

Online Appendix

The Returns to Physical Capital in Knowledge Production: Evidence from Lab Disasters

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Content

A	Conceptual Framework	3
A.1	Physical capital shocks with a finite time horizon	3
A.2	Graphical illustration of predictions	5
B	Adverse Events	6
B.1	Data collection	6
B.2	Sources	9
B.3	Sources list	12
B.4	Survey	22
B.5	Survey questions	23
B.6	Adverse events characteristics	25
C	Control Group Construction	30
C.1	Publications data and author disambiguation	32
C.2	Defining the pool of potential controls	33
C.3	Matching on productivity	33
C.4	Accounting for career trajectories	34
C.5	Ranking and selecting controls	39
C.6	Robustness checks	40

D	Lab Head and Damage Descriptives	42
D.1	Lab head descriptives	42
D.2	Laboratory damage descriptives	44
D.3	Panel descriptives	46
E	Further Results	47
E.1	Bivariate analysis	47
E.2	Research output	48
E.3	Alternative mechanisms	54
E.4	Research direction	63
E.5	Heterogeneity	68
F	Robustness Checks	76
F.1	Different model specifications	76
F.2	Different operationalizations of dependent variable	79
F.3	Interaction-weighted estimator	80
F.4	Spared lab heads as natural control group	81
F.5	Differently matched control groups	82
F.6	Adverse event subsamples	87
F.7	Heterogeneity subsamples	88

A Conceptual Framework

A.1 Physical capital shocks with a finite time horizon

We discuss the implications of a finite time horizon for our conceptual framework. We demonstrate, in particular, that the predictions outlined in Section 2 are, qualitatively, the same and remain valid if generic capital does not depreciate. The limit case in which the time horizon is very short is not of particular interest because it implies that only considerations about the short term are meaningful, and empirically testable. However, it remains plausible that scientists are time-constrained and this specification of the model takes this better into account.

Thus, after a shock, the scientist is less likely to return to an investment phase with a finite time horizon than in the case where the time horizon is large. Specifically, unless specialized capital is completely lost, there exists a minimum time horizon below which the scientist does not reinvest despite the loss of specialized capital. Then, the change in research productivity in the long run from Equation 5 in Section 2 generalizes to:

$$\frac{\partial R_{1_x}(t)^*/\partial K_{1_x}}{R_{1_x}(t)^*} = \frac{\theta \beta e^{T_x \theta}}{\theta K_{1_x} e^{T_x \theta} + K_{g_x} e^{T_x \theta} - K_{g_x}}, \quad (5a)$$

where T_x is the time remaining after the shock. This equation corresponds to a positive constant, also if the depreciation rate of generic physical capital is null ($\theta = 0$). In fact, for θ that tends to 0, the equation simplifies to:

$$\frac{\partial R_{1_x}(t)^*/\partial K_{1_x}}{R_{1_x}(t)^*} = \frac{\beta}{T_x K_{g_0} + K_{1_x}}. \quad (5b)$$

We then consider changes in research topics, with reference to Equation 6 in Section 2. For the sake of readability, we assume $\beta = 1$ and $K_{g_x} = 1$. We find:

$$J(R_{2_x}^*) > J(R_{1_x}^*) \implies A_{2_x} > \frac{A_{1_x} (K_{1_x} \theta e^{T_x \theta} + e^{T_x \theta} - 1)^2}{(1 - e^{T_x \theta})^2}. \quad (6a)$$

For θ that tends to 0, this simplifies to:

$$J(R_{2_x}^*) > J(R_{1_x}^*) \implies A_{2_x} > \frac{A_{1_x} (K_{1_x} + T_x)^2}{T_x^2}. \quad (6b)$$

The implications of both equations are the same as for Equation 6: unless there is no specialized capital, A_{2_x} has to be substantially larger than A_{1_x} to justify a change in topic, and

a negative shock to specialized capital increases the probability of a change in topic. A very short time horizon would reduce the probability of changes in topic (because the denominator tends to zero). The characteristics of Equation 7 in Section 2 are a direct consequence of these conclusions and, therefore, also remain equivalent: for sufficiently high values of A_{2_x} , research productivity can recover in the long run.

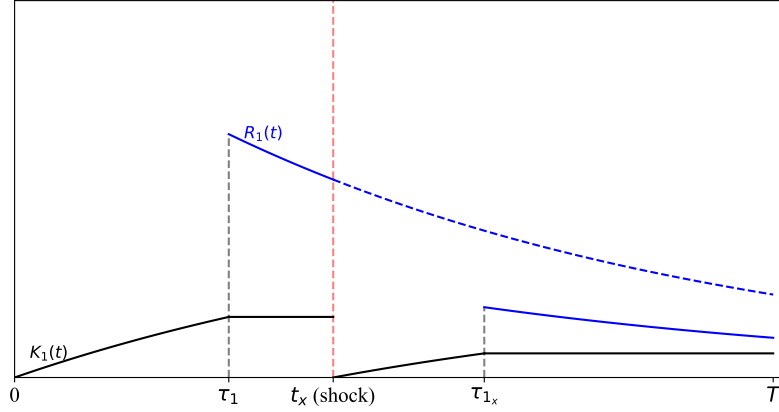
All of these expressions derive from the model in which generic capital and specialized capital depreciate at the same rate. However, a model in which these rates are allowed to differ and only the depreciation rate of generic capital is zero would, qualitatively, reach the same conclusions.

To conclude, the time horizon being finite and the obsolescence rate of generic capital being positive are both sufficient assumptions for the validity of our predictions. In other words, the consequences of shocks to specialized capital would only be temporary and irrelevant to research direction if the time horizon were infinite *and* there were no technological progress (or, alternatively generic capital were being constantly renewed). In this case, the scientist would always switch immediately to the most worthwhile topic before any shock, and after a shock they would accumulate the same level of specialized capital as before it.

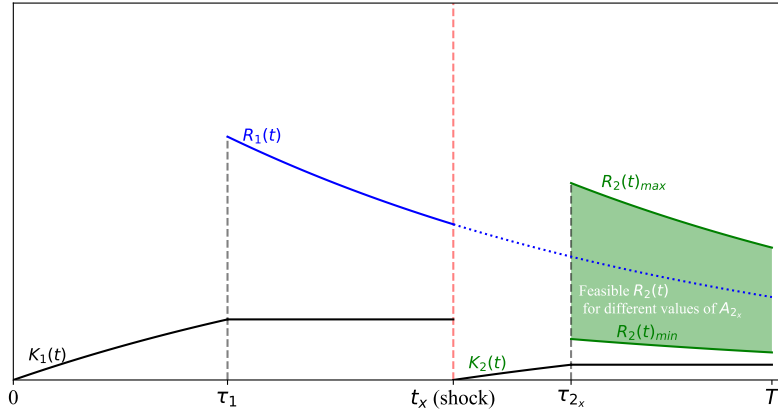
A.2 Graphical illustration of predictions

Figure A-1: Illustration of physical capital shock in theoretical model

(a) Modern laboratory



(b) Old laboratory



Notes: The two figures show the results of simulations based on the theoretical model with a complete loss of specialized capital. In Figure A-1a, specialized capital is not yet obsolete ($A_{1x} > A_{2x}$). In Figure A-1b, specialized capital has become obsolete ($A_{2x} > A_{1x}$). The green-colored area shows the range of feasible values of the research output $R_2(t)$, for different values of A_{2x} . The lower bound limit of $R_2(t)_{min}$ is defined by the case in which $A_{2x} = A_{1x}$. The upper bound limit ($R_2(t)_{max}$) is defined by the value of A_{2x} that renders the scientist indifferent to topic change in the absence of a shock. For higher values, the scientist would have changed the research topic regardless of the shock and the counterfactual $R_1(t)$ (dashed line) would not exist.

B Adverse Events

B.1 Data collection

At the start of the data collection, we search for information on adverse events at universities and research institutes in newspapers, incident reports, campus gazettes, books, and other pieces of gray literature. We identify potentially relevant adverse events with systematic keyword queries in news archives. Most importantly, we use NewsLibrary, which is an online newspaper archive with a corpus of over 7,700 U.S. newspapers with articles dating back to 1977. In addition, we use LexisNexis and Google Search, which both cover non-U.S. newspapers as well. All three archives contain machine-readable articles that can be searched through the internal search function.

The search queries for the news archives are based on meaningful Boolean combinations of research-related terms and an adverse event-related term. The latter terms include causes (e.g., fire, outage, storm) and consequences (e.g., destruction, disruption, loss). The search terms are as follows:

Research-related terms

Academic, Campus, College, Department, Experiment, Hospital, Installation, Lab(-oratory), Observatory, Research, Research center, Research complex, Research equipment, Research facilities, Research institute, Research material, Science, Science center, Scientific equipment, Scientific facilities, Scientific institute, Scientific material, University

+

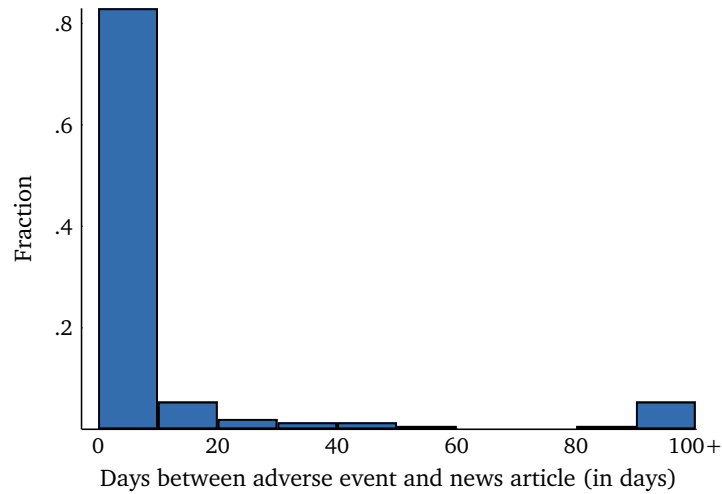
Adverse event-related terms

Accident, Adverse, Arson, Assault, Attack, Blackout, Blast, Blaze, Breakage, Breakdown, Burn, Contamination, Crash, Damage, Destruction, Detonation, Disaster, Disruption, Earthquake, Emergency, Evacuation, Explosion, Failure, Fault, Fire, Flame, Flood, Hack, Havoc, Hazard, Hurricane, Leak, Loss, Lost, Malfunction, Outage, Overheating, Shatter, Short circuit, Spill, Spillage, Spoilage, Storm, Strike, Vandalism, Vandals

The respective search results list the news article’s title, date, and excerpt/snippet (of varying length). If a search result appears relevant, we obtain the respective news article. Depending on the information in the article, we search for additional articles about the same event with more specific search terms (e.g., the university name). Most of the (newspaper) articles have been published within the first ten days following the adverse event (see Figure B-1).

We collect, read, and process about 500 news articles, reports, and book chapters (see Section B.2 for examples of newspaper articles and Section B.3 for a list of the most relevant

Figure B-1: Time lag between adverse event and news article (in days)

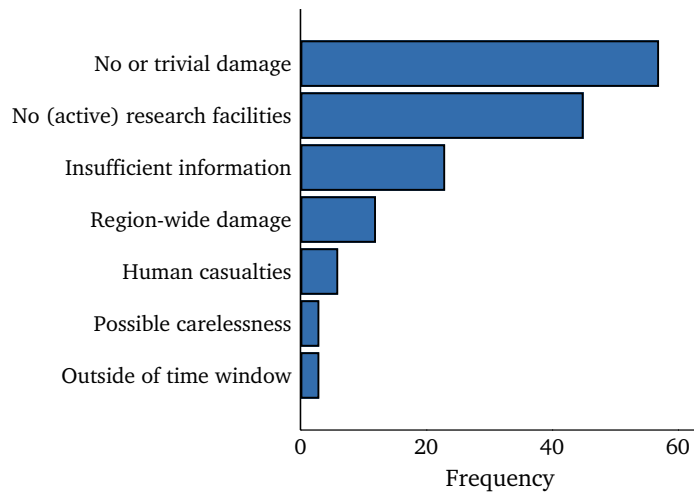


Notes: This figure illustrates the distribution of the time lag between the occurrence of the adverse event and the publication of the first source of information in our data (primarily news articles). Lag is truncated at 100 days. The unit of observation is the adverse event.

sources). Several public data bases help us identify additional adverse events or fill in missing information for those already in our collection: the U.S. FEMA Disaster Open Database, which includes information on damages to public institutions due to officially declared disasters; the U.S. FEMA National Fire Incident Database, which includes fires reported by the majority of fire departments; non-compliance reports published by the Office of Laboratory Animal Welfare (OLAW) (Mohan et al., 2017); the Global Terrorism Database, which lists eco-terrorist attacks against research institutions, among others; the diary of the Animal Liberation Front (2010), which was the most active militant animal rights group in the late 20th century. We also learn about further cases through personal communication with scientists.

From this array of sources, we compile a list of 296 adverse events with key basic information: 1) the event date, 2) the type/cause of the event, 3) the affected institution and department, 4) whether physical capital loss occurred, and 5) whether any human casualties occurred. Based on this information, we apply additional criteria to select valid cases for our analysis: 1) we retain events that took place between 1980 and 2012; 2) we exclude adverse events that are linked to scientists' carelessness or disregard of rules and regulations, which undermines plausible exogeneity; 3) we exclude institutions with no research output in scientific publications; 4) we exclude cases of false alarms or damage to classrooms instead of laboratories, keeping only cases in which the damage was non-trivial; 5) we exclude cases that

Figure B-2: Reasons for exclusion of adverse events in the initial set



Notes: This figure lists the reason for exclusion of adverse events in the initial set. The unit of observation is at the adverse event level.

involved human casualties or serious injuries among scientists and research personnel.⁵⁰

From the initial set of 296 adverse events, we maintain 147 for further processing. Figure B-2 provides an overview of the (primary) reason why a given adverse event was excluded. The main reason for the exclusion of adverse events relates to the damage being trivial or irrelevant to research. We exclude some other adverse events because we are unable to obtain sufficient information. This is the case, for instance, if there is no reference to the department or research field, which prevents us from sending our survey to likely informed scientists.

We can confidently argue that the list obtained is comprehensive of most adverse events in research laboratories during our period of analysis for which information can be obtained with reasonable effort from English, German, Italian, or French written sources. However, the list is not to be considered a representative sample of adverse events overall; it is intentionally limited to cases with physical capital loss at research laboratories in universities or research institutes. Because of the greater media coverage and higher availability of databases (in particular, NewsLibrary, which focuses on U.S. news outlets), the list focuses on cases occurring in North America and Western Europe and at more renowned institutions.

⁵⁰Given the propensity of journalism to report the sensational, news reports are unlikely to omit details of human casualties if there were any. Furthermore, we can compare a considerable subset of adverse events with incident records of the the Occupational Safety and Health Administration, which is part of the U.S. Department of Labor.

B.2 Sources

Newspaper article: example 1

San Jose Mercury News (CA)

January 15, 2002

SOME RESEARCH ESCAPES BLAZE AT CAMPUS LAB

Scientists in Santa Cruz feared more work had been destroyed

The amount of research lost in Friday's fire that destroyed two biology labs at the University of California-Santa Cruz was not as great as scientists originally feared, university officials said Monday. "There's a real sense of relief because much of the research data was in a separate area of the building," said university spokeswoman Elizabeth Irwin.

The two labs were operated by Manuel Ares and Jane Silverthorne of the Department of Molecular, Cell and Developmental Biology. In Ares' lab, the blaze destroyed lab and computer equipment and DNA samples. Silverthorne is on academic leave with the National Science Foundation, and, therefore, officials don't believe the lab contained extensive research materials. Most of the damage was in the southwest corner of the Sinsheimer Labs—the campus's main biology building—and computers used to back up Ares' data were in the north wing, which was not as seriously affected by water and smoke damage.

Ares, chairman of the department, is studying how genes are expressed in cells and how gene functions change in diseased cells such as cancer cells. Silverthorne researches the molecular biology of plant development.

Irwin said that a preliminary investigation by the state Fire Marshal's Office has determined that the blaze was not intentionally set. But its cause probably won't be known until later this week, she said. The fire, which began at 5:30 a.m. Friday when Sinsheimer was unoccupied, closed five buildings and a multistory parking structure. All of the structures except Sinsheimer were opened when classes resumed Monday morning. Some researchers have been allowed to enter the building under the supervision of teams from the university's Department of Environmental Health and Safety. But the four-story Sinsheimer Labs is expected to remain closed for several weeks.

The building will be reopened incrementally, and the damaged labs on the fourth floor aren't expected to reopen for several months, Irwin said. The university is working with Belfor, a Denver-based company, to help rescue data from computer hard drives. The company had great success doing just that after July's chemistry-lab explosion and fire at UC-Irvine. Researchers from UC-Santa Cruz's engineering school are also helping out.

In addition to computer equipment, highly sensitive optical and laser equipment may have been damaged. "We're trying to determine the condition of everything affected by the smoke and water damage, seeing if it can be cleaned or repaired," Irwin said.

About 65 firefighters in 15 engines from throughout Santa Cruz County responded to the blaze. The firefighters, alerted by scientists, rescued fruit flies being used in genetic experiments. Investigators believe the fire originated in Ares' lab, flaring up a few hours later in Silverthorne's lab.

Newspaper article: example 2

The Dallas Morning News (TX)

March 24, 1993

FIRE GUTS MEDICAL CENTER LAB

\$800,000 blaze caused by short in electrical outlet, officials say

A fire gutted a biology laboratory and destroyed several costly pieces of equipment Tuesday morning at the University of Texas Southwestern Medical Center at Dallas.

The fire, sparked by a short in an electrical outlet, caused about \$800,000 damage, Fire Department officials said. Two security guards suffered smoke inhalation, but no serious injuries were reported.

Medical center officials said little data was affected but the lost equipment and work space will set researchers back at least two months. They plan to have the lab rebuilt.

The fire was reported shortly after 5 a.m. in the 5300 block of Harry Hines Boulevard and was under control about two hours later. Firefighters soon learned that the lab contained dangerous chemicals and low-level radioactive isotopes. The department's hazardous materials team examined the room and determined that no firefighters had been exposed to any chemicals or radiation. The dangerous substances were protected by fire-resistant barriers, said Roy Bode, president of public affairs for the medical center.

The room was the core laboratory used by about 15 research groups in the cell biology and neuroscience department. Experiments there have focused on the mechanisms of cancer and aging, on how cells take in vitamins and cholesterol and on understanding the operation of nerve cells.

About 10 to 12 experiments depended on the lab's equipment, said Dr. Richard Anderson, acting chairman of cell biology and neuroscience. Among the biggest losses was a \$160,000 machine called a Phosphorimager that records radioactive material in cells. The fire also destroyed a device that would make DNA, Dr. Anderson said.

Newspaper article: example 3

The San Francisco Chronicle (CA)

October 4, 1985

YEARS OF WORK DESTROYED IN FIRE AT OCEAN LABORATORY

Researchers at the National Marine Fisheries Laboratory are moving ahead with their work after a fire destroyed most of 25 years of irreplaceable data on ocean life and up to \$500,000 worth of equipment.

Peter Berrien, a specialist in fish eggs and larvae, lost 25,000 vials of eggs, most on loan from foreign laboratories. Clyde MacKenzie, who has been studying water chemistry and pollution in the New York Bight and Continental Shelf, lost 20 years of collected data on seed clams and stock. The fire also destroyed 2 1/2 years of data that Andrew Drexler, chief of environmental chemistry investigation, derived from weekly samplings over the past three summers at a 12-mile sewage dump site.

The September 21 fire at the converted Army hospital burned out of control for six hours and destroyed much of the commercial fish facility which served as the laboratory for the National Oceanic and Atmospheric Administration.

The losses include decades of research, rare scientific journals and valuable laboratory materials, said officials at the center. "We lost from \$300,000 to \$500,000 worth of equipment," said John O'Reilly, chief of the chemical processes branch at the laboratory. "We had one of the top three marine libraries in the world, along with Woods Hole (Massachusetts) and the Scripps Institute of Oceanography (California)," said Claire Steimle, librarian of the Lionel A. Walford Library, named after the founder of the laboratory.

Laboratory Director Stuart Wilk said scientists at the facility were not defeated by the tragedy. "Our basic business now is to get on with it," he said. A makeshift library and reading room have been set up on the second floor of the building. The staff have been assembling equipment needed to function in their new quarters, the old C Battery the Army built as a housing and mess hall. The interior of the center has been reduced to a blackened heap of water-soaked rubble. Slowly and sadly, the 70 scientists, researchers and staff members pick and pull from the heap, hoping to salvage something. Members of the Monmouth County prosecutor's office said the blaze was intentionally set, but that they had no suspects.

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B.4 Survey

We proceed with the 147 adverse events selected from our secondary sources. For each event, we compile a set of "most likely informed" scientists based on bibliographic information. We identify these scientists by searching in the Scopus publications database for scientists affiliated to the affected institution at the time of the adverse event and active in research fields that matched those in the case description. We use a manually constructed list of keywords for each event to discern publications in relevant fields. For instance, if the source locates the affected laboratory/scientists in the "Department of biology", we search for publications of the university with "biology" in the affiliation name field. If we have information on the specific research activity of damaged laboratories, we use a list of keywords closely related to the topic.⁵¹

We limit the list to a maximum of 120 scientists per adverse event.⁵² We contact them via their most recent corresponding email address in publications data. To validate this approach, we use the names of scientists from events for which we have complete information. We check whether these names occur in the list of likely informed scientists. As this is true for virtually all cases, we have confidence in the recall rate of our method.

The questionnaire includes a short set of closed-ended questions (see Section B.5 for the questions). We first ask whether the respective adverse event caused damage to the scientist's laboratory, other laboratories in the same department, or laboratories in other departments. If the scientist's laboratory was damaged, we inquire about the types of lost physical capital and the damage extent in monetary terms. We distinguish between workplace, material, equipment, and research results. We further distinguish between off-the-shelf generic equipment/material (available from multiple sources), specific equipment/material (available from one or few sources) and processed (internally developed). Altogether, we send out about 16,000 emails, of which about 2,800 failed to be delivered. We received 1,475 answers, which corresponds to an overall response rate of 9%.

Thanks to the survey responses and detailed descriptions of the adverse events in the secondary sources, we gain sufficiently complete information for 102 out of 147 adverse events (see Figures B-3 and B-4 and Table B-1 for some descriptive statistics of these adverse events). Most of these 102 adverse events affected multiple laboratories. Altogether, we identify 249 directly affected laboratories (and 178 spared laboratories) as linked to our 102 adverse events.

⁵¹For example, if we know that the research activities in the laboratory related to HIV we would search for publications of the university with keywords such as "AIDS", "HIV", and "immunodeficiency".

⁵²In case there are more than 120 scientists per adverse event, we rank scientists by their number of publications with event affiliation, in the relevant fields and in the years immediately before the event.

B.5 Survey questions

Dear [REDACTED],

The **Max Planck Institute for Innovation and Competition** [link] is currently conducting a **research project** on the **role of research equipment and material for scientists**. Based on your scientific publications, we have identified you as an affiliate of a research facility that potentially experienced considerable physical damage due to an unexpected event. We think that you might have information on the nature and extent of the damage caused by the event.

From our data search we learned that on **December 31, 1999 a fire occurred at Michigan State University's Agriculture Hall**.

(Source: *South Bend Tribune (IN)*, January 3, 2000, "Historic Agriculture Hall at MSU damaged by blaze") [link].

Your information on the nature and extent of the damage caused by the event is of **great value** to our research project.

We have put together a **short survey (2 minutes to answer)**. We would kindly ask you to answer a maximum of **5 short questions**. All information will be treated confidentially. The results of this study will be presented only in aggregate form and will at no time allow any individual to be identified.

Please answer by filling out this **online survey** [link]. Alternatively, you may answer by replying to this email (see instructions at the end of this email).

Thank you very much for your support.

Q1. The event above caused damage to:

Multiple answers possible. Please check all that apply.

- ☐ My research unit or laboratory.
- ☐ Other research units or laboratories in the same department.
- ☐ Other departments in the same institution.
- ☐ At the time of the event I was not affiliated to that institution.
- ☐ I have never been affiliated to that institution.
- ☐ I do not know.

Q2. In case the event caused damage to your research unit or laboratory, this involved:

Multiple answers possible. Please check all that apply.

Workplace (structural damage to buildings, laboratories, office or co-working space that prevented access or forced relocation):

- ☐ Short-term (less than 3 months)
- ☐ Temporarily (3 months or more)
- ☐ Permanently

Equipment (*hardware, software, laboratory devices: such as cameras, lasers, sequencers, spectrometers, telescopes, etc.*):

- ☐ Generic equipment (*standardized; available from multiple sources*)
- ☐ Specific equipment (*highly specific and tailored; only available from one or few sources*)
- ☐ Processed equipment (*internally developed or modified for specific research use*)

Material (*animals, plants, tissues, experiments, historical documents, etc.*):

- ☐ Generic material (*standardized; available from multiple sources*)
- ☐ Specific material (*highly specific and tailored; only available from one or few sources*)
- ☐ Processed material (*internally developed or modified for specific research use*)

Research results (*intermediate or final*):

- ☐ Data
- ☐ Notes and other unpublished information (*laboratory diaries, documentations, manuscripts, software code, etc.*)
- ☐ Other damage. Please specify: _____
- ☐ I do not know.

Q3. In case the event caused damage to your research unit or laboratory, the monetary value of damage at that time was approximately:

- ☐ Less than \$10,000.
- ☐ \$10,000 or more, but less than \$100,000.
- ☐ \$100,000 or more, but less than \$1,000,000.
- ☐ \$1,000,000 or more, but less than \$10,000,000.
- ☐ More than \$10,000,000.
- ☐ I do not know.

Q4. The event caused a setback to:

Multiple answers possible. Please check all that apply.

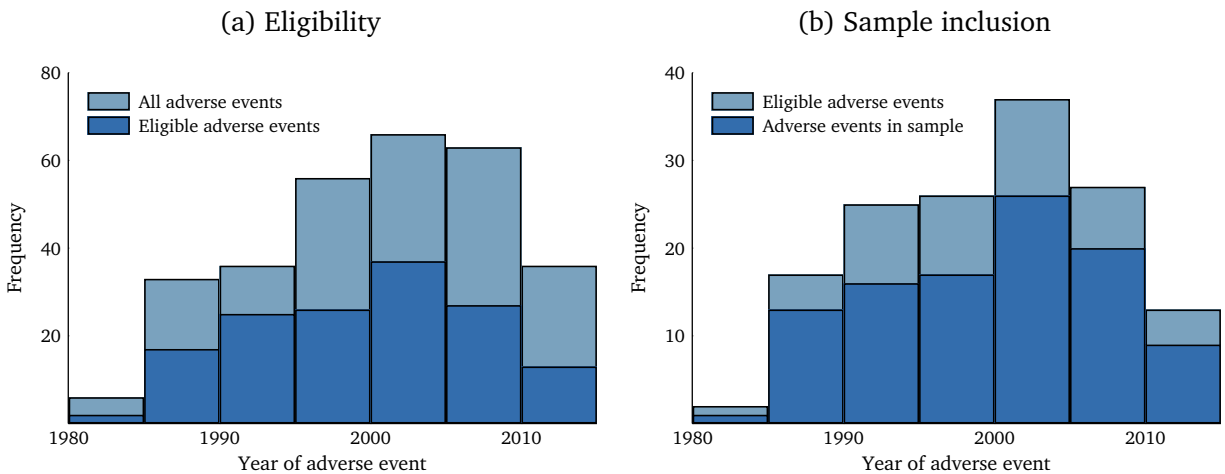
- ☐ My own research.
- ☐ Other research in my research unit or laboratory.
- ☐ Other research in my department.
- ☐ Other research in other departments of my institution.
- ☐ It did not affect research at my institution.
- ☐ I do not know.

Q5. Are you available for a follow-up questionnaire:

- ☐ Yes.
- ☐ No.

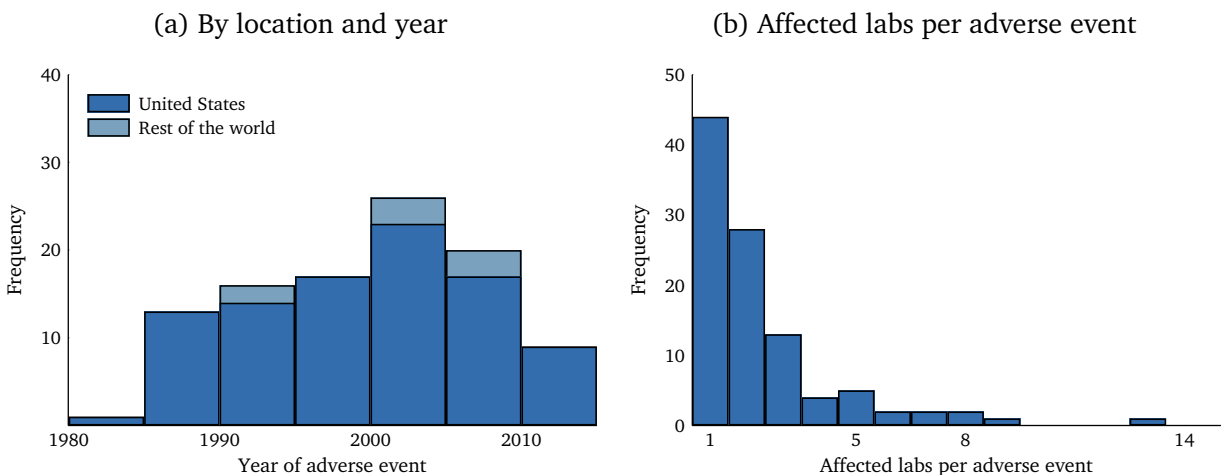
B.6 Adverse events characteristics

Figure B-3: Adverse events over time by eligibility and sample inclusion



Notes: The left-hand figure illustrates the distribution of the adverse events over time by their eligibility as plausibly exogenous physical capital losses. The right-hand figure illustrates the distribution of the adverse events over time and survey (non-)response. In both graphs, the unit of observation is the adverse event.

Figure B-4: Adverse events over time and affected labs



Notes: The left-hand figure illustrates the distribution of the adverse events over time by type of the affected research institution. The right-hand figure presents the number of affected labs per adverse event (as identified in our data). In both graphs, the unit of observation is the adverse event.

Table B-1: Adverse event characteristics by sample inclusion

Adverse events	Included (N = 102)		Excluded (N = 45)		Diff.	p-value
	Mean	Std. Err.	Mean	Std. Err.		
Year	1999.35	7.48	1998.73	7.11	−0.62	0.639
University (d)	0.77	0.42	0.82	0.39	0.05	0.517
Scimago rank	294.48	228.83	334.08	227.45	39.60	0.362
United States (d)	0.92	0.27	0.98	0.15	0.06	0.193
Agriculture (d)	0.14	0.35	0.20	0.40	0.06	0.338
Engineering (d)	0.17	0.37	0.13	0.34	−0.03	0.611
Medicine (d)	0.05	0.22	0.04	0.21	0.00	0.905
Other (d)	0.18	0.38	0.22	0.42	0.05	0.518
Science (d)	0.47	0.50	0.40	0.50	−0.07	0.431

Notes: This table presents characteristics of adverse events that are part of the final sample and of those that are excluded due to lack of information. The unit of observation is at the adverse event level. Reported *p*-values based on an unpaired *t*-test.

Table B-2: List of adverse events in final dataset

Affiliation of affected scientists	Country	Year	Type of adverse event	Key reference	Other references	Affected	Spared
Harvard University	US	1984	Fire	[3]		1	1
National Oceanic and Atmospheric Administration	US	1985	Eco-terrorism/Vandalism	[8]		1	1
University of California, Riverside	US	1985	Eco-terrorism/Vandalism	[7]		2	3
University of Washington	US	1985	Fire	[6]		1	0
University of Minnesota, Twin Cities	US	1986	Fire	[9]		1	2
Lawrence Livermore National Laboratory	US	1988	Technical malfunction	[27]	[28], [29], [30], [31], [32]	1	0
National Institute of Standards and Technology	US	1988	Fire	[37]		2	1
University of California, Irvine	US	1988	Eco-terrorism/Vandalism	[23]	[24]	1	0
University of Washington	US	1989	Other	[44]	[45], [46], [47]	1	2
Oregon State University	US	1989	Technical malfunction	[54]	[55], [56]	2	0
University of Rhode Island	US	1989	Technical malfunction	[58]		1	0
University of Wisconsin, Madison	US	1989	Technical malfunction	[49]	[50]	1	2
University of Arizona	US	1989	Eco-terrorism/Vandalism	[38]	[39], [40], [41]	1	3
Texas Tech University	US	1989	Eco-terrorism/Vandalism	[42]	[43]	2	5
University of Colorado, Boulder	US	1990	Technical malfunction	[60]		3	0
University of North Carolina, Chapel Hill	US	1990	Technical malfunction	[69]	[67], [68]	1	2
McGill University	CA	1990	Eco-terrorism/Vandalism	[66]		2	4
Rutgers, The State University of New Jersey	US	1990	Natural disaster	[70]		1	1
Washington State University, Pullman	US	1991	Eco-terrorism/Vandalism	[78]		1	3
Michigan State University	US	1992	Eco-terrorism/Vandalism	[82]	[83], [84]	1	0
Clarkson University	US	1992	Fire	[88]	[89], [90]	2	2
Virginia Institute of Marine Science	US	1992	Technical malfunction	[92]		1	2
University of Texas, Dallas	US	1993	Technical malfunction	[95]		4	2
North Carolina State University	US	1993	Technical malfunction	[96]		2	1
Case Western Reserve University	US	1993	Technical malfunction	[94]		1	0
California State University, Northridge	US	1994	Natural disaster	[99]		7	0
University of Texas, Austin	US	1994	Other	[103]	[104]	2	4
North Dakota State University	US	1994	Natural disaster	[102]		2	0
Brookhaven National Laboratory	US	1994	Technical malfunction	[105]	[106], [107]	1	1
Umea University	SE	1994	Eco-terrorism/Vandalism	[111]		4	2
United States Department of Agriculture	US	1995	Fire	[119]		2	1
Cornell University	US	1995	Fire	[116]	[114], [115]	2	2
United States Department of Agriculture	US	1995	Technical malfunction	[118]	[117]	2	0
University of Wisconsin, Madison	US	1995	Fire	[125]	[120], [121], [122], [123], [124]	2	1
Duke University	US	1996	Fire	[142]	[143]	1	0
Indiana University-Bloomington	US	1996	Fire	[132]	[131]	1	2

Affiliation of affected scientists	Country	Year	Type of adverse event	Key reference	Other references	Affected	Spared
University of Texas, Austin	US	1996	Technical malfunction	[137]	[133], [134], [135], [136]	1	1
University of Wisconsin, Madison	US	1997	Fire	[161]	[162]	1	1
University of North Dakota	US	1997	Natural disaster	[166]		5	0
University of Virginia	US	1997	Fire	[145]		3	1
University of Washington	US	1997	Technical malfunction	[156]	[153], [154], [155], [157], [158]	2	3
Ohio State University, Columbus	US	1998	Fire	[175]		1	0
University of California, Berkeley	US	1999	Eco-terrorism/Vandalism	[191]		1	2
Ohio State University, Columbus	US	1999	Technical malfunction	[197]		1	1
Columbia University	US	1999	Technical malfunction	[195]	[196]	6	0
University of Minnesota, Twin Cities	US	1999	Eco-terrorism/Vandalism	[194]		2	1
Institut national de la recherche agronomique	FR	2000	Eco-terrorism/Vandalism	[212]		2	1
Wichita State University	US	2000	Technical malfunction	[206]	[205], [207]	2	1
Los Alamos National Laboratory	US	2000	Technical malfunction	[221]	[217], [218], [219], [220], [222]	4	2
University of Washington	US	2000	Fire	[214]	[213]	1	3
Princeton University	US	2001	Technical malfunction	[254]		3	0
University of Texas M.D. Anderson Cancer Center	US	2001	Natural disaster	[231]		2	0
Baylor College of Medicine	US	2001	Natural disaster	[232]		1	0
National Oceanic and Atmospheric Administration	US	2001	Eco-terrorism/Vandalism	[228]	[224], [225], [226], [227]	3	3
University of Glasgow	UK	2001	Fire	[253]	[252]	3	3
University of Washington	US	2001	Eco-terrorism/Vandalism	[229]		2	2
British Antarctic Survey	UK	2001	Fire	[251]	[250]	2	5
United States Department of Agriculture	US	2001	Natural disaster	[245]		6	3
University of California, Irvine	US	2001	Technical malfunction	[234]	[235], [236], [237], [238], [239], [240]	3	4
University of California, Santa Cruz	US	2002	Technical malfunction	[271]	[268], [269], [270], [272], [273], [274], [275]	5	1
Texas A&M University, College Station	US	2003	Technical malfunction	[282]		2	2
University of Colorado, Boulder	US	2003	Technical malfunction	[278]		3	2
University of Nebraska, Lincoln	US	2003	Technical malfunction	[279]		1	0
University of Louisiana, Lafayette	US	2003	Technical malfunction	[277]		1	2
University of Southern California	US	2003	Technical malfunction	[283]	[280], [281]	1	1
Ohio State University, Columbus	US	2003	Technical malfunction	[276]		1	2
San Diego State University	US	2003	Natural disaster	[288]		1	1
University of Minnesota, Duluth	US	2004	Eco-terrorism/Vandalism	[310]	[308], [309], [311]	1	1
Eastern Illinois University	US	2004	Fire	[301]		2	1
Purdue University	US	2004	Fire	[307]		2	1
University of California, Davis	US	2004	Technical malfunction	[304]	[305]	1	7
University of Iowa	US	2004	Eco-terrorism/Vandalism	[306]		6	5
University of Hawaii, Manoa	US	2004	Natural disaster	[300]	[299]	4	2
University of Southampton	UK	2005	Technical malfunction	[329]	[328]	14	1

Affiliation of affected scientists	Country	Year	Type of adverse event	Key reference	Other references	Affected	Spared
Tulane University	US	2005	Natural disaster	[320]	[319], [321], [322], [323], [325], [326]	8	0
University of Sydney	AU	2005	Fire	[327]		1	0
Ohio State University, Columbus	US	2005	Technical malfunction	[315]	[316], [317]	1	3
University of Southern Mississippi	US	2005	Natural disaster	[324]	[318]	1	0
Indiana University-Bloomington	US	2005	Other	[330]	[331]	1	1
Duke University	US	2006	Fire	[349]		3	1
Mote Aquaculture Park	US	2006	Fire	[347]	[346]	1	1
Scripps Research Institute	US	2006	Fire	[338]	[339]	3	2
Jet Propulsion Laboratory	US	2006	Fire	[334]	[335]	1	2
University of New Mexico	US	2007	Natural disaster	[358]	[357]	3	2
University of Maryland Medical Center	US	2007	Fire	[362]	[359], [360], [361]	2	4
University of Hawaii, Manoa	US	2007	Fire	[364]	[363], [365]	4	2
University of Iowa	US	2008	Natural disaster	[383]		3	0
University of Illinois, Chicago	US	2008	Fire	[370]	[369], [371], [372]	8	0
Hasselt University	BE	2008	Eco-terrorism/Vandalism	[374]	[373]	2	1
University of Tennessee, Knoxville	US	2009	Fire	[394]		1	4
SLAC National Accelerator Laboratory	US	2009	Eco-terrorism/Vandalism	[388]		1	2
University of South Carolina	US	2009	Technical malfunction	[387]		2	3
University of California, Santa Cruz	US	2009	Fire	[389]		1	1
Southern Illinois University, Carbondale	US	2010	Fire	[401]	[397], [398], [399], [400]	2	5
Ohio State University, Columbus	US	2010	Natural disaster	[421]	[419], [420]	5	1
Virginia Institute of Marine Science	US	2010	Fire	[426]	[427]	1	0
University of Missouri, Columbia	US	2010	Other	[406]	[407], [408], [409]	1	7
Colorado State University	US	2011	Fire	[443]		2	3
Eastern Illinois University	US	2011	Eco-terrorism/Vandalism	[446]		2	3
Rutgers, The State University of New Jersey	US	2012	Natural disaster	[460]	[461]	1	1
Utah State University	US	2012	Other	[456]		3	3
New York University	US	2012	Natural disaster	[452]	[449], [450], [451], [453], [454]	8	1

Notes: The table provides basic information about the adverse events in our final sample. The referenced sources can be found in Appendix B.3. We distinguish between five different types of adverse events: natural disasters, eco-terrorist attacks/vandalism, fires, technical malfunctions, and other causes. These types are not all perfectly delineated between adverse events. For instance, a technical malfunction may be followed by a fire. In these cases, we give priority to the root cause of the adverse event. The category *Natural disaster* includes tornadoes, hurricanes, earthquakes, floods, oil spills, and natural wildfires. *Technical malfunction* refers to chemical explosions, crashes, gas leakages, pipe breaks, power outages, and essential HVAC (heating, ventilation, and air conditioning) system failures. The single category *Fire* refers to fires and heat damages that are not the consequence of one of the other event types. These fires typically have incidental (overheated oven, faulty light fixtures, etc.), external (e.g. fires starting from other buildings or surrounding) or unidentified causes. The category *Eco-terrorism/Vandalism* extends to intentionally destructive actions by non-scientists, such as arson and cyber-attacks. Finally, *Other* captures all remaining adverse events (e.g., due to human error or theft).

C Control Group Construction

The construction of our matched control group of scientists requires a series of common steps, which we briefly outline. First, we need to *disambiguate author names* as authors are often listed inconsistently in bibliographic databases (Sanyal et al., 2021). Second, it is necessary to *define a pool of potential controls* that balances two requirements: being large enough to increase the probability of finding matches, yet constrained enough to allow meaningful comparisons and feasible data construction. Third, we must *ensure comparable career trajectories* between treated and potential control scientists to address selective attrition in science and the fact that bibliographic information provides only an imperfect measure of an individual's career position at any given point in time (Liu et al., 2023). Fourth, we have to *match on productivity* indicators to determine the most similar control candidates for each treated scientist. Lastly, when multiple matches emerge for a given treated scientist, decision criteria are required to *rank and select* the best (i.e., most similar) control candidate.

Previous studies have approached the outlined steps in different ways. Most studies achieve the disambiguation and the identification of a pool of potential controls by cross-referencing scientists' publication profiles with faculty rosters and (online) CV information (e.g., Azoulay et al., 2010; Kahn and MacGarvie, 2016; Waldinger, 2012). This predominantly manual task requires a small and homogeneous group of scientists, delineated by research field, country, and professional achievements (e.g., grants, prizes). In these studies, treated and potential control scientists then originate from the same narrow population, already guaranteeing that career trajectories are comparable. Some other studies combine manual efforts with heuristic filters, such as minimum publication thresholds to exclude "accidental" researchers or staff members (Mohnen, 2022), and the removal of common names to aid disambiguation (Oettl, 2012). The final steps of matching productivity measures and selecting control candidates are typically performed using Coarsened Exact Matching (CEM), Nearest Neighbor matching (NNM), or similar methods.

We develop an automated process that builds upon existing approaches but also accommodates challenges specific to our context. In particular, the lab heads in our study, while all being accomplished senior scientists, vary substantially in their research focus, geography, and productivity. This results in a vast pool of potential controls that renders manual steps impractical and the link to external data (e.g., faculty rosters) next to impossible.

We therefore pursue the following fully automated steps (see the overview table below). We start with the entire population of authors in the *Scopus* database and implement a large-scale automatic disambiguation upstream. We then identify the pool of potential candidates

based on bibliographic characteristics within the population. We use CEM to match scientists on productivity indicators, narrowing down the sample of potential controls. Fourth, we automatically gather individual online CV information and parse it using a Large Language Model (LLM) to exclude control candidates on different career trajectories. Finally, we rank the remaining control candidates based on their career position and similarity to the respective lab head, selecting the top-ranked candidate as our matched control. We detail these steps in the following and conclude with a discussion of the robustness of our results to alternative methodological choices.

Control group construction – Overview

C.1 Publications data and author disambiguation

- Collect publications data and merge journal impact factor (JIF) and affiliation rank information
- Aggregate profiles with the same name and common coauthors
- Drop profiles with highly frequent names and ambiguous profiles
- Build author-year publication counts and information
- Exclude "accidental" researchers (with less than three publications)

C.2 Defining the pool of potential controls

- Affiliated to a comparable institution in the pre-treatment year
- Same research area as treated

C.2 Coarsened exact matching (CEM) on productivity indicators

- Similar age, based on first year of publication.
- Similar JIF-weighted publication stock
- Similar JIF-weighted publication summed count in $t-1$ and $t-2$
- Similar affiliation rank

C.3 Accounting for career trajectories

- Keep corresponding authors
- Keep controls with field or journal overlap
- Remove inadequate controls based on automatically parsed CV information

C.4 Ranking and selecting control candidates

- Prioritize controls with similar affiliation rank and career position
- Rank controls by similarity in productivity (nearest neighbor matching)
- Select the top-ranked control

C.5 Robustness checks

- Two instead of one top-ranked control candidate.
- No nearest-neighbor matching (NNM).
- No consideration of career position.
- Random draw among control candidates.
- CEM and NNM based on $t-5$ instead of $t-1$ productivity indicators.

C.1 Publications data and author disambiguation

We begin with the population of authors and scientific publications listed in Elsevier’s *Scopus* bibliographic database. We obtained the core data via the *Scopus* API in 2023. We complement the data with journal impact factor (JIF) information from the annual SCImago Journal Rank indicator.⁵³ Moreover, we link authors’ affiliations to the SCImago Institutions Ranking to capture their quality and type. As the rank of several institutions varies considerably across fields, we consider both general and field-specific ranks.

Although *Scopus* provides curated author identifiers, the disambiguation of individual scientists remains conservative.⁵⁴ To achieve a more comprehensive disambiguation, we automatically aggregate *Scopus* profiles based on the compatibility of names and coauthorship networks. To this end, we harmonize names (e.g., removing accents and diacritical marks), construct the network of direct coauthorships, and build the connected components, i.e., groups of profiles with at least one coauthor in common. Within each connected component, we identify *cliques* of profiles with compatible names (e.g., by accounting for middle names and initials). We then aggregate profiles within the same connected component that could be assigned to a unique clique. In other words, we assume that profiles with a compatible name and one coauthor in common belong to the same author. In line with prior literature, we drop profiles with highly frequent names that remain intractable or that could not be unambiguously aggregated.⁵⁵ A total of 1,437,859 profiles are aggregated into 672,769 new profiles. However, productive authors are more likely to have multiple profiles to be aggregated.⁵⁶

We then build aggregate publication counts and further information (affiliations, research fields, etc.) at the author-year level. At this stage, we drop authors with fewer than three publications over their career to exclude "accidental" authors.⁵⁷ The resulting dataset comprises a total of 14,991,240 authors, which forms the basis for our search for control authors.

⁵³The JIF information corresponds to the average number of citations received in a given year by articles published in the journal over the three preceding years. It extends back to the early 1990s; we extrapolate the rankings for publications before this period.

⁵⁴In most incorrect instances, multiple author identifiers are associated with a single scientist. The second type of error—where one identifier is linked to more than one scientist—is rare. In other words, precision is high at the expense of recall. Baas et al. (2020) estimate precision equal to 98.1% and recall equal to 94.4%. Note that, for our purpose, even one missing publication can be problematic as it can change the scientist’s academic age.

⁵⁵More precisely, we drop: i) all profiles in connected components larger than 1,500; ii) all profiles from cliques where one or more profiles have common coauthors in more than one clique. These are all extremely common names. A random draw is as follows: O’Connor, T; Guo, Y; Wang, C; Yoo, S; Gray, J; Tang, Y; Lam, K; Chen, C; Li, H; Kim, J. The number of profiles dropped due to high ambiguity is 3,988,117, roughly 8% of the initial sample.

⁵⁶Notably, in our final sample, about 13% of matched controls are linked to two or more aggregated profiles. Manual inspection of a random sample did not reveal any wrong aggregation.

⁵⁷All treated lab heads already have in the pre-treatment period three or more publications.

C.2 Defining the pool of potential controls

We define the pool of potential controls as scientists from the respective lab head’s cohort who are active in the same research area and at a research institution in a comparable country. This brings us closer to contexts in previous studies, which start from a more homogeneous population of scientists regarding research area and country of affiliation.

Specifically, we define the pool of potential controls relative to each lab head as all scientists that *exactly* match the following two criteria:

- at least one publication in the last pre-treatment year in which the respective lab head published (typically $t-1$, which we use for simplicity hereafter), with an affiliation in the academic or public sector in a selected number of countries,⁵⁸
- the same modal research area as the respective lab head, based on publications in the pre-treatment period.⁵⁹

Applying these criteria leaves, on average, 145,478 potential controls per lab head. This pool of potential controls is used in the subsequent coarsened exact matching step.

C.3 Matching on productivity

Following prior research (e.g., Azoulay et al., 2010; Mohnen, 2022; Oettl, 2012), we use Coarsened Exact Matching (CEM) (Iacus et al., 2018) to match each lab head to a narrower set of control candidates. This match is based on the following productivity indicators: i) the first year of publication, to proxy for academic age; ii) the stock of JIF-weighted publications in $t-1$, iii) the summed count of JIF-weighted publications in $t-1$ and $t-2$, and iv) the field-specific SCImago rank of the scientist’s latest affiliation in $t-1$. The first three variables are commonly used in previous studies. We add the last one to account for the heterogeneity in affiliations in our sample of treated lab heads.

These variables are coarsened along pre-specified percentile cutoffs (see Table C-1). Note that the percentile cutoffs can result in different cutoff values as the distribution of the matching

⁵⁸The countries are: United States, Belgium, Germany, Australia, France, Sweden, Canada, United Kingdom, Netherlands, Switzerland, Norway, Denmark, Luxembourg, Finland, Italy, Spain, Ireland, Austria, Portugal.

⁵⁹We assign publications to research areas based on the ASJC classification linked to journals in Scopus. The areas and associated ASJC codes are: Health (DENT, HEAL, MEDI, MULT, NURS, VETE), Life sciences (AGRI, BIOC, IMMU, NEUR, PHAR), Physical sciences (CENG, COMP, ENER, ENGI, ENVI, MATE), Natural sciences (CHEM, EART, MATH, PHYS), Social sciences (ARTS, BUSI, DECI, ECON, PSYC, SOCI). In several cases, more than one ASJC code is assigned to a journal; we pick the code corresponding to the area where the authors of papers in the journal publish the most.

variables is specific to the lab head’s cohort and research area. This accommodates the variation in publication counts across disciplines and the overall increase in publication numbers in recent decades.

Table C-1: Coarsened exact matching variables and cutoffs

Variable	Cutoffs
First year of publication	Interval: ± 2 years
JIF-weighted publication stock in $t-1$	Percentiles: 0, 5, 10, 25, 35, 50, 65, 75, 90, 95, 99, 100
JIF-weighted publication count for $t-1$ and $t-2$	Percentiles: 0, 10, 35, 50, 75, 90, 95, 100
Affiliation rank (field-specific) in $t-1$	Percentiles: 0, 5, 10, 35, 50, 75, 90, 95, 100

Notes: The interval and percentile cutoffs follow those used by Azoulay et al. (2010). The mass of 0s in the JIF-weighted summed publication count for $t-1$ and $t-2$ renders an additional cutoff at the 5th percentile meaningless.

In using both the stock and the most recent count of publications in the pre-treatment period, we follow the matching approach of Azoulay et al. (2010). The reason for considering the scientist’s productivity right before the adverse event is twofold. First, it ensures a closer match in the distribution of publications over the career life-cycle between treated lab heads and control candidates. Second, it mitigates attrition issues, considering that academic trajectories are susceptible to random negative shocks, including publication lags and funding delays, that can significantly impact careers (Petersen et al., 2012).

To avoid contamination of the control group, we follow prior literature and exclude scientists who may have been affected by the respective adverse event. First, we eliminate scientists who coauthor with the lab head. Second, we exclude those with the same affiliation or city as the lab head, as it cannot be ruled out that they were affected by the adverse event.

The results from the CEM are as follows: 424 out of the 427 lab heads have at least one control candidate within their respective stratum. The median size of these strata is 89, with the largest stratum containing 1,289 control candidates.

C.4 Accounting for career trajectories

After narrowing the pool of potential controls to a tractable sample, we conduct a more thorough screening based on additional data to ensure treated and control scientists are similar not only in productivity but also in their career trajectories.

Toward this goal, we consider further bibliographic information as indicators of career trajectories akin to those of our lab heads. First, we discard scientists who are never corresponding

authors and without a full first name.⁶⁰ Notably, this also aligns with the data generation process of our treated lab heads, where contact details and full names were crucial for inclusion in the sample. Additionally, we exclude a small number of scientists who do not show any publication activity in the adverse event year or any year after, which we take as evidence that they were no longer research active already at the time of the event.⁶¹ Finally, we remove scientists with a different modal research field (at ASJC code level) and no publication in a journal where also the respective lab head has published.⁶² This last indicator helps us identify researchers with a different, such as a more applied, research orientation compared to the treated lab heads, which likely indicates a different career trajectory.⁶³ This additional screening based on bibliographic information results in 418 lab heads with at least one control candidate, and a median size of the strata of 49, with the largest stratum containing 811 control candidates.

We further draw on CV information to construct indicators that are difficult to ascertain from bibliographic information alone. In particular, we seek to infer the control candidate's career position, empirical research involvement, and research activity in the adverse event year. First, for a similar level of seniority and responsibility, control candidates should occupy positions such as research professors, principal investigators, and senior researchers, excluding technicians, consultants, or research assistants. Second, control candidates should engage in empirical research, indicating a need for physical capital in their work. Finally, control candidates should have been active researchers in the year of the adverse event. We detail in the following how we collect CV information through internet search engine results and parse the relevant information using a large language model (LLM).

Collecting CV information

We collect search engine results by querying the control candidate's full name and affiliation in $t-1$, retaining the first 50 results.⁶⁴ The combination of full name and affiliation almost always identifies one scientist unambiguously, guaranteeing that we collect correct information for each scientist. We then repeat the search by adding "PhD" to the query, again keeping the first 50 results. This increases the chances of capturing information about the scientist's PhD

⁶⁰Virtually all authors listed only with initials in the database have never been corresponding authors.

⁶¹Note that all our treated lab heads show publication activity in the year of the adverse event and/or thereafter.

⁶²This is a stricter requirement than the previous selection of research areas, which involves data effort only possible with the contained sample.

⁶³To illustrate, biomedical scientists who publish in applied journals are more likely to turn to medical practice and abandon their scientific careers than biomedical scientists who publish in less basic research journals.

⁶⁴Note that we use a search engine that does not personalize search results; i.e., the same query leads to the same search results for the same query.

year. For approximately 5% of the control candidates, the number of results is less than 100, yet always more than zero. All results were collected in early 2024.

The collected search results consist of four fields: the website's host, web address, title, and snippet (see Table C-2 for an example). The title and snippet, limited to 60 and 400 characters, respectively, hold the most relevant information. While many search results are in English, there are also results in various foreign languages. To filter to results most likely containing CV information about the control candidate, we remove results where the control candidate's first/last name is not mentioned in any of the four fields.

Processing CV information

To parse and classify the relevant information, we send the search engine results of each control candidate via the *openAI* API to a *GPT-3.5* LLM. The collected text typically contains information sufficient to infer the control candidate's career characteristics. However, the information is too unstructured to permit parsing with standard Natural Language Processing tools and too vast for a manual approach. In contrast, LLMs can effectively extract data from large amounts of unstructured text (Korinek, 2023).

We design a prompt that allows the CV information to be parsed consistently and replicable. Following specific instructions in the prompt, the LLM model processes the results to determine the scientist's career position, involvement in empirical research, and research activity in the year of the adverse event. Figure C-1 details the prompt and parameters sent to the *openAI* API. We advise the model to use only the data from the provided search engine results. Additionally, we set the "temperature" parameter to zero, ensuring deterministic and consistent output.

The LLM responds with structured information as per our prompt instructions (see Table C-3 for example output). These responses are typically in a standardized format and require little further processing. Specifically, the model returns the scientist's academic or research position, yes/no answers regarding the scientist's involvement in empirical research and research activity in the adverse event year. Additionally, the model can list further information, including the scientist's birth year, PhD year, and the years the scientist held an assistant, associate, or full professor position, along with retirement and death years.

The completeness of the processed CV information varies across control candidates and depends mainly on the relevant search engine results. For instance, information on career positions is available for approximately 90% of control candidates, while indicators for empirical research involvement and research activity in the year of the adverse event are available for about 75% and 79% of control candidates, respectively.

Table C-2: Internet search engine results (example)

Host	Link	Title	Snippet
biology.ucdavis.edu	https://biology.ucdavis.edu/people/eric-sanford	Eric Sanford - UC Davis College of Biological Sciences	Home Faculty Eric Sanford Professor Evolution and Ecology 707-875-2040 edsanford@ucdavis.edu Lab website Google Scholar ORCID (0000-0001-9053-6826) Bodega Marine Lab, Box 247, Bodega Bay, CA 94923 Research Interests Marine community ecology. Climate change. Biogeography. Local adaptation. Regulation of geographic range limits.
stories.ucdavis.edu	https://stories.ucdavis.edu/stories/faculty/sanford.html	Eric Sanford UC Davis Stories	Location:Bodega Bay Impact:Preserving marine life Find more One California stories The California coastline is Eric Sanford's classroom. The evolution and ecology professor teaches students at the UC Davis Bodega Marine Laboratory, a world-class institution for research and education in coastal and marine sciences located in Bodega Bay, Calif.
researchgate.net	https://www.researchgate.net/profile/Eric-Sanford	Eric SANFORD Professor University of California, Davis, California ...	Eric SANFORD Professor University of California, Davis, California UCD Bodega Marine Laboratory Research profile Home University of California, Davis Bodega Marine...
sanford-lab.com	https://www.sanford-lab.com/eric-sanford	Eric Sanford Coastal Ecology and Evolution	Professor, UC Davis (2014-present) Associate Professor, UC Davis (2010-2014) Assistant Professor, UC Davis (2005-2010) Research Associate, Brown University (2002-2004) Post-doctoral Fellow, Stanford University (1999-2002) Ph.D., Zoology, Oregon State University (1999) B.A., Biology, Brown University (1990)
sanford-lab.com	https://www.sanford-lab.com/	Coastal Ecology and Evolution	Eric Sanford's lab in Coastal Ecology and Evolution at the University of California Davis, Bodega Marine Laboratory.
scholar.google.com	https://scholar.google.com/citations?user=jj9GNyQAAAAJ	Eric Sanford - Google Scholar	i10-index. 71. 63. Eric Sanford. Bodega Marine Laboratory, University of California Davis. Verified email at ucdavis.edu - Homepage. Ecology Evolution Biogeography Climate Change. Title.
sanford-lab.com	https://www.sanford-lab.com/current-lab	Current Lab Members Coastal Ecology and Evolution	ERIC SANFORD, PH.D. Professor of Evolution and Ecology Bodega Marine Laboratory P.O. Box 247 Bodega Bay, CA 94923 Email: edsanford "at" ucdavis.edu Graduate Students EMILY LONGMAN Ph.D. Student, Population Biology Graduate Group
researchgate.net	https://www.researchgate.net/scientific-contributions/Eric-Sanford-2147871720	Eric Sanford's research works University of California, Davis ...	Eric Sanford's 4 research works with 163 citations and 3,334 reads, including: Supplementary Material ... Eric Sanford's research while affiliated with University of California, Davis and other ...
cmsi.ucdavis.edu	https://cmsi.ucdavis.edu/blog/upwelling	What is Coastal Upwelling and Why is it Important?	This graphic from a 2011 publication by Eric Sanford and Morgan W. Kelly shows how coastal upwelling plumes (shown in purple) create a mosaic of variations in water temperature, ... John Largier is a Professor of Coastal Oceanography at the University of California Davis (UCD), resident at Bodega Marine Laboratory. Prior to 2004, he was ...
...	...	...	...

Notes: This table lists a subset of internet search engine results for a queried control candidate.

Table C-3: CV output of large language model (example)

Academic title	Research title	Birth year	PhD year	Assistant Prof. years	Associate Prof. years	(Full) Prof. years	Retirement year	Death year	Active researcher	Empirical researcher
Professor	Professor		1999	2005-2010	2010-2014	2014-present	–	–	YES	YES

Notes: This table lists the prompted CV output of the large language model for the control candidate mentioned in Table C-2.

Using the obtained indicators, we discard control candidates who are evidently inadequate matches according to four criteria: i) they were inactive researchers at the time of the relevant event, ii) their academic age, calculated from PhD and birth year, significantly deviates from expectations based on their publication record, iii) they passed away within four years after the adverse event, and iv) they are not empirical researchers. Importantly, we do not exclude control candidates simply because some of this information is unavailable.

Figure C-1: Prompt used to process internet search engine results via the openAI API

```

response = openai.ChatCompletion.create(
    model="gpt-3.5-turbo-1106",
    messages=[
        {"role": "system",
         "content": "You are a helpful, diligent, and precise data analyst with excellent background knowledge of
academia and the scientific community. Your task is to provide specific CV information for {
SCIENTIST_NAME} based on the provided text, which represents search engine results from 2024. These
results include truncated snippets instead of full sentences. YOU ONLY USE THE INFORMATION PROVIDED TO
YOU IN THE PROMPT; NO HALLUCINATION, NO UNREASONABLE SPECULATION. YOU PAY PARTICULAR ATTENTION TO
OBITUARIES! SCIENTISTS ARE WELL-KNOWN PEOPLE, AND THEIR PASSING IS OFTEN PUBLICLY REPORTED. YOU READ
THE ENTIRE TEXT AND THE INSTRUCTIONS TWICE AND THINK HARD WHAT YOU CAN INFER FROM COMBINING
INFORMATION. WRITE N/A IF YOU CANNOT ANSWER."},
        {"role": "assistant",
         "content": 'Based on the information provided by the user, please create a CV for {SCIENTIST_NAME} with
the following simple structure. Provide the following CV information of {SCIENTIST_NAME}:
academic_title: Provide the highest generic academic position or job title of {SCIENTIST_NAME}. Do not
specify the subject or department details. Examples: PhD, assistant professor, associate
professor, (full) professor, chair, director, dean,...
research_title: Provide the highest generic otherwise research-related position or job title of {
SCIENTIST_NAME}. Examples: scientist, senior scientist, research group leader, principal
investigator,...
birth_year: Provide the birth year (YYYY) of {SCIENTIST_NAME}.
phd_year: Provide the PhD year (YYYY) of {SCIENTIST_NAME}.
assist_prof_years: Provide the range of years (YYYY-YYYY) in which {SCIENTIST_NAME} was an assistant
professor.
assoc_prof_years: Provide the range of years (YYYY-YYYY) in which {SCIENTIST_NAME} was an associate
professor.
full_prof_years: Provide the range of years (YYYY-YYYY) in which {SCIENTIST_NAME} was a (full)
professor.
retirement_year: Provide the retirement year (YYYY) of {SCIENTIST_NAME} (if applicable).
death_year: Provide the death year (YYYY) of {SCIENTIST_NAME} (if applicable).
active_researcher: Confirm with YES or NO whether {SCIENTIST_NAME} was an active researcher in {
EVENT_YEAR}.
empirical_researcher: Confirm with YES or NO whether {SCIENTIST_NAME} conducts empirical research.'},
        {"role": "user", "content": all_data},
    ],
    temperature=0.0,
    max_tokens=300,
    top_p=0.5,
    frequency_penalty=0,
    presence_penalty=0,
    n=1,
    request_timeout=8,
    seed=1234
)

```

Notes: This figure provides the *Python* code detailing the prompt and the parameters sent to the *openAI* API. Note that {SCIENTIST_NAME} and {EVENT_YEAR} are global variables specific to the respective control candidate. The variable all_data refers to the respective concatenated search engine results.

Our approach to gathering and processing online CV information raises some potential concerns. First, LLMs can hallucinate and generate incorrect information. However, setting parameters to avoid any creativity taken by the model and precisely structuring the prompt minimizes this risk. Second, stereotypical bias from the model’s training data may influence how it interprets information (e.g., women are less likely to be associated with a senior career position). However, providers of LLMs appear to mitigate such biases proactively. In fact, upon manually reviewing a subset of responses against the search results, we find no evidence of hallucination or bias. Finally, a recency bias might arise from using search engine results because they tend to emphasize more current information and are more detailed for accomplished and active scientists. However, by design, more comprehensive CV information results rather in a control candidate’s exclusion than their inclusion. Notably, the manual reconstruction of the treated lab heads’ careers followed a similar approach, relying on internet-based CV information. Indeed, when applying the same method of processing CV information with the LLM for the treated sample, we find very consistent results overall.

C.5 Ranking and selecting controls

To select the most similar control candidate for each lab head, we rank all remaining 32,440 control candidates in the respective strata based on bibliographic and CV information.

First, we prioritize control candidates who meet certain conditions, but we do not exclude those who fail to satisfy them. In this way, we can consider important binary characteristics without enforcing their strict fulfillment, which could eliminate all control candidates for lab heads with small strata. These conditions are i) the same coarsened (general) rank of the affiliation in $t-1$ and the same coarsened (field-specific) rank of the earliest affiliation (which typically corresponds to the scientist’s PhD institution), ii) a senior academic or otherwise research-related position, iii) empirical research engagement, and iv) research activity in the year of the adverse event.

Second, in the frequent case where two or more control candidates fulfill the above conditions, we determine their rank through nearest-neighbor matching (NNM). Specifically, we calculate the Mahalanobis distance between the treated lab head and the control candidates. The variables that enter the distance measure are as follows: i) the JIF-weighted and simple publication summed counts for $t-1$ and $t-2$, ii) the share of last-author publication in $t-1$ and $t-2$, iii) the average JIF per publication in $t-1$ and $t-2$, iv) the average number of coauthors per publication. Taking into account the Mahalanobis distance, the resulting rank for each control candidate becomes unique.

Finally, we select the top-ranked control for the matched control group in each stratum. We thereby impose that each matched control be assigned to only one lab head. If a control candidate is the top-ranked candidate for multiple lab heads, we assign them to the earliest treated lab head and select the next-ranked candidate for the other lab heads. Altogether, we obtain a matched control for 418 out of 427 lab heads.

C.6 Robustness checks

In the following, we briefly discuss the robustness of our main results to the use of differently constructed control groups. We construct five control group variants in total, each representing an alternative approach to a key methodological decision made in our preferred matching strategy. These variants are as follows:

1. Two instead of one top-ranked control candidate.
2. No nearest-neighbor matching (NNM).
3. No consideration of career position.
4. Random draw among control candidates.
5. CEM and NNM based on $t-5$ instead of $t-1$ productivity indicators.

We can replicate our main result, the persistent negative effect of adverse events on research output, with all five control groups (see Appendix F.5 for the bivariate and multivariate results). That said, the effect dynamics in the treatment period, vary with the chosen control group. For instance, using the control group randomly drawn from the control candidates leads to visibly smaller negative effects.

Notably, the common pre-trend condition is satisfied even for the control group based on $t-5$ productivity characteristics. The research output of the affected lab heads only diverges from the counterfactual after the event year.⁶⁵ This suggests that our matching approach selects valid controls that provide a counterfactual productivity path for the treated lab heads.

We can further assess the validity of our preferred control group and the alternative control groups by drawing on the sample of spared lab heads. Under the assumption that the spared lab heads have "placebo" status, i.e., they remained unaffected by the adverse event, any divergence between their productivity and that of their respective controls after the adverse event would signal a suboptimal control group construction. Indeed, we find no negative effect for the spared lab heads with any of the control groups. Instead, the more we deviate from our

⁶⁵Note that matching on $t-5$ productivity indicators results in the omission of lab heads who started their career not long before the adverse event.

preferred matching strategy, the more the spared lab heads' productivity diverges positively from their controls. This can be interpreted as a bias that renders the estimated effect on the affected lab heads conservative.

Taken together, the results of these robustness checks suggest that the main findings of our paper do not hinge on a particular methodological choice in our control group construction.

Alternative matching approach with manually curated information

The described control group construction approach is fully automatic, guaranteeing a high level of objectivity and replicability. However, it is computationally demanding as it requires accessing and processing large-scale publications data and online information. Moreover, despite the notable performance of LLM in parsing unstructured information, the resulting CV information is unlikely to have the same level of precision and completeness attainable through manual efforts. A major limitation is that the LLM only considers search engine results instead of full CV documents, web pages, acknowledgments in scientific publications, PhD theses, and other potential sources.

Our results are robust to a substantially different matching approach, which is less computationally demanding and entails manual steps.⁶⁶ In this approach, we rely on an open-source software (Rose and Baruffaldi, 2020) to scan the universe of authors in the online Scopus database. For each lab head, we find control candidates in the same research field, with similar scientific productivity and first year of publication, within a limited period before the treatment (10 years). We then rank these candidates in ascending order based on their average difference to the lab head in productivity indicators. Starting from the top-ranked candidate, we perform the following steps manually: we disambiguate the candidate's author profile, build the productivity indicators for the entire pre-treatment period, and collect additional CV information. We select the control candidate if deemed adequate in light of the additional information. Otherwise, we move to the next-ranked candidate and repeat the manual steps until we find an adequate control candidate.

⁶⁶This matching approach is implemented and described in the working paper version (2021) of this article.

D Lab Head and Damage Descriptives

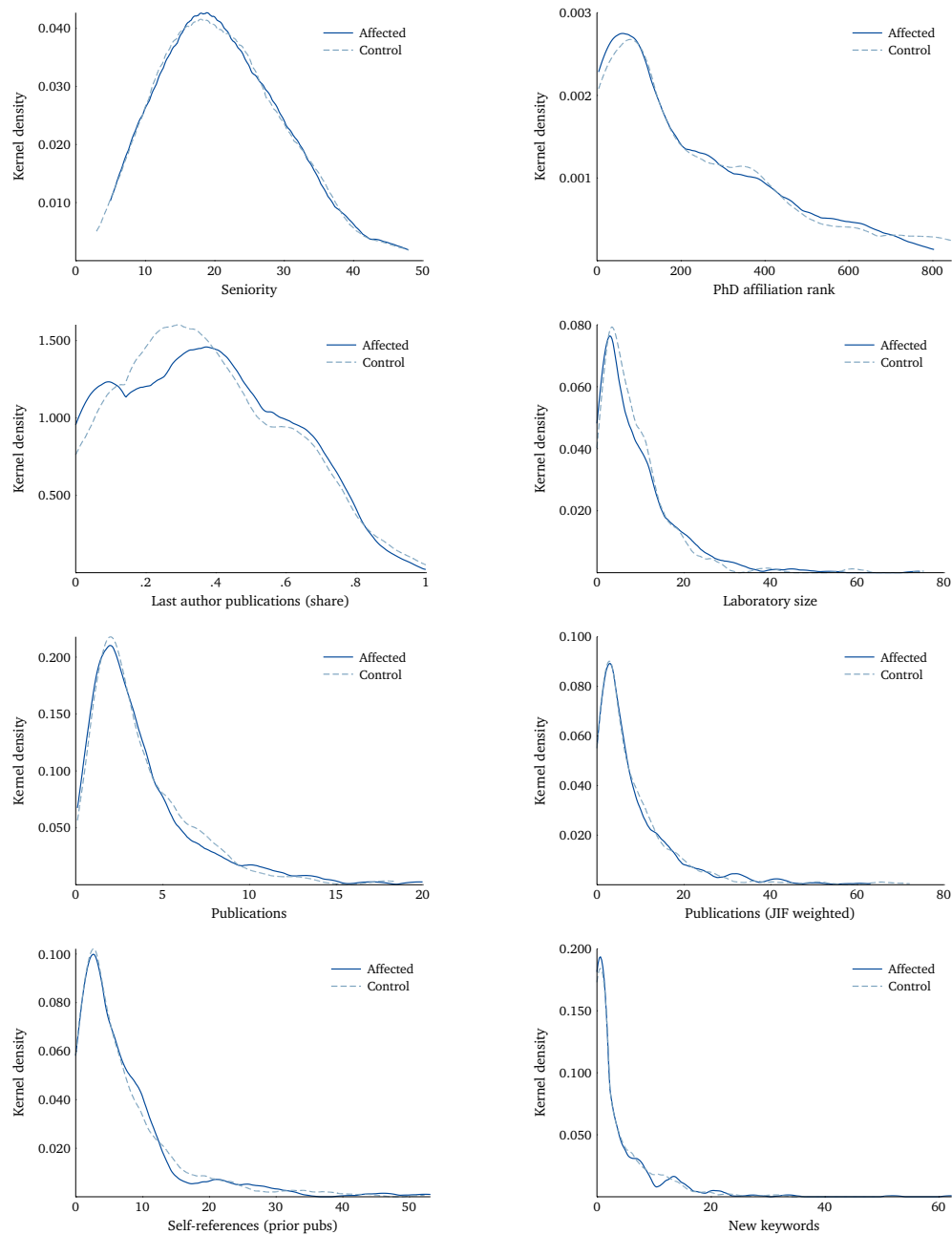
D.1 Lab head descriptives

Table D-1: Pre-event characteristics of spared lab heads with matched controls

Spared vs Control	Spared (N = 174)			Controls (N = 174)			Diff.	p-value
	Mean	Median	Std. Err.	Mean	Median	Std. Err.		
Seniority	20.23	20.00	9.64	20.12	19.50	9.62	−0.11	0.916
Male	0.83	1.00	0.37	0.82	1.00	0.39	−0.02	0.673
PhD affiliation rank	201.81	156.00	188.05	242.50	165.00	237.24	40.69	0.077*
Affiliation rank	318.22	369.00	231.07	315.54	289.00	224.70	−2.68	0.913
Affiliation expenses (\$ mio)	155.78	133.52	133.18	180.06	118.60	214.40	24.28	0.293
External funding (\$ mio)	0.16	0.02	0.41	0.15	0.00	0.62	0.00	0.983
Laboratory age	12.55	10.50	9.04	12.92	10.00	9.45	0.37	0.719
Laboratory size	8.07	5.10	8.03	7.75	5.60	7.94	−0.32	0.709
Empirical publications (share)	0.41	0.39	0.20	0.43	0.44	0.21	0.03	0.245
Last author publications (share)	0.32	0.30	0.23	0.34	0.33	0.25	0.03	0.289
Publications	3.66	2.70	3.18	3.73	2.85	2.92	0.07	0.837
Publications (JIF weighted)	7.65	5.09	7.63	7.89	4.97	8.70	0.24	0.784
References	113.56	86.35	90.05	106.27	84.63	77.72	−7.30	0.419
Self-references (prior pubs)	6.74	4.53	7.43	7.39	4.67	8.55	0.64	0.454
Keywords	4.18	1.73	6.33	3.92	1.64	5.48	−0.27	0.673
New keywords	3.83	1.73	5.65	3.50	1.50	4.81	−0.33	0.555

Notes: This table presents summary statistics of pre-event characteristics of spared lab heads and their matched control group. The unit of observation is at the scientist level. Reported p -values based on an unpaired t -test. Significance levels: * $p < 0.1$, ** $p < 0.05$.

Figure D-1: Distributions of pre-event characteristics of affected and control lab heads



Notes: The graphs present the kernel densities of several pre-event characteristics of affected and control lab heads. The unit of observation is at the scientist level.

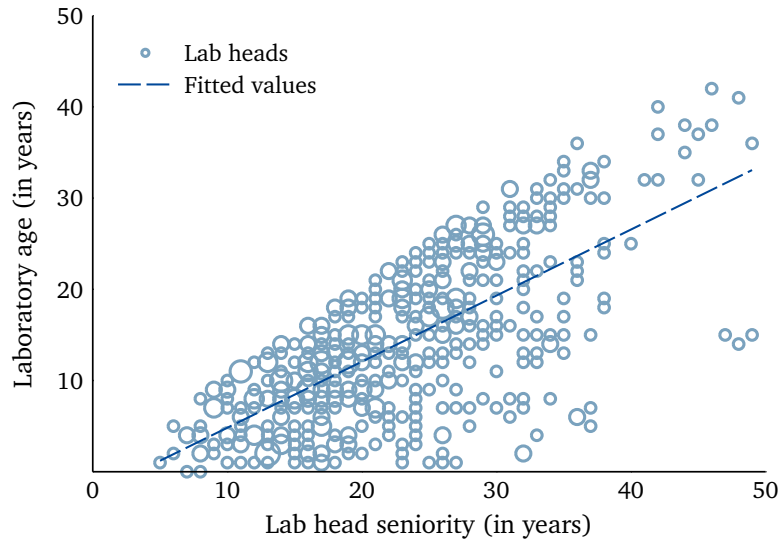
D.2 Laboratory damage descriptives

Table D-2: Pairwise correlations of affected lab head and adverse event characteristics

Affected	(1)	(2)	(3)	(4)	(5)	(6)
(1) Affiliation rank	1.000					
(2) Lab head seniority	−0.112*	1.000				
(3) Laboratory age	0.017	0.650***	1.000			
(4) Laboratory size	−0.146**	0.119*	0.021	1.000		
(5) Damage extent (in USD)	0.000	−0.054	−0.023	0.093	1.000	
(6) Loss of specialized capital	−0.063	0.053	0.056	0.036	0.364***	1.000

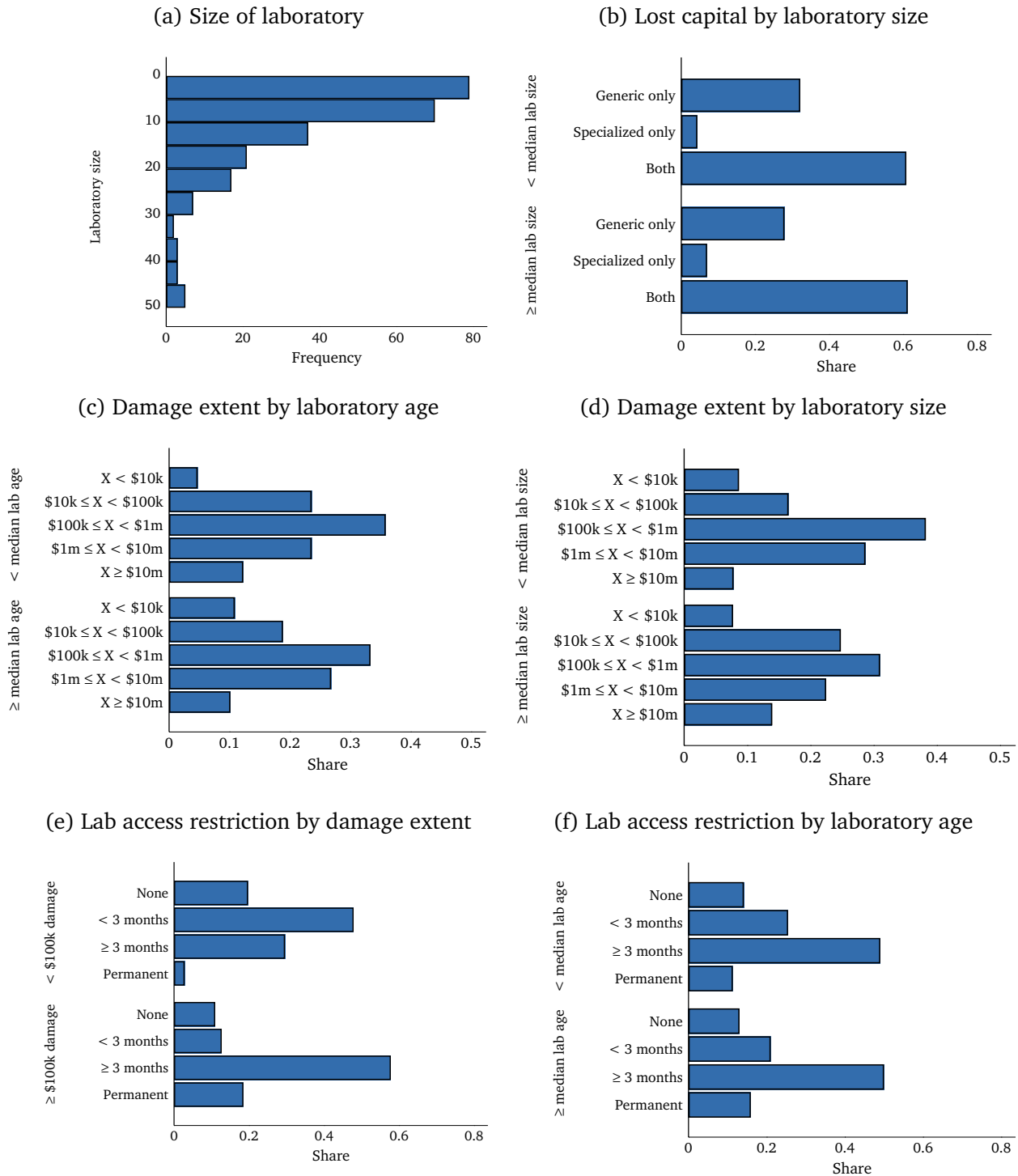
Notes: This table presents pair-wise correlations of affected lab head and adverse event characteristics. The unit of observation is at the scientist level. Significance levels: ** $p < 0.05$, *** $p < 0.01$.

Figure D-2: Relationship between laboratory age and lab head seniority



Notes: The graph presents the distributions of laboratory age and lab head seniority in years. The unit of observation is at the scientist level. The sample consists of all affected lab heads.

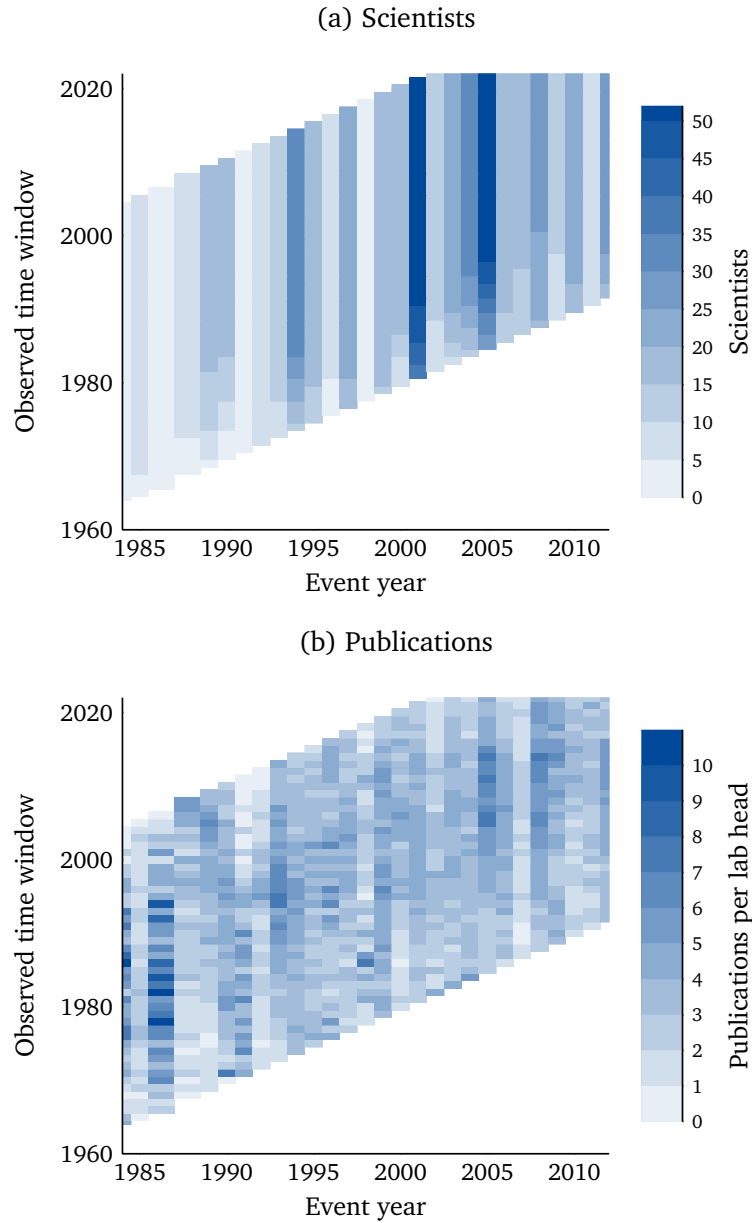
Figure D-3: Damage caused by adverse events



Notes: This figure illustrates the heterogeneity in laboratory damage due to adverse events. The unit of observation is at the laboratory (i.e., lab head) level.

D.3 Panel descriptives

Figure D-4: Panel distributions by event cohort

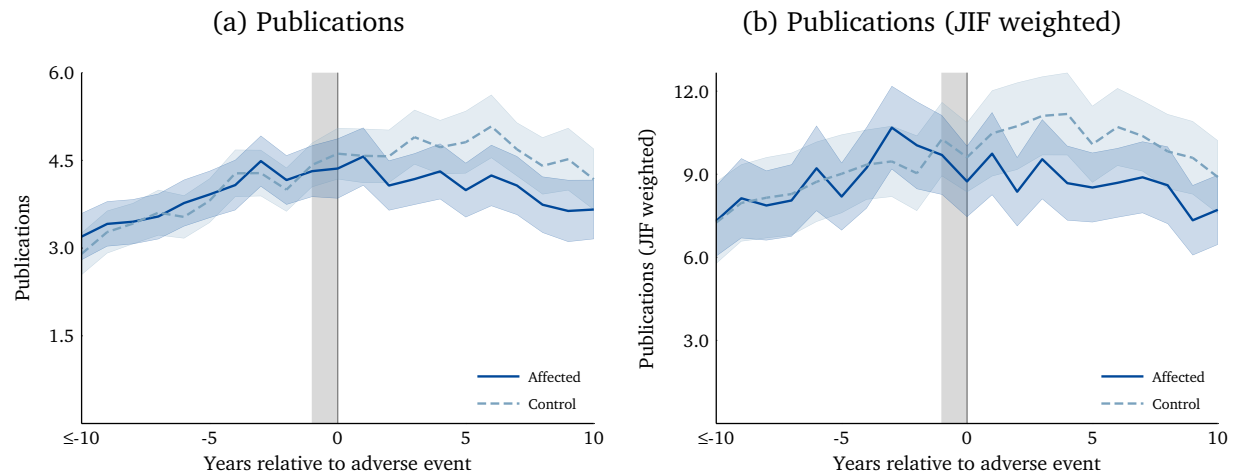


Notes: The two graphs present panel densities in terms of the number of observed lab heads and their publications by event year. Window of observation censored at 20 years before the event. The sample consists of all affected lab heads and their respective controls.

E Further Results

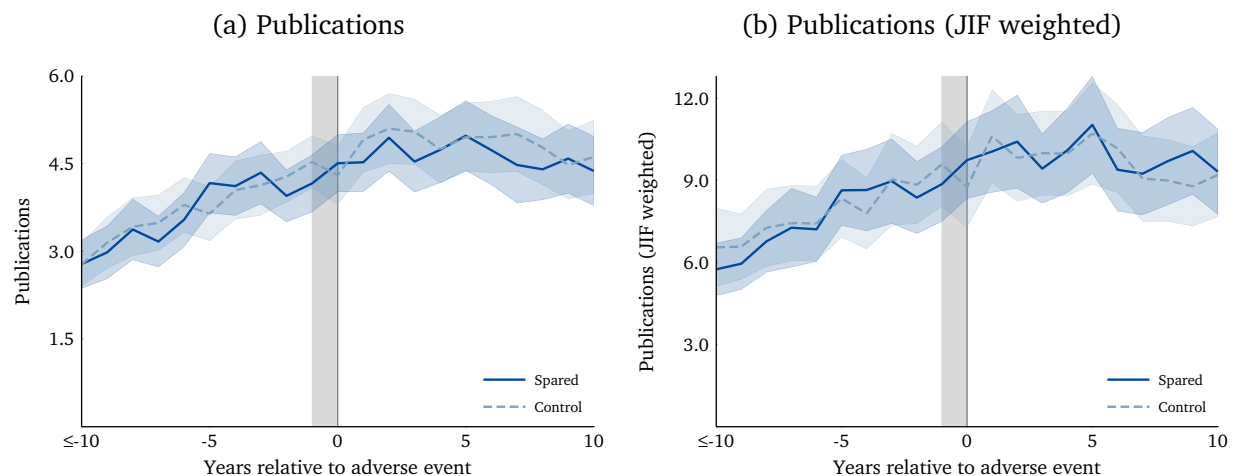
E.1 Bivariate analysis

Figure E-1: Research output of affected and control lab heads over time



Notes: The two graphs present the average annual research output of affected and control lab heads up to ten years before and after the adverse event. Research output is measured by simple publication counts (*Publications*) in Figure E-1a and by impact-weighted publication counts (*Publications (JIF weighted)*) in Figure E-1b. Both variables are log-transformed to account for their right-skewed distribution. The sample consists of all affected lab heads and their respective controls. Confidence intervals are at the 95% level.

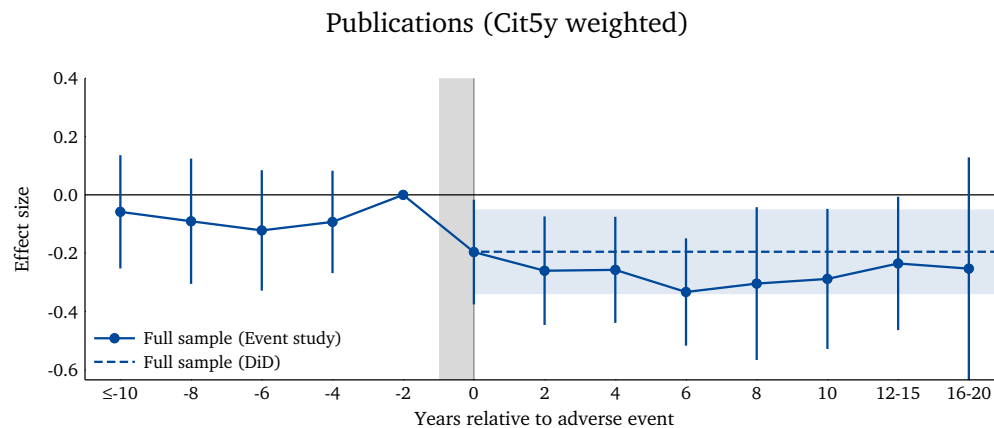
Figure E-2: Research output of spared and control lab heads over time



Notes: The two graphs present the average annual research output of affected and control lab heads up to ten years before and after the adverse event. Research output is measured by simple publication counts (*Publications*) in Figure E-2a and by impact-weighted publication counts (*Publications (JIF weighted)*) in Figure E-2b. The sample consists of all spared lab heads and their respective controls. Confidence intervals are at the 95% level.

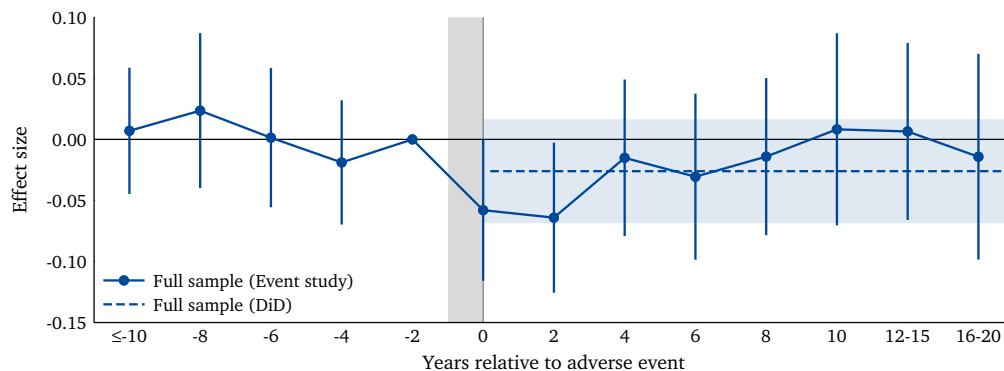
E.2 Research output

Figure E-3: Impact of adverse events on research output - Event study and DiD estimates



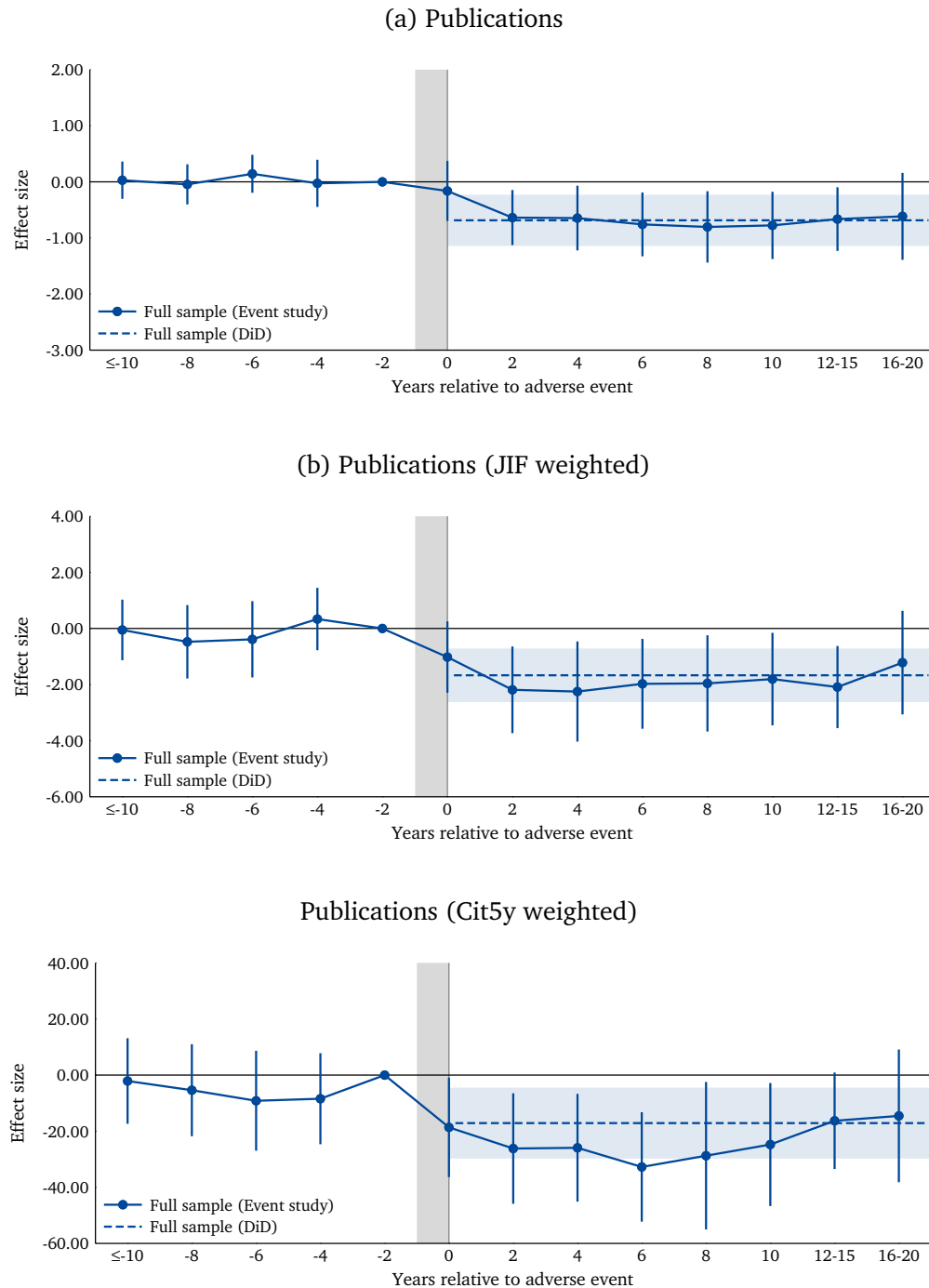
Notes: The graph presents point estimates of the interactions of the variable *Affected* with binned event year dummies (Event study), and with a binary variable that takes a value of one from the adverse event year onward (DiD). The dependent variable is the publication count weighted by the number of citations received within five years after publication (*Publications (Cit5y weighted)*). The sample consists of all affected lab heads and their respective controls. The coefficients correspond to the ones reported in Appendix Table E-1 (Event study) and Appendix Table E-2 (DiD). Confidence intervals are at the 95% level.

Figure E-4: Impact of adverse events on share of last author publications



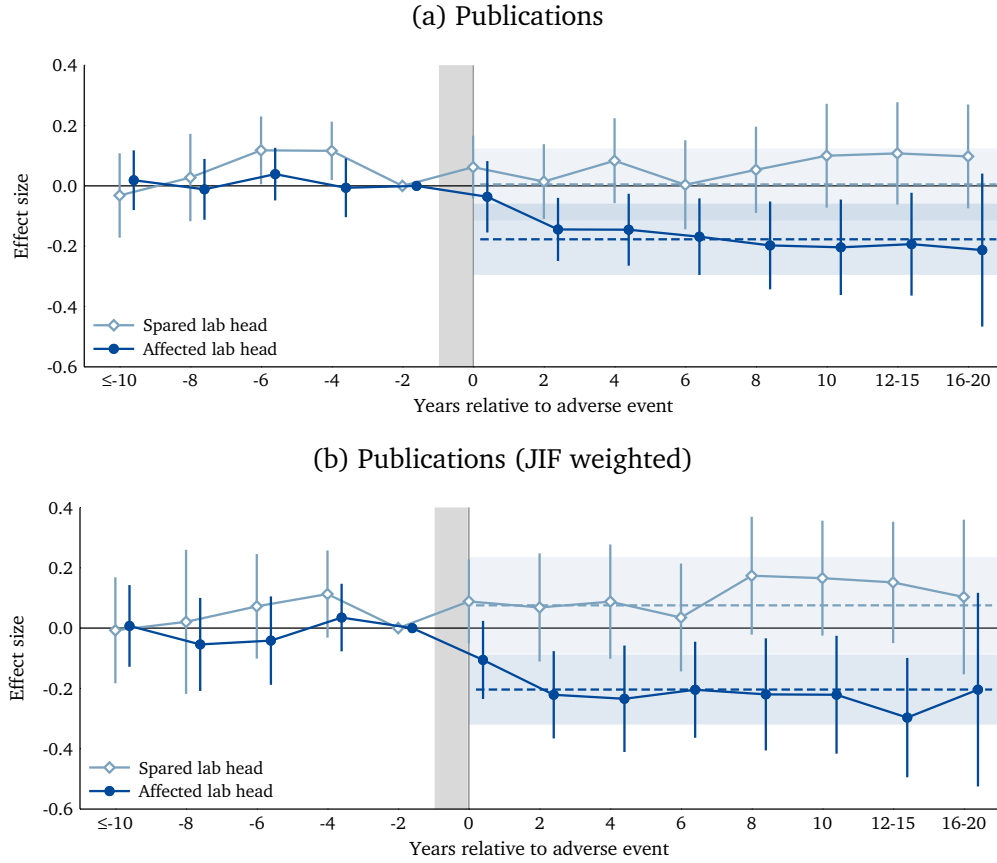
Notes: The graph presents point estimates of the interactions of the variable *Affected* with binned event year dummies (Event study), and with a binary variable that takes a value of one from the adverse event year onward (DiD). The dependent variable is the share of publications that list the respective lab head as last author relative to all publications (*Share of last author publications*). The sample consists of all affected lab heads and their respective controls. Confidence intervals are at the 95% level.

Figure E-5: Impact of adverse events on research output – Event study and DiD estimates – dependent variable non-transformed



Notes: The six graphs present OLS point estimates of the interactions of the variable *Affected* with binned event year dummies (Event study), and with a binary variable that takes a value of one from the adverse event year onward (DiD). The dependent variable is either the simple publication count (*Publications*) or the impact-weighted publication count (*Publications (JIF weighted)*). The sample consists of all affected lab heads and their respective controls. The coefficients correspond to those reported in Appendix Table E-1 (Event study) and Appendix Table E-2 (DiD). Confidence intervals are at the 95% level.

Figure E-6: Impact of adverse events on research output – Event study and DiD estimates



Notes: The two graphs present point estimates of the interactions of the variable *Affected* with binned event year dummies (Event study), and with a binary variable that takes a value of one from the adverse event year onward (DiD). The dependent variable in Figure F-2c is the simple publication count (*Publications*), and in Figure F-2d it is the impact-weighted publication count (*Publications (JIF weighted)*). The sample consists of all affected lab heads and their respective controls. Confidence intervals are at the 95% level.

Table E-1: Impact of adverse events on research output

Affected vs Control	(1)	(2)	(3)	(4)	(5)	(6)
	Publications		Publications (JIF weighted)		Publications (Cit5y weighted)	
	Poisson	OLS	Poisson	OLS	Poisson	OLS
Affected						
× ≤ −10	0.019 (0.051)	0.029 (0.168)	0.007 (0.069)	−0.052 (0.545)	−0.058 (0.099)	−2.103 (7.692)
× −8	−0.011 (0.051)	−0.045 (0.180)	−0.054 (0.079)	−0.475 (0.660)	−0.091 (0.110)	−5.387 (8.266)
× −6	0.039 (0.044)	0.143 (0.170)	−0.041 (0.075)	−0.386 (0.685)	−0.122 (0.105)	−9.158 (8.979)
× −4	−0.006 (0.050)	−0.027 (0.212)	0.035 (0.057)	0.336 (0.561)	−0.093 (0.090)	−8.422 (8.182)
× −2	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)
× 0	−0.036 (0.060)	−0.162 (0.270)	−0.106 (0.066)	−1.020 (0.641)	−0.196** (0.092)	−18.627** (8.939)
× 2	−0.144*** (0.053)	−0.637** (0.247)	−0.221*** (0.074)	−2.186*** (0.779)	−0.260*** (0.095)	−26.170*** (9.929)
× 4	−0.145** (0.061)	−0.645** (0.291)	−0.234*** (0.090)	−2.249** (0.900)	−0.257*** (0.093)	−25.912*** (9.685)
× 6	−0.169*** (0.065)	−0.758*** (0.287)	−0.204** (0.081)	−1.973** (0.808)	−0.333*** (0.094)	−32.738*** (9.835)
× 8	−0.197*** (0.074)	−0.803** (0.321)	−0.220** (0.095)	−1.958** (0.865)	−0.304** (0.134)	−28.738** (13.249)
× 10	−0.204** (0.081)	−0.776** (0.302)	−0.221** (0.100)	−1.804** (0.832)	−0.288** (0.123)	−24.747** (11.055)
× 12-15	−0.193** (0.087)	−0.664** (0.286)	−0.297*** (0.101)	−2.089*** (0.738)	−0.235** (0.117)	−16.286* (8.672)
× 16-20	−0.213 (0.129)	−0.615 (0.391)	−0.204 (0.164)	−1.217 (0.931)	−0.253 (0.195)	−14.539 (11.925)
Matched group × Event year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16770	18878	16548	18878	16472	18878
Scientists	488	488	488	488	488	488
Events	102	102	102	102	102	102
log likelihood	−32914	−42098	−51210	−61154	−322958	−106780

Notes: Columns (1), (3), and (5) show the estimates of Poisson pseudo-maximum likelihood regressions with high-dimensional fixed effects, the other columns show the estimates of linear regressions. All models in are specified as in Equation E1. The dependent variable is the simple publication count (*Publications*) in columns (1) and (2), the impact-weighted publication count (*Publications (JIF weighted)*) in columns (3) and (4), and the 5-year citation weighted publication count (*Publications (Cit5y weighted)*) in columns (5) and (6). The baseline year is t−2. The sample consists of all affected lab heads and their respective controls. Robust standard errors clustered at the adverse event level shown in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E-2: Impact of adverse events on research output

Affected vs Control	(1)	(2)	(3)	(4)	(5)	(6)
	Publications		Publications (JIF weighted)		Publications (Cit5y weighted)	
	Poisson	OLS	Poisson	OLS	Poisson	OLS
Affected $\times$ post	-0.177*** (0.060)	-0.685*** (0.230)	-0.204*** (0.059)	-1.669*** (0.482)	-0.195*** (0.074)	-17.118*** (6.373)
Matched group $\times$ Event year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13180	13998	13084	13998	13026	13998
Scientists	488	488	488	488	488	488
Events	102	102	102	102	102	102
log likelihood	-26875	-32461	-40821	-45621	-280531	-80763

Notes: Columns (1), (3), and (5) show the estimates of Poisson pseudo-maximum likelihood regressions with high-dimensional fixed effects, the other columns show the estimates of linear regressions. All models are specified as in Equation E2. The dependent variable is the simple publication count (*Publications*) in columns (1) and (2), the impact-weighted publication count (*Publications (JIF weighted)*) in columns (3) and (4), and the 5-year citation weighted publication count (*Publications (Cit5y weighted)*) in columns (5) and (6). The sample consists of all affected lab heads and their respective controls. Robust standard errors clustered at the adverse event level shown in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E-3: Impact of adverse events on research output – scientific impact

Affected vs Control	(1)	(2)	(3)	(4)	(5)
	Publications (by scientific impact)				
	Bottom 50%	Top 50%	Top 25%	Top 10%	Top 5%
Affected $\times$ post	-0.157* (0.085)	-0.193*** (0.067)	-0.243*** (0.079)	-0.401*** (0.107)	-0.334*** (0.097)
Matched group $\times$ Event year FE	Yes	Yes	Yes	Yes	Yes
Observations	11680	10482	7472	4286	2638
Scientists	488	488	456	400	336
Events	102	102	99	90	81
log likelihood	-20235	-16652	-10329	-4994	-2769

Notes: Columns (1) to (5) show the estimates of Poisson pseudo-maximum likelihood regressions with high-dimensional fixed effects. The models are specified as in Equation E2. The dependent variable (*Publications (by scientific impact)*) is the publication count in the respective part of the scientific impact distribution (i.e., the number of citations received within five years of publication). The quality distribution is stratified by decade. The sample consists of all affected lab heads and their respective controls. Robust standard errors clustered at the adverse event level are shown in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E-4: Impact of adverse events on research output – damage heterogeneity

Affected/Spared vs Control	(1)	(2)	(3)	(4)	(5)
	Publications				
Damage:	None (spared)	X<\$100k	\$100k≤X<\$1m	\$1m≤X<\$10m	\$10m≤X
Affected × post	0.005 (0.061)	0.057 (0.115)	−0.273** (0.127)	−0.349*** (0.080)	−0.140 (0.092)
Matched group × Event year FE	Yes	Yes	Yes	Yes	Yes
Observations	9454	3878	4562	3338	1402
Scientists	348	142	168	124	54
Events	79	45	50	34	8
log likelihood	−19482	−7470	−9285	−6621	−3351

Notes: Columns (1) to (5) show the estimates of Poisson pseudo-maximum likelihood regressions with high-dimensional fixed effects. The models are specified as in Equation E2. The dependent variable is the simple publication count (*Publications*). The baseline is the pretreatment period. The sample consists of: spared lab heads and their respective controls (Column (1)); affected lab heads with monetary damage below \$100k and their respective controls (Column (2)); affected lab heads with monetary damage between \$100k and \$1m and their respective controls (Column (3)); affected lab heads with monetary damage between \$1m and \$10m and their respective controls (Column (4)); and affected lab heads with monetary damage of \$10m or more and their respective controls (Column (5)). Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E-5: Impact of adverse events on research output – author position

Affected vs Control	(1)	(2)	(3)	(4)
	Publications (by author position)			
	First	Middle	Last	Last (share)
Affected × post	0.000 (0.118)	−0.246*** (0.079)	−0.182** (0.080)	−0.026 (0.022)
Matched group × Event year FE	Yes	Yes	Yes	Yes
Observations	6600	10596	11068	9466
Scientists	484	486	488	488
Events	102	102	102	102
log likelihood	−10930	−27678	−27957	82

Notes: Columns (1) to (3) show the estimates of Poisson pseudo-maximum likelihood regressions with high-dimensional fixed effects. Column (4) shows the estimate of a linear regression with high-dimensional fixed effects. The models are specified as in Equation E2. The dependent variables in Columns (1) to (3) are the simple publication count (*Publications*) restricted, respectively, to publications that list the lab head as first author, middle author, or last author. The dependent variable in Column (4) is the proportion of last-author publications in all publications. Robust standard errors clustered at the adverse event level are shown in parentheses. The event study estimates for the respective dependent variables can be found in Appendix Figure F-1. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

E.3 Alternative mechanisms

In the following, we explore whether alternative mechanisms can account for the permanent reduction in research output. Specifically, we assess the relevance of three potential channels: career changes, changes in human capital input, and reputational damage.

Career changes

Adverse events may compel the affected lab heads to leave academia, retire prematurely, or move to institutions with less favorable research conditions. While official exits to the industry are rare occurrences in our data, many lab heads cease to publish in the twenty years following the adverse event, which we broadly categorize as retirement from research.

We find the share of affected lab heads who retire within twenty years after the adverse event to be strictly larger than for the matched control group in each year (see Figure E-7). Notably, when examining spared lab heads and their matched control groups, we do not observe this difference in shares, which suggests that the prior finding is not a result of how our control group is constructed. At the same time, we find no significant difference in the cumulative share of affected lab heads and control lab heads moving to another institution.

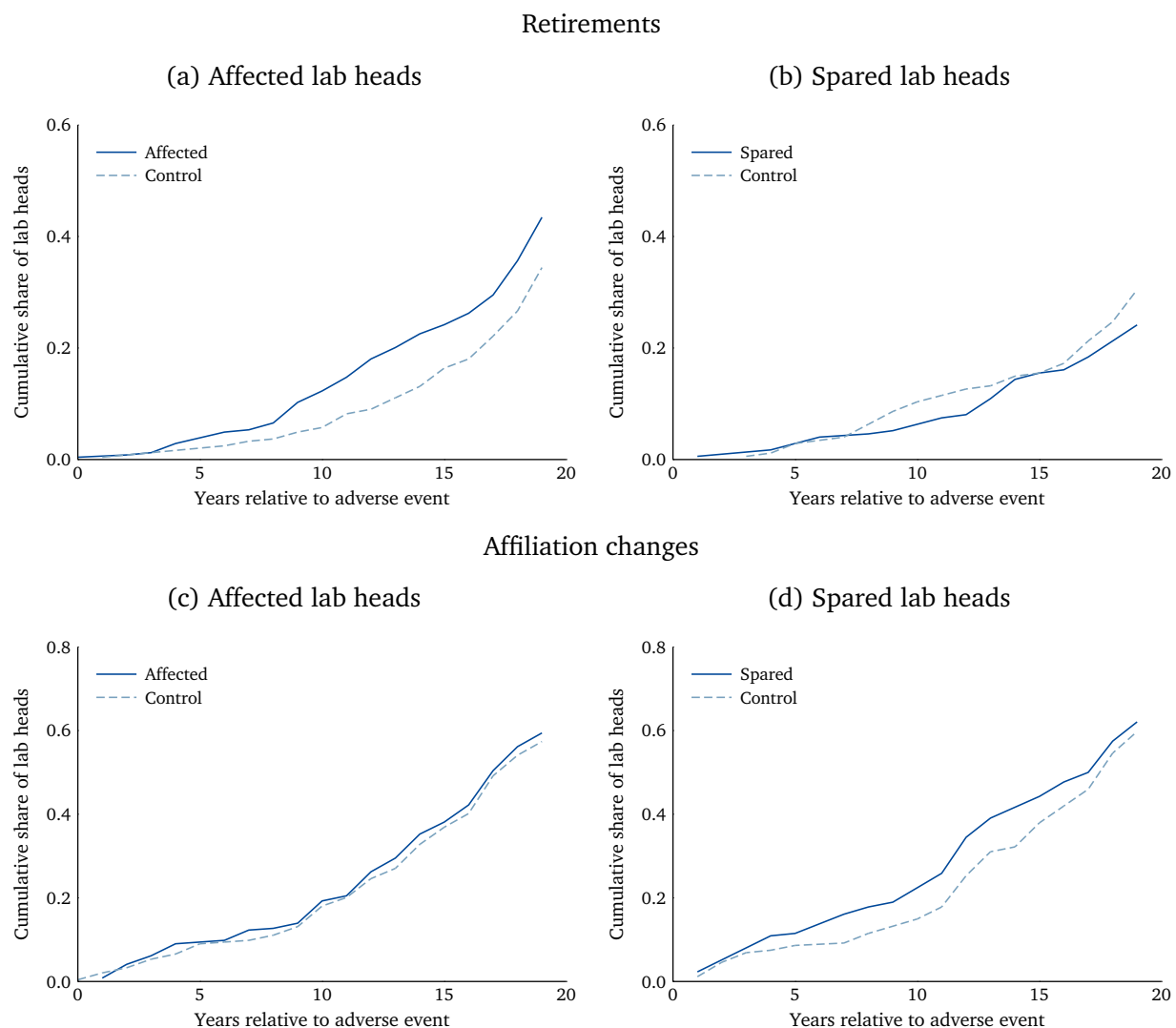
Examining the effect of adverse events on career events in our DiD setup, we can confirm the positive effect on retirements (see Table E-6). Furthermore, we find that although the overall probability of moving to another institution is comparable between affected and control lab heads, affected lab heads are more likely to transition to an institution with a lower ranking than their previous one.

Table E-6: Impact of adverse events on career events

Affected vs Control	(1) Retirement	(2)	(3) Move		(4)
		All	Better ranked	Worse ranked	
Affected $\times$ post	0.035** (0.017)	0.013 (0.024)	−0.010 (0.018)		0.031* (0.018)
Matched group $\times$ Event year FE	Yes	Yes	Yes		Yes
Observations	13998	13998	13998		13998
Scientists	488	488	488		488
Events	102	102	102		102
log likelihood	6248	4745	8123		8259

Notes: Columns (1) to (4) show the estimates of linear regressions with high-dimensional fixed effects. The models are specified as in Equation E2. *Retirement* is defined as the last year of publication activity within our time frame. *Move* is defined as a change in affiliation. Both dependent variables are binary and remain 1 in the years afterward. The sample consists of all affected lab heads and their respective controls. Robust standard errors clustered at the adverse event level shown in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

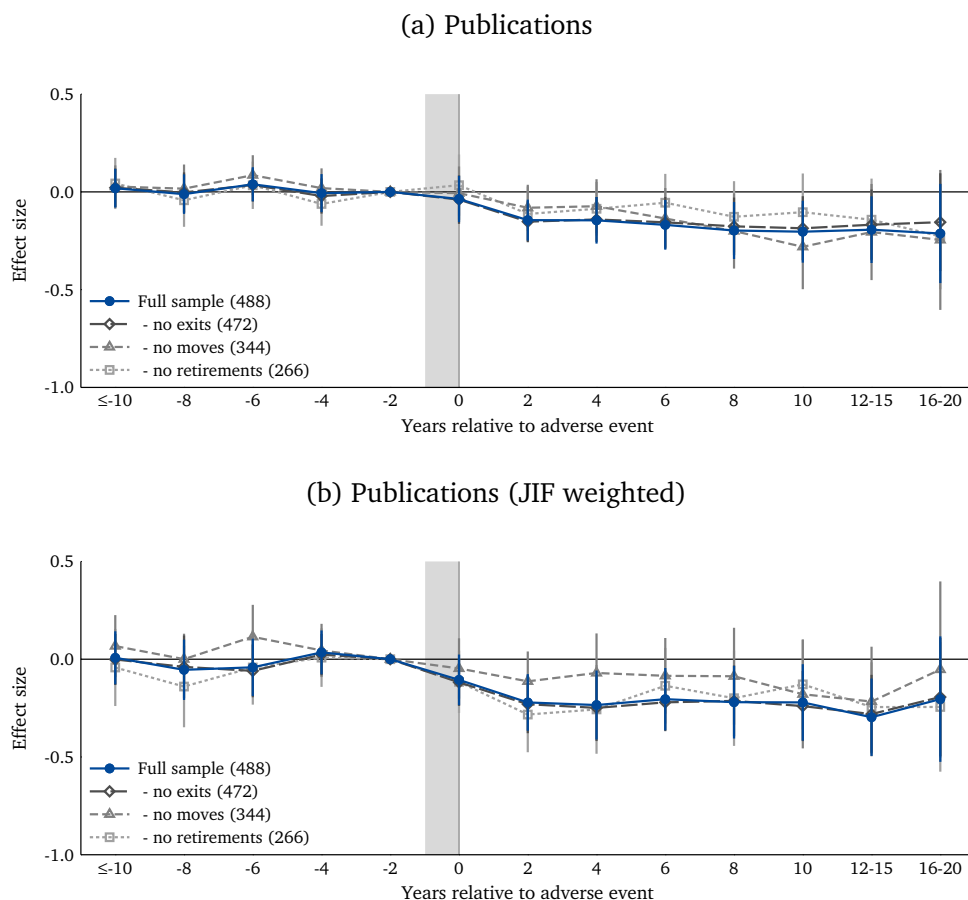
Figure E-7: Retirements and moves of affected/spared and control lab heads



Notes: This figure plots the share of retirements and affiliation changes for affected/spared and control lab heads. Retirement is defined as the last year of publication. Only the first affiliation change after the adverse event is considered.

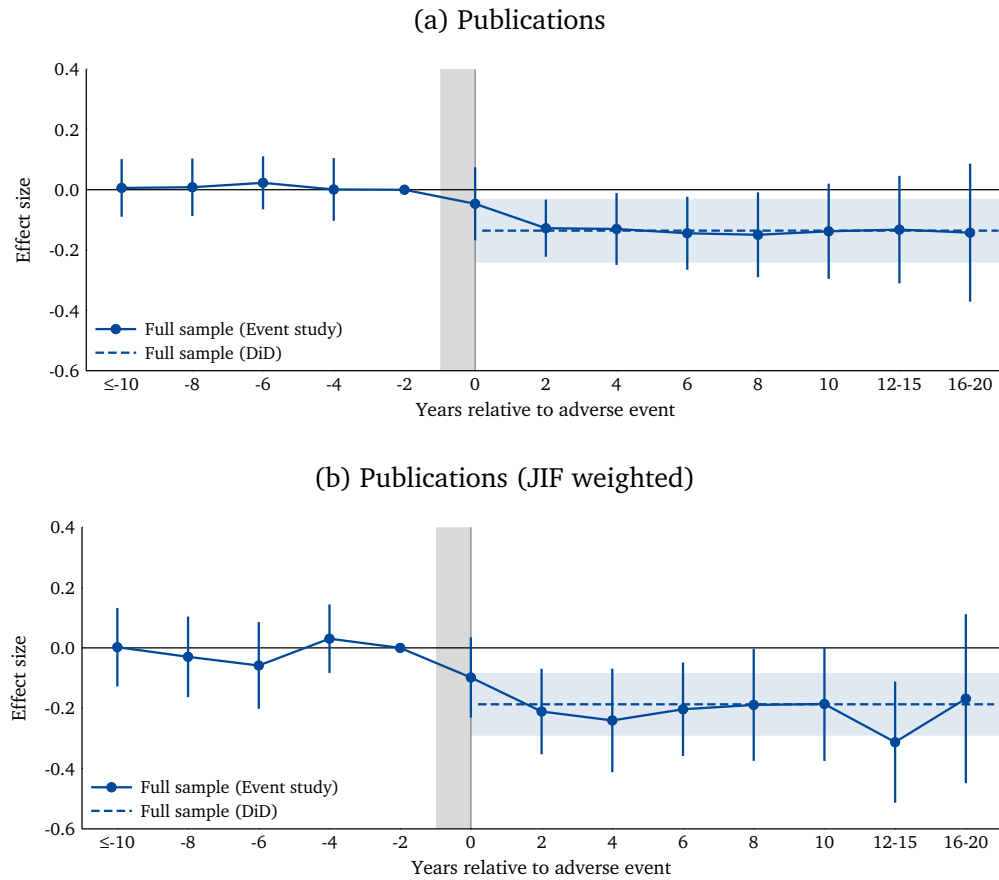
To investigate whether the higher likelihood of career changes explains the permanent reduction in research output, we repeat our main analysis with subsamples that exclude lab heads who experience career exit, affiliation change, or retirement. The dynamic treatment effects resemble those of our main analysis (see Figure E-8). Furthermore, we estimate the intensive margin effect on research output in the full sample by setting all scientist-year observations with zero publications missing. The resulting dynamic effects look practically identical to the ones with the corresponding unmodified dependent variable (see Figure E-9). Together, these results suggest that career moves alone do not fully account for the long-term effects on research output.

Figure E-8: Impact of adverse events on research output – Event study estimates – career outcome subsamples



Notes: The graphs present point estimates of the variable *Affected* interacted with binned event year dummies. Each graph plots the estimates of the full sample of affected lab heads and their respective controls, and three subsamples that exclude an increasing number of lab heads depending on their career outcome in the post-treatment period: exits (e.g., an observed move to industry), moves (change in the primary affiliation) and retirements (last year of publication before the end of the post-treatment time window). The coefficients correspond to those reported in Appendix Table E-7. Confidence intervals are at the 95% level.

Figure E-9: Impact of adverse events on research output (intensive margin) – Event study and DiD estimates



Notes: The two graphs present point estimates of the interactions of the variable *Affected* with binned event year dummies (Event study), and with a binary variable that takes a value of one from the adverse event year onward (DiD). The dependent variable in Figure E-9a is the simple publication count (*Publications*), and in Figure E-9b the impact-weighted publication count (*Publications (JIF weighted)*). All scientist-year observations with zero (impact-weighted) publications are set missing. The sample consists of all affected lab heads and their respective controls. Confidence intervals are at the 95% level.

Table E-7: Impact of adverse events on research output – career subsamples

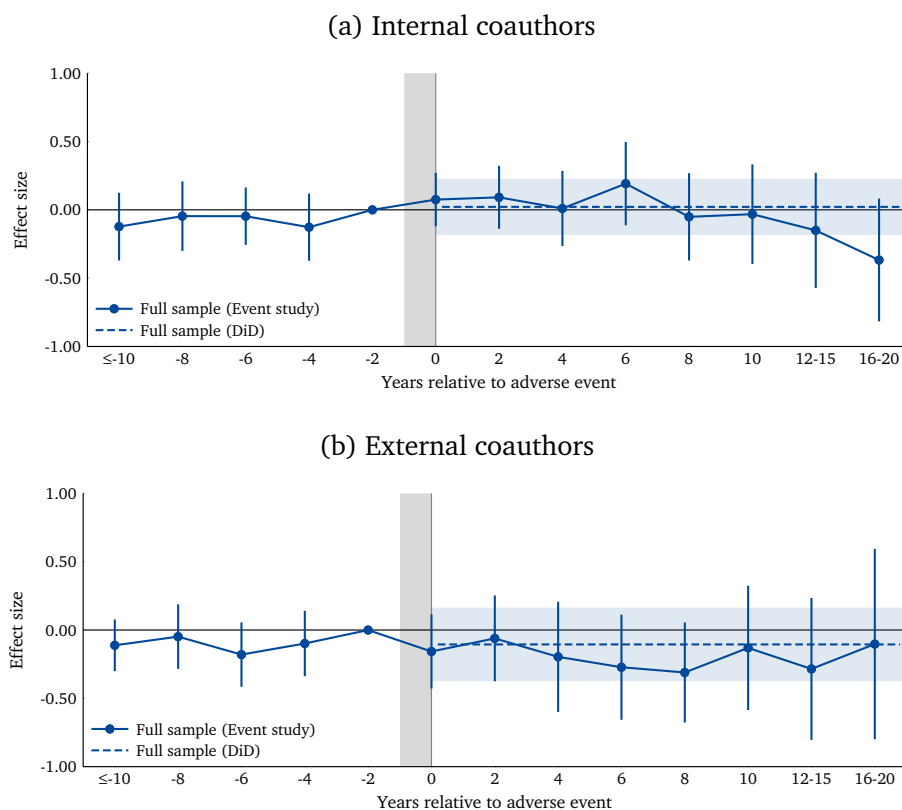
Affected vs Control	(1)	(2)	(3)	(4)	(5)	(6)
	Publications			Publications (JIF weighted)		
Sample:	No exits	No moves	No retirements	No exits	No moves	No retirements
Affected						
× ≤ −10	0.021 (0.050)	0.028 (0.055)	0.043 (0.067)	−0.001 (0.067)	0.067 (0.081)	−0.042 (0.101)
× −8	−0.003 (0.052)	0.017 (0.063)	−0.043 (0.069)	−0.039 (0.082)	0.000 (0.066)	−0.140 (0.106)
× −6	0.036 (0.043)	0.086* (0.052)	0.034 (0.062)	−0.060 (0.069)	0.115 (0.083)	−0.042 (0.097)
× −4	−0.021 (0.046)	0.019 (0.052)	−0.062 (0.057)	0.023 (0.054)	0.045 (0.069)	0.008 (0.076)
× −2	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)
× 0	−0.039 (0.063)	−0.007 (0.070)	0.034 (0.080)	−0.118* (0.062)	−0.047 (0.079)	−0.116 (0.081)
× 2	−0.152*** (0.054)	−0.081 (0.060)	−0.113 (0.072)	−0.230*** (0.076)	−0.113 (0.078)	−0.283*** (0.098)
× 4	−0.141** (0.059)	−0.073 (0.070)	−0.086 (0.070)	−0.249*** (0.087)	−0.070 (0.103)	−0.257** (0.116)
× 6	−0.156** (0.066)	−0.136* (0.080)	−0.055 (0.075)	−0.221*** (0.075)	−0.085 (0.099)	−0.136 (0.099)
× 8	−0.176** (0.075)	−0.200** (0.098)	−0.127 (0.093)	−0.213** (0.092)	−0.087 (0.126)	−0.199 (0.124)
× 10	−0.186** (0.084)	−0.281** (0.111)	−0.104 (0.101)	−0.240*** (0.091)	−0.179 (0.141)	−0.129 (0.118)
× 12-15	−0.168* (0.092)	−0.205 (0.125)	−0.142 (0.107)	−0.281*** (0.103)	−0.216 (0.143)	−0.245** (0.117)
× 16-20	−0.155 (0.128)	−0.246 (0.183)	−0.228* (0.138)	−0.194 (0.154)	−0.053 (0.230)	−0.244 (0.169)
Matched group × Event year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16206	11874	9628	15992	11736	9496
Scientists	472	344	266	472	344	266
Events	100	80	71	100	80	71
log likelihood	−31864	−23106	−19756	−49644	−35177	−32100

Notes: Columns (1) to (6) show the estimates of Poisson pseudo-maximum likelihood regressions with high-dimensional fixed effects. All models are specified as in Equation E1. The dependent variable is the simple publication count (*Publications*) in columns (1) to (3) and the impact-weighted publication count (*Publications (JIF weighted)*) in columns (4) to (6). The baseline year is t−2. Each sample excludes an increasing number of lab heads depending on their career outcome in the post-treatment period: exits (e.g., an observed move to industry), moves (change in the primary affiliation) and retirements (last year of publication before the end of the post-treatment time window). Robust standard errors clustered at the adverse event level shown in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Changes in human capital input

We further investigate whether the adverse events cause changes in the human capital input related to the affected lab heads' research output. To this end, we examine whether the average number of internal and external coauthors per publication changes for the affected lab heads after the adverse event (see Figure E-10). Overall, we find no evidence of such changes in human capital input: the average number of internal or external coauthors per publication remains fairly constant, exhibiting statistically insignificant effects of 0.03 for internal and 0.11 for external coauthors. While these findings speak against major changes in human capital input, they are not entirely conclusive because they rely only on human capital input that resulted in published research output. Furthermore, the findings do not rule out that coauthors' *quality* may have been affected by the adverse event (e.g., the lab head cannot attract the same talented PhD students as previously).

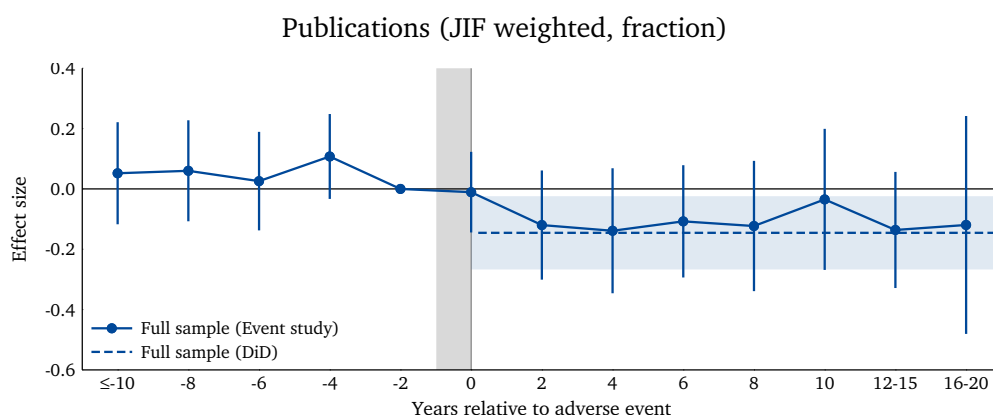
Figure E-10: Impact of adverse events on coauthors per publication – Event study and DiD estimates



Notes: The two graphs present OLS point estimates of the interactions of the variable *Affected* with binned event year dummies (Event study), and with a binary variable that takes a value of one from the adverse event year onward (DiD). The dependent variables are the average number of internal coauthors per publication and the average number of external coauthors per publication. The sample consists of all affected lab heads and their respective controls. Confidence intervals are at the 95% level.

To account for possible changes in human capital input, we examine the effect on an adjusted measure of research output: fractional publications. We create this variable by dividing each impact-weighted publication by its number of authors. Adverse events retain a significant negative effect on research output, which is slightly smaller in magnitude (-0.16) but equally stable over time (see Figure E-11). The average treatment effect is slightly smaller in magnitude (-0.16) but equally stable over time. This implies that decreases in labor input explain the effect's size to some degree; however, they fall short when it comes to explaining the effect's persistence.

Figure E-11: Impact of adverse events on research output - Event study and DiD estimates



Notes: The graph presents point estimates of the variable *Affected* interacted with binned event year dummies (Event study) and of the variable *Affected* interacted with a binary variable that equals one from the adverse event year onward (DiD). The dependent variable is the impact-weighted publication count weighted by the inverse of the author count (*Publications (JIF weighted, fraction)*). The sample consists of all affected lab heads and their respective controls. Confidence intervals are at the 95% level.

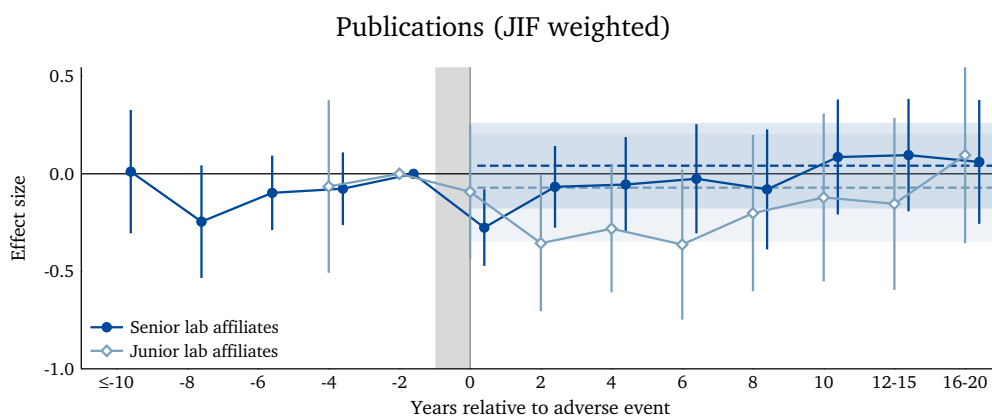
A related question concerns the general impact of adverse events on the productivity of other researchers affiliated with the affected lab. Initially, it is unclear whether the research output of these lab affiliates would be more or less affected in the long term. On the one hand, being subordinate to the lab head might make their research careers more susceptible to negative productivity shocks and financial distress. On the other hand, these lab affiliates might depend less on the lab head's physical capital stock and have greater mobility to move to a different lab for their research activities.

While a comprehensive analysis of the impact on lab affiliates is beyond the scope of this study, we provide an initial examination of how their productivity is affected by the adverse event. To this end, we focus on 1,106 (1,059) scientists who have co-published with the re-

spective affected (control) lab head and shared the same specific affiliation the year before the adverse event. We deem that these scientists were still affiliated with the lab when the adverse event occurred. To account for the different positions these lab affiliates likely held, we distinguish between juniors (with an academic age of 4 or fewer years) and seniors (with an academic age of 5 or more years). Mirroring our analysis for the lab heads, we examine the research output of the affected and control lab affiliates in an event study design.

We find that lab affiliates are less affected by adverse events than their respective lab heads (see Figure E-12). For junior as well as senior lab affiliates, we observe a statistically significant negative effect on research output shortly after the adverse event. However, the annual research output for both groups converges back to the counterfactual level, with seniors recovering faster than juniors.

Figure E-12: Impact of adverse events on research output of lab affiliates - Event study and DiD estimates



Notes: The graph presents point estimates of the variable *Affected* interacted with binned event year dummies (Event study) and of the variable *Affected* interacted with a binary variable that equals one from the adverse event year onward (DiD). Junior (senior) lab affiliates are those with an academic age of 4 or fewer (5 or more) years. The dependent variable is the impact-weighted publication count (*Publications (JIF weighted)*). The sample consists of scientists affiliated with the affected lab heads or their respective controls in the year before the adverse event. Observations are weighted by the inverse number of affiliates per lab head. Confidence intervals are at the 95% level.

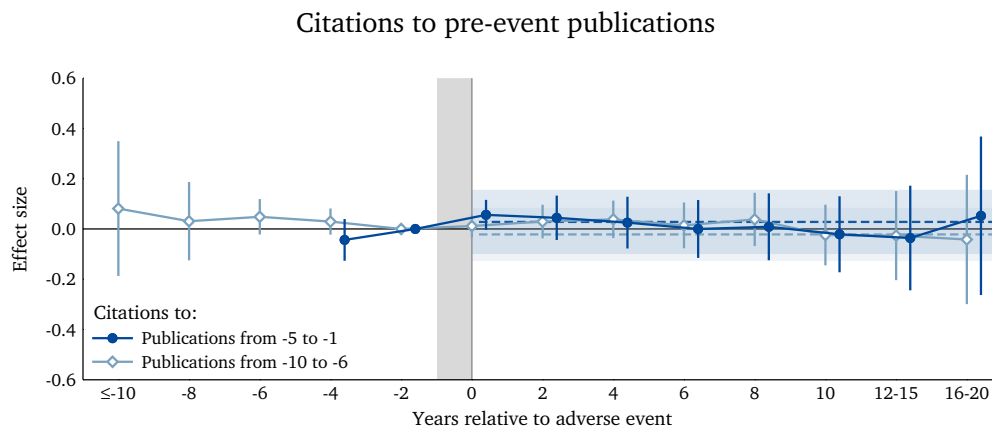
Reputational damage

The involvement in an adverse event may negatively affect the reputation of affected lab heads in the scientific community, with implications for their (accredited) research output (cf. Merton, 1968). If an adverse event reduces a lab head's reputation among their peers, we would expect to observe a "citation penalty" on their research output—regardless of whether it relates to the work published before or after the adverse event.

In line with prior literature (Azoulay et al., 2014), we focus on citations of publications from the pre-event period to isolate reputational effects from quality-related ones. We distinguish between two sets of publications: those published 10 to 6 years before the adverse event and those published 5 to 1 years before the event. We focus on non-self citations; i.e., citations that originate from publications not (co-)authored by the focal lab head. In this context, a decline in the number of citations of such publications in the years following the adverse event would indicate a negative reputational effect.

We find that the citation patterns of pre-event publications remain statistically indistinguishable between affected and control lab heads (see Figure E-13). This renders reputational damage an unlikely driver of the long-term effect on research output. Indeed, quotes from our primary sources suggest that affected lab heads experienced solidarity from colleagues and the scientific community at large.

Figure E-13: Impact of adverse events on citation trends



Notes: The graph presents point estimates of the variable *Affected* interacted with binned event dummies (Event study) and of the variable *Affected* interacted with a binary variable that equals one from the adverse event year onward (DiD). The dependent variable is the annual count of citations that pre-event publications receive (*Citations to pre-event publications*). Citations originating from the lab head's own publications are excluded. The sample consists of all affected lab heads and their respective controls. Confidence intervals are at the 95% level.

E.4 Research direction

In this section, we examine the effect of adverse events on the lab heads' research direction for the full sample. In Figure E-14, we report linear regression estimates for the effect of adverse events on *Self-references (share)*, *New keywords (share)* and *Abstract similarity*, respectively. All pre-event estimates are statistically insignificant and close to zero.

We find a large and significant effect of adverse events on research direction as measured by the share of self-references. The coefficients turn all negative after the adverse event, with most of them statistically significant ($p\text{-value} < 0.05$). Relative to the control lab heads, the share of self-references of affected lab heads declines on average by -0.011 in the post-treatment period. The effect is overall significant and seems persistent. Given a mean share of self-references of about 0.04, this decrease is an economically sizable effect. The publications of affected lab heads include fewer references to the own prior work, suggesting a change in research direction after the physical capital loss. We further find a significant change in direction when using abstract similarity as a measure of research direction changes. The effect is strongest within the first 5 years period and sees some convergence in the later periods.

The decline in self-references and abstract similarity possibly conflates topic- and method-related changes in research. The lab head may refer less to their prior work solely because the new research output is based on different equipment and material than the research output in prior publications. We therefore draw on an additional measure of research direction: the share of new keywords. This measure should reflect actual changes in research topics.

The effect on the share of new keywords is positive, but becomes marginally significant only 6 to 8 years after the adverse event. Relative to the control lab heads, the share of new keywords of affected lab heads increases on average by 0.022 in the post-treatment period. This effect is statistically insignificant and small in size given the average share of new keywords is about 0.9.

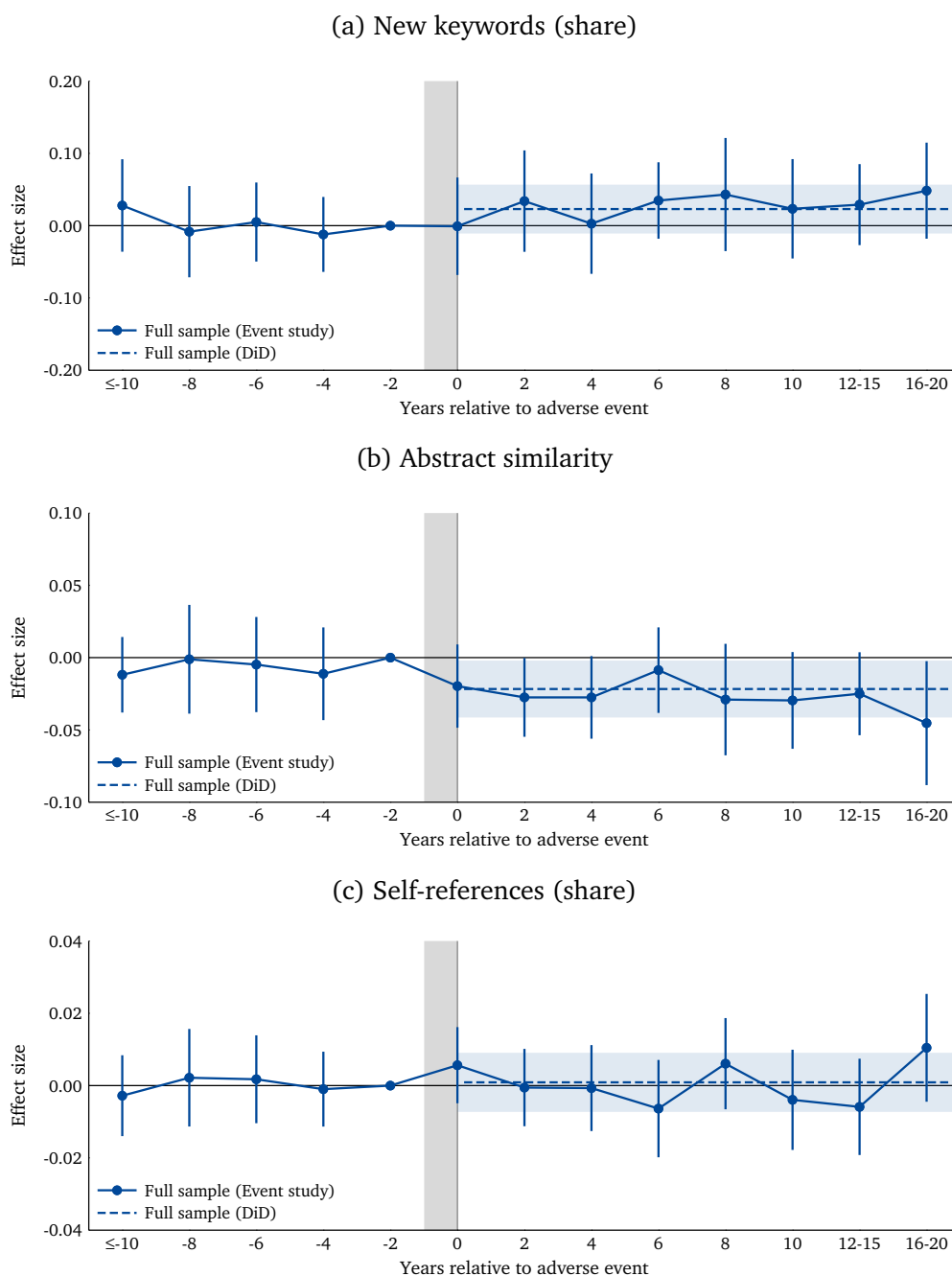
We can exclude that the observed changes in research direction are driven by a shift from empirical to more theoretical research: the share of empirical publications does not decrease after the adverse event (Figure E-15). Lastly, we show the robustness of the results to alternative specifications with different sets of fixed effects (Appendix F.1).

Table E-8: Impact of adverse events on research direction

Affected vs Control	(1)	(2)	(3)	(4)	(5)	(6)
	New keywords (share)		Abstract similarity		Self-references (share)	
	Pre	Pre-event	Pre	Pre-event	Pre	Pre-event
Affected $\times$ post	0.023 (0.017)	0.018 (0.016)	−0.022** (0.010)	−0.019** (0.008)	0.001 (0.004)	0.000 (0.004)
Matched group $\times$ Event year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3830	3830	8816	8774	9064	9064
Scientists	402	402	484	478	488	488
Events	92	92	102	101	102	102
log likelihood	2647	3946	6921	8698	15377	17790

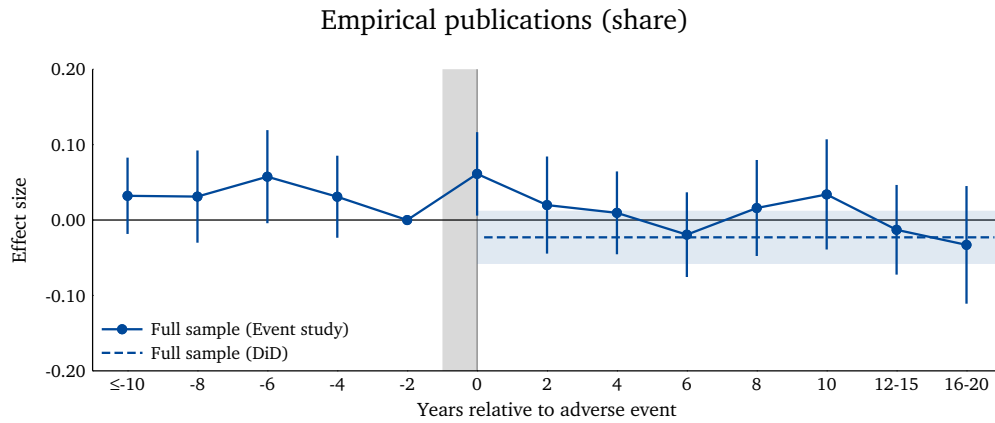
Notes: Columns (1) to (6) show the estimates of linear regressions with high-dimensional fixed effects. The models are specified as in Equation E2. The dependent variable is the share of keywords that do not show up in the lab head's prior (pre-event) publications relative to all of the keywords in their publications (*New keywords (share)*) in columns (1) and (2), the abstract similarity in a given year to the abstracts of the respective lab head's prior (pre-event) publications (*Abstract similarity*) in columns (3) and (4), and the share of references to the respective lab head's own prior (pre-event) publications relative to all of their references (*Self-references (share)*) in columns (5) and (6). The sample consists of all affected lab heads and their respective controls. Robust standard errors clustered at the adverse event level shown in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure E-14: Impact of adverse events on research direction – Event study and DiD estimates



Notes: The three graphs present point estimates of the variable *Affected* interacted with binned event year dummies (Event study) and of the variable *Affected* interacted with a binary variable that equals one from the adverse event year onward (DiD). The dependent variable is the share of keywords that do not show up in the lab head's prior publications relative to all of the keywords in their publications (*New keywords (share)*) in Figure E-14a, the abstract similarity in a given year to the abstracts of the respective lab head's prior publications (*Abstract similarity*) in Figure E-14b, and the share of references to the respective lab head's own prior publications relative to all of their references (*Self-references (share)*) in Figure E-14c. The sample consists of all affected lab heads and their respective controls. The coefficients correspond to those reported in Tables F-2 (Event study) and Tables E-8 (DiD). Confidence intervals are at the 95% level.

Figure E-15: Impact of adverse events on research direction – Event study and DiD estimates



Notes: The graph presents point estimates of the variable *Affected* interacted with binned event year dummies (Event study) and of the variable *Affected* interacted with a binary variable that equals one from the adverse event year onward (DiD). The dependent variable is the share of empirical publications relative to all publications (*Empirical publications (share)*). The sample consists of all affected lab heads and their respective controls. Confidence intervals are at the 95% level.

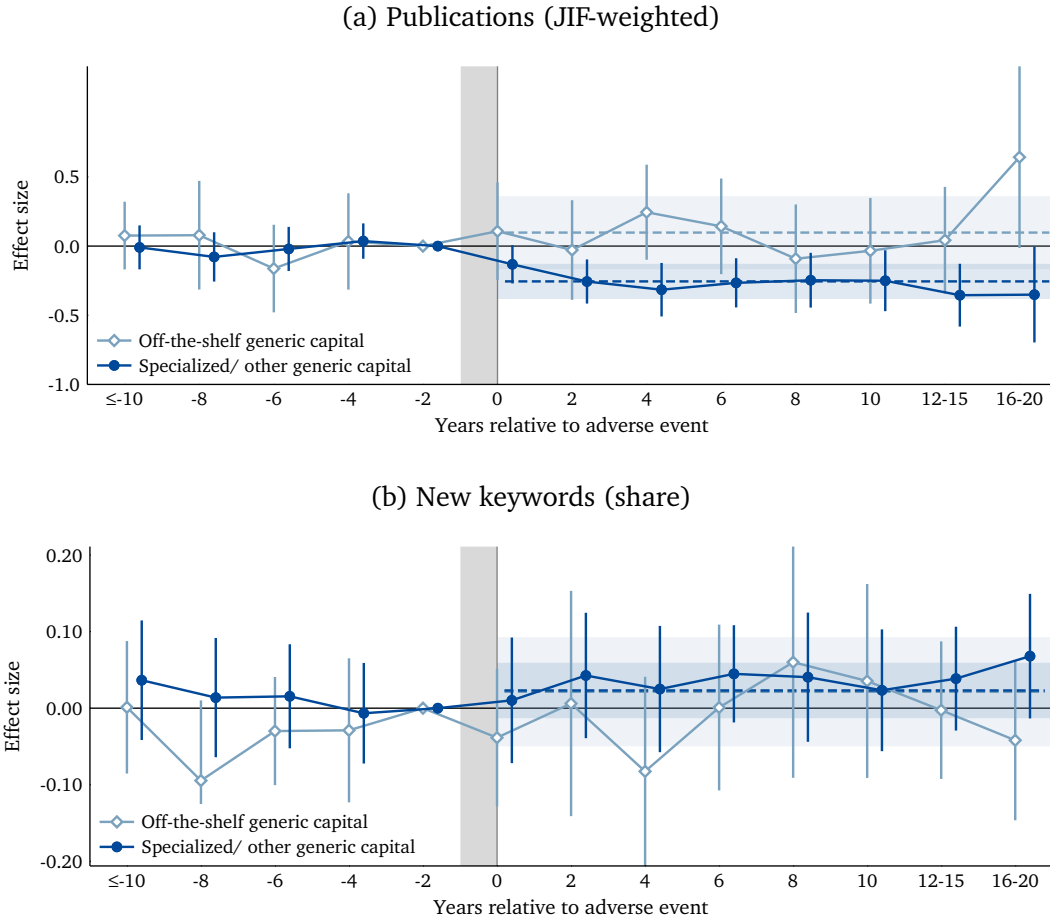
Table E-9: Impact of adverse events on research direction

Affected vs Control	(1)	(2)	(3)	(4)	(5)	(6)
	New keywords (share)		Abstract similarity		Self-references (share)	
	Pre	Pre-event	Pre	Pre-event	Pre	Pre-event
Affected						
× ≤ −10	0.028 (0.032)	0.028 (0.032)	−0.012 (0.013)	−0.012 (0.013)	−0.003 (0.006)	−0.003 (0.006)
× −8	−0.008 (0.032)	−0.008 (0.032)	−0.001 (0.019)	−0.001 (0.019)	0.002 (0.007)	0.002 (0.007)
× −6	0.005 (0.028)	0.005 (0.028)	−0.005 (0.017)	−0.005 (0.017)	0.002 (0.006)	0.002 (0.006)
× −4	−0.012 (0.026)	−0.012 (0.026)	−0.011 (0.016)	−0.011 (0.016)	−0.001 (0.005)	−0.001 (0.005)
× −2	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)
× 0	−0.001 (0.034)	0.007 (0.031)	−0.020 (0.015)	−0.023* (0.013)	0.006 (0.005)	0.006 (0.005)
× 2	0.034 (0.035)	0.022 (0.033)	−0.027** (0.014)	−0.024* (0.013)	−0.001 (0.005)	0.000 (0.005)
× 4	0.003 (0.035)	0.025 (0.030)	−0.027* (0.014)	−0.018 (0.013)	−0.001 (0.006)	0.002 (0.005)
× 6	0.035 (0.027)	0.030 (0.029)	−0.009 (0.015)	−0.014 (0.013)	−0.006 (0.007)	−0.003 (0.005)
× 8	0.043 (0.039)	0.024 (0.030)	−0.029 (0.019)	−0.026* (0.015)	0.006 (0.006)	0.000 (0.005)
× 10	0.023 (0.035)	0.022 (0.027)	−0.030* (0.017)	−0.019 (0.013)	−0.004 (0.007)	−0.005 (0.005)
× 12-15	0.029 (0.028)	0.027 (0.027)	−0.025* (0.014)	−0.024** (0.012)	−0.006 (0.007)	−0.005 (0.005)
× 16-20	0.048 (0.033)	0.025 (0.027)	−0.045** (0.022)	−0.036** (0.014)	0.010 (0.008)	0.000 (0.005)
Matched group × Event year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4092	4092	10578	10536	10734	10734
Scientists	408	408	484	478	488	488
Events	93	93	102	101	102	102
log likelihood	2857	4137	8409	10155	18316	20662

Notes: Columns (1) to (6) show the estimates of linear regressions with high-dimensional fixed effects. The models are specified as in Equation E1. The dependent variable is the share of references to the respective lab head's own prior publications relative to all of their references (*Self-references (share)*) in columns (1) to (3) and the share of keywords that do not show up in the lab head's prior publications relative to all of the keywords in their publications (*New keywords (share)*) in columns (4) to (6). The baseline year is t−2. The sample consists of all affected lab heads and their respective controls. Robust standard errors clustered at the adverse event level shown in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

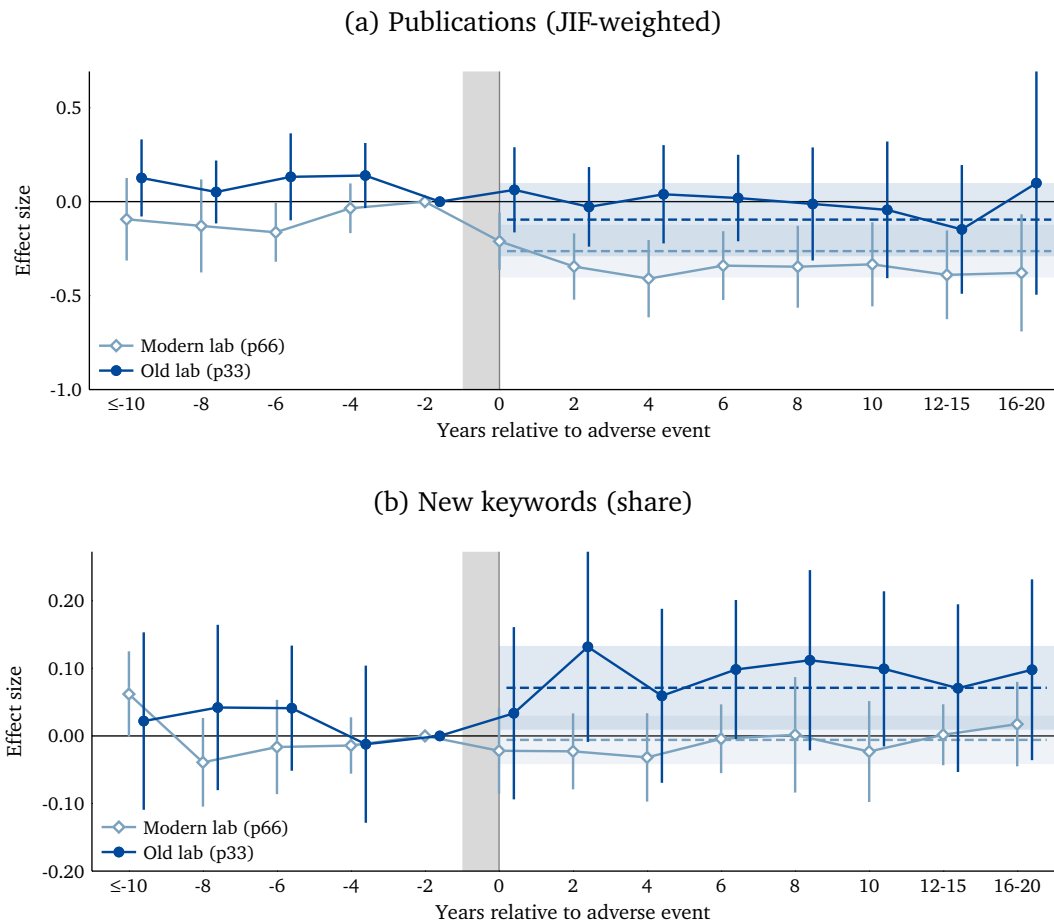
E.5 Heterogeneity

Figure E-16: Impact of adverse events on research output and direction by capital specialization – alternative threshold



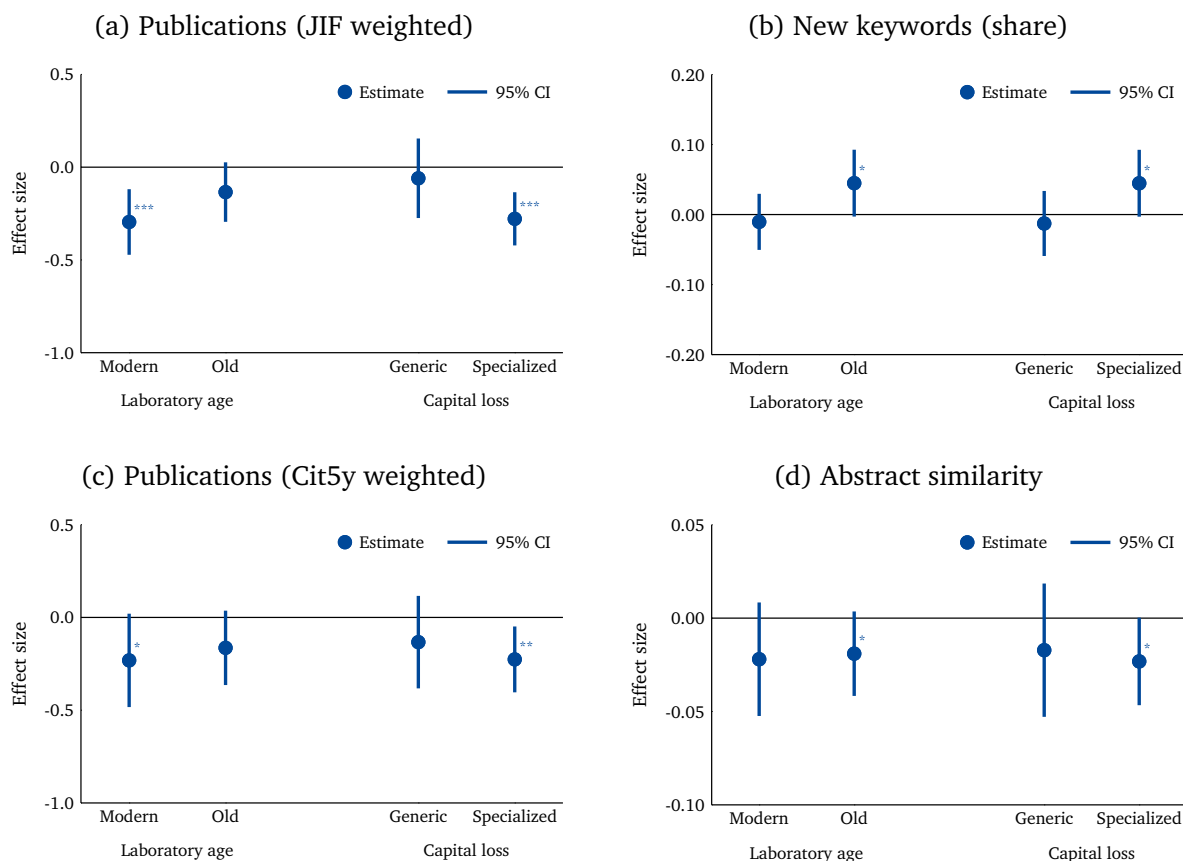
Notes: The two graphs present point estimates of the variable *Affected* interacted with binned event year dummies (Event study) and of the variable *Affected* interacted with a binary variable that equals one from the adverse event year onward (DiD). We introduce further interactions with a binary variable that indicates affected lab heads (and their respective controls) who lost specialized physical capital (see Equation E3). Here, specialized capital is more broadly defined: it also includes lost physical capital that is hard to acquire from external sources. The dependent variable is the impact-weighted publication count (*Publications (JIF weighted)*) in Figure E-16a, and the share of keywords that do not show up in the lab head's prior publications relative to all of the keywords in her publications (*New keywords (share)*) in Figure E-16b. The sample consists of all affected lab heads and their respective controls. Confidence intervals are at the 95% level.

Figure E-17: Impact of adverse events on research output and direction by laboratory age – alternative threshold



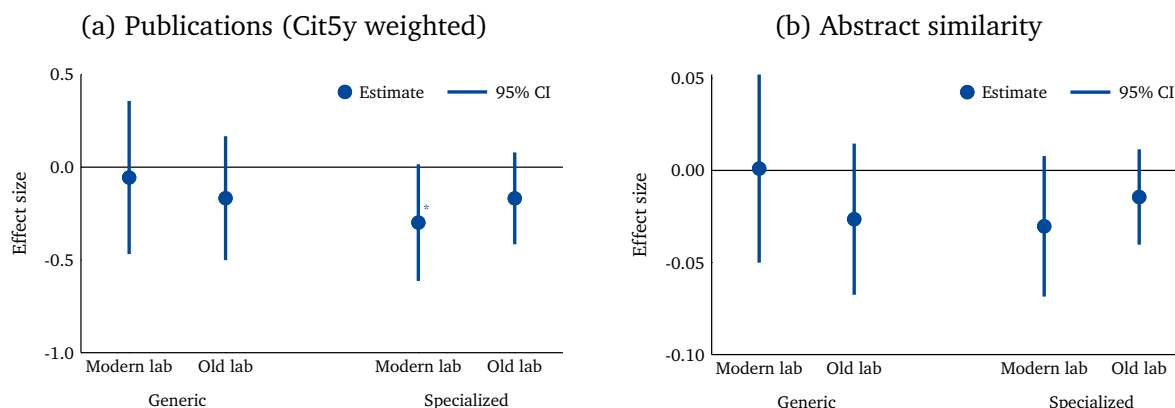
Notes: The two graphs present point estimates of the variable *Affected* interacted with binned event year dummies (Event study) and of the variable *Affected* interacted with a binary variable that equals one from the adverse event year onward (DiD). We introduce further interactions with a binary variable that indicates affected and control lab heads who worked at the time of the adverse event in a laboratory that belongs to the upper tertile (66th percentile) in terms of age (see Equation E3). The dependent variable is the impact-weighted publication count (*Publications (JIF weighted)*) in Figure E-17a, and the share of keywords that do not show up in the lab head's prior publications relative to all of the keywords in her publications (*New keywords (share)*) in Figure E-17b. The sample consists of all affected lab heads and their respective controls. Confidence intervals are at the 95% level.

Figure E-18: Impact of adverse events on research output and direction by specialization or laboratory age (DiD) – alternative measures of research output and direction



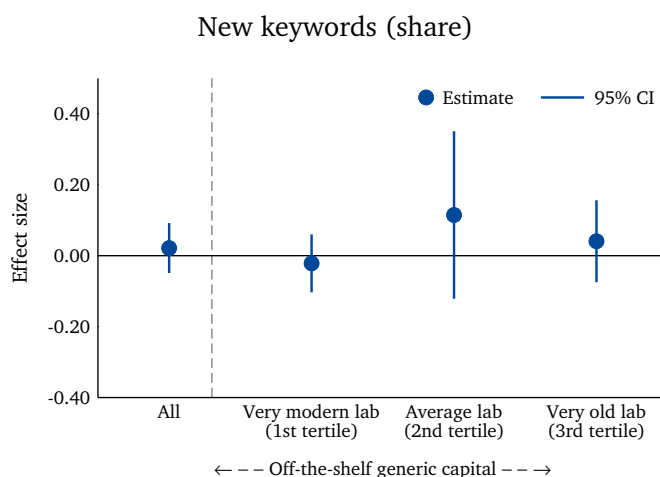
Notes: The two graphs present point estimates of the total average treatment effect (DiD) from pooled regressions that include full interactions with two binary variables. The first variable indicates affected lab heads (and their respective controls) who lost specialized physical capital. The second one indicates affected and control lab heads who worked at the time of the adverse event in a laboratory older than the median age. The dependent variable in Figure E-19a is the citation-weighted publication count (*Publications (Cit5y weighted)*), and in Figure E-19b it is the abstract similarity to the lab head's prior publications (*Abstract similarity*). The coefficients correspond to those reported in Appendix Table E-14. The sample consists of all affected lab heads and their respective controls. Confidence intervals are at the 95% level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure E-19: Impact of adverse events on research output and direction by specialization and laboratory age (DiD) – alternative measures of research output and direction



Notes: The two graphs present point estimates of the total average treatment effect (DiD) from pooled regressions that include full interactions with two binary variables. The first variable indicates affected lab heads (and their respective controls) who lost specialized physical capital. The second one indicates affected and control lab heads who worked at the time of the adverse event in a laboratory older than the median age. The dependent variable in Figure E-19a is the citation-weighted publication count (*Publications (Cit5y weighted)*), and in Figure E-19b it is the abstract similarity to the lab head's prior publications (*Abstract similarity*). The coefficients correspond to those reported in Appendix Table E-14. The sample consists of all affected lab heads and their respective controls. Confidence intervals are at the 95% level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure E-20: Impact of adverse events on research output by laboratory age (generic capital renewal)



Notes: The graph presents point estimates of the total average treatment effect (DiD) from pooled regressions that include full interactions with two discrete variables. The first one indicates affected lab heads (and their respective controls) who lost only off-the-shelf generic physical capital. The second one splits affected and control lab heads into three tertiles by laboratory age at the time of the adverse event. The dependent variable is the impact-weighted publication count (*Publications (JIF weighted)*). The coefficients correspond to those reported in Appendix Table E-15. The sample consists of all affected lab heads and their respective controls. Confidence intervals are at the 95% level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E-10: Impact of adverse events on research output and direction by capital specialization and laboratory age (event study)

Affected vs Control	(1)		(2)		(3)		(4)	
	Publications (JIF weighted)				New keywords (share)			
	Laboratory age		Lost capital		Laboratory age		Lost capital	
	Modern	Old	Generic	Specific	Modern	Old	Generic	Specific
Affected								
× ≤ −10	−0.023 (0.118)	0.039 (0.091)	−0.010 (0.098)	0.016 (0.092)	0.022 (0.033)	0.045 (0.047)	−0.025 (0.045)	0.062 (0.046)
× −8	−0.218 (0.175)	0.041 (0.063)	−0.048 (0.084)	−0.057 (0.113)	−0.052 (0.038)	0.022 (0.044)	−0.055 (0.043)	0.022 (0.046)
× −6	−0.222** (0.089)	0.069 (0.097)	−0.195* (0.115)	0.035 (0.089)	−0.013 (0.022)	0.021 (0.042)	0.015 (0.036)	0.002 (0.040)
× −4	−0.029 (0.099)	0.080 (0.072)	0.017 (0.088)	0.045 (0.076)	−0.027 (0.022)	−0.006 (0.042)	−0.009 (0.036)	−0.009 (0.039)
× −2	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)
× 0	−0.112 (0.101)	−0.105 (0.093)	−0.165 (0.112)	−0.077 (0.076)	−0.027 (0.034)	0.015 (0.050)	0.010 (0.036)	−0.006 (0.051)
× 2	−0.296** (0.118)	−0.168* (0.092)	−0.170 (0.137)	−0.247*** (0.091)	−0.030 (0.029)	0.078 (0.055)	−0.033 (0.047)	0.078 (0.057)
× 4	−0.418*** (0.118)	−0.105 (0.124)	−0.070 (0.176)	−0.316*** (0.108)	−0.047 (0.036)	0.037 (0.051)	−0.065 (0.042)	0.046 (0.054)
× 6	−0.348*** (0.110)	−0.097 (0.111)	−0.056 (0.128)	−0.281*** (0.107)	−0.027 (0.031)	0.077** (0.038)	−0.003 (0.044)	0.060 (0.044)
× 8	−0.355*** (0.130)	−0.119 (0.126)	−0.203 (0.171)	−0.228** (0.110)	−0.004 (0.051)	0.075 (0.052)	−0.010 (0.058)	0.078 (0.054)
× 10	−0.395*** (0.138)	−0.094 (0.147)	−0.175 (0.177)	−0.243** (0.123)	−0.038 (0.037)	0.067 (0.047)	−0.006 (0.054)	0.044 (0.048)
× 12-15	−0.514*** (0.145)	−0.134 (0.150)	−0.113 (0.173)	−0.397*** (0.136)	−0.016 (0.026)	0.058 (0.042)	−0.008 (0.039)	0.054 (0.043)
× 16-20	−0.477** (0.205)	0.017 (0.230)	0.163 (0.259)	−0.427** (0.214)	−0.006 (0.035)	0.086 (0.056)	−0.032 (0.048)	0.097* (0.052)
Matched group × Event year FE	Yes		Yes		Yes		Yes	
Observations	16548		16548		4092		4092	
Scientists	488		488		408		408	
Events	102		102		93		93	
Log-likelihood	−51089		−51041		2870		2875	

Notes: Columns (1) and (2) show the estimates of Poisson pseudo-maximum likelihood regressions and columns (3) and (4) the estimates of linear regressions with high-dimensional fixed effects. All models are specified as in Equation E3. The estimates in each right-hand sub-column (*Old* and *Specialized*) are the sum of the baseline effect and the interaction effect. The dependent variable is the impact-weighted publication count (*Publications (JIF weighted)*) in columns (1) and (2), and the share of keywords that do not show up in the lab head's prior publications relative to all of the keywords in her publications (*New keywords (share)*) in columns (4) to (6). Coefficients of trend interactions omitted. The baseline year is t−2. The sample consists of all affected lab heads and their respective controls. Robust standard errors clustered at the adverse event level shown in parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table E-11: Impact of adverse events on research output and direction by capital specialization and laboratory age (DiD)

Affected vs Control	(1)		(2)		(3)		(4)	
	Publications (JIF weighted)				New keywords (share)			
	Laboratory age		Lost capital		Laboratory age		Lost capital	
	Modern	Old	Generic	Specific	Modern	Old	Generic	Specific
Affected × post	−0.295*** (0.090)	−0.134 (0.082)	−0.060 (0.109)	−0.278*** (0.073)	−0.010 (0.020)	0.045* (0.024)	−0.013 (0.024)	0.045* (0.024)
Matched group × Event year FE	Yes		Yes		Yes		Yes	
Observations	13084		13084		3830		3830	
Scientists	488		488		402		402	
Events	102		102		92		92	
Log-likelihood	−40764		−40741		2654		2652	

Notes: Columns (1) and (2) show the estimates of Poisson pseudo-maximum likelihood regressions and columns (3) and (4) the estimates of linear regressions with high-dimensional fixed effects. The estimates in each right-hand sub-column (*Old* and *Specialized*) are the sum of the baseline effect and the interaction effect. The dependent variable is the impact-weighted publication count (*Publications (JIF weighted)*) in columns (1) and (2), and the share of keywords that do not show up in the lab head's prior publications relative to all of the keywords in her publications (*New keywords (share)*) in columns (4) to (6). Coefficients of *Old $\times$ post* and *Specialized $\times$ post* omitted. The sample consists of all affected lab heads and their respective controls. Robust standard errors clustered at the adverse event level shown in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E-12: Impact of adverse events on research output and direction by capital specialization and laboratory age (DiD) – alternative measures of research output and direction

Affected vs Control	(1)		(2)		(3)		(4)	
	Publications (Cit5y weighted)				Abstract similarity			
	Laboratory age		Lost capital		Laboratory age		Lost capital	
	Modern	Old	Generic	Specific	Modern	Old	Generic	Specific
Affected × post	−0.232*	−0.164	−0.133	−0.226**	−0.022	−0.019*	−0.017	−0.023*
	(0.128)	(0.102)	(0.127)	(0.091)	(0.016)	(0.012)	(0.018)	(0.012)
Matched group × Event year FE	Yes		Yes		Yes		Yes	
Observations	13026		13026		8816		8816	
Scientists	488		488		484		484	
Events	102		102		102		102	
Log-likelihood	−280028		−280343		6935		6926	

Notes: Columns (1) and (2) show the estimates of Poisson pseudo-maximum likelihood regressions and columns (3) and (4) the estimates of linear regressions with high-dimensional fixed effects. The estimates in each right-hand sub-column (*Old* and *Specialized*) are the sum of the baseline effect and the interaction effect. The dependent variable is the publication count weighted by the number of citations received within five years after publication (*Publications (Cit5y weighted)*) in columns (1) and (2), and the abstract similarity in a given year to the abstracts of the respective lab head's prior publications (*Abstract similarity*) in columns (4) to (6). Coefficients of *Old $\times$ post* and *Specialized $\times$ post* omitted. The sample consists of all affected lab heads and their respective controls. Robust standard errors clustered at the adverse event level shown in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E-13: Impact of adverse events on research output and direction by capital specialization and laboratory age (DiD)

Affected vs Control	(1)				(2)			
	Publications (JIF weighted)				New keywords (share)			
	Generic		Specialized		Generic		Specialized	
	Modern lab	Old lab	Modern lab	Old lab	Modern lab	Old lab	Modern lab	Old lab
Affected $\times$ post	-0.028 (0.169)	-0.075 (0.151)	-0.397*** (0.112)	-0.173* (0.089)	-0.071** (0.036)	0.020 (0.031)	0.021 (0.018)	0.062* (0.037)
Matched group $\times$ Event year FE	Yes				Yes			
Observations	13084				3830			
Scientists	488				402			
Events	102				92			
Log-likelihood	-40672				2661			

Notes: Column (1) shows the estimates of a Poisson pseudo-maximum likelihood regression and column (2) the estimates of a linear regression with high-dimensional fixed effects. The estimates in the sub-columns are the sum of the baseline effect and the interaction effect(s). The dependent variable is the impact-weighted publication count (*Publications (JIF weighted)*) in column (1), and the share of keywords that do not show up in the lab head's prior publications relative to all of the keywords in her publications (*New keywords (share)*) in column (2). Coefficients of *Old $\times$ post*, *Specialized $\times$ post*, and *Old $\times$ Specialized $\times$ post* omitted. The sample consists of all affected lab heads and their respective controls. Robust standard errors clustered at the adverse event level shown in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E-14: Impact of adverse events on research output and direction by capital specialization and laboratory age (DiD) – alternative measures of research output and direction

Affected vs Control	(1)				(2)			
	Publications (Cit5y weighted)				Abstract similarity			
	Generic		Specialized		Generic		Specialized	
	Modern lab	Old lab	Modern lab	Old lab	Modern lab	Old lab	Modern lab	Old lab
Affected $\times$ post	-0.056 (0.211)	-0.167 (0.170)	-0.299* (0.160)	-0.168 (0.126)	0.001 (0.026)	-0.026 (0.021)	-0.030 (0.019)	-0.014 (0.013)
Matched group $\times$ Event year FE	Yes				Yes			
Observations	13026				8816			
Scientists	488				484			
Events	102				102			
Log-likelihood	-279084				6943			

Notes: Column (1) shows the estimates of a Poisson pseudo-maximum likelihood regression and column (2) the estimates of a linear regression with high-dimensional fixed effects. The estimates in the sub-columns are the sum of the baseline effect and the interaction effect(s). The dependent variable is the publication count weighted by the number of citations received within five years after publication (*Publications (Cit5y weighted)*) in column (1), and the abstract similarity in a given year to the abstracts of the respective lab head's prior publications (*Abstract similarity*) in column (2). Coefficients of *Old $\times$ post*, *Specialized $\times$ post*, and *Old $\times$ Specialized $\times$ post* omitted. The sample consists of all affected lab heads and their respective controls. Robust standard errors clustered at the adverse event level shown in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E-15: Impact of adverse events on research output and direction – heterogeneity by off-she-shelf capital

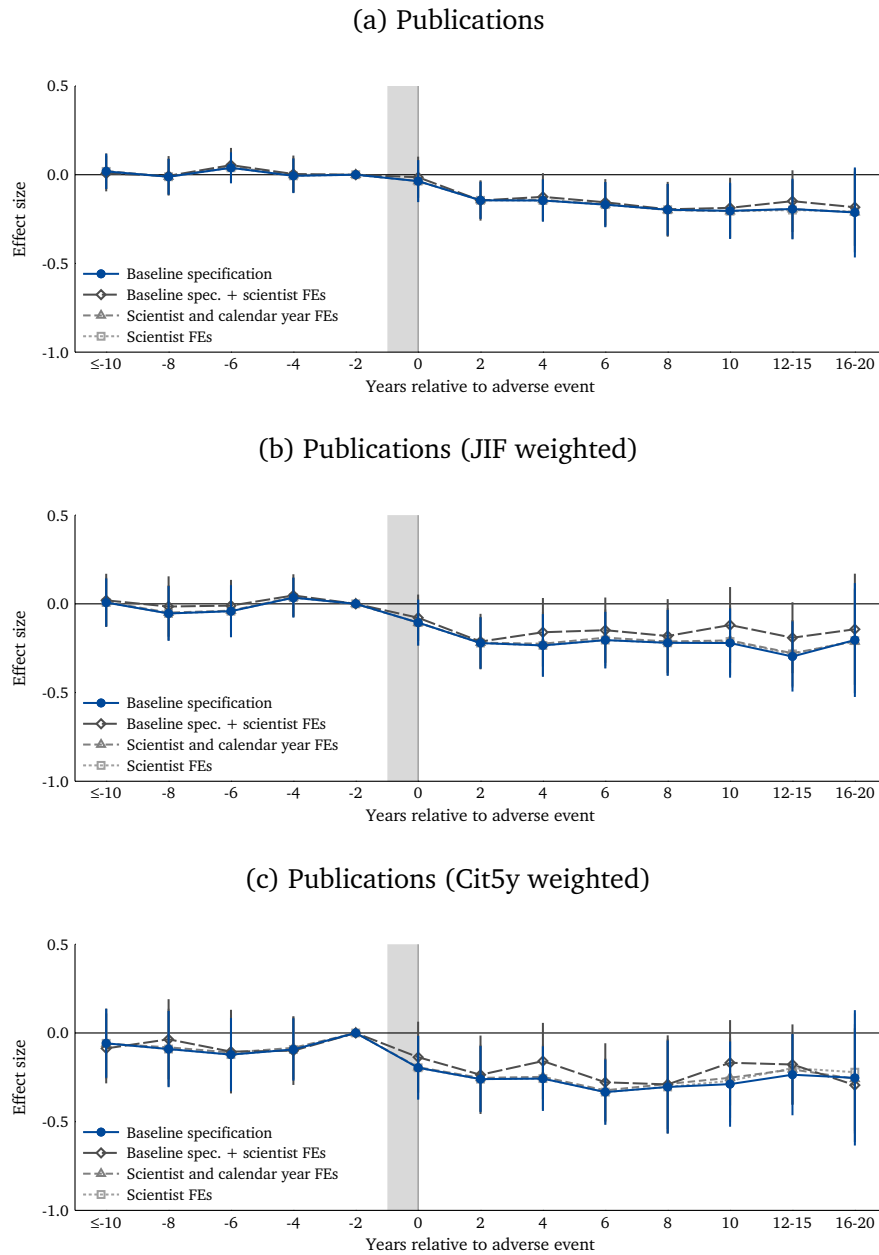
Affected vs Control	Publications (JIF weighted)				New keywords (share)			
	(1)	(2)			(3)	(4)		
	All	Tertiles by lab age			All	Tertiles by lab age		
		1st	2nd	3rd		1st	2nd	3rd
Affected × post	0.098 (0.135)	−0.238 (0.196)	0.312 (0.353)	0.490*** (0.136)	0.021 (0.036)	−0.022 (0.042)	0.115 (0.120)	0.041 (0.059)
Matched group × Event year FE	Yes	Yes			Yes	Yes		
Observations	13084	13084			3830	3830		
Scientists	488	488			402	402		
Events	102	102			92	92		
Log-likelihood	−40514	−39764			2647	2691		

Notes: Columns (1) and (2) show the estimates of a Poisson pseudo-maximum likelihood regression and columns (3) and (4) the estimates of a linear regression with high-dimensional fixed effects. The tables reports the point estimates of the total average treatment effect (DiD) from pooled regressions that include full interactions with two discrete variables. The first one indicates affected lab heads (and their respective controls) who lost only off-the-shelf generic physical capital. The second one splits affected and control lab heads into three tertiles by laboratory age at the time of the adverse event. The estimates in the sub-columns are the sum of the baseline effect and the interaction effect(s). The dependent variable is the impact-weighted publication count (*Publications (JIF weighted)*) in columns (1) and (2), and the share of new keywords (*New keywords (share)*) in columns (3) and (4). Other coefficients of the triple interaction were omitted. The sample consists of all affected lab heads and their respective controls. Robust standard errors clustered at the adverse event level shown in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

F Robustness Checks

F.1 Different model specifications

Figure F-1: Impact of adverse events on research output and direction – Event study estimates – alternative specifications



Notes: The graphs present point estimates of the variable *Affected* interacted with binned event year dummies. Each graph plots the estimates of three separate models with different sets of fixed effects. The sample consists of all affected lab heads and their respective controls. Confidence intervals are at the 95% level.

Table F-1: Impact of adverse events on research output

Affected vs Control	(1)	(2) Publications	(3)	(4) Publications (JIF weighted)	(5)	(6)
Affected						
× ≤ −10	0.007 (0.051)	0.021 (0.051)	0.019 (0.051)	0.020 (0.076)	0.011 (0.070)	0.007 (0.069)
× −8	−0.006 (0.057)	−0.011 (0.051)	−0.011 (0.051)	−0.015 (0.087)	−0.049 (0.079)	−0.054 (0.079)
× −6	0.054 (0.049)	0.044 (0.044)	0.039 (0.044)	−0.010 (0.074)	−0.038 (0.073)	−0.041 (0.075)
× −4	0.004 (0.053)	−0.001 (0.050)	−0.006 (0.050)	0.047 (0.061)	0.038 (0.056)	0.035 (0.057)
× −2	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)
× 0	−0.014 (0.059)	−0.036 (0.060)	−0.036 (0.060)	−0.078 (0.067)	−0.107 (0.067)	−0.106 (0.066)
× 2	−0.145** (0.058)	−0.143*** (0.053)	−0.144*** (0.053)	−0.213*** (0.080)	−0.219*** (0.074)	−0.221*** (0.074)
× 4	−0.125* (0.068)	−0.141** (0.061)	−0.145** (0.061)	−0.160 (0.099)	−0.225** (0.091)	−0.234*** (0.090)
× 6	−0.155** (0.067)	−0.167*** (0.064)	−0.169*** (0.065)	−0.148 (0.094)	−0.191** (0.081)	−0.204** (0.081)
× 8	−0.195** (0.079)	−0.199*** (0.074)	−0.197*** (0.074)	−0.181* (0.106)	−0.212** (0.096)	−0.220** (0.095)
× 10	−0.187** (0.086)	−0.205*** (0.079)	−0.206** (0.080)	−0.119 (0.109)	−0.206** (0.099)	−0.212** (0.098)
× 12-15	−0.149* (0.089)	−0.194** (0.084)	−0.199** (0.084)	−0.191* (0.102)	−0.278*** (0.095)	−0.282*** (0.097)
× 16-20	−0.183* (0.111)	−0.211* (0.116)	−0.208* (0.117)	−0.143 (0.160)	−0.212 (0.149)	−0.207 (0.151)
Matched group × Event year FE	Yes	No	No	Yes	No	No
Scientist FE	Yes	Yes	Yes	Yes	Yes	Yes
Calendar year FE	No	Yes	No	No	Yes	No
Observations	16770	18878	18878	16548	18878	18878
Scientists	488	488	488	488	488	488
Events	102	102	102	102	102	102
log likelihood	−29449	−41383	−41586	−45329	−79840	−80813

Notes: Columns (1) to (6) show the estimates of Poisson pseudo-maximum likelihood regressions with high-dimensional fixed effects. The models in columns (3) and (6) are specified as in Equation E1. The dependent variable is the simple publication count (*Publications*) in columns (1) to (3) and the impact-weighted publication count (*Publications (JIF weighted)*) in columns (4) to (6). The baseline year is $t-2$. The sample consists of all affected lab heads and their respective controls. Robust standard errors clustered at the adverse event level shown in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

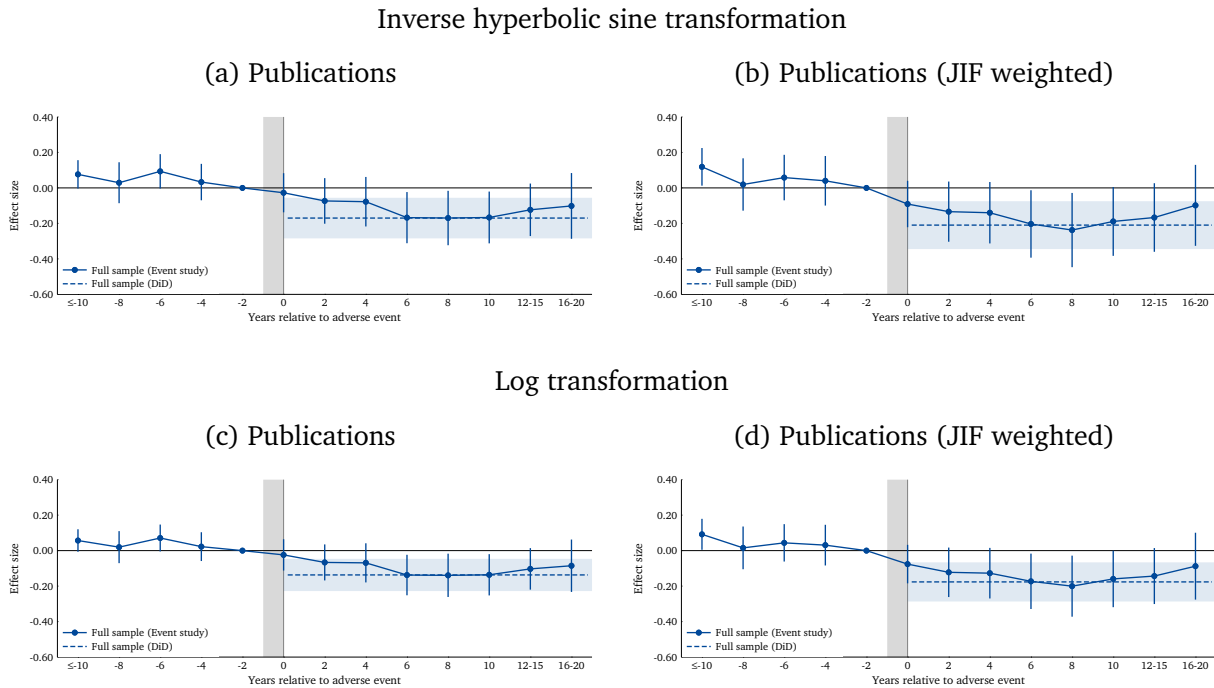
Table F-2: Impact of adverse events on research direction

Affected vs Control	(1)	(2)	(3)	(4)	(5)	(6)
	New keywords (share)			Abstract similarity		
Affected						
× ≤ −10	−0.014 (0.028)	0.036 (0.029)	0.029 (0.029)	−0.022* (0.013)	−0.016 (0.012)	−0.017 (0.012)
× −8	−0.030 (0.028)	−0.002 (0.026)	−0.008 (0.026)	−0.004 (0.018)	−0.003 (0.017)	−0.003 (0.017)
× −6	−0.020 (0.024)	0.003 (0.025)	−0.008 (0.026)	−0.004 (0.016)	−0.004 (0.014)	−0.004 (0.014)
× −4	−0.034 (0.024)	0.022 (0.025)	0.014 (0.025)	−0.005 (0.016)	−0.011 (0.014)	−0.011 (0.014)
× −2	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)
× 0	−0.026 (0.029)	0.021 (0.027)	0.025 (0.028)	−0.015 (0.014)	−0.022 (0.013)	−0.021 (0.013)
× 2	0.020 (0.030)	0.036 (0.027)	0.035 (0.028)	−0.027** (0.014)	−0.032** (0.013)	−0.032** (0.013)
× 4	−0.026 (0.029)	−0.001 (0.026)	0.006 (0.027)	−0.025* (0.014)	−0.029** (0.013)	−0.029** (0.013)
× 6	0.017 (0.025)	0.054** (0.025)	0.051** (0.025)	−0.006 (0.015)	−0.007 (0.015)	−0.009 (0.015)
× 8	0.025 (0.035)	0.067* (0.037)	0.056 (0.037)	−0.032 (0.019)	−0.033* (0.018)	−0.034* (0.018)
× 10	−0.009 (0.035)	0.034 (0.034)	0.038 (0.035)	−0.032* (0.017)	−0.035** (0.015)	−0.036** (0.015)
× 12-15	−0.013 (0.027)	0.067** (0.029)	0.066** (0.029)	−0.021 (0.014)	−0.030** (0.013)	−0.030** (0.013)
× 16-20	0.010 (0.030)	0.060* (0.032)	0.059* (0.033)	−0.038** (0.019)	−0.040** (0.017)	−0.042** (0.017)
Matched group × Event year FE	Yes	No	No	Yes	No	No
Scientist FE	Yes	Yes	Yes	Yes	Yes	Yes
Calendar year FE	No	Yes	No	No	Yes	No
Observations	4056	6772	6774	10574	13351	13351
Scientists	372	452	452	480	485	485
Events	88	101	101	101	102	102
log likelihood	3424	2338	1872	10051	7445	7347

Notes: Columns (1) to (6) show the estimates of linear regressions with high-dimensional fixed effects. The models in columns (1) and (4) are specified as in Equation E1. The dependent variable is the simple publication count (*Publications*) in columns (1) to (3) and the impact-weighted publication count (*Publications (JIF weighted)*) in columns (4) to (6). The baseline year is $t-2$. The sample consists of all affected lab heads and their respective controls. Robust standard errors clustered at the adverse event level shown in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

E.2 Different operationalizations of dependent variable

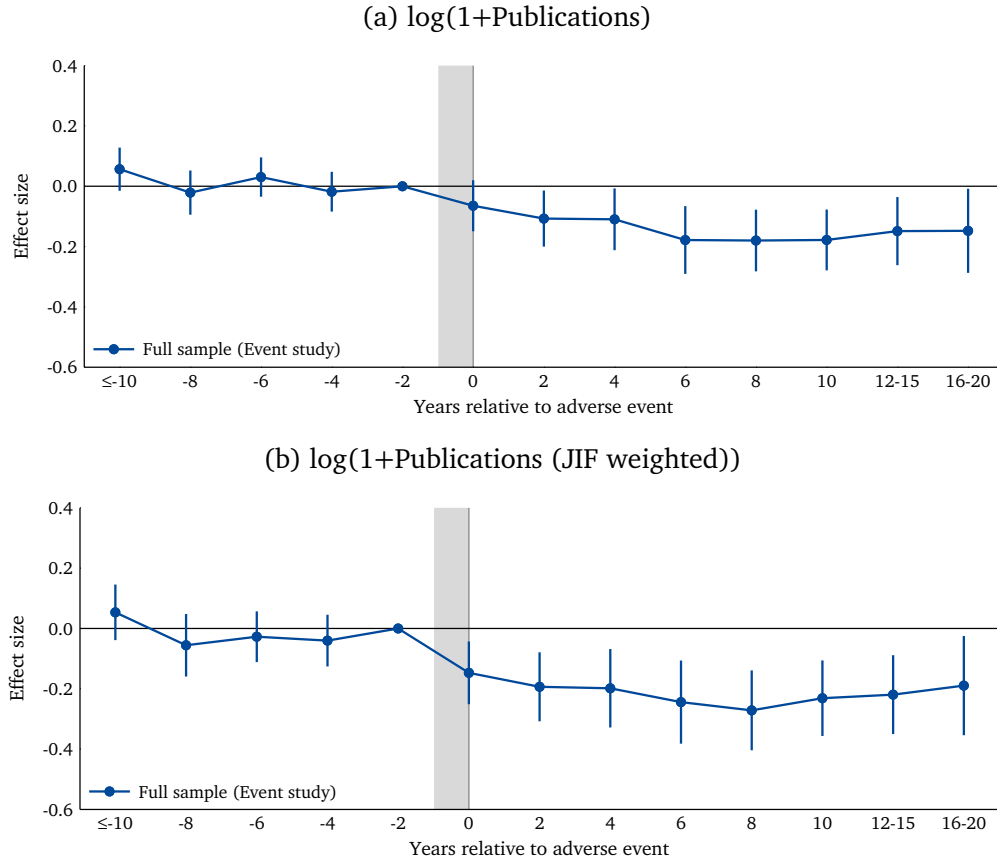
Figure F-2: Impact of adverse events on research output – Event study and DiD estimates from OLS regressions



Notes: The six graphs present OLS point estimates of the interactions of the variable *Affected* with binned event year dummies (Event study), and with a binary variable that takes a value of one from the adverse event year onward (DiD). The dependent variable is either the simple publication count (*Publications*) or the impact-weighted publication count (*Publications (JIF weighted)*). The sample consists of all affected lab heads and their respective controls. The coefficients correspond to those reported in Appendix Table E-1 (Event study) and Appendix Table E-2 (DiD). Confidence intervals are at the 95% level.

F.3 Interaction-weighted estimator

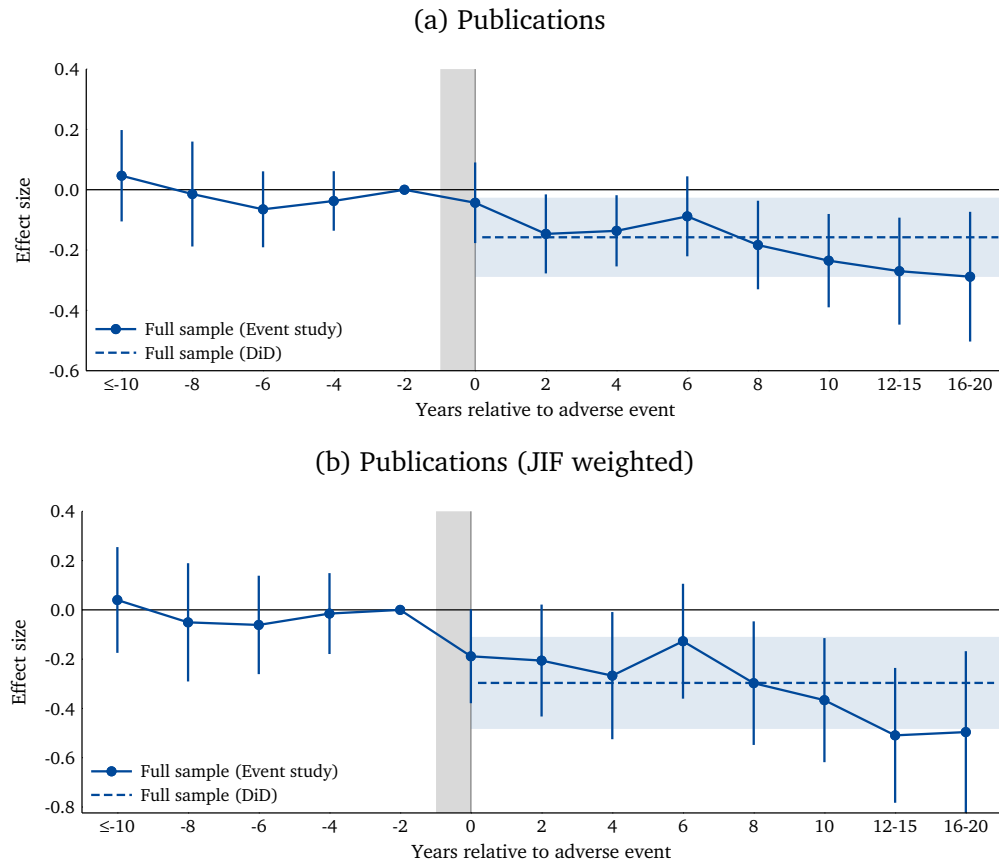
Figure F-3: Impact of adverse events on research output – Event study (interaction-weighted estimator)



Notes: The two graphs present point estimates of the variable *Affected* interacted with binned event year dummies (Event study). The results are based on the interaction-weighted (IW) estimator for estimating dynamic treatment effects (Sun and Abraham, 2021). The dependent variable is the log-transformed simple publication count (*Publications*) in Figure F-3a, and the log-transformed impact-weighted publication count (*Publications (JIF weighted)*) in Figure F-3b. The sample consists of all affected lab heads and their respective controls. Confidence intervals are at the 95% level.

F.4 Spared lab heads as natural control group

Figure F-4: Impact of adverse events on research output – Event study and DiD estimates

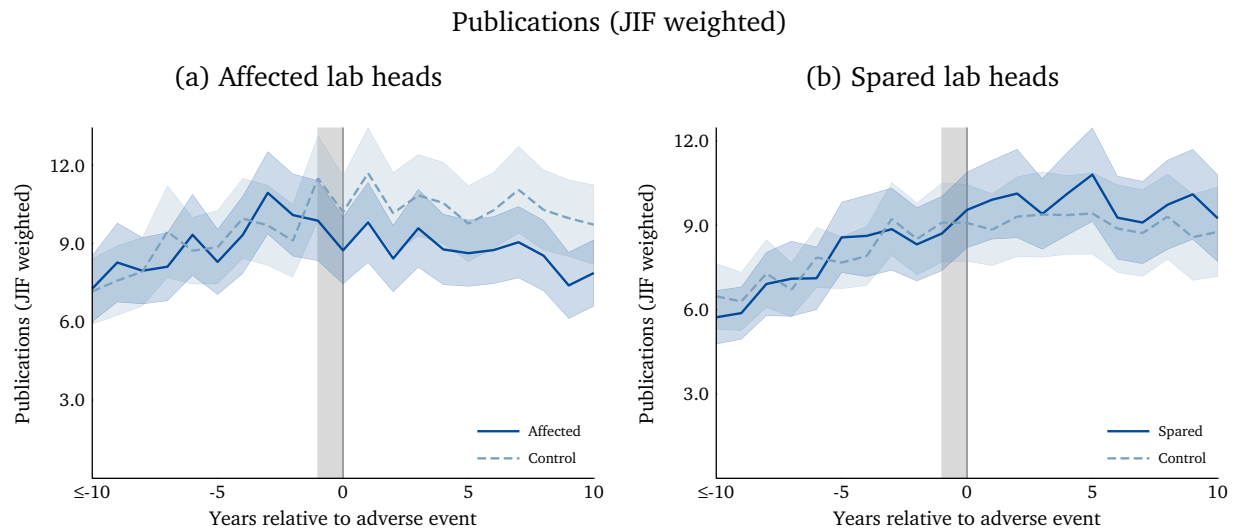


Notes: The two graphs present point estimates of the interactions of the variable *Affected* with binned event year dummies (Event study), and with a binary variable that takes a value of one from the adverse event year onward (DiD). The dependent variable in Figure F-4a is the simple publication count (*Publications*), and in Figure F-4b it is the impact-weighted publication count (*Publications (JIF weighted)*). The sample consists of all affected and spared lab heads. Confidence intervals are at the 95% level.

F5 Differently matched control groups

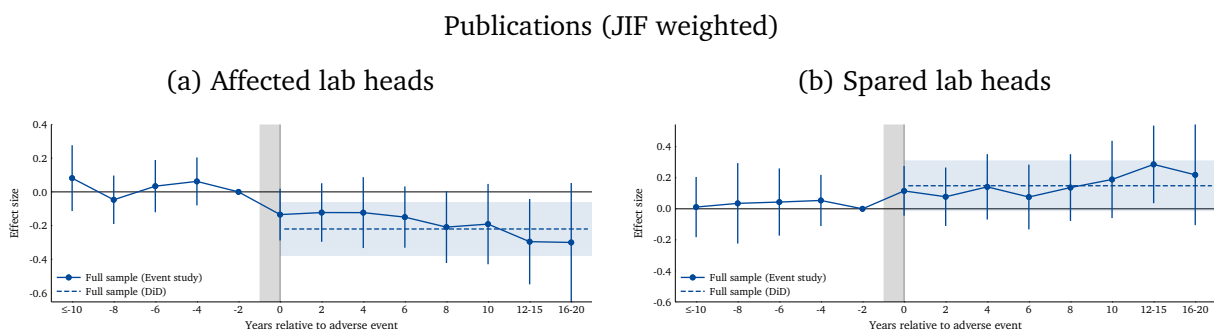
Comparison between affected and matched controls (match on $t-5$ characteristics)

Figure F-5: Research output of affected/spared lab heads and controls over time



Notes: The two graphs present the average annual research output of affected (spared) and control lab heads up to ten years before and after the adverse event. Research output is measured by impact-weighted publication counts (*Publications (JIF weighted)*) in both figures. The sample consists of all affected (spared) lab heads and their respective matched controls based on $t-5$ productivity characteristics. Confidence intervals are at the 95% level.

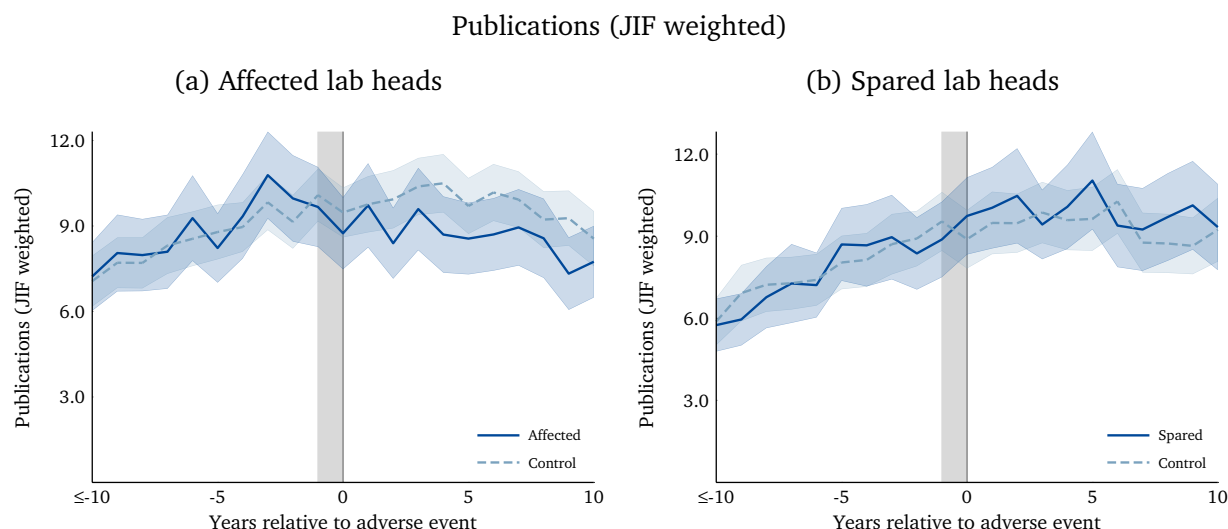
Figure F-6: Impact of adverse events on research output – Event study and DiD estimates



Notes: The two graphs present point estimates of the interactions of the variable *Affected* with binned event year dummies (Event study), and with a binary variable that takes a value of one from the adverse event year onward (DiD). The dependent variable in both figures is the impact-weighted publication count (*Publications (JIF weighted)*). The sample consists of all affected (spared) lab heads and their respective matched controls based on $t-5$ productivity characteristics. Confidence intervals are at the 95% level.

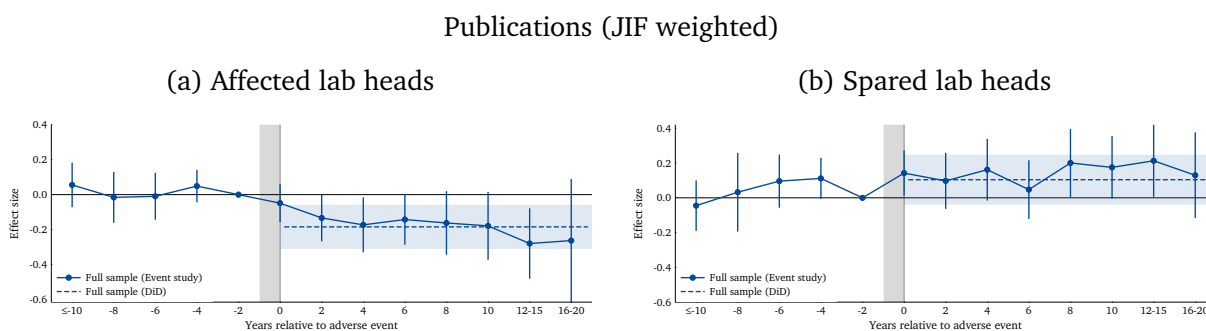
Comparison between affected and matched controls (1:2 matching)

Figure F-7: Research output of affected/spared lab heads and controls over time



Notes: The two graphs present the average annual research output of affected (spared) and control lab heads up to ten years before and after the adverse event. Research output is measured by impact-weighted publication counts (*Publications (JIF weighted)*) in both figures. The sample consists of all affected (spared) lab heads and up to two matched controls. Confidence intervals are at the 95% level.

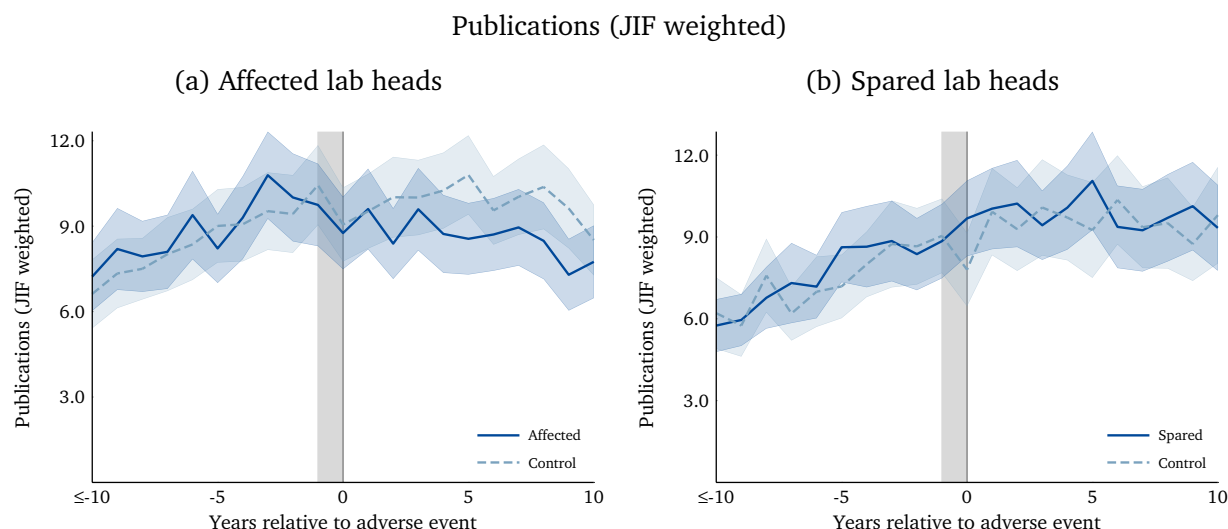
Figure F-8: Impact of adverse events on research output – Event study and DiD estimates



Notes: The two graphs present point estimates of the interactions of the variable *Affected* with binned event year dummies (Event study), and with a binary variable that takes a value of one from the adverse event year onward (DiD). The dependent variable in both figures is the impact-weighted publication count (*Publications (JIF weighted)*). The sample consists of all affected (spared) lab heads and up to two matched controls. Confidence intervals are at the 95% level.

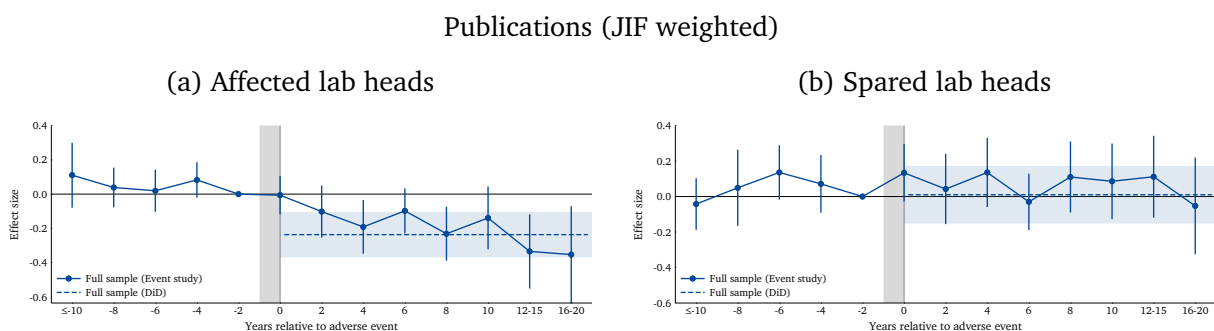
Comparison between affected and matched controls (no nearest-neighbor matching)

Figure F-9: Research output of affected/spared lab heads and controls over time



Notes: The two graphs present the average annual research output of affected (spared) and control lab heads up to ten years before and after the adverse event. Research output is measured by impact-weighted publication counts (*Publications (JIF weighted)*) in both figures. The sample consists of all affected (spared) lab heads and their respective matched controls randomly drawn among the prioritized control candidates. Confidence intervals are at the 95% level.

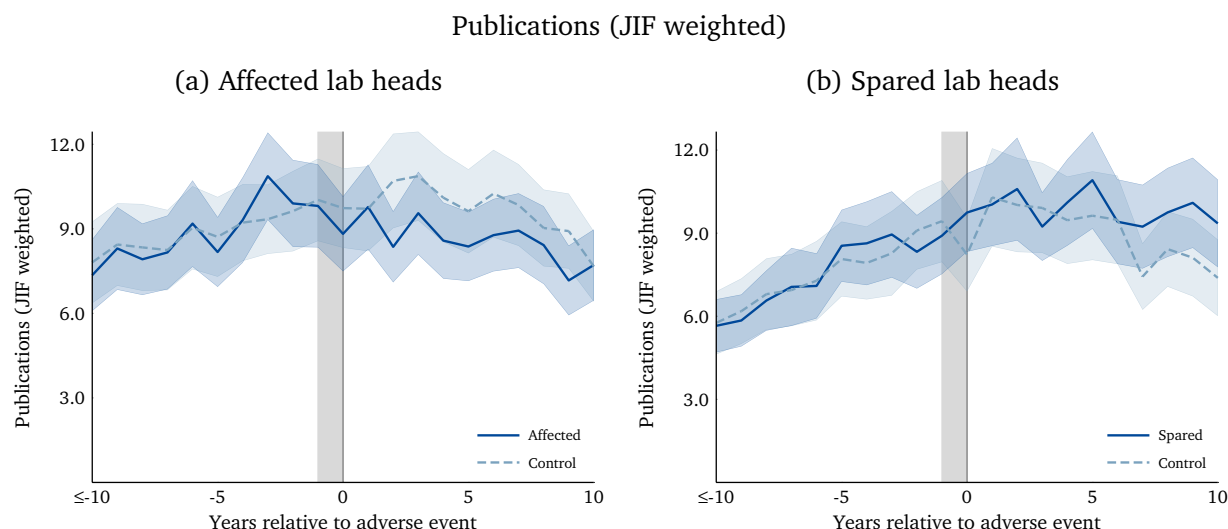
Figure F-10: Impact of adverse events on research output – Event study and DiD estimates



Notes: The two graphs present point estimates of the interactions of the variable *Affected* with binned event year dummies (Event study), and with a binary variable that takes a value of one from the adverse event year onward (DiD). The dependent variable in both figures is the impact-weighted publication count (*Publications (JIF weighted)*). The sample consists of all affected (spared) lab heads and their respective matched controls randomly drawn among the prioritized control candidates. Confidence intervals are at the 95% level.

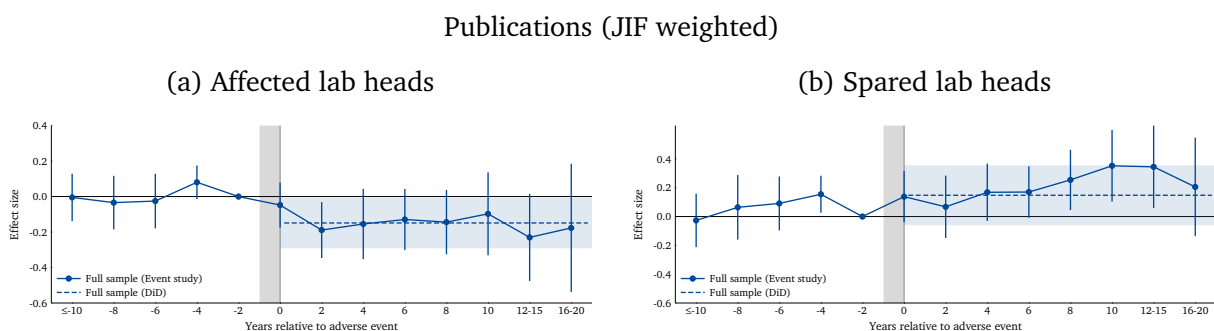
Comparison between affected and matched controls (no match on "career position")

Figure F-11: Research output of affected/spared lab heads and controls over time



Notes: The two graphs present the average annual research output of affected (spared) and control lab heads up to ten years before and after the adverse event. Research output is measured by impact-weighted publication counts (*Publications (JIF weighted)*) in both figures. The sample consists of all affected (spared) lab heads and their respective matched controls without prioritizing candidates with a similar career position. Confidence intervals are at the 95% level.

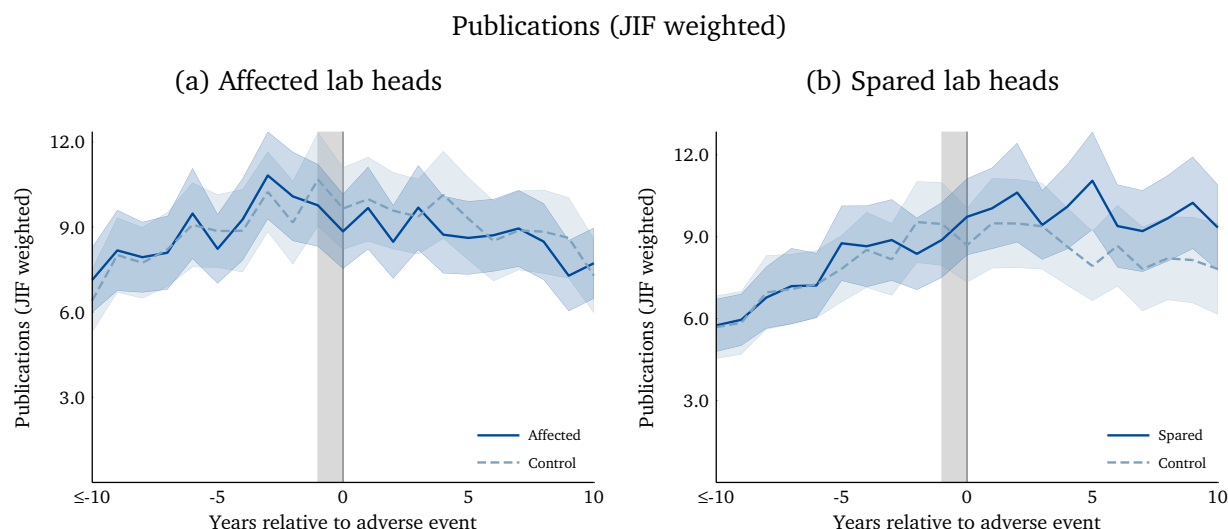
Figure F-12: Impact of adverse events on research output – Event study and DiD estimates



Notes: The two graphs present point estimates of the interactions of the variable *Affected* with binned event year dummies (Event study), and with a binary variable that takes a value of one from the adverse event year onward (DiD). The dependent variable in both figures is the impact-weighted publication count (*Publications (JIF weighted)*). The sample consists of all affected (spared) lab heads and their respective matched controls without prioritizing candidates with a similar career position. Confidence intervals are at the 95% level.

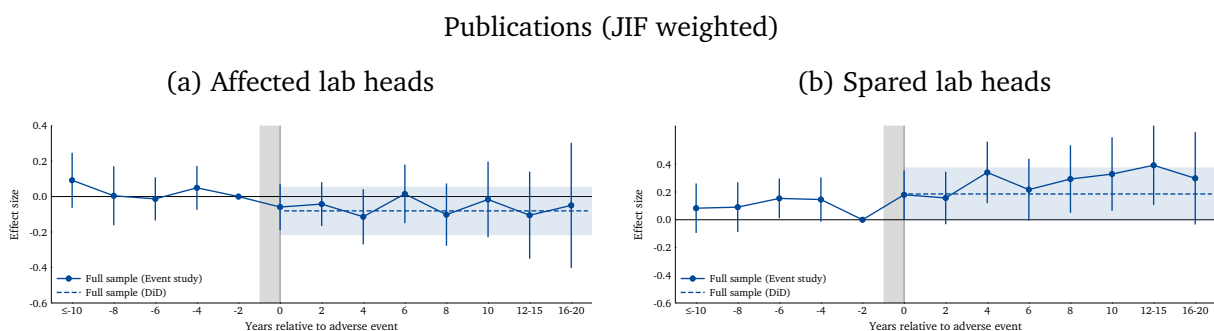
Comparison between affected and matched controls (random draw)

Figure F-13: Research output of affected/spared lab heads and controls over time



Notes: The two graphs present the average annual research output of affected (spared) and control lab heads up to ten years before and after the adverse event. Research output is measured by impact-weighted publication counts (*Publications (JIF weighted)*) in both figures. The sample consists of all affected (spared) lab heads and their respective matched controls randomly drawn from the control candidates. Confidence intervals are at the 95% level.

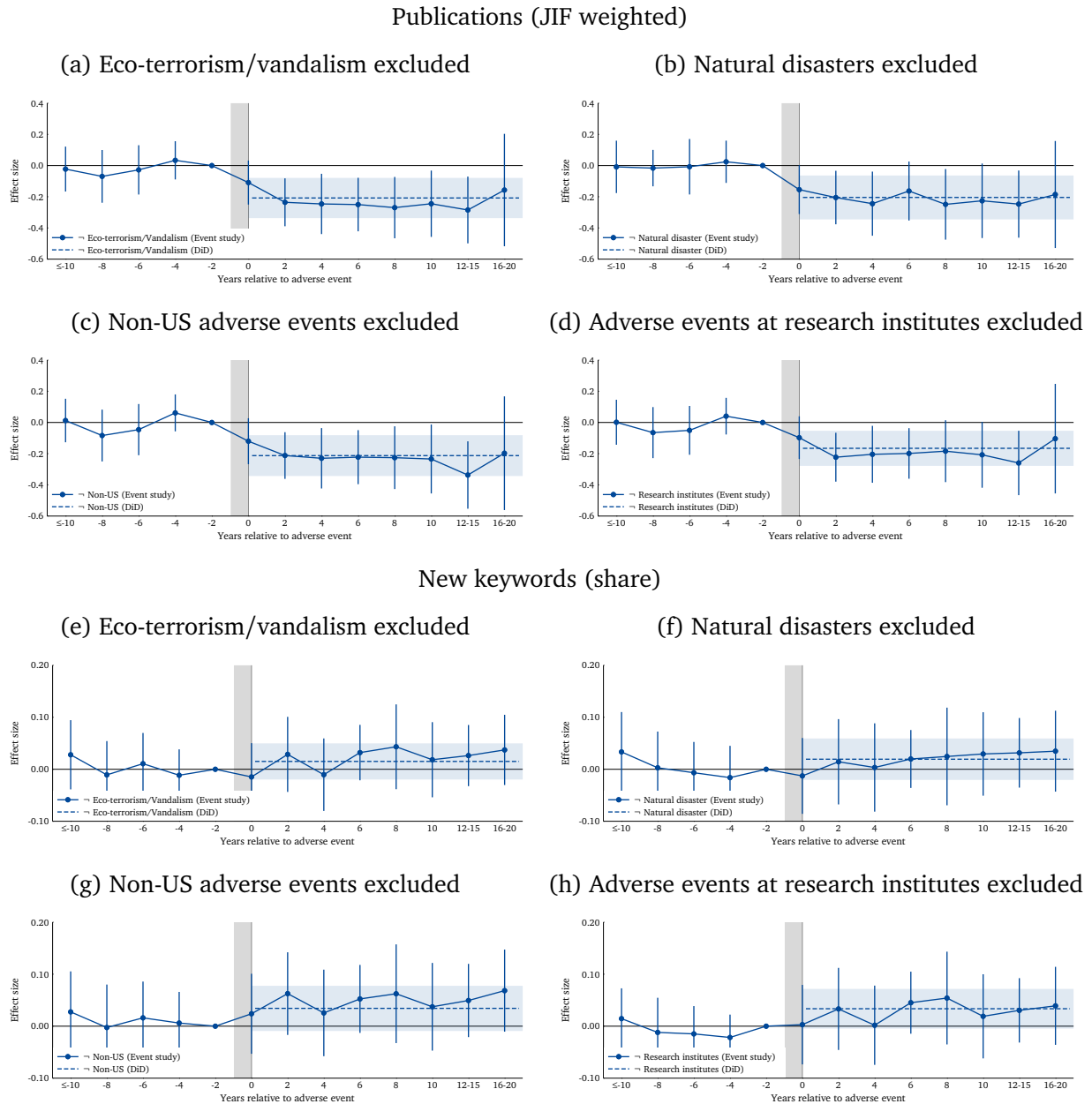
Figure F-14: Impact of adverse events on research output – Event study and DiD estimates



Notes: The two graphs present point estimates of the interactions of the variable *Affected* with binned event year dummies (Event study), and with a binary variable that takes a value of one from the adverse event year onward (DiD). The dependent variable in both figures is the impact-weighted publication count (*Publications (JIF weighted)*). The sample consists of all affected (spared) lab heads and their respective matched controls randomly drawn from the control candidates. Confidence intervals are at the 95% level.

F6 Adverse event subsamples

Figure F-15: Impact of adverse events on research output – exclusion of particular adverse events



Notes: The graphs present point estimates of the variable *Affected* interacted with binned event year dummies (Event study) and of the variable *Affected* interacted with a binary variable that equals one from the adverse event year onward (DiD). In Figure F-15e the sample excludes adverse events caused by eco-terrorism and vandalism, in Figure F-15f the sample excludes natural disasters (e.g., Hurricane Katrina), in Figure F-15g the sample excludes non-US adverse events, and in Figure F-15h the sample excludes focuses on adverse events at universities and excludes research institutes. Confidence intervals are at the 95% level.

F.7 Heterogeneity subsamples

Table F-3: Impact of adverse events on research output and direction by capital specialization – heterogeneity within subsamples

Affected vs Control	(1)				(2)			
	Publications (JIF weighted)				New keywords (share)			
	Agr/Hum/Med/Soc		Engin/Sciences		Agr/Hum/Med/Soc		Engin/Sciences	
	Generic	Specialized	Generic	Specialized	Generic	Specialized	Generic	Specialized
Affected × post	−0.088 (0.109)	−0.281** (0.114)	−0.052 (0.135)	−0.292*** (0.091)	0.012 (0.056)	0.007 (0.054)	−0.020 (0.026)	0.053* (0.028)
Matched group × Event year FE	Yes				Yes			
Observations	13084				3830			
Scientists	488				402			
Events	102				92			
Log-likelihood	−40689				2655			
Affected vs Control	(1)				(2)			
	Publications (JIF weighted)				New keywords (share)			
	Low USD damage		High USD damage		Low USD damage		High USD damage	
	Generic	Specialized	Generic	Specialized	Generic	Specialized	Generic	Specialized
Affected × post	−0.147 (0.158)	0.002 (0.178)	0.029 (0.152)	−0.347*** (0.067)	0.019 (0.026)	0.006 (0.029)	−0.044 (0.036)	0.048* (0.027)
Matched group × Event year FE	Yes				Yes			
Observations	13084				3830			
Scientists	488				402			
Events	102				92			
Log-likelihood	−40547				2657			
Affected vs Control	(1)				(2)			
	Publications (JIF weighted)				New keywords (share)			
	No data loss		Data loss		No data loss		Data loss	
	Generic	Specialized	Generic	Specialized	Generic	Specialized	Generic	Specialized
Affected × post	−0.030 (0.113)	−0.178 (0.111)	−0.100 (0.212)	−0.379*** (0.082)	0.004 (0.033)	0.046* (0.026)	−0.033 (0.031)	0.044 (0.034)
Matched group × Event year FE	Yes				Yes			
Observations	13084				3830			
Scientists	488				402			
Events	102				92			
Log-likelihood	−40682				2653			

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Table F-3: Impact of adverse events on research output and direction by capital specialization – heterogeneity within subsamples (continued)

Affected vs Control	(1)				(2)			
	Publications (JIF weighted)				New keywords (share)			
	Small lab		Large lab		Small lab		Large lab	
	Generic	Specialized	Generic	Specialized	Generic	Specialized	Generic	Specialized
Affected × post	−0.045 (0.174)	−0.266* (0.149)	−0.059 (0.158)	−0.297*** (0.109)	0.038 (0.075)	0.063* (0.036)	−0.041 (0.026)	0.036 (0.035)
Matched group × Event year FE	Yes				Yes			
Observations	13084				3830			
Scientists	488				402			
Events	102				92			
Log-likelihood	−40453				2662			
Affected vs Control	(1)				(2)			
	Publications (JIF weighted)				New keywords (share)			
	Junior lab head		Senior lab head		Junior lab head		Senior lab head	
	Generic	Specialized	Generic	Specialized	Generic	Specialized	Generic	Specialized
Affected × post	−0.020 (0.176)	−0.431*** (0.102)	−0.054 (0.163)	−0.148 (0.108)	−0.044 (0.032)	0.020 (0.024)	0.021 (0.035)	0.062* (0.032)
Matched group × Event year FE	Yes				Yes			
Observations	13084				3830			
Scientists	488				402			
Events	102				92			
Log-likelihood	−40361				2666			
Affected vs Control	(1)				(2)			
	Publications (JIF weighted)				New keywords (share)			
	Low-ranked		High-ranked		Low-ranked		High-ranked	
	Generic	Specialized	Generic	Specialized	Generic	Specialized	Generic	Specialized
Affected × post	−0.017 (0.140)	−0.508*** (0.151)	−0.051 (0.164)	−0.182** (0.085)	0.027 (0.039)	0.055* (0.030)	−0.060*** (0.022)	0.042 (0.036)
Matched group × Event year FE	Yes				Yes			
Observations	13084				3830			
Scientists	488				402			
Events	102				92			
Log-likelihood	−40417				2668			

Notes: Columns (1), (3), (5), (7), (9) and (11) show the estimates of Poisson pseudo-maximum likelihood regressions and columns (2), (4), (6), (8), (10) and (12) the estimates of linear regressions with high-dimensional fixed effects. The estimates in each right-hand sub-column (*Specialized*) are the sum of the baseline effect and the interaction effect. Likewise, the estimates in each right-hand part (e.g., *Medicine/Science*) are the sum of the baseline effect and the respective interaction effect. The dependent variable is the impact-weighted publication count (*Publications (JIF weighted)*), and the share of keywords that do not show up in the lab head's prior publications relative to all of the keywords in her publications (*New keywords (share)*). Other interaction coefficients omitted. The sample consists of all affected lab heads and their respective controls. Robust standard errors clustered at the adverse event level shown in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table F-4: Impact of adverse events on research output and direction by laboratory age – heterogeneity within subsamples

Affected vs Control	(1)				(2)			
	Publications (JIF weighted)				New keywords (share)			
	Agr/Hum/Med/Soc		Engin/Sciences		Agr/Hum/Med/Soc		Engin/Sciences	
	Modern lab	Old lab	Modern lab	Old lab	Modern lab	Old lab	Modern lab	Old lab
Affected × post	−0.294** (0.121)	−0.208* (0.120)	−0.308** (0.127)	−0.090 (0.113)	−0.033 (0.057)	0.032 (0.053)	−0.006 (0.020)	0.045* (0.027)
Matched group × Event year FE	Yes				Yes			
Observations	13084				3830			
Scientists	488				402			
Events	102				92			
Log-likelihood	−40685				2657			
Affected vs Control	(1)				(2)			
	Publications (JIF weighted)				New keywords (share)			
	Low USD damage		High USD damage		Low USD damage		High USD damage	
	Modern lab	Old lab	Modern lab	Old lab	Modern lab	Old lab	Modern lab	Old lab
Affected × post	−0.082 (0.226)	−0.096 (0.147)	−0.355*** (0.095)	−0.155 (0.097)	0.022 (0.022)	0.013 (0.030)	−0.021 (0.027)	0.058* (0.032)
Matched group × Event year FE	Yes				Yes			
Observations	13084				3830			
Scientists	488				402			
Events	102				92			
Log-likelihood	−40585				2660			
Affected vs Control	(1)				(2)			
	Publications (JIF weighted)				New keywords (share)			
	No data loss		Data loss		No data loss		Data loss	
	Modern lab	Old lab	Modern lab	Old lab	Modern lab	Old lab	Modern lab	Old lab
Affected × post	−0.218* (0.130)	−0.024 (0.100)	−0.405*** (0.111)	−0.237* (0.121)	−0.012 (0.036)	0.043* (0.024)	−0.014 (0.023)	0.047 (0.038)
Matched group × Event year FE	Yes				Yes			
Observations	13084				3830			
Scientists	488				402			
Events	102				92			
Log-likelihood	−40694				2656			

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Table F-4: Impact of adverse events on research output and direction by laboratory age – heterogeneity within subsamples (continued)

Affected vs Control	(1)				(2)			
	Publications (JIF weighted)				New keywords (share)			
	Small lab		Large lab		Small lab		Large lab	
	Modern lab	Old lab	Modern lab	Old lab	Modern lab	Old lab	Modern lab	Old lab
Affected × post	−0.098 (0.188)	−0.250* (0.131)	−0.380*** (0.126)	−0.105 (0.119)	0.022 (0.048)	0.079 (0.054)	−0.022 (0.020)	0.027 (0.039)
Matched group × Event year FE	Yes				Yes			
Observations	13084				3830			
Scientists	488				402			
Events	102				92			
Log-likelihood	−40446				2662			
Affected vs Control	(1)				(2)			
	Publications (JIF weighted)				New keywords (share)			
	Junior lab head		Senior lab head		Junior lab head		Senior lab head	
	Modern lab	Old lab	Modern lab	Old lab	Modern lab	Old lab	Modern lab	Old lab
Affected × post	−0.354*** (0.099)	−0.092 (0.200)	−0.057 (0.180)	−0.128 (0.090)	−0.012 (0.021)	0.005 (0.039)	0.015 (0.048)	0.060** (0.028)
Matched group × Event year FE	Yes				Yes			
Observations	13084				3830			
Scientists	488				402			
Events	102				92			
Log-likelihood	−40508				2669			
Affected vs Control	(1)				(2)			
	Publications (JIF weighted)				New keywords (share)			
	Low-ranked		High-ranked		Low-ranked		High-ranked	
	Modern lab	Old lab	Modern lab	Old lab	Modern lab	Old lab	Modern lab	Old lab
Affected × post	−0.214 (0.145)	−0.360** (0.144)	−0.341*** (0.126)	−0.035 (0.097)	−0.063 (0.039)	0.102*** (0.031)	0.009 (0.022)	0.013 (0.034)
Matched group × Event year FE	Yes				Yes			
Observations	13084				3830			
Scientists	488				402			
Events	102				92			
Log-likelihood	−40515				2677			

Notes: Columns (1), (3), (5), (7), (9) and (11) show the estimates of Poisson pseudo-maximum likelihood regressions and columns (2), (4), (6), (8), (10) and (12) the estimates of linear regressions with high-dimensional fixed effects. The estimates in each right-hand sub-column (*Old*) are the sum of the baseline effect and the interaction effect. Likewise, the estimates in each right-hand part (e.g., *Medicine/Science*) are the sum of the baseline effect and the respective interaction effect. The dependent variable is the impact-weighted publication count (*Publications (JIF weighted)*), and the share of keywords that do not show up in the lab head's prior publications relative to all of the keywords in her publications (*New keywords (share)*). Other interaction coefficients omitted. The sample consists of all affected lab heads and their respective controls. Robust standard errors clustered at the adverse event level shown in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.