in teams consisting of knowledge workers, since tacit knowledge held by any of the members cannot be replaced in the short run. We build on the existing literature on the relationship between social capital and team performance and investigate the consequences of a loss of team social capital of knowledge workers (i.e., via the premature death of co-inventors) for the career trajectories of the remaining team members. Career trajectories are characterized in this paper in terms of employees' job mobility and in terms of promotions.

We argue that an unexpected and permanent loss of team social capital, i.e., via the premature death of one of the inventors, has two opposing effects. First, the loss of an inventor leaves a gap which will have to be filled if the benefits of continuing particular lines of research and invention are sufficiently high. This 'filling the gap requirement' makes the remaining inventors more attractive for the employer, as it is more efficient to expand and complement the existing team than to restart invention activities from scratch. Second, the premature death of a fellow-inventor reduces the social capital and productivity of the surviving inventors. This decrease in productivity makes them less attractive in the short run, both for their own employer and for the labor market in general.

To isolate the various effects at work, we distinguish between two settings: (1) the deceased inventor worked for the same establishment as the surviving co-inventors and (2) the deceased inventor and his or her co-inventors worked in different organizational sub-units (establishments) or companies.[1]

In the first scenario, we expect that surviving co-inventors are less likely to move to other employers. This is because despite of the gap left by the deceased inventor, coordination costs within

[1]The concept of establishments as used in the IAB data is not equivalent to firms. Firms can have their social security data recorded in multiple establishments. We argue that establishments are self-contained units, that collaboration across establishment boundaries always involves 'boundary-spanning' activities and coordination efforts not required in projects undertaken within the same establishment. Rebuilding a team is therefore more costly if the deceased inventor was part of the labor force of a different establishment.

the establishment will be relatively low and it is likely that the line of research and invention can be continued profitably. But the surviving inventors serve an important function in 'filling the gap,' which in turn induces the current employer to offer the remaining team members favorable conditions in order to keep them from leaving (Chang and Wang, 1996; Greenwald, 1986). Additionally, the decrease in productivity reduces the outside options of the inventors (Hoisl, 2007).

Similar arguments apply for a possible promotion into a management position. We expect a promotion to become more likely in case the deceased inventor had a management position. Inventors usually assume such a position when the coordination requirements are high. In this case the surviving inventors would, again, substitute for the deceased inventors. In case the deceased inventor did not have a management position, we do not expect to find a positive effect on promotion, since coordination requirements are likely to be relatively low. Hence, no management gap needs to be filled and the decrease in productivity makes it unlikely that the surviving inventors will be promoted for other reasons, such as performance.

In the second scenario, in which the deceased inventor worked for a different establishment, we expect a considerably smaller change in the probability of the survivors to move or to receive a promotion. This is because the continuation of research projects and inventions will have to be coordinated between establishments and their managers. The rebuild the team, the surviving co-inventors would have to move between firms or their sub-organizations. This would lead to high coordination costs. Furthermore, we expect that the decrease in productivity prevents both attractive outside job offers and promotion as a reward for exceptional achievements.

The analysis of the causal effect of a negative shock to the team social capital on the career trajectories of the team members requires random variation of the team social capital. We use an empirical setting that comes close to the ideal experiment. We follow up on the empirical strategy established by Azoulay et al. (2010) in the context of scientific publications, and more recently used in the context of patented inventions by Jaravel et al. (2018). We exploit premature, sudden deaths of active inventors as plausibly exogenous variation in the inventor teams' social capital.

We use a novel and unique employer-employee dataset, the INV-BIO dataset (Dorner et al., 2018) which records complete biographies of 152,350 inventors from 1980 until 2014. For this period, inventor 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 were combined in a research data set. 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 with a German residential address. The identification of unique inventors relies on a sophisticated method that combines probabilistic record linkage and machine learning techniques. Based on their names and residential addresses, the disambiguated inventor IDs are linked to entries in the social security data between 1999 and 2011. This procedure resulted in 152,350 unique inventors who were employed in a total of 148,965 unique establishments over the period from 1980 to 2014.

In a 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 WIPO (World Intellectual Property Office). The matching was done based on inventor names, as well as on applicant/employer data recorded in the patent register and the social security data. The INV-BIO data include 643,856 patent families. 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.[2]

The linked employer-employee data enable us to track each inventor's employment status and inventive output over time and across firms at the highest precision. We identify in our data about 800 registered premature deaths of inventors at the age of 60 or younger (the regular retirement age at the time underlying our study was between the age of 61 and 63) and had worked full-time in the preceding months. We construct a matched control group that comprises surviving, or 'pseudo-deceased,' inventors with whom the deceased inventors share the same (or highly similar) characteristics right before the time of death.

Using difference-in-differences (DiD), event study, and hazard model estimations, we investigate the effect of the premature death of an inventor on the career trajectories (job mobility and promotion) of the surviving co-inventors (about 3,000 for each group). As an extension to the analysis, we also consider whether the deceased inventor was a highly productive 'star' inventor.

The DiD estimates show a sizeable and statistically significant negative average treatment effect of inventor death on co-inventor productivity. On average, the co-inventors of a deceased inventor file about 5% fewer patents per year compared to the co-inventors of a pseudo-deceased inventor. The effects become even stronger when we account for patent quality (citations, patent family size). In a first set of heterogeneity tests, we find differentials in the effect depending on the deceased inventor's as well as the co-inventor's previous productivity. The death of a star inventor has a much stronger effect on co-inventor productivity than the death of a less productive co-inventor. These results replicate the findings of previous studies such as Jaravel et al. (2018).

We contribute new results to the literature by analyzing the time dimension of the changes in productivity following the premature death of a co-inventor. From event study estimates, we can infer that the effect sets in immediately (already in the year of the death). Moreover, we do not see a clear trend in the subsequent five years that would suggest a convergence back to the average productivity level of the control group. In summary, a loss of team social capital has an immediate and lasting negative effect on inventor productivity. This suggests that inventors and their employers face considerable difficulties in rebuilding team social capital.

With respect to mobility we find that inventors who lost one of their co-inventors prematurely are less likely to leave their current employer compared to the inventors in the control group, who did not experience such a loss. The effect is, as expected, only significant in case the deceased and the surviving co-inventors worked in the same establishment. We also find a lower likelihood of a move of the survivors in case the deceased inventor was a star, i.e., a highly productive, inventor. These results provide support for the explanation that the survivors play a role in continuing previous research and in replacing the deceased co-inventor. Hence, the employers will attempt to keep their employees from leaving. We further find an increase in the likelihood that the surviving inventors are promoted into a management positions but, as expected, only if the deceased and the surviving

[2]The IAB employment data contains employees subject to social security contributions. Hence, self-employed inventors, freelancers, civil servants, retirees, or students are not covered.

inventors worked for the same establishment and in case the deceased inventors held a management position before they died unexpectedly. Due to coordination costs and competition, surviving co-inventors are unlikely to move between establishments or companies.

Our results have important implications for the literature on knowledge creation and knowledge sharing by showing that the loss of social team capital leads to a decrease in productivity of the survivors and to a decrease in job mobility. We also contribute to the understanding of learning in the team context. After experiencing an unexpected loss of the team social capital, the remaining team members do not seem to be able to compensate fully for the loss. Hence, even though inventors generate spillovers onto their co-authors, part of the knowledge, possibly the tacit part of the knowledge, seems to be lost forever. Finally, the paper also contributes to the literature on the careers of knowledge workers by showing that exogenous shocks can re-route career trajectories, both in terms of promotion and in terms of between-firm mobility.

2 Theory

2.1 Prior literature

Both in terms of identification strategy and our interpretation of the nature of collaboration in knowledge-intensive jobs, we build on the seminal work of Azoulay et al. (2010) who study the impact of an unexpected death of a star scientist on the productivity of her co-authors. According to Azoulay et al. (2010), the decrease in productivity of the co-authors may be explained by imperfect skill substitution. Author teams are created to pool the expertise of scientists, who, as individuals would face the 'burden of knowledge' problem, which was identified by Jones (2009). After the death of a key collaborator, other team members might not be able to (immediately) replace the knowledge that was embodied in the star. Stars may have acted as gatekeepers, providing their collaborators with important resources within or beyond their organizational boundaries. Furthermore, stars may have generated knowledge spillovers onto their co-authors.

Using data on US inventors, Jaravel et al. (2018) argue that inventors may be more productive in case they repeatedly work with the same co-inventors. This is because team-specific capital, comprising skills, expertise and knowledge that are useful only in a particular collaboration, makes a team unique and improves its output. In case collaborations exogenously end and co-inventors (or their contribution to the team-specific capital) cannot easily be replaced, this has a negative long-lasting negative impact on the inventive output of the remaining inventors. The authors also carefully delienate their results from alternative explanations such as firm disruption, network effects and top-down spill-overs. Their results appear to be in line with the view that closely-nit teams are characterized by reduced moral hazard which would be consistent with Holmstrom (1982), and by increased trust in the line of arguments developed by Simmel (1908).

Mohnen (2018) investigates the importance of network position for the productivity of scientists. As a natural experiment, she uses 122 premature deaths of star scientists in a co-author network.

Analyzing 19 million publications in biosciences between 1965 and 2013, she finds that depending on the network position of the deceased star scientist, the productivity of average co-authors decreases up to between 11% (average scientists) and 49% (brokers). The productivity decrease seems to be permanent, i.e., she does not find a convergence back to the average productivity level that was observed before the star scientist deceased.

Bernstein et al. (2019) match 236 million partial US social security numbers to US patents to identify immigrants. When analyzing premature inventor deaths, they find that deceased immigrants incite particularly negative consequences for their co-inventors. Immigrants are found to be especially productive and are argued to have unique knowledge backgrounds, which drives the stronger effect. The effects gradually increase and persist. For an immigrant co-inventor, the decline is about 26%, for US-born inventors, it is only about 10%.

Jaeger and Heining (2019) use matched employer-employee data extracted from the population of German social security records and investigate the substitutability of workers following unexpected deaths of 34,000 co-workers. The unexpected death of a high-skilled co-worker leads to an increase in the wages and the retention probabilities of co-workers in the same occupation. This increase lasts for a period of several years. Workers in other occupations experience wage decreases in case a highly skilled co-worker dies. Hence, whereas co-workers in the same occupation seem to be substitutes, co-workers in other occupations seem to be complements.

Liu et al. (2011) provide further evidence of how deceased co-workers are substituted. The authors use publication data retrieved from PubMED to analyze the effect of premature deaths of star scientists on their collaborators' network. In terms of network structure, the premature death of a scientist is equivalent to removing the center of an egocentric network. Scientists are connected in case they co-authored a journal article in the past. Liu et al. (2011) do not find a negative effect of the death of a star scientist on the topological development of the residual network. They explain this finding by the redundancy of the structure of the network, which acts as a protection mechanism against network disruption. In other words, the existing co-authors substitute for the decreased scientist.

In summary, the existing literature shows that the premature death of a co-worker negatively affects the productivity of the survivors. The effect becomes more pronounced in case the decreased co-workers were stars or held a broker position in the co-worker network. Furthermore, the studies indicate that the survivors seem to substitute for the deceased co-workers. However, the existing literature is largely silent about how a negative shock to an inventor's team social capital affects her career trajectory, i.e., employees' job mobility and promotions. One of the reasons for this is a lack of precise mobility and job status information. With the exception of Jäger and Heining (2019), other studies that rely on patent or publication data have to deduce mobility events from information about the applicants or affiliations. Sufficiently precise mobility information is only available for highly productive inventors (scientists), since it requires continuous patenting (publishing). Information about promotions are not contained in patent or publication data at all.

2.2 Premature death and career trajectories

We argue that an unexpected death of an inventor has two opposing effects on the co-inventors: a positive replacement effect and a negative productivity effect.

First, the gap left by the deceased inventor must be filled. The gap can be filled by outside workers, i.e., by hiring a suitable new worker. This would mean that the premature death of a co-inventor does not affect the demand for the remaining, already employed co-inventors (Jaeger and Heining, 2019). Outside inventors are, however, only imperfect substitutes of the decreased inventors in case the job relies heavily on firm-specific human capital. Whereas general human capital consists of knowledge and skills that are applicable to different firms, firm-specific human capital is only relevant to a particular firm (Hashimoto, 1981; Lazear, 2009). Additionally, labor market frictions, i.e., factors that constrain labor mobility, may prevent hiring a perfect substitute for the deceased inventor. In particular, firms may be unable to identify the right inventor because they cannot assess the quality of the human capital of the potential hire or they are not able to convince the identified inventor to move (Campbell et al., 2012; Mawdsley and Somaya, 2016). If the gap cannot be filled by an external hire, an internal inventor can replace the deceased inventor. This makes the surviving inventors more attractive for the employer, i.e., the labor demand for the existing inventors increases. A higher demand results in higher wages, since firms share their rents with these valuable survivors to keep them from leaving the firm (Becker, 1964; Jaeger and Heining, 2019).

We are interested in the consequences of an unexpected loss of team social capital of knowledge workers (i.e., inventors) for the career trajectories of the survivors. Both, the fact that inventors are knowledge workers and that they work in teams affect the decision of hiring an inventor from outside vs. replacing the deceased inventor with one of the surviving co-inventors.

Teams are special in the sense that they do not only convey human capital but also social (or relational) capital. Whereas human capital is mobile, since it is tied to one particular individual, social capital is rooted in the relationships between the team members and is, therefore, immobile (Jacobs, 1961; Nahapiet and Ghoshal, 1998; Mawdsley and Somaya, 2016). In case one co-worker dies unexpectedly, part of the social capital is destroyed. Even if the firm can find a substitute for the (general) human capital, the relational capital has to be rebuilt in the long term.

Knowledge workers are workers who are highly educated and who apply and recombine knowledge to develop new products and services (Drucker, 1959; Nelson and Winter, 2009). The most valuable type of knowledge is tacit knowledge, i.e., conscious and unconscious knowledge which is stored in the heads of individuals and, consequently, only accessible to the originator of the knowledge (Grant, 1996; Howells, 2002). Codified or explicit knowledge, on the contrary, is accessible to other people than the originator of the knowledge, as well. Even though part of the tacit knowledge can be converted into explicit knowledge, intuition and gut feeling are hard, if not even impossible to make accessible to others (Leonard and Sensiper, 1998; Spender, 1993). Or as Sorenson (2018) noted, whereas codified knowledge, like articles published in scientific journals, focus on things that worked, especially important information about failures, i.e., about what not to do, remains inaccessible if tacit knowledge cannot be retrieved. Teams dispose of collective tacit knowledge which was developed jointly over time. Hiring an external worker does not replace the individual tacit knowledge that was held by the deceased co-worker and does also not contribute to the collective tacit knowledge of the team, at least not in the short run. This would again speak in favor of replacing the deceased inventor by an internal inventor.

Second, the premature death of a co-inventor results in an unexpected loss of social capital. Nahapiet and Ghoshal (1998, p. 243) refer to social capital as 'a set of resources rooted in relationships.' Social capital has three dimensions, a structural, a relational, and a cognitive dimension (Nahapiet and Ghoshal, 1998). Structural social capital refers to the structure of the network that ties together different individuals. It is related to the amount and value of the information that is shared between ties (Burt, 1997). Relational social capital induces trust and reciprocity and enables cooperation and collective action (Kale et al., 2000; Jacobs, 1961). Finally, cognitive social capital refers to shared representations, values and language and, hence, affects coordination costs (Mawdsley and Somaya, 2016).

Networks provide access to knowledge, which may otherwise be beyond an individual's reach or (too) costly to create. A loss of structural social capital means that a social network decreases in size. The larger a network is, the more diverse the knowledge from which inventors can draw. Knowledge diversity was shown to increase the likelihood that inventors produce more novel and creative output (Tzabbar and Vestal, 2015). The loss of relational social capital is particularly pronounced in case the deceased inventor was a gatekeeper or an intermediary (Mohnen, 2018), whom others trusted. If an intermediary is gone, this could mean either that less valuable knowledge is shared or that knowledge flows decline considerably (Granovetter, 1973). Cognitive social capital leads to a shared understanding. This is important, since it means that team members are aware of who knows what and how the expertise of the different team members can help to solve problems (Srikanth and Puranam, 2011; Reagans et al., 2005). A disruption of cognitive social capital, therefore, increases the coordination and communication costs within teams and decreases performance. Any decline in social capital, regardless of which dimension is affected, will lead to a decline in the productivity of survivors. A lower productivity, in turn, decreases the attractiveness of the workers, both for their own employer and for the labor market in general.

In summary, if a co-inventor dies unexpectedly, the gap has to be filled. From the literature we know that it is difficult to fill the gap left by a knowledge worker in a team with an external knowledge worker. This increases the attractiveness of the survivors for the current employer, since they are likely to be the best available replacement for the deceased inventor. Consequently, the employers will provide the survivors with incentives to keep them from leaving the firm (Chang and Wang, 1996; Greenwald, 1986). This decreases the probability of a move. Similar arguments apply for a possible promotion to a management position. We expect a promotion to become more likely. In case the deceased inventor had a management position and the position has to be filled, again, a former co-inventor, i.e., an inventor from inside, may be the optimal substitute of the deceased inventor.

However, at the same time, the premature death of a co-inventor decreases the productivity of the survivors due to a loss of social capital. This makes the survivors less attractive for the current employer and the external labor market (Hoisl, 2007) and there is no reason to reward the inventor with a promotion (except for the substitution). In case the deceased inventor and the surviving co-inventors had been employed at the same establishment, we assume that the positive replacement effect outweighs the negative productivity effect. This leads to our first two hypotheses:

Hypothesis 1: A premature death of a co-inventor from the *same* establishment *decreases* the probability of a move of the surviving co-inventors.

Hypothesis 2: A premature death of a co-inventor from the *same* establishment *increases* the probability of a promotion of the surviving co-inventors, but only if the deceased inventor had a management position.

According to Jaravel et al. (2018), the premature death of an inventor only affects the direct co-inventors. Second-degree connections in an inventor network (i.e., co-inventors of co-inventors) are not significantly affected by the death of the vocal inventor. We distinguish between co-inventors employed by the same vs. by different establishments or companies. In case the deceased co-inventor was employed by a different establishment or company than the surviving co-inventors, we expect a considerably smaller change in the probability of the survivors to move. This is because the surviving co-inventors would have to move between establishments or companies. This would lead to high coordination costs. Furthermore, the current employer of the survivors does not have an incentive to leave her employees to potential competitors. The drop in productivity means that the current employer does not make a special effort to keep the survivors from leaving. However, there won't be (attractive) job offers from outside, either. The same applies to a possible promotion. On the one hand, coordination costs and competition prevent across establishment or company moves and, on the other hand, the surviving inventors do not deserve promotion due to their lower productivity. Hence, in case the deceased and the surviving inventors worked for the same establishment or company, there is no positive replacement effect, the negative productivity effect, however, prevails.

Hypothesis 3: A premature death of a co-inventor from a *different* establishment does *not affect* the probability of a move of the surviving co-inventors.

Hypothesis 4: A premature death of a co-inventor from a *different* establishment does *not affect* the probability of a promotion of the surviving co-inventors.

3 Data and Empirical Strategy

3.1 Data

Our linked inventor biography data cover 152,350 inventors in Germany who were active as inventors between 1999 and 2011. This data set combines labor market biographies as recorded in social security data and patent register data of the European Patent Office and the German Patent and Trademark Office. It comprises a rich set of socio-demographic variables on the inventor, detailed patent track records, and characteristics of the employing establishment. For a detailed account of the dataset construction, see Dorner et al. (2018).

Social security data on labor market careers in Germany have been used extensively in research on productivity and human capital of workers and firms (Dustmann et al., 2009, 2017; Fuest et al., 2018; Jaeger and Heining, 2019). Administrative labor market data has important advantages over using only patent-based datasets because they contain additional complementary information. Employees can be tracked even when they do not patent. In our study, we will exploit knowledge about detailed occupation classifications, unavailable in more traditional data sources. In particular, the role of employees in (middle) management occupations will be important. Further, the place of work is available on the detailed establishment (plant) level, which allows to distinguish inventors working at the same physical location from such that collaborate over a distance.

Most important of all, these data record deaths of employees with great precisions. In particular, when employees leave an employer, the employer has to report the reason for the separation. Death of an employee has a specific code in the social security data. This information has previously been used by Jaeger and Heining (2019), who have also established that death notifications are exogenous events and unrelated to employment spells and employer characteristics, but we will confirm this finding for the subset of inventors.

Despite its coverage and level of detail, the data set has some shortcomings, which, however, can partly be addressed by the combination with patent data. First and foremost, the data do not record the organizational structure within the firm establishments, i.e. which workers actually work together. By using matched inventor-employee data, we can infer with higher precision who has actually worked together as recorded on patents. We exploit the information on teams and collaborations of inventors in combination with the recorded deaths to examine the productivity impact of exogenous changes in teams inventor networks on the productivity of survivor inventors. Further, income information is top-coded, so that for the high-income knowledge workers that are typically listed on patents, hardly any variance is left. Here, we can use patent data to learn about individual productivity. Finally, whether two establishments belong to the same firm or holding structure is not relevant for social security purposes and therefore difficult to know.

In the subsequent analysis, we will occasionally refer to star inventors – individuals who have in the past shown exceptionally high productivity levels, as measured by cumulative patent application counts. We operationalize this concept by considering inventors – deceased and surviving – as stars if they belong to the top 5% of the productivity distribution two years before the premature death.

Some interesting differences in results will be observable when comparing a co-inventor death occurring in the same establishment with a co-inventor death occurring in a difference establishment. Co-inventor deaths in a different establishment can occur in several ways. First, recall that the definition of co-inventors looks at the patenting history of the deceased inventor in the past ten years. In some cases, the deceased inventor and the co-inventor were in the same establishment in the past but one of them moved. Then, the impact of the death is likely smaller. Both inventors used to know each other and are possibly still in contact, but do not currently work together. Second, it is possible that deceased inventor and co-inventor are currently working together, across the boundaries of two establishments. Here, it is important to note that two establishments can, but need not belong to the same firm. Figure A-1 in the Appendix shows the frequency of patents which were developed across establishment borders. Especially in areas around chemistry, $30-40\%$ of all patents are developed with inventors from two or more establishments. In some engineering areas, that number is smaller than 20%.

Promotions are a distinctive and important event in the career of each employee. In particular, promotions to (middle) management occupations are critical as they delineate a shift in roles. We define management occupations according to the five-digit classification of occupations[3]. Management occupations are not employees tasked with overseeing whole companies, such as employees in the C-suite, but have overseer or management functions within the lines of work of the company, i.e. middle management.[4]

Figure A-2 in the Appendix investigates usage of management occupations in inventor teams. In particular, team size and the number of different occupations – both excluding employees with management occupations – are investigated regarding their reliance on co-inventor with management function. We find that both team size and number of occupations seems to increase the use of managers, but the combination of both really sees the most frequent usage. Bringing together many employees, especially if they are endowed with diverse knowledge, require management to integrate personnel and knowledge. Indeed, a related analysis in Figure A-3 in the Appendix shows that this nexus of many employees and many occupations is exactly where the integration of various technology streams into one patent (high originality score) is possible.

3.2 Empirical strategy

For identification, we exploit the quasi-natural experiment of the premature death of a co-inventor. Estimation strategies based on death assume that the death of a coworker removes a person from a workplace or team, which potentially reduces social (team) capital, leads to a loss of tacit knowledge, and creates temporary disturbances.

We consider the co-inventors of a prematurely *deceased* inventor. We create a one-to-one control

[3]This classification is based on the *Klassifikation der Berufe 2010* (Bundesagentur fuer Arbeit, 2011)

[4]For example, the group '41494' would indicate that this employee works in physics (3-digit code 414) but has management responsibility (digit 9) on expert level (last digit 4). Managers themselves have distinctive occupations (digits 71XXX) and thus not considered here.

group and match each deceased inventor to a surviving *pseudo-deceased* inventor with whom he/she shares the same (or highly similar) observational characteristics right before the time of death. We estimate effects by comparing co-inventors of the deceased and pseudo-deceased inventors. While one group is affected by a premature death, the other is not. We call these groups treatment and control group, respectively. We demonstrate that while trends in outcome variables before the death are very similar, they show important differences afterwards.

Using the treatment and control groups, differences-in-difference (DiD) estimates can be obtained, which under typical assumptions yield causal effects of the death of a co-inventor. Using event studies, we can investigate the exact timing of the effects. We use DiD estimates to study inventor productivity using canonical measures of patenting. A second set of outcomes relates to labor market events. Job transitions and promotions are important events in the careers of each employee. However, the different nature of this outcome variable (events) necessitates a different estimation strategy. Here, we rely on survival analysis, i.e. the analysis of timing until the first such event occurs. Again, we compare treatment and control group.

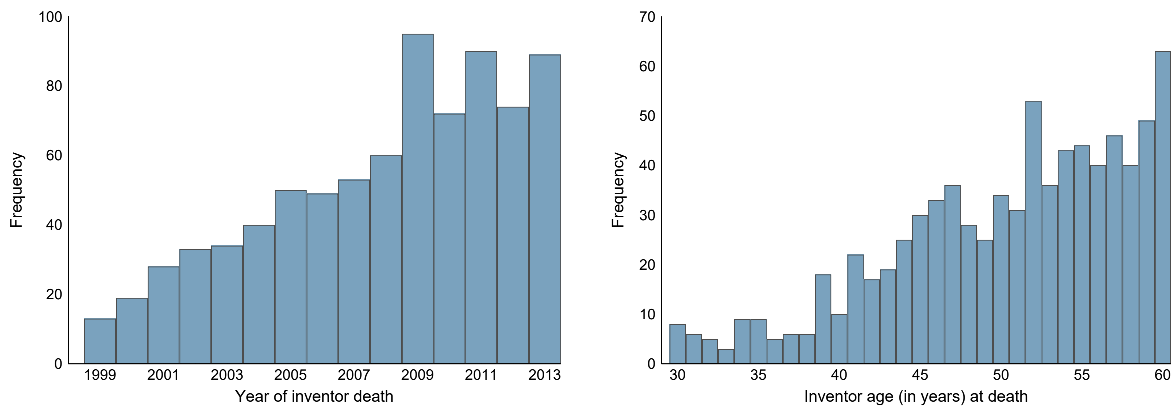
Inventor matching

Our empirical approach proceeds stepwise. First, the social security data allows us to precisely identify inventors who prematurely died. We further restrict our selection of deaths to employees that died with age 60 or below. Figure 1 shows the distribution of ages at death for the deceased inventors as well as the years in our data. In our population of inventors, a large fraction is still employed after reaching the age of 60 and still contribute with 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).

Figure 1: Inventor deaths by year and age

(a) Inventor deaths over time

(b) Inventor deaths by age



Notes: The graphs show death year (left) and death age (right) for the deceased inventors.

In our estimation strategy, we follow Jaravel et al. (2018) by selecting comparable pseudo-deceased inventors who did not die. We do so iteratively, by selecting pseudo-deceased inventors for earlier death years first. Inventors are selected to have the exact same age, gender, patenting count, firm size, and technological focus. In case of ties in the match, we further restricted the set of control group candidates to inventors who have firm tenure, last patenting date and exact number of patents as similar as possible to the deceased inventor, in that order.[5] From the control group candidates set, we exclude any inventor who was employed in the same establishment as the deceased inventor and has ever had a joint patent with the deceased inventor.

To each matched pseudo-deceased inventor, we assign the (pseudo) death date of the deceased inventor. For the real and the pseudo-deceased inventors, we setup up the inventor network up the first degree of separation, i.e. those inventors who were listed on a patent filing with the deceased inventor within the 10 calendar years prior to the year of the death date. We also drop all inventors that are within one degree of separation for more than one (pseudo-)deceased inventor to avoid contamination.

The (surviving) co-inventors in the networks of deceased and pseudo-deceased inventors are units of interest in our empirical analysis. We investigate potential differences in inventor productivity and labor market outcomes between co-inventors after the death of the deceased inventor compared to co-inventors of the pseudo-death of the matched inventor.

Econometric models

Our DiD estimation strategy is as follows:

$$\log(1 + Y_{it}) = \alpha_i + \text{death}_i \times \beta_{t>0} + \gamma Z_{it} + \delta_t + \epsilon_{it}. \qquad \text{(Eq 1)}$$

All DiD specification use inventor-specific fixed effects, which incorporate death year fixed effects. Further, we include relative time period fixed effects. The variable Z contains additional, time-varying control variables on the inventor level, particularly age and age squared. Standard errors are clustered on the inventor level. This estimation strategy delivers the causal effect of an inventor death on the coworkers if, absent the death, productivity of the deceased and the network would have evolved as in the matched control group.

In the event study specification, this expands to

$$\log(1 + Y_{it}) = \alpha_i + \text{death}_i \times \sum_{k=-5;k\neq-2}^{5} \beta_k + \gamma Z_{it} + \delta_t + \epsilon_{it}. \qquad \text{(Eq 2)}$$

For each deceased or surviving inventor, we consider the years $t = -5$ to $t = 5$ around the death year. We use $t - 2$ as the baseline period to observe potential differences already in the pre-

[5]We coarsen the patenting count to groups of 10-14, 15-19, 10s between 20 and 100, 50s between 100 and 300, and a final one for 400 and everything above. Firm size is coarsened in group of <50, 50-249, 250-999, 1,000+. Technology fields are broadly grouped into five main technology areas (Chemistry, Instruments, Electrical Engineering, Mechanical Engineering, Other) using the modal value within inventors. The reason for the additional weak matching criteria is to strike a balance between stable matching and retaining a high number of successful matches.

period. The reason for choosing $t-2$ is that due to the nature of the patent system, it is possible that the death of a co-inventor already has effects on productivity outcomes in prior years. For example, if a patent application was pursued using the PCT system and the death of an inventor renders prosecution or further development impossible, the PCT application may never materialize at the EPO or the German patent office. Similar, additional patent applications in other jurisdictions may now be missing, creating pre-trends in patent family size measures. Similarly, if the death impedes follow-on work, self-references contained in future patent applications will be missing in the treatment group. Hence, pre-trends may be conceivable in forward-citation measures as well. Choosing an earlier time period allows us to highlight these effects where they exist.

In a second set of analyses, we analyze the effect of inventor death on the duration outcome of co-inventor labor market events, i.e. the first post-death career change. We use a Cox proportional hazard rate model with time-invariant regressors which is specified as a continuous-time hazard rate function. The model consists of a nonparametric baseline hazard rate and a multiplicative term allowing the regressors to have a proportional impact relative to the baseline. We let h_{change} denote the hazard rate of a labor market event, stratified by the surviving inventor's modal technology area l. We further include inventor characteristics, Z, and death calendar year fixed effects, $year_i$, as control variables. The model is then as follows:

$$h_{\text{change}}\,(t|\text{death}_i, l_i, Z_i) = h^{l_i}(t)\ \exp(\alpha + \beta\ \text{death}_i + \gamma Z_i + \epsilon_i). \qquad \text{(Eq 3)}$$

where β represents the effect of a truly deceased co-inventor on the *change* hazard rate. The potential bias from a correlation between *death* and unobserved heterogeneity in the hazard rate, ϵ_i, should be minimized given our carefully selected control group.[6] To capture the influence of inventor life-cycle and macro-economic events on the baseline hazard rate of *change*, we control for age, age squared and the year of death, which are all part of the vector Z_i.

We consider two dependent variables in the hazard rate analysis. For both job separation (*leave*) and promotion to management (*promotion*), only the first post-death event for an inventor is considered. For heterogeneity analysis, the *death* variable is included in the regression fully interacted with the heterogeneity variable of interest. Since Kaplan-Meier estimates indicate heterogeneous effects depending on the time frame, we truncate the event data at different time spans: 200, 400, 600 and 800 days.

[6]We however assume that *death* is independent of ϵ_i given our matching procedure, the stratification and control variables such as age and death year. The estimation strategy is not diff-in-diff as above as the pre-post difference is not considered. Therefore, the parallel trends assumption is not sufficient for the causality of estimates. Instead, similar mobility rates in treatment and control group absent the death have to be assumed.

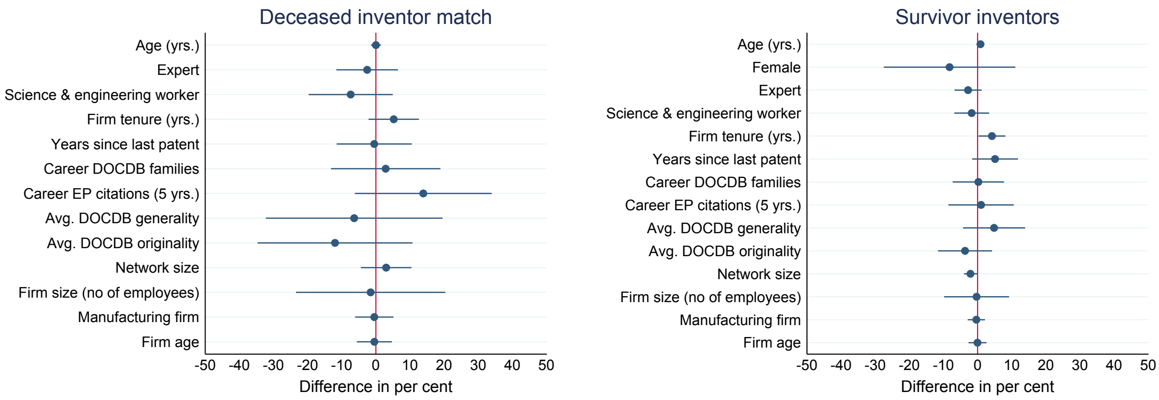
4 Results

Match quality and pre-trends

Of about 850 deceased inventors that we observe in our data, 799 are successfully matched to observationally similar pseudo-deceased inventors. Figure 2 and Table 1 illustrate that our matching exercise was successful by testing the balancedness of a large covariates set. We find that matched as well as unmatched characteristics are strikingly similar between focal and co-inventors. The small relative differences in means (and medians) provide strong support for the quality of our match.

Figure 2: Mean differences comparison of (co-)inventor pre-death characteristics

(a) Deceased inventors (b) Surviving co-inventors



Notes: The two graphs present comparisons of mean differences of key pre-death characteristics of the deceased inventors (left) and their surviving co-inventors (right). The unit of observation is at the inventor level.

Figure A-4 in the Appendix further investigates whether the levels and trends of productivity between deceased and pseudo-deceased inventors is similar. As expected, the individual productivity of the actually deceased inventors drops to zero in the year following the death, while before the death, levels and trends are comparable between them and the group of pseudo-deceased inventors.

Productivity effects

The most immediate outcome of a co-inventor death – and which has also been the focus of prior studies – is a change in individual productivity (Jaravel et al., 2018; Bernstein et al., 2019) Here, we replicate their analyses to confirm their findings in the German context.

Figure 3 and 4 each show event study estimates for the full sample of deceased inventors and by subgroups of previous productivity.[7] In Figure 3 depicts estimates of simple patent count (at family level). We find moderate decreases in patenting of around 4%. These decreases set in immediately after the death and can also be found in later time periods. Analyzing sub-groups, we explore

[7]These estimates are also shown as tables in the Appendix (A-1 to A-2).

Table 1: Pre-death characteristics of focal inventors and their co-inventors

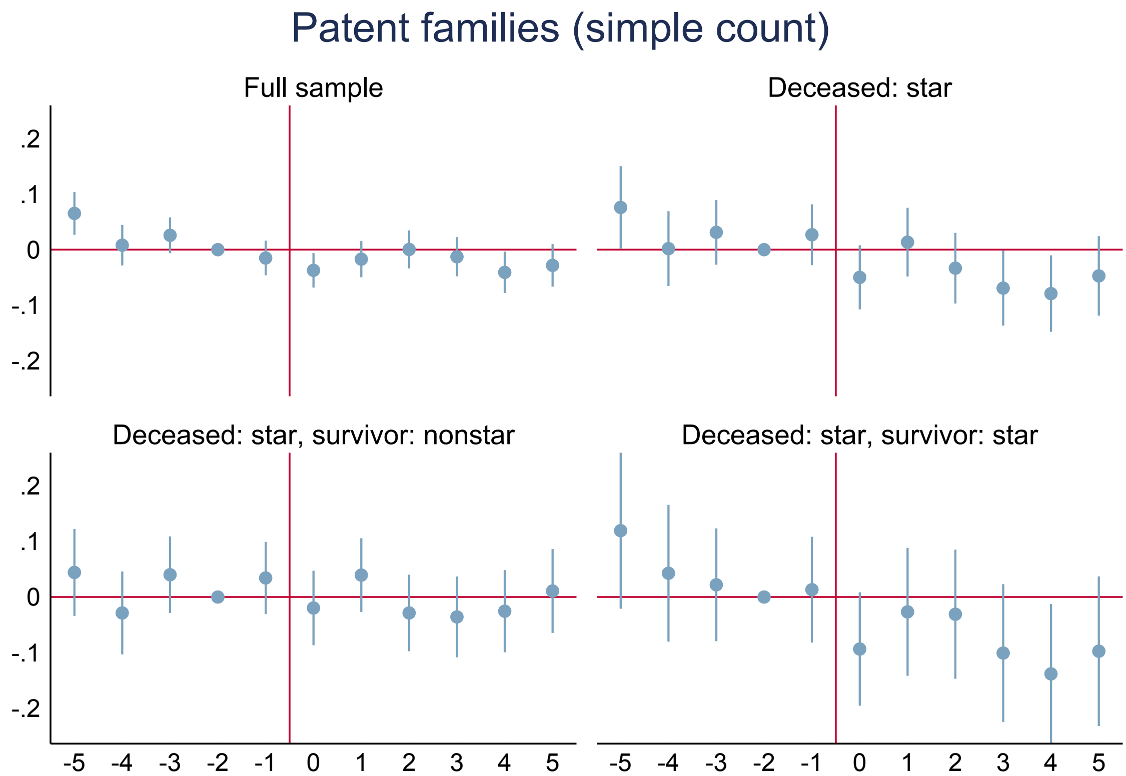
Deceased inventors	Deceased (N = 799)			Pseudo-deceased (N = 799)				
	Mean	Median	Std. Error	Mean	Median	Std. Error	Diff.	p-value
Age	49.37	51.00	7.40	49.35	51.00	7.41	0.01	0.976
Expert	0.54	1.00	0.50	0.55	1.00	0.50	−0.01	0.581
Science & eng. worker	0.39	0.00	0.49	0.42	0.00	0.49	−0.03	0.241
Firm tenure (in years)	12.04	10.00	9.24	11.41	9.00	8.87	0.63	0.164
Years since last patent	2.93	2.00	3.20	2.94	2.00	3.37	−0.01	0.933
Career patent families	6.18	3.00	10.51	6.00	3.00	9.69	0.18	0.725
Career 5yr EP citations	7.79	2.00	17.69	6.71	2.00	13.94	1.08	0.175
Patent generality (avg)	0.06	0.00	0.16	0.06	0.00	0.16	0.00	0.631
Patent originality (avg)	0.08	0.00	0.19	0.09	0.00	0.20	−0.01	0.302
Network size	3.73	3.00	2.80	3.62	3.00	2.83	0.11	0.424
Firm size (employees)	4050.89	772.00	9150.28	4112.63	791.50	8921.01	−61.73	0.891
Manufacturing firm	0.75	1.00	0.43	0.76	1.00	0.43	0.00	0.873
Firm age	22.39	26.00	11.71	22.49	26.00	11.74	−0.10	0.869

Surviving co-inventors	Deceased (N = 3308)			Pseudo-deceased (N = 3210)				
	Mean	Median	Std. Error	Mean	Median	Std. Error	Diff.	p-value
Age	45.05	44.00	8.47	44.67	44.00	8.48	0.38	0.080*
Female	0.07	0.00	0.25	0.07	0.00	0.26	−0.01	0.403
Expert	0.60	1.00	0.49	0.61	1.00	0.49	−0.02	0.169
Science & eng. worker	0.49	0.00	0.50	0.50	1.00	0.50	−0.01	0.505
Firm tenure (in years)	10.35	8.00	8.25	9.92	8.00	7.96	0.44	0.037**
Years since last patent	1.58	1.00	2.14	1.50	1.00	2.06	0.08	0.136
Career patent families	13.50	7.00	19.38	13.47	6.00	20.89	0.03	0.953
Career 5yr EP citations	19.92	7.00	37.49	19.72	7.00	38.15	0.20	0.835
Patent generality (avg)	0.10	0.00	0.19	0.10	0.00	0.18	0.00	0.298
Patent originality (avg)	0.14	0.00	0.22	0.15	0.00	0.23	−0.01	0.362
Network size	6.15	8.00	2.36	6.28	8.00	2.33	−0.13	0.033**
Firm size (employees)	5185.34	1350.50	9790.26	5200.75	1531.00	9757.85	−15.41	0.951
Manufacturing firm	0.80	1.00	0.40	0.80	1.00	0.40	0.00	0.775
Firm age	22.75	27.00	11.78	22.76	27.00	11.92	−0.01	0.978

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

the origin of the effects. In particular, the death of star inventors seems to especially matter for their former co-inventors. Interestingly, the effect is strongest when both deceased inventor and co-inventor were highly productive individuals. The exact reason requires further investigation, but below we provide evidence that these individuals did possibly patent together particularly frequently. The analysis elicits even more pronounced effects when looking at the quality dimension in Figure 4. Here, it becomes clear that the effects are immediate, strong and long-lasting. However, the effect seems to set in already in the year before the death. As discussed above, this can be driven by contamination through missing self-references from later patent filings in the treatment group. The previously observed pattern concerning productivity differentials is corroborated: when a star dies, co-inventors are especially affected, which is again driven by surviving stars. This pattern can also be found when using a quality weighted patent count based on the patent family size (Table A-3 in the Appendix).

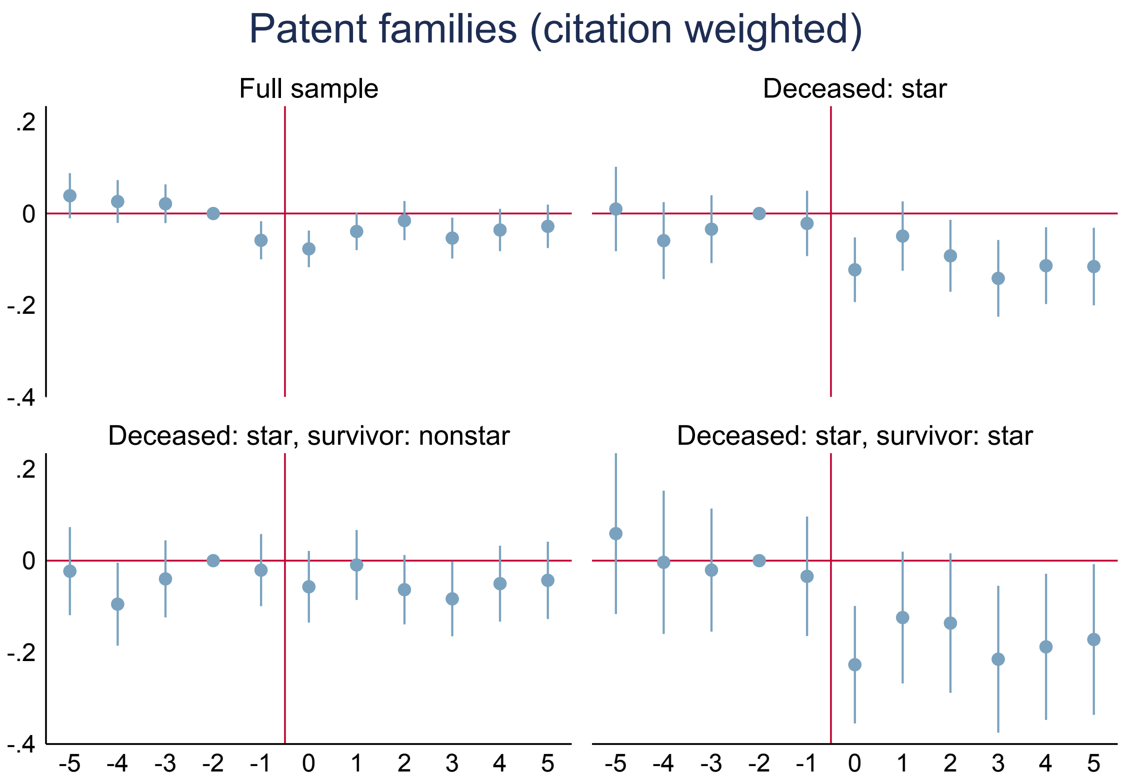
Figure 3: Impact of inventor death on co-inventor productivity (event study estimates)



Notes: The two graphs present plotted point estimates of the variable *death* interacted with event year dummies. The unit of observation is the individual surviving co-inventor-year. Baseline year is $t-2$. The graphs correspond to the coefficients reported in Table A-1. Confidence intervals are at the 95% level.

We can confirm these productivity results in reduced DiD specifications, where dynamics are ignored and a single effect for the treatment group can be calculated. Tables A-4 to A-6 in the Appendix list such specifications. On average, elasticities between -4% (simple counts) and -6% (weighted by family size) can be found. These elasticities are consistently stronger in subsamples where either the deceased inventor or the surviving co-inventor were highly productive. In split samples, effects in the range of -7% to -11% (patent applications) or -9% to -14% (family size weighting) are found. The interacting star status of the deceased drives a large part of the average effect in the full sample. This confirms findings from the previous literature on the death of star scientists, i.e., the loss of highly productive peers matters most.

Figure 4: Impact of inventor death on co-inventor productivity (event study estimates)



Notes: The two graphs present plotted point estimates of the variable *death* interacted with event year dummies. The unit of observation is the individual surviving co-inventor-year. Baseline year is $t-2$. The graphs correspond to the coefficients reported in Table A-2. Confidence intervals are at the 95% level.

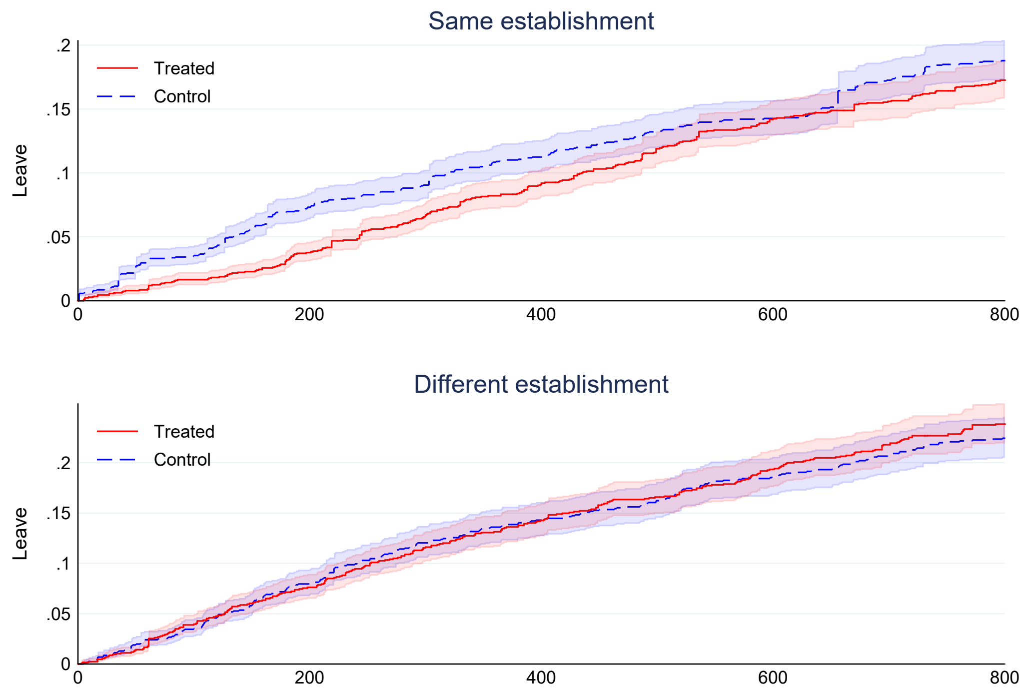
Labor market events

We investigate the effect of premature deaths on labor market events in two stages. First, we estimate failure rates using Kaplan-Meier estimators and visually inspect the results. Subsequently, we estimate Cox proportional hazard models and control for additional variables.

The first set of estimates analyzes the probability of a job separation event in the treatment group relative to the control group. Figure 5 plots in a first panel Kaplan-Maier estimates, distinguishing by co-inventors who were in the same establishment as the focal inventor in the year of the death. In comparison, the second panel looks at co-inventors who were in a different establishment at the time of death. In both cases, around 20% of inventors have left their initial employer by day 800, indicating frequent turnover of highly skilled knowledge workers.

We find that for co-inventors in the same establishment, separation probability is significantly reduced in the first 400 days, but the difference between the rates subsequently decreases and becomes small. Regression estimates in Table A-7 in the Appendix confirm this pattern, initial significant differences level off. The treatment group catches up by a higher rate of leaves at a later point in time. For co-inventors in different establishments, the separation probability of the treatment group

Figure 5: Leave events by establishment of deceased and survivor (Kaplan-Meier estimates)



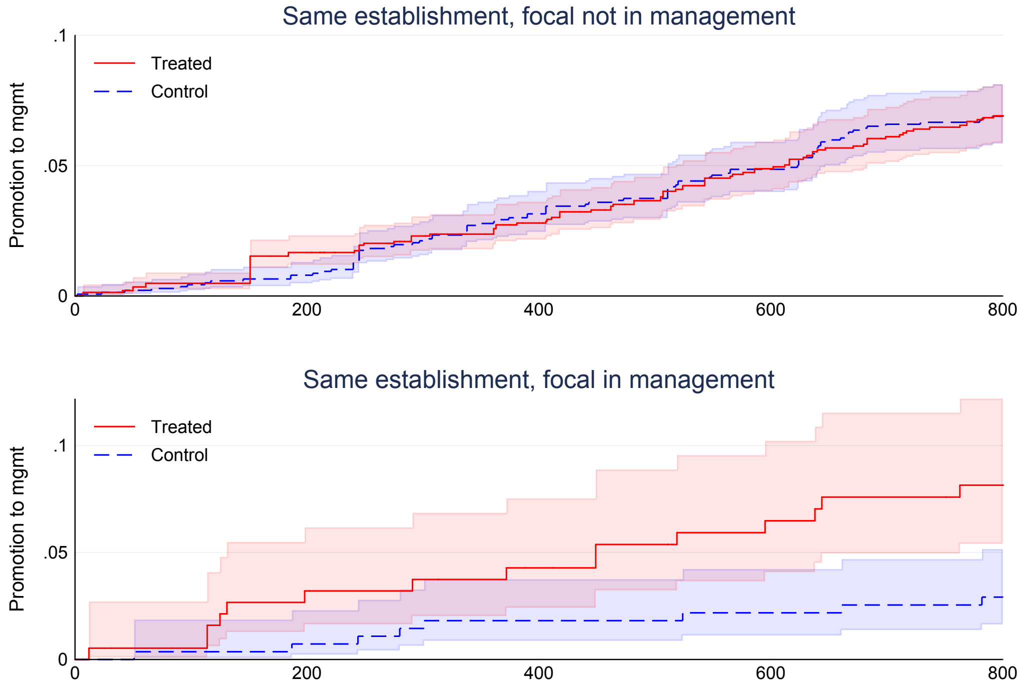
exactly tracks the control group. This is confirmed by the regression estimates in the lower part of Table A-7 in the Appendix. These findings confirm Hypothesis 1 and Hypothesis 3.

It is difficult to infer from standard patent data the exact role an inventor had in a team and how essential her specific contribution was. With administrative labor market data, we can achieve some progress in this matter. In particular, we leverage available occupation information to determine whether a particular inventor held a management occupation during a specific employment spell. As discussed in Section 3, management occupations refer to employees with management responsibilities within a specific field of work. They do not refer to general management, such as CEOs, but rather describe middle management positions.[8]

We proceed to estimate the probability of promotion to a management occupation following a premature death. Figure 6 shows Kaplan-Meier estimates for this event, when the focal inventor and co-inventor worked in the same establishment. We further distinguish whether the deceased inventor was in a management occupation. The probability of a promotion towards a management position approaches 8% by day 800 when the deceased inventor was not in a management position. In contrast, when the focal inventor was in a management position, the treated co-inventors show a substantially and persistently higher probability to advance to a management occupation. At day 800, the treatment group has – on average – a cumulative promotion probability that is twice as large as that of the matched control group (8% vs. 4%). This finding confirms Hypothesis 2.

[8]We disregard occupation changes where the inventor had already been in a management occupation before the occupation change.

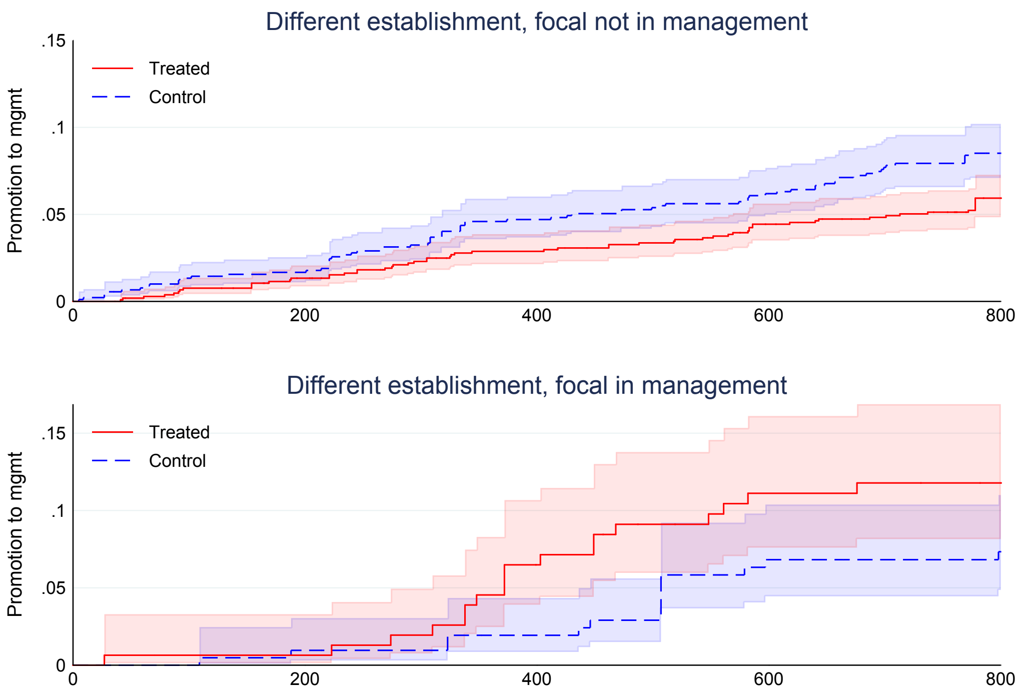
Figure 6: Promotion to management, same establishment (Kaplan-Meier estimates)



Finally, Figure 7 compares the probability of promotion to a management occupation when deceased and surviving inventor worked in a different establishment. According to our reasoning in Section 2, we would not expect an effect here, as there is no immediate gap at the surviving inventor's establishment to be filled. However, the estimates in Figure 7 contradicts with this hypothesis. Even when deceased and surviving inventor worked in different establishments, the premature death event increases the survivor's probability of promotion. Therefore, we fail to confirm Hypothesis 4.

A possible explanation for this failure is that management capability in complex teams is actually a boundary-spanning function. Perhaps it is important that in long-term collaboration between two establishments a manager is present, but immaterial which of the two establishments contributes the manager. Instead, management ability and prior experience may be more decisive for deciding who enters a management position.

Figure 7: Promotion to management, different establishment (Kaplan-Meier estimates)



5 Conclusion

This paper has studied the effects of premature deaths on inventor teams. We use a unique new dataset combining register data from various patent offices with employer-employee panel data derived from social security records in Germany. The overall dataset comprises information on the career paths of more than 150.000 inventors from 1980 to 2014. We identify 799 cases of premature deaths and construct a control group of pseudo-deceased inventors. We study then the patenting output and patent quality of the co-inventors of these focal individuals, using both DiD and event study designs.

We confirm that such a loss affects co-inventors negatively, and that the effects are immediate, strong and long-lasting. Patent counts typically decline by 4%, citation-weighted counts by 6%. The effects are much stronger when either the deceased inventor or the surviving co-inventors are ‘stars’ (particularly productive). Then the pure quantity effects range between 7% and 11%, and quality-weighted counts decline by 9% to 14%. The effects are strongly driven by the presence of stars among the deceased inventors or the surviving co-inventors. These results confirm earlier studies of inventor teams (e.g., Jaravel et al., 2018) for the US labor market.

We go beyond the existing literature by exploring labor market outcomes in terms of mobility and promotion events. If the employer is confronted with the sudden death of an inventor, he or she has to consider continuing or abandoning existing lines of research and of invention. If there were no team- or project-specific capital to consider, then the employer would not be dependent on the surviving team members. However, we find strong evidence that employers seek to retain surviving co-inventors. We find that the hazard of leaving the establishment is significantly lowered after a premature death. Conversely, the chances of promotion of a surviving co-inventor are significantly enhanced, in particular if the deceased inventor had previously assumed coordinating (i.e., managerial) responsibilities. These results are in line with our theoretical arguments stating that employers seeking to ‘fill the gap’ are most likely to build their efforts on surviving members of the team.

In further research we intend to provide further robustness checks and analyses regarding the occupational mix and other forms of heterogeneity in the team. Ultimately we hope to identify the mechanisms by which firms seek to respond to the loss of critical human capital, and the success of such responses.

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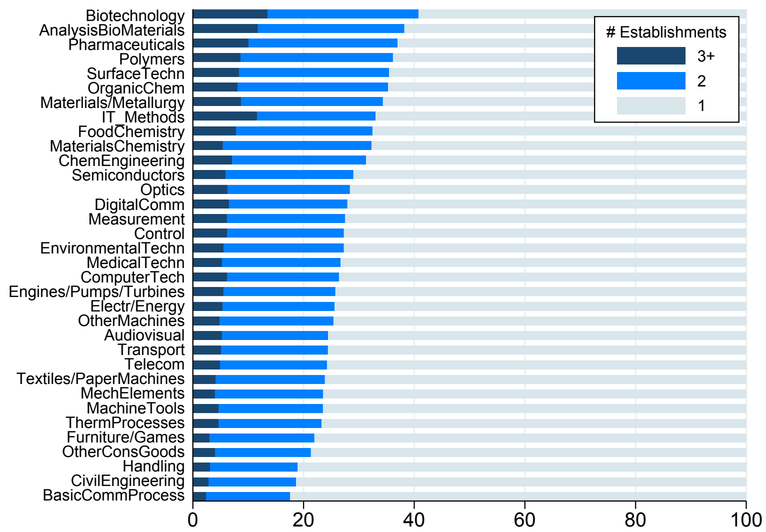
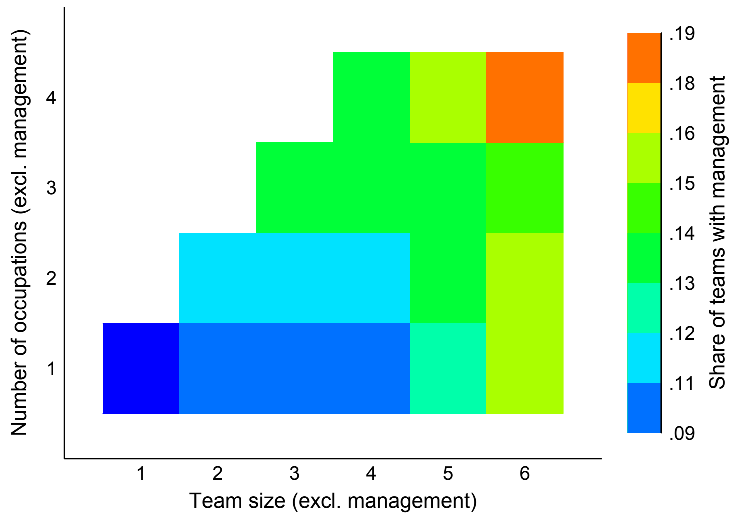
Appendix

Figure A-1: Number of establishments in inventor teams



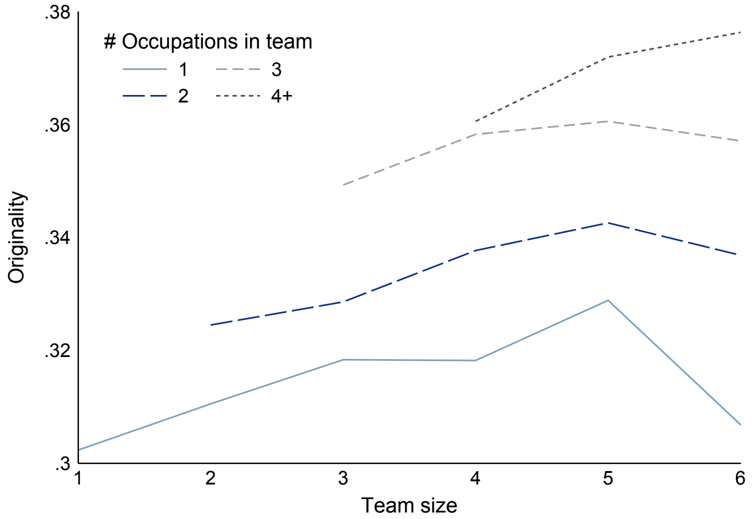
Notes: This graph shows the number of different establishments that inventors listed on a patent are working in, by technological area. If only one inventor is listed on a patent, the establishment number is one. Note that two establishments can be part of the same company. Inventors not matched in the German linked employer-employee data are disregarded.

Figure A-2: Share of inventor teams with an inventor-manager (at patent level)



Notes: This graph plots the share of inventor teams with at least one inventor-manager among them. Inventor-managers are listed with an occupation that implies a management role, such as 'physicist with supervisory role', but also exclusive management positions. When calculating the number of occupations and team sizes, the inventor-managers are excluded.

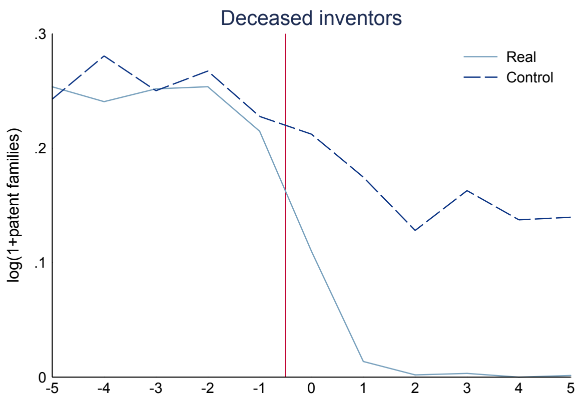
Figure A-3: Originality by team size and occupation diversity (at patent level)



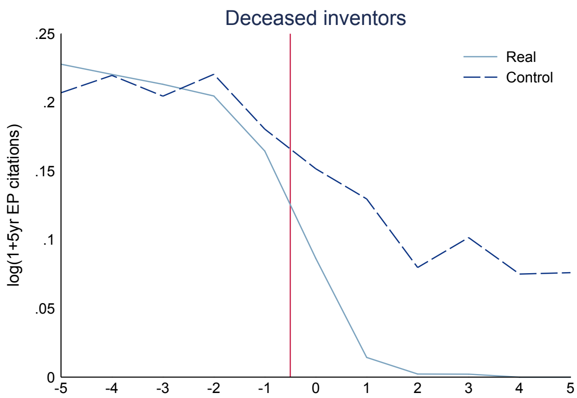
Notes: This graph plots the originality (related to the variety of technology classes in backward references) by team size and occupation count within the inventor team.

Figure A-4: Average productivity by deceased inventors

(a) Patent families (simple count)

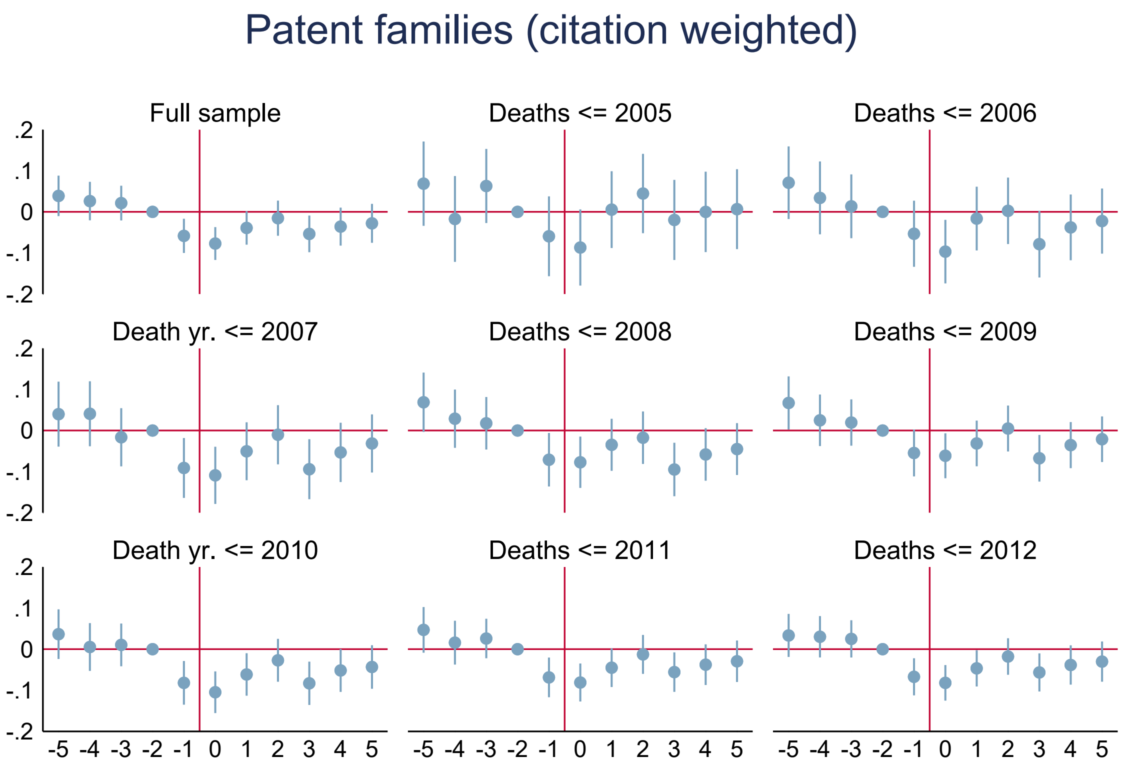


(b) Patent families (citation weighted)



Notes: The two graphs show the yearly average for patent family counts (left) and citation-weighted patent counts (right) for deceased inventors.

Figure A-5: Impact of focal inventor death on productivity (event study estimates)



Notes: The two graphs present plotted point estimates of the variable *focal death* interacted with event year dummies. The unit of observation is the individual co-inventor. Baseline year is $t-2$. Confidence intervals are at the 95% level.

Table A-1: Impact of inventor death on co-inventor productivity (event study estimates)

DV: log Patents	(1) Full sample	(2) Deceased Star	(3) Deceased Nonstar	(4) Both Star
Death year−5	0.065***	0.076**	0.049**	0.119*
	(0.020)	(0.038)	(0.023)	(0.072)
Death year−4	0.008	0.002	0.007	0.043
	(0.019)	(0.034)	(0.022)	(0.063)
Death year−3	0.026	0.031	0.017	0.022
	(0.016)	(0.030)	(0.020)	(0.052)
Death year−2	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)
Death year−1	−0.015	0.027	−0.037*	0.013
	(0.016)	(0.028)	(0.019)	(0.049)
Death year	−0.037**	−0.050*	−0.029	−0.094*
	(0.016)	(0.029)	(0.019)	(0.052)
Death year+1	−0.017	0.013	−0.032*	−0.027
	(0.017)	(0.032)	(0.019)	(0.059)
Death year+2	0.000	−0.033	0.019	−0.031
	(0.017)	(0.032)	(0.021)	(0.059)
Death year+3	−0.013	−0.069**	0.018	−0.101
	(0.018)	(0.034)	(0.021)	(0.063)
Death year+4	−0.041**	−0.079**	−0.020	−0.138**
	(0.019)	(0.035)	(0.023)	(0.064)
Death year+5	−0.028	−0.047	−0.014	−0.098
	(0.020)	(0.036)	(0.023)	(0.069)
N clusters	6518	2203	4315	914
N Observations	65494	22010	43484	9046
Adj. R2	0.07	0.09	0.06	0.17

Notes: Elasticity estimates from a linear regression with inventor and year fixed effects and age, age squared covariates. Standard errors clustered on the inventor level in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table A-2: Impact of inventor death on co-inventor productivity (event study estimates)

DV: log EP cit	(1) Full sample	(2) Deceased Star	(3) Deceased Nonstar	(4) Both Star
Death year−5	0.039	0.010	0.040	0.059
	(0.025)	(0.047)	(0.030)	(0.089)
Death year−4	0.026	−0.059	0.061**	−0.004
	(0.024)	(0.043)	(0.029)	(0.080)
Death year−3	0.021	−0.034	0.043	−0.021
	(0.022)	(0.038)	(0.026)	(0.068)
Death year−2	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)
Death year−1	−0.058***	−0.022	−0.077***	−0.034
	(0.021)	(0.036)	(0.026)	(0.066)
Death year	−0.077***	−0.123***	−0.052**	−0.227***
	(0.020)	(0.036)	(0.025)	(0.065)
Death year+1	−0.039*	−0.049	−0.034	−0.124*
	(0.021)	(0.039)	(0.024)	(0.073)
Death year+2	−0.015	−0.092**	0.024	−0.136*
	(0.022)	(0.040)	(0.026)	(0.078)
Death year+3	−0.054**	−0.141***	−0.006	−0.215***
	(0.023)	(0.043)	(0.027)	(0.082)
Death year+4	−0.036	−0.114***	0.001	−0.188**
	(0.024)	(0.043)	(0.028)	(0.081)
Death year+5	−0.028	−0.116***	0.017	−0.172**
	(0.024)	(0.043)	(0.029)	(0.084)
N clusters	6518	2203	4315	914
N Observations	65494	22010	43484	9046
Adj. R2	0.07	0.09	0.06	0.17

Notes: Elasticity estimates from a linear regression with inventor and year fixed effects and age, age squared covariates. Standard errors clustered on the inventor level in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table A-3: Impact of inventor death on co-inventor productivity (event study estimates)

DV: log Family size	(1) Full sample	(2) Deceased Star	(3) Deceased Nonstar	(4) Both Star
Death year−5	0.053*	0.024	0.045	0.086
	(0.028)	(0.049)	(0.034)	(0.071)
Death year−4	0.035	−0.024	0.054	0.131**
	(0.027)	(0.045)	(0.034)	(0.065)
Death year−3	0.050**	0.043	0.040	0.071
	(0.025)	(0.043)	(0.032)	(0.062)
Death year−2	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)
Death year−1	−0.034	0.019	−0.070**	0.034
	(0.024)	(0.040)	(0.030)	(0.059)
Death year	−0.079***	−0.112***	−0.066**	−0.138**
	(0.023)	(0.039)	(0.029)	(0.059)
Death year+1	−0.033	0.012	−0.064**	0.036
	(0.023)	(0.039)	(0.029)	(0.063)
Death year+2	0.000	−0.054	0.021	−0.027
	(0.024)	(0.041)	(0.030)	(0.068)
Death year+3	−0.030	−0.118***	0.007	−0.150**
	(0.025)	(0.043)	(0.031)	(0.070)
Death year+4	−0.057**	−0.143***	−0.021	−0.192***
	(0.026)	(0.045)	(0.032)	(0.074)
Death year+5	−0.055**	−0.100**	−0.034	−0.122
	(0.027)	(0.048)	(0.033)	(0.080)
N clusters	6518	2203	4315	914
N Observations	65494	22010	43484	9046
Adj. R2	0.08	0.10	0.07	0.18

Notes: Elasticity estimates from a linear regression with inventor and year fixed effects and age, age squared covariates. Standard errors clustered on the inventor level in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table A-4: Impact of inventor death on co-inventor productivity (DiD estimates)

DV: log Patents	(1) Full sample	(2) Deceased star	(3) Survivor star	(4) Full sample	(5) Full sample
Post	−0.060***	−0.029*	−0.020	−0.050***	−0.053***
	(0.009)	(0.018)	(0.021)	(0.010)	(0.009)
Deceased × Post	−0.039***	−0.067***	−0.108***	−0.018	−0.015
	(0.010)	(0.020)	(0.025)	(0.012)	(0.011)
Post × Deceased Star (10%)				−0.036**	
				(0.017)	
Deceased × Post × Deceased Star (10%)				−0.048**	
				(0.023)	
Post × Deceased Star (5%)					−0.039*
					(0.020)
Deceased × Post × Deceased Star (5%)					−0.084***
					(0.027)
Individual FE	Yes	Yes	Yes	Yes	Yes
Death Year FE	Yes	Yes	Yes	Yes	Yes
N clusters	6518	2203	1871	6518	6518
N Observations	65494	22010	18653	65494	65494
Adj. R2	0.07	0.09	0.16	0.07	0.07

Notes: Elasticity estimates from a linear regression. Regressions further include age and age squared covariates. Standard errors clustered on the inventor level in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table A-5: Impact of inventor death on co-inventor productivity (DiD estimates)

DV: log EP cit	(1) Full sample	(2) Deceased star	(3) Survivor star	(4) Full sample	(5) Full sample
Post	-0.052^{***}	-0.019	-0.004	-0.037^{***}	-0.046^{***}
	(0.011)	(0.020)	(0.026)	(0.012)	(0.012)
Deceased × Post	-0.049^{***}	-0.080^{***}	-0.135^{***}	-0.026^{*}	-0.026^{*}
	(0.013)	(0.024)	(0.031)	(0.015)	(0.014)
Post × Deceased Star (10%)				-0.047^{**}	
				(0.020)	
Deceased × Post × Deceased Star (10%)				-0.052^{*}	
				(0.028)	
Post × Deceased Star (5%)					-0.030
					(0.023)
Deceased × Post × Deceased Star (5%)					-0.081^{**}
					(0.032)
Individual FE	Yes	Yes	Yes	Yes	Yes
Death Year FE	Yes	Yes	Yes	Yes	Yes
N clusters	6518	2203	1871	6518	6518
N Observations	65494	22010	18653	65494	65494
Adj. R2	0.07	0.09	0.16	0.07	0.07

Notes: Elasticity estimates from a linear regression. Regressions further include age and age squared covariates. Standard errors clustered on the inventor level in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table A-6: Impact of inventor death on co-inventor productivity (DiD estimates)

DV: log Family size	(1) Full sample	(2) Deceased star	(3) Survivor star	(4) Full sample	(5) Full sample
Post	-0.096^{***}	-0.058^{***}	-0.008	-0.086^{***}	-0.093^{***}
	(0.012)	(0.022)	(0.023)	(0.013)	(0.012)
Deceased × Post	-0.063^{***}	-0.091^{***}	-0.140^{***}	-0.042^{***}	-0.042^{***}
	(0.013)	(0.024)	(0.028)	(0.016)	(0.015)
Post × Deceased Star (10%)				-0.034^{*}	
				(0.020)	
Deceased × Post × Deceased Star (10%)				-0.048^{*}	
				(0.029)	
Post × Deceased Star (5%)					-0.015
					(0.023)
Deceased × Post × Deceased Star (5%)					-0.077^{**}
					(0.033)
Individual FE	Yes	Yes	Yes	Yes	Yes
Death Year FE	Yes	Yes	Yes	Yes	Yes
N clusters	6518	2203	1871	6518	6518
N Observations	65494	22010	18653	65494	65494
Adj. R2	0.08	0.10	0.16	0.08	0.08

Notes: Elasticity estimates from a linear regression. Regressions further include age and age squared covariates. Standard errors clustered on the inventor level in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table A-7: Impact of death on co-inventor leave events (Cox proportional-hazards model estimates)

Leave event	(1) <200 days	(2) <400 days	(3) <600 days	(4) <800 days
Deceased	−0.339***	−0.108	0.014	−0.012
	(0.105)	(0.077)	(0.066)	(0.059)
N events	383	700	950	1176
N subjects	5939	5939	5939	5939
Pseudo-R2	0.05	0.04	0.04	0.04

Leave event	(5) <200 days	(6) <400 days	(7) <600 days	(8) <800 days
Deceased	−0.009	0.025	0.064	0.074
	(0.148)	(0.109)	(0.096)	(0.087)
Same establishment	0.052	−0.120	−0.158*	−0.108
	(0.142)	(0.108)	(0.096)	(0.085)
Deceased × Same establishment	−0.676***	−0.267*	−0.101	−0.169
	(0.215)	(0.156)	(0.134)	(0.120)
N events	383	700	950	1176
N subjects	5937	5937	5937	5937
Pseudo-R2	0.05	0.04	0.04	0.04

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

Table A-8: Impact of death on co-inventor promotion events (Cox proportional-hazards model estimates)

Full sample	(1) <200 days	(2) <400 days	(3) <600 days	(4) <800 days
Deceased	0.583**	0.144	0.167	0.097
	(0.240)	(0.150)	(0.120)	(0.104)
N events	75	183	286	383
N subjects	5954	5954	5954	5954
Pseudo-R2	0.16	0.16	0.12	0.11

Same establishment	(5) <200 days	(6) <400 days	(7) <600 days	(8) <800 days
Deceased	0.770**	0.025	0.115	0.065
	(0.343)	(0.209)	(0.171)	(0.145)
Deceased Manager	−0.688	−1.185**	−1.213***	−1.223***
	(0.840)	(0.539)	(0.462)	(0.392)
Deceased × Deceased Manager	1.166	1.270*	1.177**	1.149**
	(0.964)	(0.683)	(0.552)	(0.477)
N events	43	96	153	213
N subjects	3453	3453	3453	3453
Pseudo-R2	0.18	0.20	0.15	0.14

Different establishment	(9) <200 days	(10) <400 days	(11) <600 days	(12) <800 days
Deceased	−0.070	−0.223	−0.111	−0.206
	(0.364)	(0.240)	(0.199)	(0.174)
Deceased Manager	−0.434	−0.676	0.155	−0.111
	(0.761)	(0.513)	(0.299)	(0.290)
Deceased × Deceased Manager	−0.220	1.588**	0.842**	0.845**
	(1.268)	(0.630)	(0.412)	(0.393)
N events	32	86	132	169
N subjects	2413	2413	2413	2413
Pseudo-R2	0.21	0.17	0.13	0.11

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