Collapsing Stars and the Diffusion of Scientific Knowledge*

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ABSTRACT

This paper studies the role of star scientists in the knowledge production process. Stars not only account for a great proportion of research contributions, but also elevate the output trajectories of their co-authors through spillover effects. We estimate these effects based on a comprehensive dataset with more than 15.6 million publication records. More specifically, we are able to delineate a group of 162 stars that died both prematurely and unexpectedly. In the aftermath of these lethal shocks, treated co-authors are exposed to a publication and citation deficit that ranges from 4.2 to 7.8% relative to a matched control group. However, neither do these effects emerge over the entire subject spectrum, nor are they traceable to one common origin. Stars enhance their colleagues' performance most visibly in life sciences and to a lesser extent in physical and health sciences. Moreover, we discover an interplay of three main effect channels. In certain fields, spillovers are driven by spatial elements and both eminent co-authors and co-authors with markedly different field expertise than their star are more severely affected upon the death event.

Keywords: Spillover Effects, Knowledge Production, Star Scientists

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1 Introduction

Some stars collapse straight into darkness (Adams, Kochanek, Gerke, Stanek, & Dai, 2017). Our understanding of these rare events is limited in an astronomical sense, as it is of the consequences for the scientific community once it loses its brightest minds. The present paper adds to the second line of inquiry. Star scientists are known to play a central role in the production of knowledge (Zucker & Darby, 1996), hereby fostering economic growth and social welfare (Romer, 1990). If their contributions were to end abruptly, what scars would be left behind?

Our attempt to answer this question revolves around the fate of scientists that formerly collaborated with a star. Unlike the romantic ideal, innovation is rarely achieved through the creativity of lone genius. Instead, teamwork has become increasingly prevalent and impactful in today's science and technology (Bercovitz & Feldman, 2011; Singh & Fleming, 2010; Wuchty, Jones, & Uzzi, 2007). Star scientists, in particular, are embedded in large co-author networks (de Solla Price & Beaver, 1966; Zuckerman, 1967). Given the level of freedom scientists are provided with, it can reasonably be assumed that these networks result from active search-and-matching processes (see e.g., Stephan, 2012, Chapter 4); in other words, they are formed endogenously. The end of a collaborative tie, in contrast, might occur exogenously and therefore open up a pathway for causal inference. To be more precise, we use the premature and unexpected death of outstanding scientists as a quasi-experiment and explore empirically how these lethal shocks affect the research productivity and quality of former co-authors. In doing so, we shed light on the nature of interpersonal knowledge spillovers.

The process of human capital formation is central for any modern society, but, as the stock of knowledge grows, also demands more and more effort from scientists on their way to the research frontier. As a consequence, it might be suspected that innovative phases are on the decline (Jones, 2009). Against this background, it appears all the more important to investigate spillover effects as a potential means to spur scientific progress. In approaching this topic, we build on a number of studies, most notably the work of Azoulay, Graff Zivin, and Wang (2010) who laid the conceptual foundations by disclosing how collaborators fare in the aftermath of "superstar extinction". Yet, we aim to extend the existing literature along several dimensions. First, hitherto evidence is drawn from specific scientific areas including physical sciences (Waldinger, 2012, 2016), life sciences (Azoulay et al., 2010), medicine (Mohnen, 2018), economics (Ductor, Fafchamps, Goyal, & van der Leij, 2014) mathematics (Borjas & Doran, 2012, 2015; Waldinger, 2010) or even more narrow disciplines such as evolutionary biology (Agrawal, McHale, & Oettl, 2017) or immunology (Oettl, 2012). In contrast, our dataset allows us to examine spillover effects over the entire subject spectrum and further compare the fields of life, health, physical, and social sciences within a uniform framework. Second, we offer new insights into the origins of spillover effects. In particular, we explore the extent of knowledge flows through interdisciplinary avenues and inspect in how far results are confined to the science system in the United States, which served as the focal point for most previous studies.

Our analysis builds on a (dynamic) conditional difference-in-difference (DiD) design, where the treatment originates from the unexpected passing of 162 star scientists. We identify these stars from a larger group of eminent scientists that either belong to the National Academy of Sciences (NAS) or possess outstanding publication records. In order to define the latter criterion, we compile a rich bibliometric dataset from Scopus, which comprises meta-information of 15.6 million publications over the period from 1996 to 2015. These core data are further complemented with information from Google Maps and GenderAPI, which enables us to follow the scientific footprints of 9.2 million individuals. Moreover, we can assign star status by means of performance indicators such as the H-Index or citation metrics. Delineating star scientists is not only required for the treatment identification, but also essential for the effect estimation. More specifically, we use the set of stars, who did not pass away, and their respective co-authors to assemble a matched control group for the scientists that experience the unexpected loss of a star collaborator.

On aggregate, we discover that the abrupt ending of a star collaboration causes a lasting decline of 4.2% in published articles of treated scientists. Accounting for output quality, we find a pronounced effect in form of a 7.8% decrease in citation-weighted articles. In neither case are recovery patterns observable. However, field-specific estimations reveal that the aggregate view masks substantial variation across the scientific spectrum. While life sciences is characterised by increased treatment effects in both output dimensions, we solely denote a quality-adjusted effect in physical sciences and nuanced, but no overall, effects in health sciences. Lastly, we cannot detect any statistically significant treatment consequences in social sciences. In the subsequent course of analysis, we focus on the mechanisms behind these effects. It hereby becomes evident that the omission of future cooperation is only a partial treatment aspect. Similarly, neither the frequency nor the timing of interaction before the stars' death offers an explanation for the effect origins. Exploring further effect channels also leads us to reject a gatekeeping story based on editorial goodwill. Yet an interplay of three main effect drivers becomes apparent. First, spillovers are in part spatially confined. More concretely, co-location is related to steeper output declines in physical sciences, while, on a broader geographical scale, dyads within the United States largely account for the effects in life and health sciences. Second, we find horizontal spillovers (or peer effects) in life sciences since the treatment especially affects scientists that are likewise stars. Third, in health and physical sciences, we further discover that the break-up of dyads with markedly different field expertise induces more severe effects, which underlines the relevance of interdisciplinary knowledge transmission.

Our paper is linked to several strands of literature. Importantly, we adopt the research design of Azoulay et al. (2010) who discover that spillovers are primarily transmitted in idea space. The work of both Oettl (2012) and Mohnen (2018) is methodologically close, but focuses on different effect channels. The former study reveals that helpful stars play a crucial role for the performance of collaborators, while the latter study yields a similar conclusion for stars with central network positions. In a related setting, Jaravel, Petkova, and Bell (2018) investigate how inventors are affected by the premature death of a (star) co-inventor and document long-lasting declines in patents and earnings. Further research on scientific spillovers has utilised identification strategies other than death events. For instance, Waldinger draws findings from the expulsion of scholars during the Nazi regime (2010, 2012, 2016) and World War II bombing campaigns (2016), while Borjas and Doran (2012, 2015) exploit the collapse of the Soviet Union as a natural experiment. Moreover, our paper relates to the growing “science of team science” literature, which is bound by the question of how to enhance the effectiveness of collaborative research (see Hall et al., 2018, for a recent review). Team composition and especially team diversity are vital aspects of this debate (National Research Council, 2015), to which our results contribute. Thematic overlap also exists with the work of Akcigit, Caicedo, Miguelez, Stantcheva, and Sterzi (2018), König, Lorenz, and Zilibotti (2016), and Lucas and Moll (2014) who examine interaction-based spillover effects through the lens of endogenous growth models. Lastly, our paper belongs to a wider literature that uses (premature) death cases as a source of identification (apart from the aforementioned studies, see Aizenman and Kletzer, 2011, Jäger and Heining, 2019, Jones and Olken, 2005, or Nguyen and Nielsen, 2010).

The remainder of the paper is structured as follows. Section 2 describes our data and the research design. Section 3 details the econometric approach and presents our aggregate results. Section 4 focuses on effect heterogeneity across scientific disciplines and further explores different channels through which the diffusion of scientific knowledge operates. Section 5 offers a discussion of our findings and concludes.

2 Data and Research Design

2.1 Data Compilation

Our research design is centred on star scientists and their potential spillovers onto collaborators. With this approach in mind, we assembled our core data laying focus on the science systems in North America and Europe, the latter extended by Israel. Especially US-based scientists and inventors have been the subject of previous studies, while their European counterparts have received markedly less attention in this stream of literature. Constructing a dataset that spans both continents therefore helps to fill a void, but also offers the opportunity to examine whether spillover effects could be rooted in structural differences between the North American and European scientific landscapes (see e.g., Aghion, Dewatripont, Hoxby, Mas-Colell, & Sapir, 2010).

Within the US, we rely on the Carnegie Classification of Institutions of Higher Education and in particular on the category of doctoral universities to delineate our set of research institutions. As of 2015, this category listed 334 institutions, which we manually linked to their Scopus profiles. Elsevier's database covers a wide range of scientific literature and enables us to collect metadata for each publication with affiliative ties to (at least one of) these research institutions. We proceeded in a similar manner with regard to Europe's higher education sector using the European Tertiary Education Register (ETER) as the start point. From this database, we compiled a set of 724 institutions from 26 countries that were consistently classified as universities based on their right to grant doctoral degrees.[1] Lastly, we added universities from both Israel and Canada to the institutional collective given that both countries are home to internationally renowned scientific communities and geographically adjacent. The outlined procedure resulted in an overall list of 1,146 research institutions, on which grounds we collected 15.6 million publication records over the period from 1996 to 2015, each comprising a citation horizon until 2016.

In the following step, we constructed an author-centric dataset for the over 9.2 million academics listed on these publications. The depth of available metadata already allowed depicting publication activities, co-author networks, affiliation histories, or research topics. Yet we further queried Scopus for each author to access data beyond our observation period, e.g., the year of first publication in order to proxy career starts. In addition, we complemented our core data with gender predictions from Gender API, site coordinates from Google Maps, and biographic information from the NAS, which will be explained in more detail over the next subsections. Taken together, our data approach enables us to track a multitude of academic careers over 20 years in time.

2.2 The Scientific Elite

Our decision to focus on the brightest scholars is guided by a fundamental property of scientific progress. As already observed by Lotka (1926), the distribution of scientific output is remarkably skewed, illustrating that a prolific minority is responsible for a great amount of contributions. In a similar vein, as Newton claimed, science is found to largely advance "on the shoulders of giants" (Bornmann, De Moya Anegón, & Leydesdorff, 2010; Cole & Cole, 1972). Considering their dominant role in the production of knowledge, star scientists

[1] Access to Scopus is limited by quotas. Thus, instead of collecting data for the entire university sample from ETER, we focused on institutions from Austria, Belgium, Bulgaria, Croatia, Cyprus, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Latvia, Lithuania, Malta, the Netherlands, Norway, Poland, Portugal, Spain, Sweden, Switzerland, and the United Kingdom. We feel confident that this sample provides an adequate level of star power for our empirical purposes.

are (most) likely to shine on their surroundings and thus provide a natural starting point to investigate spillover effects.

A first look at our raw data underlines the importance of elite scientists. Within the cohort that first published in the year 2000, we find the median scientist to record three career publication, whereas the marginal star, defined as the scientist that marks the start of the top percentile, accumulates 145 publications. Their equivalents with regard to the citation distribution see themselves separated by a comparable margin of 66 versus 3,485 career citations. Defining stardom based on relative performance is indeed common practice.[2] We follow this approach and maintain the top percentile as the threshold for awarding star status. However, we rely on a more refined set of metrics to measure accomplishments. We begin by delineating a set of stars according to their H-Index, which we calculate over both a 5-year window for publications and citations. For instance, our first star cohort is compiled in 2001 and comprises the group of scholars with the highest H-Indices based on their research output from 1996 to 2000. To account for different timings in output, we include citations if they accrued within the first five years after publication. The H-Index is essentially designed to provide a balanced measure of research quantity and quality, so that stars of either domain are not captured by it. While we are not concerned with omitting scientists that only generate large quantities of work, we do intend to include scientists that even occasionally shift the research frontier through seminal papers. Thus, we add forward citations (i.e., citation-weighted publication counts) as a second star criterion to our performance catalogue, again employing 5-year windows for calculation.

Next, we extend our star criteria with co-author adjusted versions of both metrics. We are generally in favour of measures that account for variations in team size. Yet when it comes to classifying star scientists, unadjusted metrics are likely to be thought of as providing complementary value. More specifically, they carry a network component and may help identifying stars that are very well positioned and possibly facilitate knowledge flows by connecting numerous co-authors (Mohnen, 2018).[3]

[2] Rothaermel and Hess (2007) assign star status to scientists that accumulate publications and citations three standard deviations above the mean. Using similar outcome measures, Jaravel et al. (2018) refer to stars upon exceeding the 98th percentile, while Waldinger (2016) sets the cut off at the 95th percentile.

[3] In case of forward citations, we divide the number of citations of each publication by the number of its authors before aggregating these counts at the scientist level. As for the H-Index, we use a modification that counts publications fractionally, again according to the number of listed authors (see Schreiber, 2008, for details). It is worth noting, however, that adjusted and unadjusted metrics do not capture achievement in a completely different sense since almost half of the final star sample satisfy both types of criteria.

Based on these four performance criteria, we identify stars on a yearly basis from 2001 to 2012. Since publishing practices differ considerably across the scientific spectrum, we do so separately by field. We hereby follow Elsevier's classification system and assign scientists to one of 26 scientific fields (see Appendix A)[4] based on the distribution of their past publications. More specifically, these distributions denote how often scientists have published in each specific field, i.e., in journals that are classified under a given field. We assign scientists to their mode field and, if necessary, break ties at random. Moreover, we restrict the star delineation to research articles to ensure that a certain editorial standard is met by all papers, but also to avoid potential double counting of articles and former conference papers. Overall, this procedure yields a set of 154,205 eminent scientists. As a fifth and final criterion, we define 3,458 members of the NAS as stars, who are among our author collective.[5] Accounting for the overlap, the final sample consists of 155,720 scientists, which corresponds to 1.7% of the observable scientific community. It should be stated though that the composition of the star sample changes over time. Scientists are referred to as stars as of the year they fulfil a performance criterion or are inducted to the NAS, yet once proven keep their status thereafter.

Only a small circle of the scientific elite is of immediate interest for our research design. To allow for a causal interpretation of spillover effects, we focus on stars whose careers ended abruptly due to unexpected death at a maximum age of 65 years. We identify these cases by inspecting publication histories. Once a star's publication activity falls off rapidly while being at a career age where retirement appears doubtful, we manually search for bibliographic information online. This approach leads to 594 stars that died between 2001 and 2012. After imposing the age constraint, we further exclude scientists whose research efforts already came to a halt before their death and, most importantly, scientists whose passing might have been anticipated from prolonged illnesses. We draw the distinction between unexpected and anticipated deaths primarily based on information provided by obituaries, but also from personally contacting former colleagues in a few unclear cases. Altogether, we end up with 162 deceased stars to constitute the origin of our treatment (see Appendix B). From a field perspective, we note that 40 stars belong to life sciences, 44 to health sciences, 54 to physical sciences, and 24 to social sciences. It further becomes apparent that heart attacks and accidents are mentioned most frequently among the treatment cases, while cancer is the dominating cause of death among the (unreported) group of anticipated deaths.

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[4] We omit the narrow field of multidisciplinary studies, which is not part of either of the main fields, i.e., life sciences, health sciences, physical sciences, and social sciences.

[5] We sort NAS members into our four-field taxonomy based on their affiliated section and the scheme reported in Appendix A. NAS sections are thus given priority over our publication-based classification, yet both approaches agree on 3,438 of 3,458 cases.

Variable	P5	P25	P50	Mean	P75	P95	SD
Age at death	37	48	55	53.41	60	64	8.12
Female	0	0	0	0.049	0	0	0.217
U.S. affiliated	0	0	0	0.494	1	1	0.502
No. of distinct co-authors	5	16	42	67.22	92	183	72.99
No. of articles	3	11	21.5	25.32	34	63	18.57
No. of citations	75	214	431.5	801.1	1,024	2,608	972.5
Year of death	2001	2004	2007	2006.6	2009	2012	3.18

Tab. 1: SUMMARY STATISTICS ON TREATMENT STARS

Notes: The sample consists of 162 star scientists whose active careers ended abruptly between 2001 and 2012 due to unexpected death at a maximum age of 65 years. All time-varying variables refer to the year preceding the death event. Article, citation, and distinct co-author numbers are aggregated over a prior 5-year span.

Table 1 depicts the sample of treatment stars. On average, these stars died at 53.4 years of age. Almost precisely one half was affiliated with a research institution located in the US and the vast majority was male. Female underrepresentation is fairly unsurprising in view of the collective evidence on scientific gender gaps (Ding, Murray, & Stuart, 2006; Shen, 2013).[6] Moreover, star scientists published an average of 25.3 articles, worked with 67.2 different co-authors, and received just over 800 citations over the course of five years prior to their passing.[7]

2.3 Matching Approach

Identifying 162 deceased star scientists allows us to circumscribe the treatment group, i.e., their former co-authors. While this task is straightforward, more diligence is needed to find an appropriate control group. On which outcome trajectory would the treatment group be, had they not been exposed to the death of a star collaborator?

One possibility would be to rely on the full population of scientists to derive an answer. However, treated co-authors likely form a positive selection, as star collaborations are not random. Instead, we expect assortative matching by both age and ability, which makes it doubtful to assume that the full population were to provide an accurate projection for the treatment group's outcome path (even conditional on a variety of fixed effects). A second option would be to employ an implicit control group composed of treated co-authors that experience the death at either earlier or later points in time. Yet, this approach could also pose threats to identification if, for instance, the death event leads to a change in outcome

[6] Differences in health status (Williams, 2003) and risk attitude (Hartog, Ferrer-i-Carbonell, & Jonker, 2002) could also play a part. To be clear, a heart attack or stroke might be a sudden and unexpected event, but still dependent on lifestyle factors.

[7] Cumulative figures are calculated over a fixed range to account for staggered death years.

trends. Azoulay et al. (2010) discuss this methodological issue and present a strategy to circumvent it. We follow their example and therefore build our control group based on a one-to-one matching procedure.

Although the matching algorithm iterates over the years from 2001 to 2012, we focus on the year 2005 for illustration purposes. We begin by compiling the pool of potential control scientists, which consists of scientists that essentially meet two conditions. First, as of 2005, they must have collaborated with a star scientist who does not pass away, regardless of cause. Second, at no time do they become co-authors of one of the 162 deceased stars (i.e., they remain spared from treatment). For each treated scientist with an associated death in 2005, we aim to select an appropriate control scientist from the defined pool. In order to be matched, we require that treated and control scientists have similar career ages, are embedded in co-author networks of comparable size, and show congruent outcome trends up to 2004. In addition to individual characteristics, we include further criteria to ensure that both groups are balanced regarding features of their star relationship, i.e., the number of past collaborations and the elapsed time since last collaborating, and their stars' standing as proxied by the amount of citations received until 2004. Before deferring further (technical) details to Appendix C, we note that the algorithm is implemented year by year, separately for the four main scientific fields, without replacement, and utilises the idea of coarsened exact matching introduced by Iacus, King, and, Porro (2011, 2012).

Finally, we add two constraints to ensure that we are exploring spillover effects between established scientists. Junior scientists and PhD students, to begin with, might experience a conceptually different treatment effect in the sense that the death of a senior colleague or supervisor could have career-ending consequences. We thus restrict the analysis to (both treated and control) scientists with a career age of at least five years at the time of death. Moreover, we exclude a small number of scientists whose career starts coincide with the beginning of their star collaboration to prevent our results from being intertwined with mentoring effects.[8]

The outlined procedure leads to a set of 9,297 matched collaborator pairs representing a successful matching rate of 93.6%. Summary statistics are reported in Table 2. Note that control collaborators inherit the year of star death from their matched counterparts, so that treatment timing is identically distributed in both groups. Time-varying variables are again calculated as of the year preceding the (inherited) year of star death to depict the sample right before treatment onset. Overall, we detect only minor differences between treated and control collaborators. The average treated collaborator published 14.5 articles, received 517 citations, and held co-authorship ties to 65.9 scientists over a past five-year period, while his/her control group pendant recorded 14.1 articles, 503 citations, and 65.2

[8] Both Waldinger (2010) and Azoulay, Liu, and Wang (2017) provide insights into this strand of literature.

co-authorship ties. The performance balance is further reflected by the share of stars in both groups – 25.8% of the treated and 25.0% of the control collaborators are considered stars, which indicates that assortative matching influences network formation in science. We also document a close resemblance in career ages, i.e., publication activities in both groups span 18.2 years on average. Achieving a high age balance is clearly important for our research design since scientific output typically follows life cycle patterns (Levin & Stephan, 1991).

Variable	Group	P5	P25	P50	Mean	P75	P95	SD
Career age	Treated	6	11	17	18.24	25	34	8.78
	Control	5	11	17	18.17	25	34	8.88
Female prediction	Treated	0	0	0	0.239	0	1	0.426
	Control	0	0	0	0.256	1	1	0.437
U.S. affiliated	Treated	0	0	0	0.425	1	1	0.494
	Control	0	0	0	0.409	1	1	0.492
Star status	Treated	0	0	0	0.258	1	1	0.438
	Control	0	0	0	0.250	0	1	0.433
No. of distinct co-authors	Treated	5	16	37	65.92	81	227	82.78
	Control	5	17	38	65.20	86	212	76.67
No. of articles	Treated	1	3	8	14.53	18	49	18.92
	Control	1	3	8	14.12	18	48	17.91
No. of citations	Treated	6	58	189	517.0	549	2,053	1,018.7
	Control	4	64	203	503.0	552	1,908	937.6
No. of collaborations	Treated	1	1	1	2.29	2	7	3.87
	Control	1	1	1	2.23	2	7	3.95
Years since last collaboration	Treated	0	1	3	4.04	6	11	3.61
	Control	0	1	3	3.96	6	11	3.53
No. of citations (star)	Treated	202	517	1,133	1,642.3	2,178	5,839	1,546.9
	Control	158	512	1,033	1,495.5	1,901	4,449	1,613.8

Tab. 2: SUMMARY STATISTICS ON MATCHED COLLABORATORS

Notes: The sample consists of 9,297 pairs of treated and control collaborators. All time-varying variables refer to the year preceding the (inherited) year of star death. Article, citation, and distinct co-author numbers are aggregated over a prior 5-year span. Gender information are inferred through name and country data and are available for 85.3% of the sample.

Turning to the dyadic variables, we first note that the mean number of collaborations (i.e., jointly published articles) between stars and co-authors amounts to 2.29 in the treated and to 2.23 in the control group. However, and to some degree surprising, the median dyad in both groups denotes only one collaboration. Moreover, an average of 4.04 years passed since stars and treated co-authors last collaborated, while 3.96 years elapsed in the control group. The reported time gaps in Table 2 are indeed long enough to assume that neither the average nor the median co-author was engaged in ongoing research projects with their star at the time of death. Another observation is related to the star scientists' standing. In particular, we find both treated and control stars to receive more citations than the initial star sample portrayed in Table 1. What might seem striking at first glance is merely due to a (harmless) selection effect. Deceased stars with greater citation numbers usually record both higher article and co-author numbers, which causes them to appear more frequently in the matched sample. Treated stars are slightly more accomplished than control stars, but the magnitude is not concerning.[9]

We further achieve balance on two variables that were not part of the matching process.[10] First, about one quarter of the collaborator sample is predicted to be female. Neither does Scopus provide gender information nor is it feasible to collect these data manually (as we did for deceased stars). For these reasons, we rely on the gender inference by GenderAPI, which has been found to offer the most accurate application for this task (Santamaría & Mihaljević, 2018). In essence, gender data are inferred from first names, optionally in combination with a country information. While our Scopus data cover first names, there is no direct country indication. We thus derive a home country proxy from the affiliations listed on the earliest publication records. In sum, we hereby manage to classify 85% of our sample.[11] Probing the validity of this approach, we find gender predictions to be correct for over 99% of the full sample of deceased stars. Second, we observe a little over 40% of the collaborators to be US-affiliated. Again, we denote slight uncertainty regarding this number, as some collaborators are linked with multiple affiliations as of their most recent publications (note that our data do not include within-year publication dates). In these instances, we infer a collaborator's location based on his/her mode affiliation(s), breaking possible ties at random.

In view of our field-specific estimations in Section 4, we lastly note that the described matching approach also creates balance between treated and control groups if the sample is split by fields (see Appendix D for corresponding summary statistics).

[9] Besides, we would expect that the benefits of having a star collaborator increase with his/her standing. Building a control group with stars that received fewer citations than their treated counterparts should therefore rather serve as a conservative estimation approach.

[10] The number of matching variables is limited due to the curse of dimensionality. In other words, it would become considerably more difficult to find matches if we extended our variable set any further.

[11] We started by querying first names only and considered gender predictions valid if GenderAPI reported an accuracy of over 98%. In a second step, we used first names combined with the home country proxy to classify the remaining collaborators, hereby setting the accuracy threshold to 95%.

3 Identification of Main Effects

3.1 Outcome Paths

To set the stage for the DiD framework, we begin with a purely graphical illustration of the treatment impact. To be more precise, we plot the publication output of treated and (matched) control collaborators before and after the star scientists' death. This approach gives a basic yet compelling impression of the stars' influence on the outcome trajectory of their co-authors without the need for parametric assumptions.

Figure 1 displays the output trends centred symmetrically around the time of death.[12] We will confine our assessment of publication output to two main measures, i.e., article count and forward citations, both adjusted for co-authorships. As depicted in the upper panel of Figure 1, treated and control collaborators show hardly any difference in article counts before the year of star death. On average, both groups vary synchronically between 0.50 and 0.55 annual articles. After the treatment, however, an evident gap emerges in favour of the group of scientists that does not experience the sudden passing of an outstanding co-author. The relative performance deficit of the treatment group is apparent in every year after the death event and thus, albeit slight variations in magnitude, permanent. The graphic further underlines the importance of the matching design. As can be seen, article counts tend to rise over time, even for the treatment group, which could be reflective of life cycle and/or year fixed effects. In absence of the counterfactual output path provided by the matched collaborator sample, it would remain ambiguous how to disentangle these effects from the actual treatment effect.

It is conceivable that collaborators adjust to the treatment shock by raising their effort devoted to each published paper. In this scenario, scientists would (try to) maintain their overall quality of output despite experiencing a decline in productivity in form of lower article counts. We explore this possibility by plotting citation-weighted article counts, i.e., forward citations, in the lower panel of Figure 1. This measure provides a common proxy for scientific quality (see e.g., Jaravel et al., 2018, or Kahn and MacGarvie, 2016).[13] At first sight, we note that both groups show decreasing forward citation trends, which can be

[12] The number of yearly observations monotonically decreases as the temporal distance to the year of death increases, which can lead to imprecisely estimated effects at both ends of the observation period. Uncertainty in later years can also arise from collaborators becoming inactive, likely due to retirement. In line with Jaravel et al. (2018), we address these concerns by confining observations to a nine-year window around star death and by excluding observations if collaborators exceed a career age of 45 years. Note that we apply the age constraint simultaneously to each matched pair to ensure that treated and control collaborators keep their balance in calendar and experimental time.

[13] Following the cited literature, we employ winsorized forward citations. We apply this adjustment at the 99.9th percentile, separately for each year and scientific field (life, health, physical, and social sciences). Robustness checks in Appendix E show that our results do not rely on winsorizing.

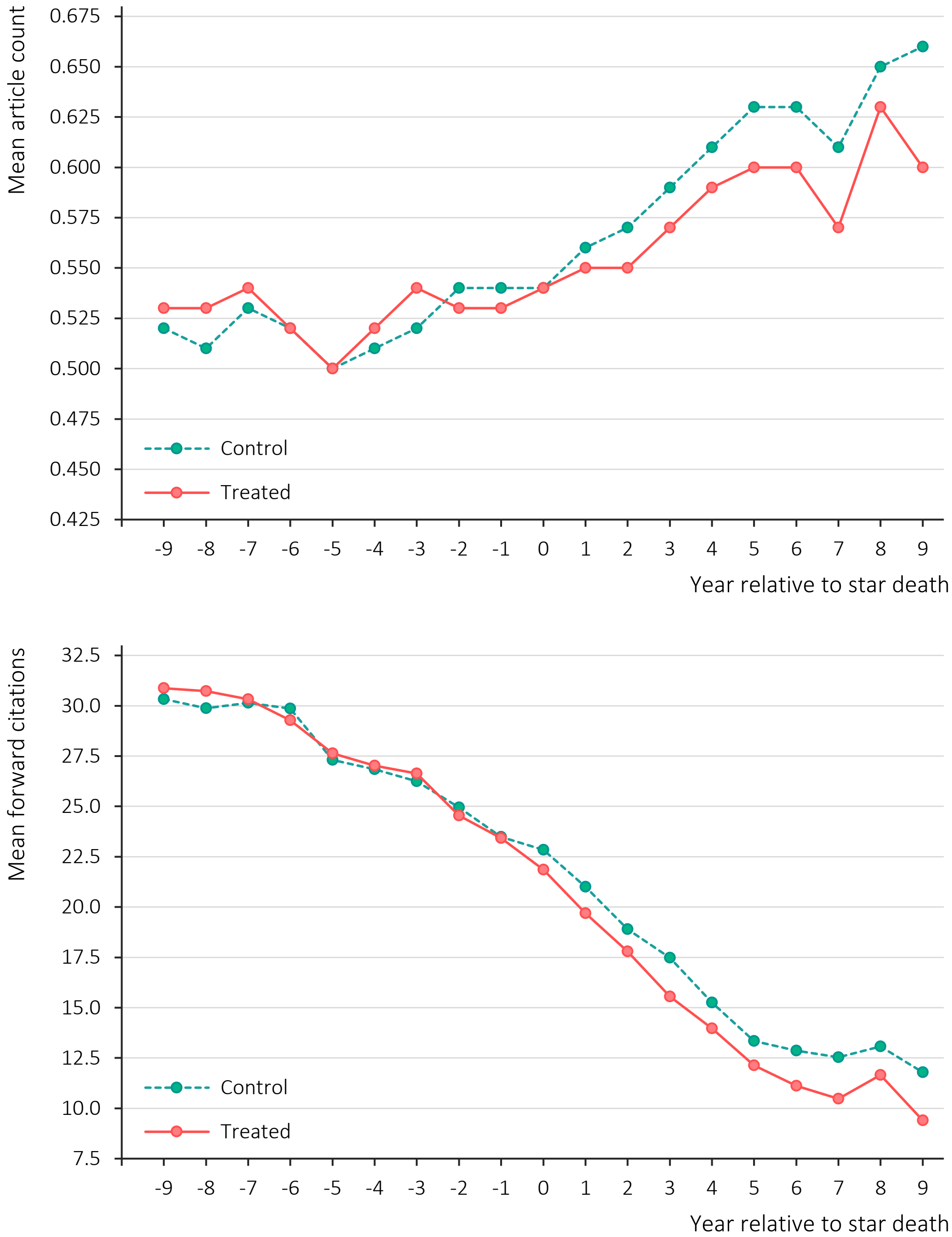

Fig. 1: OUTCOME PATHS AROUND STAR DEATH

Notes: The sample consists of 9,297 pairs of treated and control collaborators confined to a nine-year window around the (inherited) year of star death. The panel is equally unbalanced for treated and control collaborators. Both output measures are co-author adjusted. Forward citations are winsorized at the 99.9th percentile.

attributed to the truncated nature of the variable. Stated differently, forward citations represent the total number of citations received as of 2016 by all articles published in a given year, which makes high numbers at the end of the observation period less likely. However, this mechanical effect can be neglected since treatment and control scientists cover the exact same time spans. More importantly, both groups closely resemble each other until the year of death, yet treated collaborators are again outperformed by their matched counterparts in all subsequent years.

The presented evidence suggests that scientists suffer in the realms of both productivity and quality after the abrupt end of a star collaboration. Figure 1 is indeed a (raw) preview of our main results that further underlines the effectiveness of our matching approach by visually confirming the parallel course of pre-trends. We evaluate these findings in more econometric detail over the next subsections.

3.2 Econometric Model

We apply a straightforward econometric methodology that has been employed in related contexts (Azoulay, Fons-Rosen, & Graff Zivin, 2019; Jäger & Heining, 2019; Jaravel et al., 2018). Assured through the matching procedure, treated scientists are paired with control scientists that possess a multitude of similar characteristics. Moreover, matched scientists are also temporally aligned, implying that each control scientist inherits a counterfactual death year from his/her treated counterpart. These design properties allow us to estimate a dynamic DiD equation, where the causal effect of star death is identified through yearly differences in the research output of both groups (adjusted for a range of fixed effects). Our econometric approach takes the following form:

$$Y_{it} = exp\left[\alpha + \sum_{k=-9}^{9} \beta_k^{All}\, \mathbb{1}\,(L_{it} = k) + \sum_{k=-9}^{9} \beta_k^{Real}\, \mathbb{1}\,(L_{it} = k) \times Treated_i \right. \qquad (1)$$
$$\left. + \vartheta_{it} + \delta_t + \gamma_i + \epsilon_{it}\right],$$

where Y_{it} denotes either the article count or forward citations of co-author i in calendar year t. Both dependent variables are bound by a considerable fraction of zero values. We therefore estimate Equation (1) by means of Poisson pseudo-maximum likelihood (PPML) techniques. Apart from handling the skewed, non-negative distribution of the dependent variables, the PPML estimator offers compelling robustness properties. Importantly, it can be ensured that coefficient estimates are consistent as long as the conditional mean of the dependent variable is correctly specified (Gourieroux, Monfort, & Trognon, 1984). The data generating process is thus not required to be Poisson. In addition, employing robust standard errors, clustered at the star level in our application, allows for correct inference irrespective of any form of serial correlation (Wooldridge, 1997).[14]

We address the staggered treatment onset by including lead and lag terms, denoted by L_{it}, in Equation (1). Each of these terms represents an indicator variable that switches to

[14] For the estimation in Stata, we employ the ppmlhdfe command by Correira, Guimarães, and Zylkin (2019), which implements PPML regressions with multiple high-dimensional fixed effects. In contrast to conventional commands, ppmlhdfe proves robust to typical convergence issues in Poisson contexts.

1 if an observation is k years apart from the death event. As shown by Jaravel et al. (2018), the first set of leads and lags, whose effects will be identified by the β_k^{All} coefficients, fulfils a role similar to the post dummy in classic DiD frameworks. Its practical relevance stems from the concern that career age fixed effects (ϑ_{it}), calendar year fixed effects (δ_t), and individual fixed effects (γ_i) may not entirely capture trends in productivity or research quality around the time of star death.[15] One possible cause for such trends could refer to the sample construction, where we condition on star collaboration, which could coincide with unobservable factors that may change regardless of the star's passing (e.g., funding outlooks or work environments). Any of these transitory processes are absorbed by the common lead and lag terms. The second set of leads and lags, which is interacted with the indicator variable for treatment status, $Treated_i$, therefore isolates the causal treatment effect. We split the overall effect into yearly elements, each of which will be identified by their respective β_k^{Real} coefficient.

The key identifying assumption of our model is that star deaths are exogenous conditional on the covariates in Equation (1), which implies that treated and control scientists would have developed parallel output paths if the death event had not occurred. Ensuring this assumption motivates our research design, which builds on manually screened obituaries and a thorough matching procedure. While it is not possible to verify the parallel trends assumption post-treatment, its validity can be bolstered by means of pre-treatment data. Specifically, Equation (1) enables testing if death events are accompanied by preceding effect patterns, which would render the analysis doubtful. Apart from that, decomposing the effect post-death allows us to explore treatment consequences in dynamic fashion. We present our estimation results in the following subsection and note that any of these estimates can be interpreted as semi-elasticities after coefficients are exponentiated and decreased by one.

3.3 Results

Figure 2 provides a graphical depiction of the annual β_k^{Real} coefficients by plotting point estimates along with 95% confidence intervals derived from Equation (1). The upper panel depicts the treatment dynamics in terms of article counts, while the lower panel refers to forward citations. Technically, the point estimate that corresponds to the year preceding the treatment year is normalised to zero, implying that this lead marks the reference point for the presented effects.

[15] Career age fixed effects account for output shifts over the course of a scientist's career, while calendar year fixed effects capture all time-related influence factors such as the expansion of academic journals. Finally, individual fixed effects control for variation that originates from characteristics that are constant across individual scientists, e.g., innate ability, but also cover time-invariant dyadic features as, e.g., the age gap between stars and collaborators. Given that the three classes of fixed effects induce collinearity, we omit two (out of 45) career age fixed effects, which is standard practice (Jaravel et al., 2018).

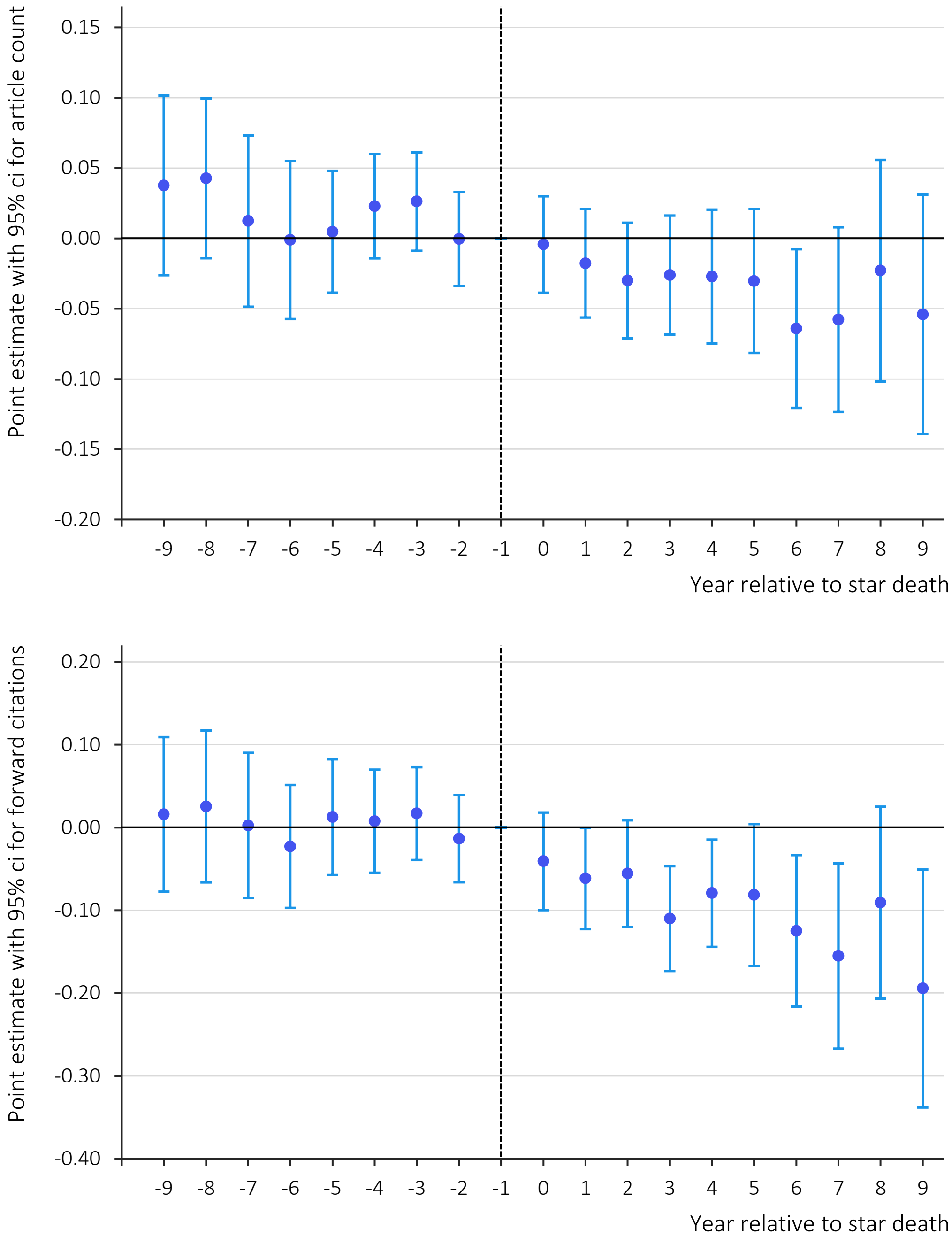

Fig. 2: TREATMENT EFFECT DYNAMICS

Notes: The sample consists of 9,297 pairs of treated and control collaborators confined to a nine-year window around the (inherited) year of star death. The panel is equally unbalanced for treated and control collaborators. Both output measures are co-author adjusted. Forward citations are winsorized at the 99.9th percentile. Collaborators without variation in output over the observation period are dropped by the estimation routine. For the econometric approach, refer to Section 3.2.

In view of the effect patterns for article counts, we first note the absence of pre-trends. While most point estimates leading up to the treatment year are slightly positive, neither of them is statistically significant, which is in line with the non-parametric résumé. After the death event, we notice a gradual shift in point estimates, which turn consistently negative. The productivity decline induced by the treatment shock appears to increase in the long run, but the picture is not entirely conclusive. The 6th lag is associated with a statistically significant effect that translates into a 6.2% reduction ($exp\,[-0.064]-1$) in article counts, but the remaining lags are smaller in magnitude and not statistically significant. Despite statistical uncertainty on the annual level, the aggregate perspective clearly indicates that the unexpected passing of a star leads to a moderately diminished productivity for co-authors without signs of a rebound effect.

As for forward citations, our proxy for output quality, we discover a broadly comparable picture to the article count analysis but with amplified effect magnitudes. Again, our research design finds support through insignificant point estimates for all leads, which underlines parallel pre-treatment trends. After the treatment, however, point estimates markedly decrease, implying that the stars' death puts collaborators on career paths with less impactful publications. In six out of nine post-treatment years, we estimate a statistically significant decline in forward citations. Reduced output quantity could play into this finding, but the absolute effect sizes are notably higher. In fact, they tend to rise over time, peaking in the 9th year where the treatment effect equates to a 17.7% decrease in forward citations. This again illustrates that the star loss unfolds long-term consequences that transcend the mere disruption of ongoing projects. From comparing both panels of Figure 2, it can be inferred that the treatment impact becomes more pronounced when output quality is taken into consideration.

4 Variations over the Scientific Spectrum

4.1 Main Field Effects

The identification of treatment effects over the complete sample sets the baseline for our next analysis steps, in which we exploit the rich diversity of our data. An integral part of the upcoming investigation is to compare effects across the scientific spectrum. We start with field-specific treatment effects, derived from the following specification:

$$Y_{it} = exp\,\Big[\alpha + \beta^{All} AfterDeath_{it} + \beta^{Real} AfterDeath_{it} \times Treated_i + \vartheta_{it} + \delta_t + \gamma_i + \epsilon_{it}\Big], \tag{2}$$

which mirrors Equation (1) with the exception of the $AfterDeath_{it}$ variable that takes the place of the former lead and lag terms. $AfterDeath_{it}$ denotes an indicator variable that switches to 1 in the year of star death. Its interaction with the $Treated_i$ variable allows us to determine the treatment effect in a time-averaged form, i.e., pooled over all leads and lags. The β^{Real} coefficient will identify this effect, while the β^{All} coefficient will capture all side effects that relate to the treatment timing but not the actual event. The advantage of Equation (2) lies in the ease of discussing total effect magnitudes but also in the improved statistical power. The latter aspect is particularly relevant for estimations on smaller datasets, which applies to the present setting, where the overall sample will be split according to the stars' field classification. Equation (2) will therefore be estimated separately for the four fields of life, health, physical, and social sciences, although we will also report the outcome of a pooled estimation, which corresponds to our main (dynamic) results. Apart from that, we adopt the inclusion of fixed effects, the level of standard error clustering, and the use of the PPML estimator from Equation (1).

	Overall Sample	Life Sciences	Health Sciences	Physical Sciences	Social Sciences
	Article count as dependent variable				
After death × treated	-0.043 *	-0.066 *	-0.044	-0.026	-0.062
	(0.022)	(0.030)	(0.034)	(0.030)	(0.151)
Log pseudo-likelihood	-189,139	-52,754	-79,330	-53,894	-3,021
No. of observations	275,344	83,541	118,212	69,107	4,484
No. of dyads	18,542	5,585	7,940	4,711	306
	Forward citations as dependent variable				
After death × treated	-0.081 **	-0.114 **	-0.043	-0.104 *	-0.015
	(0.028)	(0.041)	(0.038)	(0.043)	(0.205)
Log pseudo-likelihood	-2,800,261	-809,005	-1,154,988	-784,720	-40,122
No. of observations	275,166	83,526	118,148	69,008	4,484
No. of dyads	18,527	5,584	7,934	4,703	306

Tab. 3: IMPACT OF STAR DEATH ON COLLABORATORS' OUTPUT

Notes: The overall sample consists of 9,297 pairs of treated and control collaborators confined to a nine-year window around the (inherited) year of star death. The panel is equally unbalanced for treated and control collaborators. Both output measures are co-author adjusted. Forward citations are winsorized at the 99.9th percentile. Collaborators without variation in output over the observation period are dropped by the estimation routine. Field delineation is based on the stars' publication profile or, if available, derived from the classification of the NAS. Robust standard errors are in parentheses, clustered at the level of the star.
* $p < 0.05$, ** $p < 0.01$, and *** $p < 0.001$.

Table 3 depicts the results derived by means of Equation (2). From the upper panel, it becomes apparent that, regarding the overall sample, the death of a star affects article counts to a statistically significant extent. The effect equates to a 4.2% decline, which represents the pooled counterpart of the dynamic effects that are displayed in Figure 2 (upper panel). However, a closer look at the single fields reveals that this productivity shock can only be confirmed for life sciences, where treated collaborators face an even stronger drop of 6.4%. As for the other fields, negative effects may be measured, but point estimates do not reach statistical significance at conventional levels. Turning to the lower panel of Table 3, we find treatment effects to increase once publication quality is factored in. Overall, co-authors experience a statistically significant reduction of 7.8% in forward citations. This effect, again, becomes more pronounced in both magnitude and statistical significance for life sciences dyads, where the loss of an eminent scientist is followed by a 10.8% reduction. In case of forward citations, a similar observation can be made for physical sciences, where a 9.9% deficit is identified. Yet, in accordance with the article count results, no evident effects can be stated for the fields of both health and social sciences.[16]

	Overall Sample	Life Sciences	Health Sciences	Physical Sciences	Social Sciences
	Article count excl. star collaboration as dependent variable				
After death × treated	-0.026	-0.051	-0.028	-0.007	-0.054
	(0.022)	(0.032)	(0.032)	(0.032)	(0.160)
Log pseudo-likelihood	-181,703	-50,560	-76,254	-51,936	-2,808
No. of observations	268,794	81,844	115,561	67,138	4,251
No. of dyads	18,000	5,446	7,717	4,549	288
	Forward citations excl. star collaboration as dependent variable				
After death × treated	-0.062 **	-0.112 **	-0.017	-0.080	0.021
	(0.028)	(0.040)	(0.035)	(0.042)	(0.224)
Log pseudo-likelihood	-2,630,686	-760,591	-1,088,715	-735,906	-34,288
No. of observations	268,314	81,780	115,383	66,947	4,204
No. of dyads	17,961	5,440	7,702	4,534	285

Tab. 4: IMPACT OF STAR DEATH ON COLLABORATORS' OUTPUT BEYOND JOINT PRODUCTION

Notes: The overall sample consists of 9,297 pairs of treated and control collaborators confined to a nine-year window around the (inherited) year of star death. The panel is equally unbalanced for treated and control collaborators. Both output measures are co-author adjusted. Forward citations are winsorized at the 99.9th percentile. Collaborators without variation in output over the observation period are dropped by the estimation routine. In comparison to Table 3, this also applies to collaborators that solely published together with their star. Field delineation is based on the stars' publication profile or, if available, derived from the classification of the NAS. Robust standard errors are in parentheses, clustered at the level of the star.

* p < 0.05, ** p < 0.01, and *** p < 0.001.

A first hypothesis as to what could drive the effects reported in Table 3 concerns the role of collaborative output. Naturally, the death of a star scientist renders future cooperation impossible. If we removed this portion from the control collaborators' publication résumé, how would the assessment of treatment consequences change? We explore this question

[16] Based on similar research designs, Azoulay et al. (2010), Oettl (2012), and Mohnen (2018) document declines of 8.2%, 12.4%, and 14.3% in impact factor weighted publication counts, respectively, whereas Jaravel et al. (2018) report a 15.6% drop in forward citations of patents.

in Table 4. Technically, we use modified dependent variables that solely comprise articles that were not co-authored by the star. As can be seen from Table 4, treatment effects are less accentuated in this scenario. What might have been expected becomes particularly visible in case of articles counts (upper panel) where point estimates derived from neither life sciences nor the overall sample remain statistically significant. The productivity decrease in Table 3 can therefore largely be attributed to the unrealised potential of joint work.[17] However, repeating the analysis with forward citations (lower panel) leads to a different conclusion. With regard to the overall sample, the point estimate slightly increases, but the effect stays statistically significant. Physical sciences adjusts in a comparable manner, although the effect lies at the margin of significance (p-value of 0.056); and life sciences remains virtually unaffected. In summary, control scientists are thus found to accumulate more forward citations than treated scientists do, even after subtracting co-publications with their star. Importantly, this finding illustrates that the sudden death of a star clearly unfolds consequences that span beyond the omission of joint work.

In Appendix E, we present a series of robustness checks that result from modifying Equation (2). First, we technically delay the beginning of the after-death period by one year. Including the year of death into the pre-death period could be justified on grounds of publication lags or if death events occur towards the end of the year. Strictly speaking, the death year can be considered a transition year, where the treatment consequences start to emerge. Second, we follow Azoulay et al. (2010) and Oettl (2012) by capturing life cycle patterns with career age cohort dummies, which could mitigate collinearity concerns between year, age, and individual fixed effects. Third, we extend our fixed effects arsenal by including interacted calendar year and career age fixed effects, thereby probing the implicit separability assumption in Equation (2). Fourth, we explore if clustering standard errors at the collaborator level instead of the star level affects our results. Fifth, we re-estimate treatment effects on a (substantially) shortened panel of collaborators that are traceable for a full seven years before and after the death year. Using a balanced panel addresses the concern that collaborators with a surplus of either pre- or post-treatment observations might have a confounding influence on the estimation of true effects. Sixth, we employ forward citations without winsorizing. Taken together, we detect only minor changes in our results due to these alterations. In health and physical sciences, we both note one instance with a statistically significant article count effect, but these singular findings may not be overstated. Importantly, it can be confirmed that the main effects reported in Table 3 prove robust to a range of different model specifications.

[17] To be clear, the results in Table 4 do not imply that treatment effects are non-existent. They rather show how effects shift if joint work is taken out of the equation. In this setting, control collaborators are mainly penalised (post-death), although delayed publications are also removed for treated collaborators.

4.2 Distinct Effect Channels

The death of an outstanding scientist affects the performance of former co-authors to an appreciable extent. The documented effects are mainly driven by collaborations in the fields of life and physical sciences and in part, but by no means fully, explainable by the deprivation of future cooperation. Within this section, we aim for a deeper understanding of the effect formation. If we were to determine subgroups of the treated scientists that experience the star death to a particularly great extent, we would have strong evidence for the origins of the treatment effect. Stated differently, where does the star's death leave its primary mark? We explore heterogeneity in the treatment effect employing the following estimation equation:

$$\begin{aligned} Y_{it} = exp\ \Big[&\alpha + \beta^{All} AfterDeath_{it} + \beta^{Real} AfterDeath_{it} \times Treated_i \\ &+ \eta^{All}\, \mathrm{Z}_i \times AfterDeath_{it} + \eta^{Real}\, \mathrm{Z}_i \times AfterDeath_{it} \times Treated_i \\ &+ \vartheta_{it} + \delta_t + \gamma_i + \epsilon_{it} \Big], \end{aligned} \tag{3}$$

where Z_i constitutes a time-invariant indicator variable, which we expect to be insightful for the magnitude of the treatment effect. To be clear, Z_i will vary over the course of the analysis and delineate different sets of collaborations based on either individual or dyadic characteristics. The overall treatment effect will, according to this distinction, be divided into a common (β^{Real}) and a specific (η^{Real}) component. The coefficient of interest in this setting becomes η^{Real}, which isolates the differential treatment effect that is additionally yet exclusively felt by the delineated group of collaborators. Consistent with our former models, we incorporate Z_i not only as part of an interaction for treated dyads, but also within a second interaction, which is common to all dyads and thus accounts for general outcome shifts that are attributable to Z_i. All further estimation aspects of Equation (1) and (2) remain unchanged, as does our strategy to distinguish between scientific fields.

We first direct attention to collaborative features, which could play a moderating role. Intuitively, the assumption would be that scientists that maintained an intensive work relation with their star experience more severe treatment consequences than sporadic dyads. Two reasons lend support for this claim. First, co-authorships are not randomly assigned. Instead, they are more likely to result from a thorough matching process. Collaborations that turn out to be fruitful should thus embody higher chances of being continued. Second, even if we overstated the freedom in choosing co-authors and took potential lock-in effects into consideration (Boudreau et al., 2017), one might still expect repeated collaborations to be more valuable through accumulating team-specific capital (Jaravel et al., 2018). However, there are opposing arguments to be raised too. Notably, upholding a star collaboration could have benefits, e.g., in form of acquired knowledge

	Overall Sample	Life Sciences	Health Sciences	Physical Sciences	Social Sciences
	Article count as dependent variable				
After death × treated	-0.047 *	-0.054	-0.053	-0.029	-0.185
	(0.022)	(0.030)	(0.034)	(0.035)	(0.182)
After death × treated × dyad frequency in 3. tertile	0.015	-0.039	0.036	0.015	0.349
	(0.032)	(0.048)	(0.053)	(0.059)	(0.278)
Log pseudo-likelihood	-189,136	-52,753	-79,329	-53,892	-3,019
No. of observations	275,344	83,541	118,212	69,107	4,484
No. of dyads	18,542	5,585	7,940	4,711	306
	Forward citations as dependent variable				
After death × treated	-0.083 **	-0.089 *	-0.066	-0.098 *	-0.172
	(0.027)	(0.044)	(0.038)	(0.044)	(0.253)
After death × treated × dyad frequency in 3. tertile	0.008	-0.080	0.090	-0.019	0.438
	(0.048)	(0.069)	(0.066)	(0.096)	(0.404)
Log pseudo-likelihood	-2,800,245	-808,892	-1,154,831	-784,652	-40,019
No. of observations	275,166	83,526	118,148	69,008	4,484
No. of dyads	18,527	5,584	7,934	4,703	306

Tab. 5: EFFECT HETEROGENEITY BY COLLABORATION FREQUENCY

Notes: The overall sample consists of 9,297 pairs of treated and control collaborators confined to a nine-year window around the (inherited) year of star death. The panel is equally unbalanced for treated and control collaborators. Both output measures are co-author adjusted. Forward citations are winsorized at the 99.9th percentile. Collaborators without variation in output over the observation period are dropped by the estimation routine. Field delineation is based on the stars' publication profile or, if available, derived from the classification of the NAS. Robust standard errors are in parentheses, clustered at the level of the star.

* $p < 0.05$, ** $p < 0.01$, and *** $p < 0.001$.

or access to superior networks, that increase outside options and eventually allow for an easier transitioning towards new collaborations. Turning to our empirical assessment in Table 5, we can infer that frequent collaborators, defined as those that belong to the upper third of the distribution of co-authorships with their respective star, do not suffer a treatment effect of a markedly different size than the remaining collaborators.[18] The effect for the former group, with regard to the overall sample, corresponds to a drop of 3.1% ($exp\,[-0.047 + 0.015] - 1$) in article counts and 7.2% in forward citations, while the latter group experiences a decline of 4.6% ($exp\,[-0.047] - 1$) in article counts and 8.0% in forward citations. Importantly, these deviations are not statistically significant,

[18] Analogous to the matching approach, we calculate separate distributions for each treatment year and each scientific field (derived from the stars' classification). Descriptively, frequent collaborators published a mean number of 5.8 joint articles with their star. However, due to the large amount of one-time dyads, frequent collaborators are oftentimes synonymous with repeated collaborators.

neither overall nor in any single field. Additionally, looking into recent collaborations yields a similar conclusion, as does repeating the analysis with multi-year collaborations (see Appendix F). In sum, we find no evidence that treatment effects depend on any of these basic interaction features.

	Overall Sample	Life Sciences	Health Sciences	Physical Sciences	Social Sciences
	Article count as dependent variable				
After death × treated	-0.045	-0.058	-0.049	-0.038	0.010
	(0.026)	(0.035)	(0.050)	(0.031)	(0.144)
After death × treated × star wrote editorial	-0.005	-0.029	0.004	0.083	-0.254
	(0.049)	(0.069)	(0.069)	(0.086)	(0.420)
Log pseudo-likelihood	-189,128	-52,754	-79,326	-53,890	-3,018
No. of observations	275,344	83,541	118,212	69,107	4,484
No. of dyads	18,542	5,585	7,940	4,711	306
	Forward citations as dependent variable				
After death × treated	-0.072 *	-0.119 **	-0.020	-0.105 *	0.032
	(0.033)	(0.050)	(0.054)	(0.046)	(0.205)
After death × treated × star wrote editorial	-0.026	0.045	-0.059	0.007	-0.217
	(0.062)	(0.085)	(0.075)	(0.112)	(0.588)
Log pseudo-likelihood	2,800,201	-808,972	1,154,930	-784,554	-40,083
No. of observations	275,166	83,526	118,148	69,008	4,484
No. of dyads	18,527	5,584	7,934	4,703	306

Tab. 6: EFFECT HETEROGENEITY BY EDITORIAL INFLUENCE

Notes: The overall sample consists of 9,297 pairs of treated and control collaborators confined to a nine-year window around the (inherited) year of star death. The panel is equally unbalanced for treated and control collaborators. Both output measures are co-author adjusted. Forward citations are winsorized at the 99.9th percentile. Collaborators without variation in output over the observation period are dropped by the estimation routine. Field delineation is based on the stars' publication profile or, if available, derived from the classification of the NAS. Robust standard errors are in parentheses, clustered at the level of the star.

* $p < 0.05$, ** $p < 0.01$, and *** $p < 0.001$.

We proceed by ruling out a mechanism that would paint a less meritocratic picture of the scientific community. In particular, we examine if stars exercise a gatekeeping role, thereby elevating the career paths of their collaborators. If this believe turned out to be true, one should have less faith in fair academic assessment and instead devote more emphasis into forming profitable social ties. Our approach to test this assumption relies on data about editorials. From inspecting publication histories, we find that almost a quarter of all stars in both groups published at least one editorial over the course of five years before the year of death. However, as reported in Table 6, there is no indication that editorial goodwill offers an explanation for the treatment effect. To be more precise, co-authors of star scientists with editorial linkage are not subject to a differential effect that approaches statistical significance.[19] A comparable conclusion is indeed derived by Azoulay et al. (2010) who reject the gatekeeping hypothesis from a monetary angle, i.e., influence over the funding apparatus of the National Institutes of Health does not cause effect variations in their study of US life scientists.

While control over journal resources is apparently not a driving force, we do discover local resources to be in part meaningful. Leaning on Azoulay et al. (2010), we base our reasoning on geographical proximity. We pursue an analogous path as in Section 2.3 and first assign scientists to institutions as of their most recent publications prior to the treatment. In a second step, we query address data for these institutions from Scopus and third extend them with geographical data from Google Maps. This ultimately enables us to encircle collaborations that were co-located at the time of star death. We refer to dyads as co-located if both scientists were located in the same city. Accordingly, we do not require them to be linked to the same affiliation, in part because Scopus, in some instances, masks (parent) institutions by distinguishing between their sub-entities, which would add noise to this classification. Besides, relying on the city-oriented definition does take into account that a localised dimension of the treatment effect could encompass shared infrastructure facilities (e.g., large computing centres, telescopes, or laboratories). Empirically, we find that co-located dyads represent slightly over one fifth of both the treated and control sample. Furthermore, we detect a statistically significant interaction effect in the productivity sphere of physical sciences, which implies a decline of 13.0% in article counts, in addition to the negligible common treatment effect, for co-located collaborators following the death event (see Table 7).[20] We interpret this geographically confined component of the treatment effect as a general reflection of the stars' role in governing research environments. To illustrate this point, one might think of preferential access to expensive or highly-specialised equipment that could be at the star's disposal and may be of particular importance in physical sciences (as conjectured by Azoulay et al., 2019).

[19] Colussi (2018) underlines the benefits of being connected to editors of leading economics journals. While we are not able to confirm this result in our setting, it might be interesting to note that the differential treatment impact is largest among social scientists, although very imprecisely estimated.

[20] From a technical standpoint, one might recall that no aggregate effect was found for this field, which, however, does not preclude the possibility of nuanced effects, as presented here. Further examples in relation to health sciences follow over the course of this section.

	Overall Sample	Life Sciences	Health Sciences	Physical Sciences	Social Sciences
	Article count as dependent variable				
After death × treated	-0.029	-0.069 *	-0.034	-0.003	0.009
	(0.023)	(0.030)	(0.037)	(0.032)	(0.179)
After death × treated × co-located	-0.069 *	0.015	-0,050	-0.139 *	-0.433
	(0.033)	(0.072)	(0.044)	(0.064)	(0.310)
Log pseudo-likelihood	-188,788	-52,675	-79,144	-53,834	-2,987
No. of observations	274,210	83,314	117,559	68,907	4,430
No. of dyads	18,461	5,569	7,892	4,698	302
	Forward citations as dependent variable				
After death × treated	-0.072 *	-0.139 ***	-0.026	-0.082	0.109
	(0.031)	(0.042)	(0.043)	(0.044)	(0.250)
After death × treated × co-located	-0.047	0.112	-0.080	-0.136	-0.647
	(0.053)	(0.083)	(0.081)	(0.103)	(0.397)
Log pseudo-likelihood	-2,790,989	-806,053	-1,150,133	-783,394	-39,425
No. of observations	274,032	83,229	117,495	68,808	4,430
No. of dyads	18,446	5,568	7,886	4,690	302

Tab. 7: EFFECT HETEROGENEITY IN GEOGRAPHICAL SPACE, CO-LOCATION CHANNEL

Notes: The overall sample consists of 9,297 pairs of treated and control collaborators confined to a nine-year window around the (inherited) year of star death. The panel is equally unbalanced for treated and control collaborators. Both output measures are co-author adjusted. Forward citations are winsorized at the 99.9th percentile. Collaborators without variation in output over the observation period are dropped by the estimation routine. Field delineation is based on the stars' publication profile or, if available, derived from the classification of the NAS. Robust standard errors are in parentheses, clustered at the level of the star.

* $p < 0.05$, ** $p < 0.01$, and *** $p < 0.001$.

Co-location sheds some light on the treatment effect origin, but does not deliver a full explanation on its own. We thus turn to a distinct mechanisms class that emphasises stars as being sources of unique knowledge and skills. After the treatment, collaborators might prove incapable of filling the void that star scientists left behind, indicating that parts of their expertise might die with them. The permanent nature of this loss could explain the long-term impact revealed in Figure 2. In exploring this hypothesis, we draw on the literature that examines technological distance between firms based on patent data (e.g., Ahuja, 2000, or Rosenkopf and Almeida, 2003). We adapt the methodology to our case and employ publications, instead of patents, to position scientists in subject space. For this purpose, we first compile subject portfolios for each scientist, which are derived from the set of non-dyad publications prior to the treatment year.

	Overall Sample	Life Sciences	Health Sciences	Physical Sciences	Social Sciences
	Article count as dependent variable				
After death × treated	-0.029	-0.061 *	-0.015	-0.017	-0.035
	(0.025)	(0.027)	(0.038)	(0.034)	(0.131)
After death × treated × subject distance in 3. tertile	-0.060	-0.016	-0.108 *	-0.034	-0.113
	(0.037)	(0.072)	(0.054)	(0.067)	(0.478)
Log pseudo-likelihood	-187,601	-52,268	-78,768	-53,444	-2,971
No. of observations	265,707	80,526	114,406	66,550	4,225
No. of dyads	17,819	5,363	7,648	4,520	288
	Forward citations as dependent variable				
After death × treated	-0.049	-0.116 **	0.004	-0.058	0.024
	(0.033)	(0.042)	(0.047)	(0.049)	(0.189)
After death × treated × subject distance in 3. tertile	-0.141 ***	0.000	-0.190 **	-0.216 *	-0.116
	(0.050)	(0.081)	(0.073)	(0.097)	(0.604)
Log pseudo-likelihood	-2,761,000	-796,070	-1,139,737	-775,149	-38,745
No. of observations	265,629	80,526	114,370	66,508	4,225
No. of dyads	17,812	5,363	7,645	4,516	288

Tab. 8: EFFECT HETEROGENEITY IN SUBJECT SPACE

Notes: The overall sample consists of 9,297 pairs of treated and control collaborators confined to a nine-year window around the (inherited) year of star death. The panel is equally unbalanced for treated and control collaborators. Both output measures are co-author adjusted. Forward citations are winsorized at the 99.9th percentile. Collaborators without variation in output over the observation period are dropped by the estimation routine. Field delineation is based on the stars' publication profile or, if available, derived from the classification of the NAS. Robust standard errors are in parentheses, clustered at the level of the star.

* $p < 0.05$, ** $p < 0.01$, and *** $p < 0.001$.

Relying on Elsevier's most granular journal classification layer, these portfolios are akin to vectors with 334 elements, with each of them listing the share of publications in a specific subject category. We then calculate the Euclidean distance between these vectors, which enables us to quantify the gap that separates stars and their respective collaborators in subject dimension. As shown in Table 8, there is strong evidence that this measure proves central for understanding how treatment effects unfold. More specifically, it becomes apparent that collaborators of subject distant dyads, i.e., the upper third of the year- and field-specific distributions, suffer especially steep outcome declines in health and physical sciences. The differential effects on quality are large in magnitude and imply that these scientists see their forward citations decrease by an additional 17.3% and 19.4% in health and physical sciences, respectively.[21] As for the former field, we further determine a statistically significant drop in productivity that amounts to an extra 10.2%. Considered as a whole, research potential is primarily lost in duos that combined distant expertise. Not only does this finding lend support to the substitution theory formulated above, since stars should become harder to replace if collaborators have less inside knowledge about their colleagues' field, but it also shows that omitted knowledge transmission through interdisciplinary avenues constitutes a main treatment effect component.

	Overall Sample	Life Sciences	Health Sciences	Physical Sciences	Social Sciences
			Article count as dependent variable		
After death × treated	-0.016	-0.005	-0.045	0.020	-0.092
	(0.024)	(0.040)	(0.040)	(0.041)	(0.189)
After death × treated × star-star dyad	-0.044	-0.104 *	0.002	-0.076	0.222
	(0.029)	(0.044)	(0.046)	(0.049)	(0.262)
Log pseudo-likelihood	-189,126	-52,746	-79,328	-53,888	-3,017
No. of observations	275,344	83,541	118,212	69,107	4,484
No. of dyads	18,542	5,585	7,940	4,711	306
			Forward citations as dependent variable		
After death × treated	-0.046	-0.011	-0.058	-0.049	-0.079
	(0.029)	(0.048)	(0.042)	(0.051)	(0.241)
After death × treated × star-star dyad	-0.051	-0.160 **	0.029	-0.082	0.192
	(0.039)	(0.059)	(0.059)	(0.075)	(0.399)
Log pseudo-likelihood	-2,796,337	-807,991	-1,153,051	-783,440	-40,008
No. of observations	275,166	83,526	118,148	69,008	4,484
No. of dyads	18,527	5,584	7,934	4,703	306

Tab. 9: EFFECT HETEROGENEITY BY COLLABORATOR STATUS

Notes: The overall sample consists of 9,297 pairs of treated and control collaborators confined to a nine-year window around the (inherited) year of star death. The panel is equally unbalanced for treated and control collaborators. Both output measures are co-author adjusted. Forward citations are winsorized at the 99.9th percentile. Collaborators without variation in output over the observation period are dropped by the estimation routine. Field delineation is based on the stars' publication profile or, if available, derived from the classification of the NAS. Robust standard errors are in parentheses, clustered at the level of the star.

* $p < 0.05$, ** $p < 0.01$, and *** $p < 0.001$.

[21] The total decrease in physical sciences is presumably even higher, but cannot be stated with certainty since the common part of the treatment effect now turns statistically insignificant. However, estimating Equation (2) on the subsample of subject distant dyads yields a precisely estimated total decrease of 24.0%, which is almost identical to the additive effect in Table 8.

To this point, it remains puzzling, which mechanisms account for the (pronounced) treatment consequences faced by life sciences dyads. As will become clear, looking into this matter gives rise to a two-fold explanation. We first investigate if scientists of higher and lower calibre are differently affected upon the stars' passing. From a theoretical viewpoint, one could emphasise that collaborators of lower calibre may generally be more reliant on the stars' influence and therefore bear the higher costs of treatment. However, this influence might not prove to be overly substantial since impact analysis shows that the success of collaborative work is rather restrained by lower-ability members than lifted by higher-ability members (Ahmadpoor & Jones, 2019). Moreover, one might be sceptical about the likelihood of future interactions if dyads comprise a (too) severe ability or performance gap. In order to resolve this question empirically, we differentiate between collaborators based on their scientific achievement prior to the death event. Drawing a line between regular and star co-authors, we discover the latter group to take up almost the entire treatment effects in life sciences. As reported in Table 9, stars experience additional consequences in form of a dual decrease of 9.9% in article counts and 14.8% in forward citations. These differential effects are statistically significant yet bound to the life sciences spectrum. The stars' deaths thus turn out to be particularly harmful for related star scientists, indicating that horizontal rather than vertical spillovers fuel knowledge production in this field.

The second channel, which allows insights into the effect formation in life sciences, pertains to the (broader) geographical dimension. A priori, it is unclear if variations in the treatment impact could be attributed to the science systems in which dyads are embedded. This possibility has not been explored by previous studies (Azoulay et al., 2010; Mohnen, 2018; Oettl, 2012), yet it seems conceivable that organisational aspects as institutional autonomy, competition, or stratification could alter a star's (external) value. We shed light on this matter by focussing on intra-US dyads, i.e., collaborations where both scientists are affiliated with an US institution at the time of treatment. These dyads represent 35% of the treated sample (versus 33% of the control sample) and evidently experience treatment consequences of a higher degree in health and life sciences. Given the statistically significant interaction terms in Table 10, we determine a differential productivity decline of 12.0% in the former field and a differential quality decline of 17.5% in the latter field. Although we remain limited in assessing the exact reasons for these effects, the US science system appears to be more star-dependent.

	Overall Sample	Life Sciences	Health Sciences	Physical Sciences	Social Sciences
	Article count as dependent variable				
After death × treated	-0.013	-0.036	-0.003	-0.017	-0.177
	(0.028)	(0.042)	(0042)	(0.034)	(0.228)
After death × treated × US-US dyad	-0.090 *	-0.076	-0.128 *	-0.024	0.265
	(0.036)	(0.054)	(0.055)	(0.062)	(0.304)
Log pseudo-likelihood	-188,782	-52,674	-79,137	-53,836	-2,986
No. of observations	274,210	83,314	117,559	68,907	4,430
No. of dyads	18,461	5,569	7,892	4,698	302
	Forward citations as dependent variable				
After death × treated	-0.029	-0.026	-0.009	-0.088	-0.083
	(0.031)	(0.047)	(0.041)	(0.053)	(0.297)
After death × treated × US-US dyad	-0.141 **	-0.192 *	-0.115	-0.044	0.208
	(0.047)	(0.075)	(0.062)	(0.080	(0.412)
Log pseudo-likelihood	-2,789,367	-805,569	-1,149,362	-783,637	-39,389
No. of observations	274,032	83,299	117,495	68,808	4,430
No. of dyads	18,446	5,568	7,886	4,690	302

Tab. 10: EFFECT HETEROGENEITY IN GEOGRAPHICAL SPACE, US CHANNEL

Notes: The overall sample consists of 9,297 pairs of treated and control collaborators confined to a nine-year window around the (inherited) year of star death. The panel is equally unbalanced for treated and control collaborators. Both output measures are co-author adjusted. Forward citations are winsorized at the 99.9th percentile. Collaborators without variation in output over the observation period are dropped by the estimation routine. Field delineation is based on the stars' publication profile or, if available, derived from the classification of the NAS. Robust standard errors are in parentheses, clustered at the level of the star.

* p < 0.05, ** p < 0.01, and *** p < 0.001.

Finally, our results should be put into perspective. Uncovering heterogeneity in the causal effect of star death does not itself permit a causal interpretation. To be more concrete, our estimations do not identify how treatment effects would change if collaborators were (exogenously) moved along certain covariate dimensions. However, our analysis does reveal which types of collaborators, in fact, are exposed to higher treatment impacts, thus helping to develop a better understanding of the processes that shape scientific advancement. Before we turn to a discussion of our main results, we shortly allay some robustness concerns, which are detailed in Appendix F. First, horizontal spillovers and intra-US effects operate independently as both interactions remain statistically significant if included in the same estimation. Second, intra-US effects are neither a mere reflection of intra-country effects nor entangled with the co-location channel. Third, distance in subject space is not to be confounded with distance in topic, which is less predictive for the treatment effects. Fourth, our results do not hinge on the specific threshold definition that delineates subject distant dyads.

5 Discussion and Conclusion

The unexpected and premature death of 162 prolific scientists provides us with a quasi-experimental setting, in which we investigate how valuable a star collaborator's presence is for individual research performance. We find that scientists suffer average declines of 4.2% in article counts and 7.8% in forward citations following the exogenous passing of a star co-author. Furthermore, there are no signs of recovery patterns. Instead, treatment consequences seem permanent and rather increase over time, thus indicating that star exposure constitutes an irreplaceable asset.

Attempting to uncover the origins of the treatment effect, we first perform field-specific estimations, which we deem necessary given that cultures and practices differ along the scientific spectrum. In the course of this analysis, we generally confirm the findings of Azoulay et al. (2010) and Oettl (2012) as we determine a clear treatment impact in the field of life sciences, spanning both the productivity and quality sphere. In addition, we detect a quantitatively similar quality decrease for physical sciences dyads, which adds to the evidence presented by Borjas and Doran (2015) on high-quality mathematicians. On the contrary, collaborations in health and social sciences are (initially) found to escape any statistically significant treatment consequences. The absence of overall effects in these fields might have several reasons, which we cannot ascertain. In case of health sciences, for instance, one might argue that formal co-authorship could be less informative about true research interaction. Several studies raise the concern that guest or gift authorships lead to inflated co-author number in medical journals (Bhopal et al., 1997; Flanagin et al., 1998; Wislar, Flanagin, Fontanarosa, & DeAngelis, 2011).[22] In a separate vein, the death of a star scientist, as macabre as it may sound, could also emerge as beneficial for future performance. Prestigious research positions, journal space, funding, and accolades are all examples of scarce resources in academia, access to which could become less restrictive after the star is exempt from competition (Borjas & Doran, 2015). Although we find no evidence of positive treatment outcomes, it seems conceivable that the competition channel might (partly) offset negative effects. Moreover, we believe that this argument could carry particular relevance in fields where elite scientists form a small interlinked community, as it tends to the case for social sciences (Goyal, Van Der Leij, & Moraga-González, 2006).

[22] Our data could be reflective of this phenomenon (to some extent) as we observe health scientists to record the highest collaborator numbers (see Table D.1).

In a subsequent step, we exploit the rich heterogeneity in individual and dyadic data to develop an understanding of the mechanisms that give rise to the treatment effects. There are three findings that stand out. First, we provide evidence that knowledge production comprises spatial elements. On a broader scale, we determine US-located dyads to be a primary effect driver in both life and health sciences. The observation that US scientists that lose a star collaborator, who is likewise located in the US, experience steeper output declines points to systemic causes. What could cause them to be especially vulnerable? A probable answer relates to increased inequality levels in the US biomedical sector as documented by Katz and Matter (2019) who highlight rich-get-richer effects in terms of patents, publications, and research grants that reinforce the role of elites and limit the degree of upward mobility. Star contact could thus be more important for career paths in this environment. On a local scale, we further find co-location effects in physical sciences. Although several studies underline the general tendency towards distant collaborations (Jones, Wuchty, & Uzzi, 2008; Laband & Tollison, 2000; Waltman, Tijssen, & Eck, 2011), our analysis suggests that close workspaces can still be a relevant factor for knowledge production. More specifically, we find that some part of the spillovers generated by stars are locally confined. We take the view that the diverse range of specialised equipment and material used in physical sciences could offer an explanation, yet our conclusion is not clearly verifiable. Including data on physical capital, similar to Baruffaldi and Gaessler's (2018) approach, would therefore be a promising extension to our analysis.

Our second main result pertains solely to life sciences collaborations. In stark contrast to other fields, we notice that the sudden death of a star primarily casts a shadow on fellow star scientists. Horizontal rather than vertical spillovers are thus characteristic for frontier research in life sciences. While it lies beyond our scope to determine the exact reasons for this finding, we offer two plausible explanations. Unrealised joint production, to begin with, appears to play a minor role. Spillovers are, however, by no means restricted to activities within conventional research projects, but can likewise originate from informal interactions, e.g., from "frequent exchanges with strong minds and powerful scientific imaginations that have a deep understanding of the problems one is struggling with" (Stigler, 1988, p. 36) or from "testing out new ideas in casual conversations" (Borjas & Doran, 2015, p. 1116). We expect informal channels to be shaped by social proximity, so that knowledge sharing is primarily facilitated between scientists of similar standing and intellectual ability. Strong informal channels could thus explain why stars suffer the main treatment effects. An alternative explanation is borrowed from Azoulay et al. (2019) who shed light on the nature of entry barriers in life sciences. Following the star's death, they discover an influx of outsiders that, at the expanse of incumbent scientists, successfully challenge the leadership in the star's research domain. These dynamics illustrate that stars, while alive, can also serve as a protection that ensures that like-minded scholars keep the knowledge reins in their hands.

Third, our analysis discloses spillovers in subject space. The idea that linking divergent scientific backgrounds can accelerate the innovative process is indeed not new. Models of creativity have long highlighted that new ideas typically emerge from a recombination or synthesis of existing ideas (Campbell, 1960; Hadamard, 1945; Schumpeter, 1934; Usher, 1954; Weitzman, 1998). On a historical note, Robert Oppenheimer stated about the rise of atomic physics that it "was not the doing of any one man", but instead "involved the collaboration of scores of scientists from many lands" (cited by Becker, 1957, p. 54). More recently, several bibliometric studies have explored the relationship between disciplinary diversity and citation impact. The conclusions drawn are not entirely consensus, but mostly supportive of a positive relation (Larivière, Haustein, & Börner, 2015; Leahey, Beckman, & Stanko, 2017; Uzzi, Mukherjee, Stringer, & Jones, 2013; Wang, Thijs, & Glänzel, 2015). Interdisciplinary research might not only lead to impactful results, it could also become more of a necessity. Scientific collaborations are oftentimes motivated by gaining access to specific competences, equipment, or data (Beaver, 2001; Melin, 2000). These reasons are rather pragmatic and can be considered to reflect specialisation tendencies in several research fields (Katz & Martin, 1997), which likely continue to increase due to the (ever) growing stock of knowledge (Jones, 2009). Our results align with this literature. More concretely, in health and physical sciences, we find that research potential is mainly lost in duos that combine markedly different field expertise, which is indicative of knowledge transmission through interdisciplinary avenues.

Finally, this paper presents the first causal estimation of spillover effects over the entire spectrum of scientific fields. On aggregate, we discover that the presence of a star scientist benefits the research performance of his or her collaboration network. However, exploring the domains of life, health, physical, and social sciences separately reveals that the star effect is neither visible in each of these fields nor traceable to one common origin. To this end, our study may be viewed as a contribution that can help to develop an improved understanding of knowledge production functions and their potentially heterogeneous forms. Future research could continue in a similar (or complementary) spirit, but address some of our limitations. Importantly, our coverage of social sciences dyads is limited, in the first place due to considerably smaller collaboration networks in this field, but also because of a moderate number of treatment cases. A related question would arise from a change of scenery. Do our findings translate to fields outside of the university sector? Oettl (2012) raises this point and illustrates the perception that tech companies typically value exceptional engineers to an extent that resembles star status in academia. After all, knowing how human capital accumulates by means of interaction would clearly have far-reaching implications and ultimately shed light on a key component of economic growth (Akcigit et al., 2018; Lucas & Moll, 2014).

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Appendix A. Classification of Scientific Fields

National Academy of Sciences	Scopus	*Field*
Animal, Nutritional, and Applied Microbial Sciences	Agricultural and Biological Sciences	
Biochemistry	Biochemistry, Genetics, and Molecular Biology	
Biophysics and Computational Biology	Immunology and Microbiology	
Cellular and Developmental Biology	Neuroscience	
Cellular and Molecular Neuroscience	Pharmacology, Toxicology, and Pharmaceutics	
Evolutionary Biology		
Genetics		
Physiology and Pharmacology		
Plant Biology		
Plant, Soil, and Microbial Sciences		
Systems Neuroscience		
		Life Sciences
Immunology and Inflammation	Dentistry	
Medical Genetics, Hematology, and Oncology	Health Professions	
Medical Physiology and Metabolism	Medicine	
Microbial Biology	Nursing	
	Veterinary	
		Health Sciences
Applied Mathematical Sciences	Chemical Engineering	
Applied Physical Sciences	Chemistry	
Astronomy	Computer Science	
Chemistry	Earth and Planetary Sciences	
Computer and Information Sciences	Energy	
Engineering Sciences	Engineering	
Environmental Sciences and Ecology	Environmental Science	
Geology	Materials Science	
Geophysics	Mathematics	
Mathematics	Physics and Astronomy	
Physics		
		Physical Sciences
Anthropology	Arts and Humanities	
Economic Sciences	Business, Management, and Accounting	
Human Environmental Sciences	Decision Sciences	
Psychological and Cognitive Sciences	Economics, Econometrics, and Finance	
Social and Political Sciences	Psychology	
	Social Sciences	
		Social Sciences

Tab. A.1: CLASSIFICATION OF SCIENTIFIC FIELDS

Notes: We divide the scientific spectrum into four main fields based on the *All Science Journal Classification* by Scopus (omitting the field of multidisciplinary studies). Sections in use by the National Academy of Sciences are mapped into this taxonomy according to the reported scheme so that each of its members can be assigned to either life, health, physical, or social sciences. Sections and subfields are listed in alphabetical order.

Appendix B. List of Treatment Stars

Personal Data	Excerpt from Obituary	Field
KURT JUNGERMANN, 1938 – 2002 University of Göttingen	Died unexpectedly[+]	Life
ROBERT M. MACNAB, 1940 – 2003* Yale University	Fell at home	Life
ROBERT J. KADNER, 1942 – 2005 University of Virginia	Died unexpectedly	Life
DAVID S. SEGAL, 1942 – 2005 University of California, San Diego	Very short and aggressive course of pancreatic cancer	Life
JERRY O. WOLFF, 1942 – 2008* St. Cloud State University	Suicide	Life
DON C. WILEY, 1944 – 2001 Harvard University	Accident	Life
DAVID L. GARBERS, 1944 – 2006 University of Texas Southwestern	Heart attack	Life
UWE CLAUSSEN, 1945 – 2008 University of Jena	Heart attack	Life
REINHART HEINRICH, 1946 – 2006 Humboldt University of Berlin	Died unexpectedly	Life
STEVEN C. HEBERT, 1946 – 2008 Yale University	Sudden death after cardiovascular disease	Life
FRED F. KADLUBAR, 1946 – 2010 University of Arkansas for Medical Sciences	Died unexpectedly	Life
DOMINIQUE DORMONT, 1948 – 2003 CEA Fontenay-aux-Roses	Severe influenza	Life
MARJORIE A. ASMUSSEN, 1949 – 2004 University of Georgia	Bicycle accident	Life
JOHN C. LAWRENCE, 1949 – 2006 University of Virginia	Heart attack	Life
ROBERT W. GOLDBACH, 1949 – 2009* Wageningen University & Research	Trampled to death by an elephant while bird watching	Life
BARBARA K. BURGESS, 1950 – 2001 University of California, Irvine	Suicide	Life
EBBE S. NIELSEN, 1950 – 2001 Australian National Insect Collection	Heart attack	Life
DALE J. BENOS, 1950 – 2010 University of Alabama at Birmingham	Died suddenly while on a walk with his wife	Life
FRANÇOIS TILLEQUIN, 1950 – 2011 Paris Descartes University	Died unexpectedly	Life
THOMAS V. DUNWIDDIE, 1951 – 2001 University of Colorado Medical Campus	Accident while rock climbing	Life
ROBERT B. DICKSON, 1952 – 2006 Georgetown University	Ruptured aorta	Life
VINCENT R. FRANCESCHI, 1953 – 2005 Washington State University	Died unexpectedly	Life
DONALD W. THOMAS, 1953 – 2009 University of Sherbrooke	Stroke	Life
JEFFERY W. WALKER, 1954 – 2010* University of Arizona	Died suddenly and unexpectedly	Life
BAHMAN EGHBALL, 1956 – 2004* University of Nebraska-Lincoln	Swimming accident	Life

(continued)

Personal Data	Excerpt from Obituary	Field
BRIAN M. J. FOXWELL, 1956 – 2008 Imperial College London	Died unexpectedly	Life
RAWIE I. HOLLINGSWORTH, 1956 – 2012 Michigan State University	Collapsed in a hallway due to pulmonary emboli	Life
ANDREAS J. HELBIG, 1957 – 2005 University of Greifswald	Late diagnosed cancer, short illness	Life
ANGEL A. ALONSO, 1957 – 2005 McGill University	Infection with viral encephalitis	Life
KENJI TAKABAYASHI, 1957 – 2006 University of California, San Diego	Died unexpectedly⁺	Life
JASON D. MORROW, 1957 – 2008* Vanderbilt University	Died suddenly	Life
LLOYD R. KELLAND, 1958 – 2008* The Institute of Cancer Research, London	Died suddenly and unexpectedly	Life
ALAN P. WOLFFE, 1959 – 2001 National Institutes of Health, NICHD	Road accident	Life
STEFAN ROSEWICZ, 1960 – 2004 Charité – Berlin University of Medicine	Died suddenly and unexpectedly	Life
MICHAEL BRÜSS, 1961 – 2006 University of Bonn	Died suddenly and unexpectedly	Life
ALAA E. EL-HUSSEINI, 1962 – 2007 University of British Columbia	Drowned while on vacation	Life
MARCO F. RAMONI, 1963 – 2010 Boston Children’s Hospital	Heart failure	Life
ANDREA TONTINI, 1966 – 2012 University of Urbino	Suicide	Life
CHARLES A. LOCKWOOD, 1970 – 2008 University College London	Motorcycle accident	Life
EKARAT JANTRATID, 1975 – 2010 Goethe University Frankfurt	Died unexpectedly⁺	Life
LAWRENCE D. JACOBS, 1938 – 2001 University at Buffalo	Brief battle with cancer	Health
SIGRID POSER, 1941 – 2004 University of Göttingen	Died unexpectedly	Health
RICHARD H. WARD, 1943 – 2003 University of Oxford	Died suddenly of cardiac causes	Health
OLOF JOHNELL, 1944 – 2006* Malmö University	Died suddenly and unexpectedly	Health
LARS JANZON, 1944 – 2007* Lund University	Short illness	Health
HAIM RING, 1944 – 2008 Tel Aviv University	Short and serious illness	Health
MICHAEL J. REED, 1944 – 2009 St Mary's Hospital London	Died suddenly	Health
SEPPO S. SANTAVIRTA, 1945 – 2005 Helsinki University	Heart attack	Health
WILLIAM C. KOLLER, 1945 – 2005* University of North Carolina at Chapel Hill	Sudden cardiac problems	Health
WAYNE A. HENING, 1945 – 2008 Rutgers University	Brief struggle with pulmonary fibrosis	Health
AXEL PERNECZKY, 1945 – 2009 University of Mainz	Died suddenly and unexpectedly	Health

(continued)

Personal Data	Excerpt from Obituary	Field
MASSIRAO CHIARIELLO, 1945 – 2010* University of Naples Federico II	Short struggle with cancer	Health
MARIO STEFANELLI, 1945 – 2010 University of Pavia	Haemorrhagic stroke	Health
ROBERT M. ADRIAN, 1946 – 2007 Georgetown University	Died suddenly	Health
JECKONIAH O. NDINYA-ACHOLA, 1946 – 2010 University of Nairobi	Sudden kidney failure	Health
JEFFERY M. ISNER, 1947 – 2001 Tufts University	Heart attack	Health
DAVID B. LARSON, 1947 – 2002* Duke University	Heart attack	Health
JOHN L. BEARD, 1947 – 2009 Pennsylvania State University	Died suddenly	Health
JOB J. BWAYO, 1948 – 2007 University of Nairobi	Murdered by carjackers	Health
WERNER A. BAUTZ, 1949 – 2008 University of Erlangen-Nuremberg	Heart attack	Health
GARY J. MILLER, 1950 – 2001 University of Colorado Medical Campus	Died suddenly while jogging	Health
DANIEL P. SCHUSTER, 1950 – 2007 Washington University in St. Louis	Died suddenly while playing racquetball	Health
GREG R. ALEXANDER, 1950 – 2007 University of South Florida	Heart failure	Health
ELIZABETH S. WILLIAMS, 1951 – 2004 University of Wyoming	Traffic accident	Health
HELMUT DREXLER, 1951 – 2009 Hannover Medical School	Accident during race biking	Health
GERD HAUSDORF, 1952 – 2001 University of Göttingen	Died unexpectedly	Health
HANS J. SCHWANITZ, 1952 – 2004 Osnabrück University	Died unexpectedly	Health
RICHARD L. WALKER, 1952 – 2008 University of California, Davis	Probable suicide	Health
HELMUT MAXEINER, 1952 – 2009 Charité – Berlin University of Medicine	Bicycle accident	Health
RICHARD W. SCHWARTZ, 1952 – 2010* University of Kentucky	Very brief battle with lung cancer	Health
BARRY M. KACINSKI, 1953 – 2003 Yale University	Heart attack	Health
TONY S. KELLER, 1955 – 2006* University of Vermont	Died of gunshots, apparent homicide	Health
FRANS W. J. ALBERS, 1955 – 2007 University of Groningen	Brief illness	Health
ALAN J. FLISHER, 1956 – 2010* University of Cape Town	Brief struggle with leukaemia	Health
ROBERT B. DUNCAN, 1957 – 2007 Virginia-Maryland College of Veterinary Medicine	Died suddenly	Health
JASON D. MORROW, 1957 – 2008* Vanderbilt University	Died suddenly	Health
JEFFREY W. TYLER, 1957 – 2009 University of Missouri-Columbia	Died unexpectedly	Health

(continued)

Personal Data	Excerpt from Obituary	Field
JAE-YOUNG RHO, 1958 – 2002 University of Memphis	Heart attack	Health
WALTER J. MUIR, 1958 – 2009 University of Edinburgh	Died suddenly and unexpectedly	Health
BERNIE J. O'BRIEN, 1959 – 2004 University of Edinburgh	Died tragically while jogging	Health
HERMAN T. YEE, 1959 – 2011 New York University	Died suddenly	Health
KEVIN P. GRANATA, 1961 – 2007 Virginia Polytechnic Institute and State University	Victim of university campus shooting	Health
JEFFREY W. BERGER, 1963 – 2001 University of Pennsylvania	Stomach cancer, died two weeks after diagnose	Health
SERGIO VIDAL, 1966 – 2003 University of Santiago de Compostela	Sudden illness	Health
JAN KWIECINSKI, 1938 – 2003 Polish Academy of Sciences	Died suddenly during a cycling trip	Physical
JAMES R. HOLTON, 1938 – 2004 University of Washington	Stroke and heart attack during a mid-day run	Physical
LORENZ KRAMER, 1941 – 2005 University of Bayreuth	Died unexpectedly	Physical
DAVID J. FAULKNER, 1942 – 2002 University of California, San Diego	Complications after heart surgery	Physical
JIN AU KONG, 1942 – 2008 Massachusetts Institute of Technology	Complications from pneumonia	Physical
PAUL GRANGE, 1943 – 2003 University of Louvain	Heart attack	Physical
JÜRGEN O. BESENHARD, 1944 – 2006 Graz University of Technology	Stroke while returning from conference	Physical
ANDREI YAKOVLEV, 1944 – 2008 University of Rochester	Heart attack	Physical
REX E. SHEPHERD, 1945 – 2003 University of Pittsburgh	Heart attack	Physical
TADEUSZ PAKULA, 1945 – 2005 Max Planck Institute for Polymer Research	Short and severe illness	Physical
ROBERT F. DENNO, 1945 – 2008 University of Maryland	Heart attack	Physical
STEPHEN H. SCHNEIDER, 1945 – 2010 Stanford University	Heart attack	Physical
ROBERT A. SCHOMMER, 1946 – 2001 Cerro Tololo Inter American Observatory	Suicide	Physical
RICHARD E. EWING, 1946 – 2007 Texas A&M University	Heart attack	Physical
MICHAEL J. WEAVER, 1947 – 2002 Purdue University	Died unexpectedly	Physical
HANS J. RATH, 1947 – 2012 University of Bremen	Short and severe illness	Physical
YORAM J. KAUFMAN, 1948 – 2006 NASA Goddard Space Flight Center	Bicycle accident	Physical
PAUL G. SILVER, 1948 – 2009 Carnegie Institution of Washington	Car accident	Physical
CHARLES E. HOYLE, 1948 – 2009 University of Southern Mississippi	Died unexpectedly	Physical

(continued)

Personal Data	Excerpt from Obituary	Field
JOHN P. HUCHRA, 1948 – 2010 Harvard University	Heart attack	Physical
PHILIPPE FLAJOLET, 1948 – 2011 INRIA at Rocquencourt	Died suddenly and unexpectedly	Physical
IOANNIS VARDOULAKIS, 1949 – 2009 National Technical University of Athens	Gardening accident	Physical
ULRICH M. GÖSELE, 1949 – 2009 Max Planck Institute of Microstructure Physics	Found dead in his apartment	Physical
ISAAC GOLDHIRSCH, 1949 – 2010 Tel Aviv University	Died unexpectedly	Physical
GERHARD H. JIRKA, 1944 – 2010 Karlsruhe Institute of Technology	Heart attack	Physical
HASSAN AREF, 1950 – 2011 Virginia Polytechnic Institute and State University	Aortic dissection	Physical
SHENG YU, 1950 – 2012 Western University	Unexpectedly	Physical
JAAP G. SNIJDERS, 1951 – 2003 University of Groningen	Died unexpectedly due to short-term illness	Physical
JEAN-PIERRE MAELFAIT, 1951 – 2003 University of Ghent	Died suddenly and unexpectedly	Physical
PAUL F. BARBARA, 1953 – 2010 University of Texas at Austin	Complications following cardiac arrest	Physical
IAN P. ROTHWELL, 1955 – 2004 Purdue University	Car accident	Physical
STRATIS V. SOTIRCHOS, 1956 – 2004 University of Rochester	Car accident	Physical
RICHARD C. PLAYLE, 1956 – 2005 Wilfrid Laurier University	Heart failure after brief illness	Physical
STEPHEN P. HOPKIN, 1956 – 2006 University of Reading	Car accident	Physical
ZLATKO B. TEŠANOVIĆ, 1956 – 2012 Johns Hopkins University	Heart attack	Physical
IAN I. KOGAN, 1958 – 2003 University of Oxford	Heart attack	Physical
ADOLFO PARMALIANA, 1958 – 2008 University of Messina	Suicide	Physical
PETER G. DUYNKERKE, 1959 – 2002 Utrecht University	Tragic accident	Physical
LEOPOLDO P. FRANCA, 1959 – 2012 University of Colorado Denver	Heart attack	Physical
IAN H. LANGFORD, 1961 – 2002* University of East Anglia	Suicide or home accident	Physical
WILLIAM D. ARMSTRONG, 1961 – 2006 University of Wyoming	Plane crash	Physical
TIL AACH, 1961 – 2012 RWTH Aachen University	Died unexpectedly	Physical
WERNER S. WEIGLHOFER, 1962 – 2003 University of Glasgow	Struck by an avalanche	Physical
ALEXANDER E. FARRELL, 1962 –2008 University of California, Berkeley	Died unexpectedly	Physical
RAJEEV MOTWANI, 1962 – 2009 Stanford University	Accidental drowning	Physical

(continued)

Personal Data	Excerpt from Obituary	Field
MANUEL FORESTINI, 1963 – 2003 University of Grenoble	Heart attack	Physical
ROBERT HEITZ, 1964 – 2003 Technical University of Berlin	Cardiac aneurysm	Physical
EDOARDO CAPELLO, 1965 – 2009* Polytechnic University of Milan	Heart attack while skiing	Physical
FEMKE OLYSLAGER, 1966 – 2009 University of Ghent	Died unexpectedly	Physical
LUIS SERRANO-ANDRÉS, 1966 – 2010* University of Valencia	Died unexpectedly	Physical
JOAKIM H. PETERSSON, 1968 – 2002 Linköping University	Died suddenly and unexpectedly	Physical
KEITH FAGNOU, 1971 – 2009 University of Ottawa	Complications from influenza	Physical
SAM T. ROWEIS, 1972 – 2010 New York University	Suicide	Physical
KEVIN E. STRECKER, 1974 – 2012 Rice University	Heart attack	Physical
FRANS M. DIELEMAN, 1942 – 2005 Utrecht University	Died suddenly and unexpectedly	Social
DENNIS A. RONDINELLI, 1943 – 2007 Duke University	Died unexpectedly⁺	Social
ROB KLING, 1944 – 2003 Indiana University	Unexpectedly due to cardiovascular disease	Social
VICTOR FLORIAN, 1945 – 2002 Bar-Ilan University	Died unexpectedly⁺	Social
DICK R. WITTINK, 1945 – 2005 Yale University	Diabetic seizure while swimming in his pool	Social
MICHAEL W. PFAU, 1945 – 2009 University of Oklahoma	Brief illness	Social
KENNETH A. KAVALE, 1946 – 2008 Regent University	Died unexpectedly	Social
PETER GOLDIE, 1946 – 2011 University of Manchester	Brief illness	Social
PHILLIP L. WALKER, 1947 – 2009 University of California, Santa Barbara	Died unexpectedly	Social
IVAN MERVIELDE, 1947 – 2011 University of Ghent	Short illness	Social
PETER W. JUSCZYK, 1948 – 2001 Johns Hopkins University	Heart attack	Social
SUMANTRA GHOSHAL, 1948 – 2004 London Business School	Brain haemorrhage	Social
LYNDA L. KAID, 1948 – 2011 University of Florida	Died unexpectedly	Social
M. THEA SINCLAIR, 1950 – 2006 University of Nottingham	Riding accident	Social
MARK S. JOHNSON, 1950 – 2007* Montclair State University	Died suddenly	Social
GEORGE M. ZINKHAN, 1952 – 2009 University of Georgia	Suicide after being prime suspect in a triple homicide	Social
PETER LIPTON, 1954 – 2007 University of Cambridge	Collapsed after a squash game	Social

(continued)

Personal Data	Excerpt from Obituary	Field
BRIAN D. MULLEN, 1955 – 2006 Syracuse University	Died unexpectedly	Social
STEVEN C. POE, 1960 – 2007 University of North Texas	Heart attack	Social
JEAN O. LANJOUW, 1962 – 2005 University of California, Berkeley	Renal cancer, died three months after first symptoms	Social
JÖRG SCHUMACHER, 1962 – 2010 University of Leipzig	Died unexpectedly	Social
RODNEY CLARK, 1967 – 2006 Wayne State University	Died unexpectedly	Social
ALASDAIR CROCKETT, 1968 – 2006 University of Essex	Suicide	Social
STEPHEN O. GYIMAH, 1968 – 2012* Queen's University	Unexpectedly due to brief illness	Social

Tab. B.1: LIST OF TREATMENT STARS

Notes: The list comprises 162 outstanding scientists whose active careers ended abruptly between 2001 and 2012 due to unexpected death at a maximum age of 65 years. Asterisks indicate that the year of birth could not be ascertained and was instead estimated based on the year of death and the reported death age. Plus signs indicate that the death cause was verified after personal consultation with former colleagues. Affiliations are selected as of the last held job position.

Appendix C. Detailed Matching Procedure

Technically, the matching procedure is performed at the star-collaborator dyad level. This implies that although the majority of covariates refers to the collaborator, characteristics of the star scientist and features of their collaboration are equally important to account for. The overall goal is to construct a control group that mirrors the treatment group in these three dimensions and thus determines the hypothetical outcome path for the latter group had they not experienced the unexpected star death. We proceed by detailing our matching algorithm in three main steps.

Step 1: Identifying treatment and potential control dyads

Our bibliometric data cover substantial network information. We apply several constraints to identify treatment and control dyads therein. First, we only consider established star collaborations. Thus, as of the year of death, stars must have fulfilled a star criterion (as defined in Section 2.2) and collaborations must have emerged through jointly published articles.[23] Second, we require collaborators to be research-active at the time of death. We implement this constraint by confining the matching sample to dyads where collaborators are below 40 career years and have not ended their publication activities prior to the year of death. Third, we focus on established collaborators. This leads us to exclude collaborators with less than five career years and collaborators who simultaneously began their careers and star collaborations. Fourth and lastly, we remove collaborators that died, regardless of cause, as documented by our treatment case search.

These general constraints are common to both treatment and control dyads. In order to draw the distinction between the two groups, we lean on the star scientists. Treatment stars died unexpectedly at a maximum age of 65 years. We impose two additional constraints to infer that they were engaged in research activities at the time of their death. First, their obituaries do not indicate that they entered any kind of retirement phase. Second, they published at least one article over the two years preceding the year of death. Control stars, in contrast, must not die. Deceased stars, as disclosed through our treatment search, are therefore not eligible to be part of control dyads. From the remaining pool of potential control dyads, we first remove stars with career ages of over 35 years, which resembles the age threshold applied to treatment stars on the assumption that scientific careers start at the age of 30.[24] Second, we restrict the control pool to stars who continued publishing for a

[23] This essentially excludes a small number of treatment dyads that are solely verifiable through delayed publications, i.e., after the year of death. In these cases, it remains unclear if collaboration actually took place or if the co-author possibly served as a replacement for the deceased star.

[24] Jones (2010) points out that the age at which eminent scientists and inventors become research-active has notably increased over the past. He documents a mean age of 31 years for the end of the 20th century and further shows that age patterns are very similar across scientific fields.

minimum of five years after the considered death year. We expect these stars to be alive besides being involved in further research activities. Third and analogous to the treatment case, control stars are required to have published one article over the past two years.

Together, these constraints allow us to determine treatment dyads and to narrow down potential control dyads. As for the former group, we make a final adjustment by excluding collaborators that experience more than one treatment event. These cases are relatively rare,[25] but still problematic from a methodological standpoint since it would be hardly possible to isolate the individual treatment effects.

Step 2: Matching field-by-field and year-by-year

This step aims to identify counterparts for each treatment dyad. We begin by splitting the confined sample into four distinct groups according to the stars' field classification (life, health, physical, and social sciences). Within each field, we iterate over the years from 2001 to 2012. Every treatment year is hereby associated with a disjoint subgroup of the full set of treatment dyads. Potential control dyads, in contrast, can be linked to more than one year. To be clear, a dyad pictures a collaboration over time. Control dyads thus serve as feasible matches in any given year, in which they meet the criteria stated above. We proceed by matching treatment and control dyads field-by-field and year-by-year. Note that treatment dyads can initially match with multiple control dyads as we postpone the implementation of the one-to-one and without replacement features to Step 3.

Dyads form a match if they belong to the exact same stratum derived from partitioning the support of the joint distribution of the following covariates, with optional percentile cut-offs in parentheses:

- DYAD LEVEL: no. of joint articles (50th; 85th), years since last joint article (25th; 75th)
- STAR LEVEL: no. of received citations (25th; 75th), field classification[26]
- COLLABORATOR LEVEL: no. of distinct co-authors (25th; 75th), adjusted forward citations in each of the last five years and aggregated over a max. 5-year period prior to that (50th; 80th; 98th), career age in 5-year intervals

The selection of cut-offs is strongly guided by distributional features and therefore hard to determine a priori. For instance, we discover that casual dyads that collaborate once or twice are very common,[27] which allows us to choose a relatively high first cut-off for the number of joint articles, i.e., the 50th percentile. This decision is motivated on theoretical

[25] They account for 3% of the treated collaborator sample. Among them, an unfortunate group of eight collaborators is exposed to the maximum of three death events.

[26] The stars' field constitutes an implicit covariate since we opt to match dyads field-by-field.

[27] This finding is indeed not new. For instance, Azoulay et al. (2010) depict a very similar distribution of co-authorship intensity for US life scientists.

grounds, as we attempt to separate casual dyads from (more) regular ones, but is also reasonable on pragmatic grounds, as broad stratifications usually improve the chances of successful matches. Moreover, the assessment of collaboration intensity likely changes depending on the time horizon. To illustrate this point, in 2001, one might label a dyad frequent if more than five collaborations occurred from 1996 onwards. Yet this absolute threshold is probably not suitable to classify dyads as of 2010 given that our data (still) span until 1996. Relative cut-off points are hence preferred and eventually determined in an iterative process that intends to maximise both the degree of covariate balance and the overall matching rate.

Step 3: Selecting final control dyads

In line with the related literature (Azoulay et al., 2010; Jaravel et al., 2018), we employ a one-to-one matching without replacement. More specifically, control collaborators can only be matched once irrespective of multiple occurrences within different control dyads. In slight deviation to previous studies that have pursued a purely chronological approach, we select control dyads by first considering all allocation possibilities. This offers two advantages. First, it allows executing each matching year simultaneously and can thus lead to substantial timesavings if parallel computing resources are available. Second, it gives us the opportunity to inspect if some collaborators, who are allocated more than once, constitute mandatory matches for certain treatment dyads (in possibly later years).

We begin by locking mandatory matches, i.e., we assign control dyads that are without alternatives. In case that control collaborators are part of multiple mandatory dyads, we prioritise earlier treatment years and, if necessary, break ties at random. After removing all other occurrences of these collaborators, we proceed chronologically. In other words, we restrict all remaining control collaborators to their first match, again breaking ties at random. At this stage, matching is realised without replacement. In order to implement the one-to-one feature, we lastly select control dyads randomly in the event that treatment dyads are presented with multiple options. In sum, we manage to find a definite match for 93.6% of all treatment dyads, hereby employing 8,406 distinct strata.

Appendix D. Additional Summary Statistics

Variable	Life Sciences		Health Sciences		Physical Sciences		Social Sciences	
	Treated	Control	Treated	Control	Treated	Control	Treated	Control
Career age	18.52	18.44	18.57	18.54	17.42	17.33	16.94	16.96
Female prediction	0.268	0.291	0.273	0.283	0.140	0.163	0.293	0.279
U.S. affiliated	0.459	0.424	0.422	0.414	0.375	0381	0.630	0.468
Star status	0.243	0.253	0.265	0.251	0.269	0.253	0.175	0.104
No. of distinct co-authors	60.09	60.09	77.95	74.71	54.95	58.10	21.54	18.55
No. of articles	13.26	12.53	15.26	14.56	15.25	15.72	7.71	7.33
No. of citations	524.7	522.5	531.9	519.4	505.6	475.7	166.5	145.3
No. of collaborations	2.03	1.93	2.49	2.40	2.31	2.32	1.63	1.68
Years since last collaboration	4.40	4.30	3.77	3.67	4.07	4.01	4.20	4.27
No. of citations (star)	1,621.6	1,660.3	1,643.2	1,393.4	1,712.6	1,601.2	209.0	213.3
No. of collaborators	5,598		7,950		4,738		308	

Tab. D.1: SUMMARY STATISTICS ON MATCHED COLLABORATORS BY SCIENTIFIC FIELD

Notes: The table reports a breakdown of mean values by scientific field and treatment status. All time-varying variables refer to the year preceding the (inherited) year of star death. Article, citation, and distinct co-author numbers are aggregated over a prior 5-year span. Gender information are inferred through name and country data and are available for 85.3% of the sample.

Appendix E. Robustness Checks

	Main Model	Variant 1	Variant 2	Variant 3	Variant 4	Variant 5	Variant 6
Overall Sample)	*Article count as dependent variable*						
After death × treated	-0.043*	-0.045*	-0.043*	-0.043*	-0.043**	-0.073**	n/a
	(0.022)	(0.021)	(0.022)	(0.022)	(0.013)	(0.028)	n/a
Log pseudo-likelihood	-189,139	-189,135	-189,227	-189,138	-189,780	-67,906	n/a
No. of observations	275,344	275,344	275,344	275,344	275,344	90,600	n/a
No. of dyads	18,542	18,542	18,542	18,542	18,542	6,040	n/a
Overall Sample)	*Forward citations as dependent variable*						
After death × treated	-0.081**	-0.087**	-0.081**	-0.081*	-0.080**	-0.087**	-0.081**
	(0.028)	(0.029)	(0.028)	(0.028)	(0.019)	(0.034)	(0.030)
Log pseudo-likelihood	-2,800,261	-2,799,841	-2,804,363	-2,799,577	-2,819,493	-964,785	-2,873,838
No. of observations	275,166	275,166	275,166	275,166	275,166	90,585	275,166
No. of dyads	18,527	18,527	18,527	18,527	18,527	6,039	18,527
Life Sciences)	*Article count as dependent variable*						
After death × treated	-0.066*	-0.065*	-0.065*	-0.066*	-0.063**	-0.079*	n/a
	(0.030)	(0.030)	(0.030)	(0.030)	(0.024)	(0.036)	n/a
Log pseudo-likelihood	-52,754	-52,755	-52,776	-52,752	-52,948	-23,952	n/a
No. of observations	83,541	83,541	83,541	83,541	83,541	34,770	n/a
No. of dyads	5,585	5,585	5,585	5,585	5,585	2,318	n/a
Life Sciences)	*Forward citations as dependent variable*						
After death × treated	-0.114**	-0.119**	-0.113**	-0.115**	-0.114**	-0.107*	-0.122*
	(0.041)	(0.044)	(0.041)	(0.041)	(0.034)	(0.046)	(0.053)
Log pseudo-likelihood	-809,005	-808,823	-810,045	-808,285	-813,795	-337,475	-835,832
No. of observations	83,526	83,526	83,526	83,526	83,526	34,770	83,526
No. of dyads	5,584	5,584	5,584	5,584	5,584	2,318	5,584

(continued)

	Main Model	Variant 1	Variant 2	Variant 3	Variant 4	Variant 5	Variant 6
Health Sciences)			*Article count as dependent variable*				
After death × treated	-0.044	-0.042	-0.044	-0.044	-0.047*	-0.065	n/a
	(0.034)	(0.034)	(0.034)	(0.034)	(0.021)	(0.046)	n/a
Log pseudo-likelihood	-79,330	-79,327	-79,369	-79,327	-79,603	-27,978	n/a
No. of observations	118,212	118,212	118,212	118,212	118,212	37,125	n/a
No. of dyads	7,940	7,940	7,940	7,940	7,940	2,475	n/a
Health Sciences)			*Forward citations as dependent variable*				
After death × treated	-0.043	-0.039	-0.044	-0.043	-0.047	-0.050	-0.030
	(0.038)	(0.040)	(0.038)	(0.038)	(0.027)	(0.043)	(0.038)
Log pseudo-likelihood	-1,154,988	-1,154,805	-1,156,912	-1,154,597	-1,164,565	-390,776	-1,176,750
No. of observations	118,148	118,148	118,148	118,148	118,148	37,110	118,148
No. of dyads	7,934	7,934	7,934	7,934	7,934	2,474	7,934
Physical Sciences)			*Article count as dependent variable*				
After death × treated	-0.026	-0.033	-0.026	-0.026	-0.027	-0.089*	n/a
	(0.030)	(0.029)	(0.030)	(0.030)	(0.025)	(0.043)	n/a
Log pseudo-likelihood	-53,894	-53,892	-53,936	-53,890	-54,089	-15,207	n/a
No. of observations	69,107	69,107	69,107	69,107	69,107	17,580	n/a
No. of dyads	4,711	4,711	4,711	4,711	4,711	1,172	n/a
Physical Sciences)			*Forward citations as dependent variable*				
After death × treated	-0.104*	-0.121**	-0.106*	-0.104*	-0.102**	-0.121*	-0.115**
	(0.043)	(0.040)	(0.042)	(0.043)	(0.038)	(0.060)	(0.044)
Log pseudo-likelihood	-784,720	-784,690	-787,455	-784,029	-791,293	-218,597	-808,717
No. of observations	69,008	69,008	69,008	69,008	69,008	17,580	69,008
No. of dyads	4,703	4,703	4,703	4,703	4,703	1,172	4,703

(continued)

	Main Model	Variant 1	Variant 2	Variant 3	Variant 4	Variant 5	Variant 6
Social Sciences)	*Article count as dependent variable*						
After death × treated	-0.062	-0.133	-0.061	-0.063	-0.051	0.043	n/a
	(0.151)	(0.157)	(0.153)	(0.151)	(0.146)	(0.211)	n/a
Log pseudo-likelihood	-3,021	-3,020	-3,034	-3,017	-3,042	-706	n/a
No. of observations	4,484	4,484	4,484	4,484	4,484	1,125	n/a
No. of dyads	306	306	306	306	306	75	n/a
Social Sciences)	*Forward citations as dependent variable*						
After death × treated	-0.015	-0.137	-0.013	-0.012	-0.017	0.206	-0.015
	(0.205)	(0.222)	(0.205)	(0.206)	(0.187)	(0.356)	(0.205)
Log pseudo-likelihood	-40,122	-40,192	-40,612	-39,909	-40,837	-12,103	-40,127
No. of observations	4,484	4,484	4,484	4,484	4,484	1,125	4,484
No. of dyads	306	306	306	306	306	75	306

Tab. E.1: ROBUSTNESS CHECKS

Notes: The table reports the results of a series of robustness checks that probe our main model defined by Equation (2). In Variant 1, we prolong the pre-treatment period to include the death event, thus delaying the start of the post-treatment period to the first full calendar year after the stars' passing. In Variant 2, we switch to an alternative career age specification and employ 5-year brackets to capture life cycle effects. In Variant 3, we include interacted calendar year and career age fixed effects instead of inserting them separately. In Variant 4, we shift the level of standard error clustering from the star to the collaborator level. In Variant 5, we estimate effects based on a balanced panel of collaborators that are traceable for exactly seven years before and after their respective death year. In Variant 6, we abstain from winsorizing forward citations. Any further estimation features and variable definitions are maintained from the main model. Robust standard errors are in parentheses.

* $p < 0.05$, ** $p < 0.01$, and *** $p < 0.001$.

Appendix F. Supplementary Estimations

This section provides further estimations that are useful for probing the robustness of the findings presented in Section 4.2. Methodologically, we rely on Equation (3) or on a slightly modified version thereof, which contains either multiple three-way interactions or continuous interaction terms.

Basic Interaction Measures. Frequency, timing, and length of a collaborative relationship provide intuitive starting points for exploring treatment effect heterogeneity. However, frequency was not found to be a relevant factor. We draw similar conclusions with regard to the other two interaction measures, as reported in Tables F.1 and F.2. As for timing, we distinguish recent collaborations, who published a joint article either in the year of death or in the year before, from older collaborations. The former group comprises slightly over 30% of both the treated and control sample. In the absence of any statistically significant interaction terms (see Table F.1), we find no reliable link between recency and treatment effect levels, thus indicating that the disruption of ongoing research projects plays a negligible role. As for collaboration length, we separate collaborations that published joint articles over multiple years (30% in both samples) from one-year collaboration. As can be seen from Table F.2, treatment effect differences between these groups are statistically insignificant.

Horizontal Spillovers & Intra-US Effects. We address the concern that the effects estimated for star-star dyads and US-US dyads might be entangled by combining both interactions (together with their common terms) in the same specification. As shown in Table F.3, results hardly change under this scenario. More concretely, both effect channels stay statistically significant in life sciences despite slight reductions in absolute point estimates. In case of health sciences, we see a minor increase in both effects sizes and precision, which causes the differential quality effect for US-US dyads to become statistically significant at the five-percent level (former p-value was 0.064).

Intra-US Effects & Other Physical Proximity Effects. Our measures of physical proximity at the city-level (co-located) and at the country-level (US-US) partly overlap. We thus test the potential dependence of these channels by estimating their differential treatment effects within one specification. In view of Table F.4, we find the concern to be unfounded given that the field-specific results see only marginal changes. In addition to that, we explore the possibility that intra-US effects could just be a reflection of intra-country effects. However, as can be inferred from Table F.5, this is unlikely to be true. While intra-country effects take up some part of the productivity effect in health sciences, they point in the opposite direction of the quality effect in life sciences, thereby enhancing it.

Subject Space & Topic Space. Distance in subject space represents a key predictor for the treatment effect sizes in health and physical sciences. This finding suggests that the visible decline in research output supposedly results from the loss of complementary scientific resources that were provided by the deceased star. However, it remains relatively vague, which concrete form or combination of resources plays a decisive role. In order to improve our understanding in this regard, we distinguish between distances in subject and topic space. Methodologically, the calculation of topic space distance follows the exact same steps as outlined for subject distance with the exception of utilising keywords instead of journal categories. Moreover, keywords are cleaned and Porter-stemmed to mitigate the risk of misclassification, which could arise from Scopus using a non-standardised keyword pool. Overall, this leads us to differentiate between 162,791 keywords. However, it should be noted that keywords are not available for every publication, which causes a roughly 10% reduction in sample size (topic distance could not be determined for these dyads in absence of keywords). Combining subject and topic space metrics in one estimation gives rise to the results in Table F.6. As can be seen, focus on divergent research matters is not a central driver of the treatment effects, as none of the topic space interactions become statistically significant. On the contrary, the relevance of the subject space channel in health and physical sciences remains largely unaffected (especially in the quality dimension). In unreported estimations, we additionally tested if proximity in subject and topic space, or a combination of both, might explain treatment effect outcomes, but could not determine any reliable link.

Continuous Interactions. For the ease of interpretation, we solely used dummy variables to investigate effect heterogeneities in Section 4.2. While most variables naturally allow for a binary classification (e.g., co-location, star status, or intra-US collaborations), we applied a cut-off between the second and third tertile in some instances, most notably regarding the subject distance measure. To allay the concern that this specific cut-off may be pivotal for our results, we present additional results derived from continuous interaction effects. Technically, we allow for a non-linear relationship between the treatment effect and the distance measure by inserting two interaction terms, one regular (*After death* $\times$ *treated* $\times$ *subject distance*) and one squared (*After death* $\times$ *treated* $\times$ *squared subject distance*), in addition to the standard treatment term (*After death* $\times$ *treated).* Models that include multiple continuous interactions become hardly interpretable from estimated coefficients alone. We thus present a graphical illustration in Figure F.1 that depicts how the (overall) treatment impact varies along the subject distance range. As can be seen, higher distances are reliably linked to a higher treatment magnitude in case of the overall sample, health sciences, and the quality sphere of physical sciences, which is in line with our field-specific findings.

	Overall Sample	Life Sciences	Health Sciences	Physical Sciences	Social Sciences
	Article count as dependent variable				
After death × treated	-0.051 *	-0.086 **	-0.052	-0.014	-0.142
	(0.021)	(0.033)	(0.034)	(0.038)	(0.174)
After death × treated × recent dyad	0.018	0.065	0.026	-0.041	0.281
	(0.028)	(0.048)	(0.038)	(0.048)	(0.320)
Log pseudo-likelihood	-189,024	-52,745	-79,239	-53,873	-3,020
No. of observations	275,344	83,541	118,212	69,107	4,484
No. of dyads	18,542	5,585	7,940	4,711	306
	Forward citations as dependent variable				
After death × treated	-0.091 **	-0.092 *	-0.056	-0.134 *	-0.158
	(0.028)	(0.041)	(0.038)	(0.052)	(0.257)
After death × treated × recent dyad	0.018	-0.071	0.025	0.067	0.461
	(0.044)	(0.075)	(0.061)	(0.084)	(0.396)
Log pseudo-likelihood	-2,791,626	-808,089	-1,149,979	-782,563	-39,999
No. of observations	275,166	83,526	118,148	69,008	4,484
No. of dyads	18,527	5,584	7,934	4,703	306

Tab. F.1: EFFECT HETEROGENEITY BY COLLABORATION RECENCY

Notes: The overall sample includes 9,297 pairs of treated and control collaborators confined to a nine-year window around the (inherited) year of star death. The panel is equally unbalanced for treated and control collaborators. Both output measures are co-author adjusted. Forward citations are winsorized at the 99.9th percentile. Collaborators without variation in output over the observation period are dropped by the estimation routine. Field delineation is based on the stars' publication profile or, if available, derived from the classification of the NAS. Robust standard errors are in parentheses, clustered at the level of the star.

* $p < 0.05$, ** $p < 0.01$, and *** $p < 0.001$.

	Overall Sample	Life Sciences	Health Sciences	Physical Sciences	Social Sciences
	Article count as dependent variable				
After death × treated	-0.039	-0.057	-0.037	-0.020	-0.150
	(0.023)	(0.031)	(0.036)	(0.037)	(0.180)
After death × treated × multi-year dyad	-0.012	-0.031	-0.019	-0.014	0.261
	(0.028)	(0.053)	(0.041)	(0.050)	(0.281)
Log pseudo-likelihood	-189,223	-52,752	-79,329	-53,892	-3,020
No. of observations	275,344	83,541	118,212	69,107	4,484
No. of dyads	18,542	5,585	7,940	4,711	306
	Forward citations as dependent variable				
After death × treated	-0.076 **	-0.084	-0.069	-0.074	-0.154
	(0.029)	(0.044)	(0.040)	(0.052)	(0.246)
After death × treated × multi-year dyad	-0.015	-0.105	0.069	-0.077	0.422
	(0.045)	(0.073)	(0.058)	(0.092)	(0.405)
Log pseudo-likelihood	-2,800,185	-808,858	-1,154,909	-784,615	-40,064
No. of observations	275,166	83,526	118,148	69,008	4,484
No. of dyads	18,527	5,584	7,934	4,703	306

Tab. F.2: EFFECT HETEROGENEITY BY COLLABORATION LENGTH

Notes: The overall sample includes 9,297 pairs of treated and control collaborators confined to a nine-year window around the (inherited) year of star death. The panel is equally unbalanced for treated and control collaborators. Both output measures are co-author adjusted. Forward citations are winsorized at the 99.9th percentile. Collaborators without variation in output over the observation period are dropped by the estimation routine. Field delineation is based on the stars' publication profile or, if available, derived from the classification of the NAS. Robust standard errors are in parentheses, clustered at the level of the star.

* p < 0.05, ** p < 0.01, and *** p < 0.001.

	Overall Sample	Life Sciences	Health Sciences	Physical Sciences	Social Sciences
	Article count as dependent variable				
After death × treated	0.012	0.015	0.002	0.025	-0.153
	(0.030)	(0.050)	(0.047)	(0.045)	(0.266)
After death × treated × star-star dyad	-0.042	-0.096 *	-0.006	-0.073	0.082
	(0.029)	(0.043)	(0.045)	(0.048)	(0.252)
After death × treated × US-US dyad	-0.090 *	-0.063	-0.131 *	-0.018	0.230
	(0.037)	(0.053)	(0.056)	(0.062)	(0.297)
Log pseudo-likelihood	-188,769	-52,666	-79,135	-53,830	-2,984
No. of observations	274,210	83,314	117,559	68,907	4,430
No. of dyads	18,461	5,569	7,892	4,698	302
	Forward citations as dependent variable				
After death × treated	0.006	0.057	-0.010	-0.034	-0.122
	(0.033)	(0.053)	(0.047)	(0.060)	(0.354)
After death × treated × star-star dyad	-0.049	-0.144 *	0.017	-0.076	0.132
	(0.043)	(0.059)	(0.056)	(0.074)	(0.394)
After death × treated × US-US dyad	-0.146 **	-0.173 *	-0.130 *	-0.049	0.223
	(0.048)	(0.076)	(0.063)	(0.082)	(0.416)
Log pseudo-likelihood	-2,785,534	-804,699	-1,147,343	-782,330	-39,282
No. of observations	274,032	83,299	117,495	68,808	4,430
No. of dyads	18,446	5,568	7,886	4,690	302

Tab. F.3: EFFECT HETEROGENEITY VIA COLLABORATOR STATUS AND US CHANNEL

Notes: The overall sample includes 9,297 pairs of treated and control collaborators confined to a nine-year window around the (inherited) year of star death. The panel is equally unbalanced for treated and control collaborators. Both output measures are co-author adjusted. Forward citations are winsorized at the 99.9th percentile. Collaborators without variation in output over the observation period are dropped by the estimation routine. Field delineation is based on the stars' publication profile or, if available, derived from the classification of the NAS. Robust standard errors are in parentheses, clustered at the level of the star.

* $p < 0.05$, ** $p < 0.01$, and *** $p < 0.001$.

	Overall Sample	Life Sciences	Health Sciences	Physical Sciences	Social Sciences
	Article count as dependent variable				
After death × treated	-0.003	-0.038	0.000	-0.001	-0.077
	(0.028)	(0.039)	(0.043)	(0.034)	(0.268)
After death × treated × co-located	-0.058	0.022	-0.030	-0.135 *	-0.425
	(0.034)	(0.072)	(0.046)	(0.067)	(0.299)
After death × treated × US-US dyad	-0.084 *	-0.083	-0.122 *	-0.006	0.263
	(0.037)	(0.054)	(0.054)	(0.064)	(0.308)
Log pseudo-likelihood	-188,780	-52,673	-79,135	-53,832	-2,983
No. of observations	274,210	83,314	117,559	68,907	4,430
No. of dyads	18,461	5,569	7,892	4,698	302
	Forward citations as dependent variable				
After death × treated	-0.025	-0.047	0.003	-0.073	0.052
	(0.032)	(0.046)	(0.045)	(0.051)	(0.336)
After death × treated × co-located	-0.028	0.138	-0.062	-0.131	-0.632
	(0.053)	(0.082)	(0.082)	(0.109)	(0.382)
After death × treated × US-US dyad	-0.137 **	-0.210 **	-0.109	-0.027	0.239
	(0.047)	(0.077)	(0.061)	(0.084)	(0.406)
Log pseudo-likelihood	-2,789,319	-805,419	-1,149,316	-782,330	-39,180
No. of observations	274,032	83,299	117,495	68,808	4,430
No. of dyads	18,446	5,568	7,886	4,690	302

Tab. F.4: EFFECT HETEROGENEITY VIA CO-LOCATION AND US CHANNEL

Notes: The overall sample includes 9,297 pairs of treated and control collaborators confined to a nine-year window around the (inherited) year of star death. The panel is equally unbalanced for treated and control collaborators. Both output measures are co-author adjusted. Forward citations are winsorized at the 99.9th percentile. Collaborators without variation in output over the observation period are dropped by the estimation routine. Field delineation is based on the stars' publication profile or, if available, derived from the classification of the NAS. Robust standard errors are in parentheses, clustered at the level of the star.

* $p < 0.05$, ** $p < 0.01$, and *** $p < 0.001$.

	Overall Sample	Life Sciences	Health Sciences	Physical Sciences	Social Sciences
	Article count as dependent variable				
After death × treated	0.004	-0.017	0.015	-0.012	-0.247
	(0.031)	(0.040)	(0.046)	(0.034)	(0.417)
After death × treated × same country	-0.038	-0.038	-0.045	-0.008	0.113
	(0.043)	(0.092)	(0.063)	(0.071)	(0.479)
After death × treated × US-US dyad	-0.069	-0.058	-0.101	-0.021	0.223
	(0.046)	(0.088)	(0.067)	(0.085)	(0.279)
Log pseudo-likelihood	-188,770	-52,672	-79,120	-53,834	-2,986
No. of observations	274,210	83,314	117,559	68,907	4,430
No. of dyads	18,461	5,569	7,892	4,698	302
	Forward citations as dependent variable				
After death × treated	-0.016	-0.060	-0.003	-0.048	0.186
	(0.038)	(0.058)	(0.054)	(0.054)	(0.510)
After death × treated × same country	-0.035	0.081	-0.022	-0.135	-0.533
	(0.051)	(0.091)	(0.068)	(0.110)	(0.524)
After death × treated × US-US dyad	-0.119 *	-0.238 **	-0.099	0.051	0.478
	(0.057)	(0.092)	(0.070)	(0.122)	(0.340)
Log pseudo-likelihood	-2,789,309	-805,386	-1,149,019	-783,525	-39,304
No. of observations	274,032	83,299	117,495	68,808	4,430
No. of dyads	18,446	5,568	7,886	4,690	302

Tab. F.5: EFFECT HETEROGENEITY VIA COUNTRY CHANNEL AND US CHANNEL

Notes: The overall sample includes 9,297 pairs of treated and control collaborators confined to a nine-year window around the (inherited) year of star death. The panel is equally unbalanced for treated and control collaborators. Both output measures are co-author adjusted. Forward citations are winsorized at the 99.9th percentile. Collaborators without variation in output over the observation period are dropped by the estimation routine. Field delineation is based on the stars' publication profile or, if available, derived from the classification of the NAS. Robust standard errors are in parentheses, clustered at the level of the star.

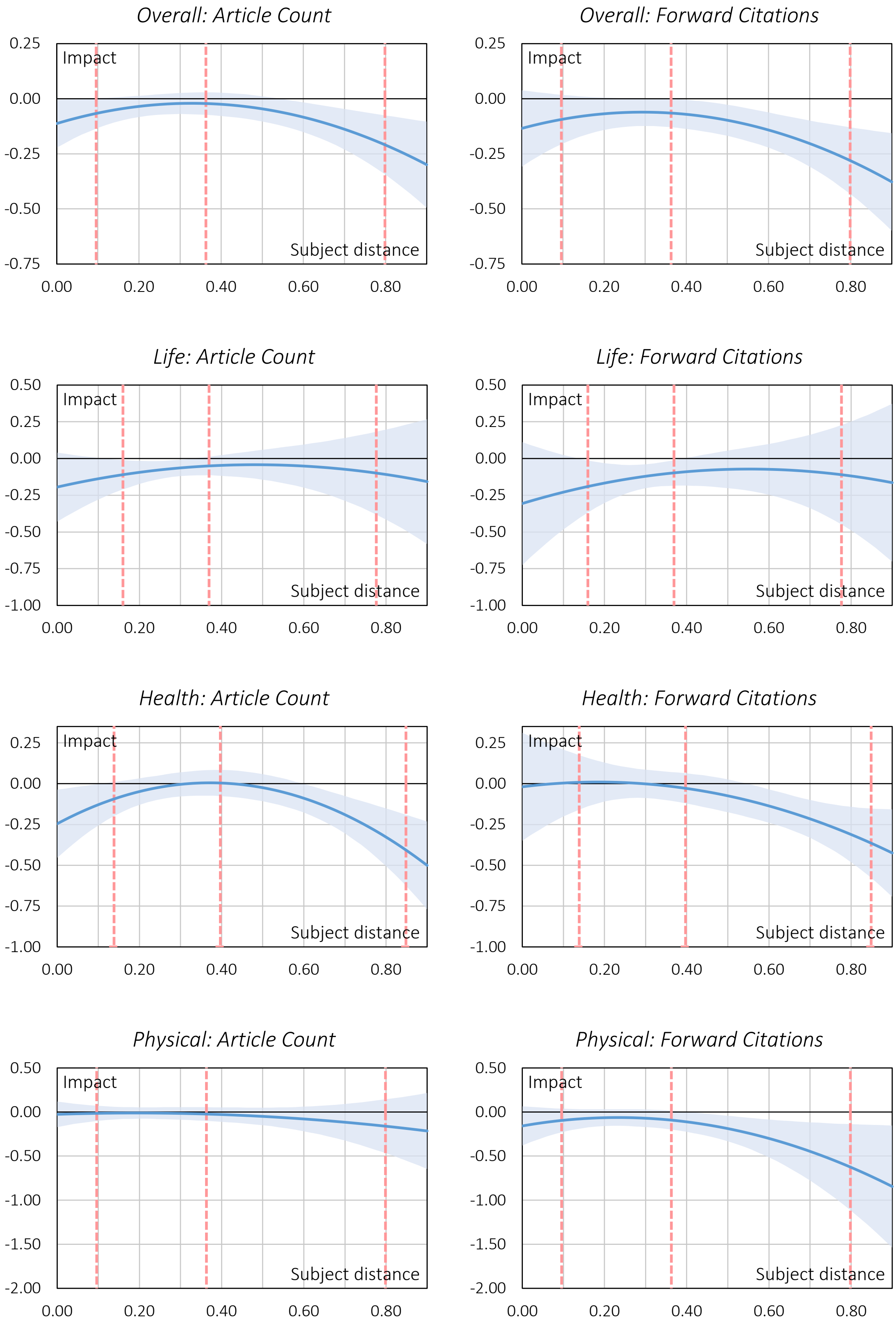
* $p < 0.05$, ** $p < 0.01$, and *** $p < 0.001$.

	Overall Sample	Life Sciences	Health Sciences	Physical Sciences	Social Sciences
	Article count as dependent variable				
After death × treated	-0.029	-0.071 *	-0.008	-0.015	-0.105
	(0.026)	(0.029)	(0.040)	(0.035)	(0.150)
After death × treated × subject distance in 3. tertile	-0.058 (0.038)	-0.025 (0.075)	-0.098 (0.054)	-0.031 (0.067)	-0.282 (0.523)
After death × treated × topic distance in 3. tertile	0.013 (0.040)	0.090 (0.072)	-0.043 (0.058)	-0.006 (0.063)	0.597 (0.384)
Log pseudo-likelihood	-183,169	-50,859	-77,644	-51,820	-2,685
No. of observations	251,756	75,993	109,817	62,350	3,596
No. of dyads	16,802	5,038	7,311	4,208	245
	Forward citations as dependent variable				
After death × treated	-0.050	-0.125 **	0.017	-0.070	-0.094
	(0.035)	(0.043)	(0.048)	(0.052)	(0.211)
After death × treated × subject distance in 3. tertile	-0.121 * (0.048)	0.020 (0.079)	-0.161 * (0.074)	-0.204 * (0.090)	-0.353 (0.637)
After death × treated × topic distance in 3. tertile	-0.010 (0.053)	-0.023 (0.095)	-0.119 (0.068)	0.092 (0.092)	0.865 (0.585)
Log pseudo-likelihood	-2,663,073	-761,129	-1,110,334	-746,954	-32,757
No. of observations	251,736	75,993	109,797	62,350	3,596
No. of dyads	16,800	5,038	7,309	4,208	245

Tab. F.6: EFFECT HETEROGENEITY IN SUBJECT AND TOPIC SPACE

Notes: The overall sample includes 9,297 pairs of treated and control collaborators confined to a nine-year window around the (inherited) year of star death. The panel is equally unbalanced for treated and control collaborators. Both output measures are co-author adjusted. Forward citations are winsorized at the 99.9th percentile. Collaborators without variation in output over the observation period are dropped by the estimation routine. Field delineation is based on the stars' publication profile or, if available, derived from the classification of the NAS. Robust standard errors are in parentheses, clustered at the level of the star.

* $p < 0.05$, ** $p < 0.01$, and *** $p < 0.001$.


Overall: Article Count
Impact
Subject distance
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Life: Article Count
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Health: Article Count
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Health: Forward Citations
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Physical: Article Count
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Subject distance

(continued)

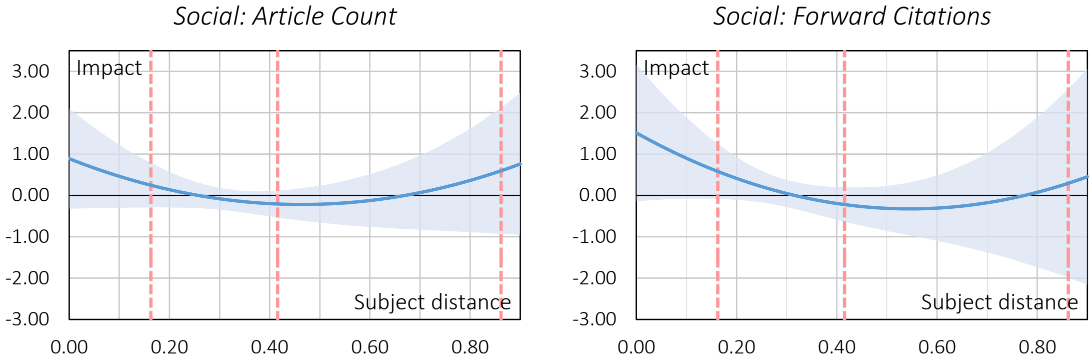

Fig. F.1: EFFECT HETEROGENEITY IN SUBJECT SPACE, CONTINUOUS INTERACTION

Notes: The panels plot the estimated treatment impact over the subject distance range from 0-0.9. In theory, subject distance can reach values up to 1.41 (square root of 2). In practice, however, most distributions are characterised by a thin right tale. The 2.5th, 50th, and 97.5th percentiles are marked by dotted lines to provide reference points. Analogous to all former estimations, treatment impacts result from a Poisson model and thus require transformation to be interpreted as a percentage change (i.e., exponentiating and decreasing by one). Point estimates are depicted by solid blue lines and 95% confidence intervals are pictured as light blue areas. Any further estimation features and variable definitions are maintained from the main model.