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

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We investigate the nature and relevance of physical capital in knowledge production. Exploiting adverse events in research laboratories, we find that scientists experience a persistent reduction in research output if they lose specialized physical capital—equipment and material they created over time for a particular research purpose. In contrast, they recover in productivity if they only lose generic physical capital. Scientists in older laboratories, who presumably lose more obsolete physical capital, are more likely to change their research direction and recover. These findings suggest that scientists' investments into their own physical capital yield lasting returns but also create path dependence. (*JEL* D24, D83, E22, G31, I23, O31)

> Without laboratories, men of science are soldiers without arms.
> —Louis Pasteur (1822–1895)

Over past decades, research productivity has been declining (Bloom et al. 2020). To counter this development, economists generally suggest expanding human capital and facilitating access to prior knowledge (Bloom, Van Reenen, and Williams 2019; Van Reenen 2021). These suggestions derive from prior evidence that the knowledge held by scientists and inventors is a key determinant of research productivity (e.g., Azoulay, Graff Zivin, and Wang 2010; Waldinger 2010; Jaravel, Petkova, and Bell 2018; Jones 2009). In contrast, physical capital, as the other input to knowledge production (Machlup 1962; Stephan 1996), has received much less

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academic interest and is rarely singled out as a potential lever in policy debates on research funding.

One reason for the inattention to physical capital as an input factor is that, unlike human capital, it is typically regarded as homogeneous and replaceable. This rings true for physical capital with generic features, such as laboratory infrastructure and basic equipment, which is readily available in the marketplace. In line with this, Waldinger (2016) shows that the scientific productivity of universities recovers from the destruction of research facilities, but not from the displacement of scientists. However, knowledge production also requires physical capital that markets fail to supply due to its initially narrow and uncertain use case (Rosenberg 1992). This form of physical capital is often created by scientists themselves (Von Hippel 1976) and could encompass, for instance, self-developed instruments, genetically engineered animal models, and collected specimens. Although both historical and contemporary examples suggest that scientific breakthroughs are often linked to such assets (Mokyr 2002),[1] the current understanding of how physical capital relates to research productivity is limited.

In this paper we seek to improve our understanding of the nature and relevance of physical capital in knowledge production. We argue that scientists not only employ *generic physical capital*, which they acquire from external sources, but also accumulate *specialized physical capital* over time. This latter type of physical capital is necessary to advance the knowledge frontier on a given topic and constitutes a major determinant of the scientists' research productivity and direction. To provide empirical evidence for this, we study the causal effect of physical capital loss due to adverse events on the research output of individual scientists. For example, in January 2002, an accidental fire at the University of California-Santa Cruz destroyed equipment and material in two laboratories committed to cancer-related research. The university estimated the costs at four million dollars. However, according to one of the affected scientists, the most devastating loss concerned genetic strains that "had taken 14 years to develop and could take that long to replace."[2] We use such adverse events as a source of exogenous variation in the physical capital stock and compare the affected scientists with a carefully constructed control group. Our findings demonstrate that the investments of scientists in their own physical capital yield lasting returns in research output on a specific research trajectory.

We derive predictions of the effect of physical capital losses from a parsimonious conceptual framework. The scientist starts in a new laboratory endowed with generic capital, which becomes obsolete over time as a result of technological progress. Specialized capital is neither commercially available nor transferable between scientists or research topics. Accordingly, we formalize the scientist's problem similarly to that of human capital accumulation (e.g., Ben-Porath 1967; McDowell 1982): The scientist employs generic capital and invests time to create the specialized capital necessary to produce results on a chosen research topic. This specialized capital

[1] Galileo Galilei discovered the moons of Jupiter thanks to his self-constructed telescope, and Gregor Mendel laid the foundation of modern genetics by cultivating thousands of pea plants. The discovery of numerous exoplanets is closely linked to the Kepler Space Telescope, and the detection of the Higgs boson—the so-called *God particle*—is the outcome of experiments at CERN's Large Hadron Collider.

[2] https://www.latimes.com/archives/la-xpm-2002-jan-13-me-fire13-story.html (accessed September 16, 2022).

stock is subject to obsolescence because research opportunities on the topic become exhausted over time and more worthwhile topics emerge in parallel. However, the specialized capital stock binds the scientist to the initial topic, creating path dependence. Within this conceptual framework, a negative shock to specialized capital can lead to a *permanent* reduction in research output. That said, scientific productivity of scientists may recover through changes in research direction if the specialized capital was obsolete, or through the renewal of obsolete generic capital. With obsolescence generally increasing over time, this implies that recovery is more likely for scientists with old laboratories.

In our empirical analysis, we leverage adverse events at research institutions to establish a causal relationship between physical capital loss and research output.[3] To this end, we gather information from an array of news articles, incident reports, and books. We focus on adverse events with unanticipated and low-probability causes (e.g., accidents, criminal acts, malfunctions, and natural disasters) and exclude cases that involve human casualties. We obtain additional firsthand information through a survey targeted at likely informed scientists. The damage descriptions from the news reports and the survey responses give us a detailed picture of the physical capital loss at laboratory level. In particular we know of its scope in monetary terms and whether the loss relates to generic capital (which includes both "off-the-shelf" and more niche equipment/material that is available from vendors) or specialized capital (i.e., self-developed by the scientists).

Ultimately, we make use of about one hundred adverse events at research institutions in Europe and North America, which caused heterogeneous physical capital loss to more than twice as many laboratories. We focus on the "lab head" as our unit of observation.[4] We link the lab heads to publication data and reconstruct their professional biographies according to curricula vitae and online information. Each lab head is then precisely matched to a scientist from a different but comparable research institution on the basis of pre-event characteristics (research focus, research output, academic age, and career position). Summary statistics show the affected and control lab heads to have similar profiles in terms of their educational background and available resources. The total number of scientists in our sample of analysis is 488, which consists of equal numbers of affected and control lab heads. In ancillary analyses we make use of an additional placebo sample of 348 *spared* lab heads (and their matched controls) who did not experience any physical capital loss but were part of the same department as the affected lab heads.

We estimate the effect of physical capital loss on individual scientific productivity in a difference-in-differences and event-study framework. We find that physical capital loss leads to an immediate and permanent reduction in a lab head's research output. On average, simple and impact-weighted publication counts decline by

[3] Physical capital loss is not a recent phenomenon in science, as a diary note by Alexander von Humboldt (1801) illustrates: "My barometer had broken and it was the last one I had. […] you are tempted to cry out 'Lucky are those […] without instruments that break, without dried plants that get wet, without animal collections that rot'."

[4] This focus has both substantive and pragmatic reasons. First, the lab head is the most autonomous and independent scientist in the lab, whose publications best reflect the research carried out in the laboratory. Second, as the most productive and senior scientist, the lab head's career and research output can be more continuously observed both before and after the adverse event.

16 percent and 18 percent, respectively. These negative effects are remarkably persistent: Even 20 years after the adverse event, the average lab head's productivity shows no sign of recovery. Moreover, the decline in publications for the top 5 percent of the quality distribution is about twice as large as that for the bottom 50 percent, suggesting that affected lab heads suffer in terms of research quality in particular.

We provide compelling evidence that this persistent negative effect on research productivity is directly tied to physical capital loss. First, the magnitude of the effect increases with the scope of the damage. Lab heads suffering substantial loss (i.e., at least $100,000) experience a particularly large effect, while spared lab heads and lab heads suffering minor damage (i.e., below $100,000) remain virtually unaffected. Second, the negative effect on research output is much more pronounced for publications in which the lab heads are listed as the last author compared to those where they are the first author. Given the conventions of author ordering in most scientific disciplines, this suggests that affected lab heads especially miss out on research output that is accredited to them by virtue of their physical capital contribution. Finally, we explore whether possible side effects of the adverse event, such as career moves, changes in human capital input, and/or reputational damage, can explain the permanent reduction in research output, but find no corresponding evidence.

To shed light on the reasons for the permanent reduction in research output, we investigate the effect formation according to the specialization of the lost capital. Guided by our conceptual framework, we also consider under what circumstances physical capital loss affects research direction and how this relates to research output. We find that specialized capital loss has a persistent negative effect on research output and a positive effect on changes in research direction as measured by an increased share of new keywords in publications. By contrast, generic capital loss has, at most, a transient negative effect on research output in the first two years after the adverse event, while research direction remains unchanged.

We further explore the role of obsolescence in physical capital loss by leveraging variation in laboratory age at the time of the adverse event, proxied as the time elapsed since the lab head joined the respective research institution. We find that lab heads in presumably more modern laboratories suffer a substantial and persistent reduction in research output but do not change their research direction. In comparison, lab heads in presumably older laboratories experience a transitory decline in productivity *and* change their research direction. We then separately consider specialized and generic capital loss for lab heads in modern and old laboratories: After specialized capital loss, only lab heads in older laboratories recover in terms of research output, also making the most significant changes in research direction. For lab heads with generic capital loss, overall long-term effects seem to be negligible. Indeed, lab heads in presumably very old laboratories that lost only "off-the-shelf" generic capital (which is most easily replaced) experience an *increase* in productivity.

Taken together, these results underscore the relevance of physical capital in knowledge production as outlined in our conceptual framework. Specifically, they support the notion that specialized capital results from time-based investments in research on specific topics, which cannot be quickly or easily recovered. Moreover, the observed effect heterogeneity is consistent with the existence of two distinct recovery paths following physical capital loss: (i) The loss of obsolete specialized capital breaks path dependence, enabling worthwhile changes in research direction; and (ii) the renewal of (obsolete) generic capital offers productivity gains that can, in the long run, offset the negative effects of physical capital loss.

In further analyses, we show that our results are robust to alternative measures of research output and direction, different model specifications, estimators, and control groups. Nonetheless, our research design does not allow us to rule out that other factors beyond the type and obsolescence of the lost capital are at play. For instance, laboratory age likely correlates with other lab head characteristics—such as seniority, access to resources, and collaborators—which may contribute to their recovery in research output. Against this backdrop of potential confounding factors, we provide ample qualitative evidence to support our theory-grounded interpretation of the results.

Our study contributes to a better understanding of the knowledge production function. So far, the related literature interprets scientific discoveries as primarily intellectual accomplishments and consequently focuses on human capital inputs (e.g., Azoulay, Graff Zivin, and Wang 2010; Jones and Weinberg 2011; Levin and Stephan 1991; Oettl 2012; Waldinger 2012). Likewise, advances at the knowledge frontier are typically attributed to the increasing specialization of human capital rather than that of physical capital (e.g., Jones 2009). This aligns with the common assumption in the economics literature that physical capital is a homogeneous input factor with a marginal role for long-term productivity growth (cf. Long and Summers 1991). Our results suggest that, at least in the context of knowledge production at the individual level, physical capital is also heterogeneous, and its specialization sustains research productivity.

Another stream of literature links variation in research funding to scientific productivity (e.g., Arora and Gambardella 2005; Azoulay, Graff Zivin, and Manso 2011; Ganguli 2017; Jacob and Lefgren 2011; Myers 2020; Babina et al. 2023). These studies may seem like a natural counterpart to our empirical design. However, such research funding can be substituted, which reduces the impact of receiving or missing out on a grant as a financial boost, and it may also enter the knowledge production function through investments in inputs other than physical capital. By contrast, we observe the isolated loss of physical capital in an almost *ceteris paribus* setting. Moreover, our results suggest that the accumulation of physical capital is not merely a function of research funding, but can also include a substantial amount of time investment.

Most importantly, a few studies have examined particular manifestations of physical capital in research. Helmers and Overman (2017) find that the establishment of a large-scale research facility in the United Kingdom increased research output in the surrounding area, and Furman and Stern (2011) show that biological resource centers facilitate follow-on studies.[5] Closest to our study, Waldinger (2016) exploits the Allied bombings of German and Austrian universities during the Second World War

[5] Some other studies investigate how particular kinds of tangibles shape the production and organization of research. These papers have shown that the adoption of information technology positively affects research productivity (Agrawal and Goldfarb 2008; Ding et al. 2010), and that the costs of transgenic mice and tools for motion detection and gene editing can have a bearing on the development of research fields and team composition (Murray et al. 2016; Teodoridis 2018; Zyontz 2019).

and finds that damaged departments experienced a significant but temporary decline in their research output. To reconcile the different results, note that we provide evidence at the individual scientist rather than department level with fine-grained information on the nature of physical capital. In line with Waldinger (2016), the loss of generic (and possibly obsolete) capital leads to a short-lived reduction in research output. Moreover, while individual scientists face enduring consequences for the loss of specialized capital that required their time investments, departments may recover by renovating or through scientists turnover.[6] More generally, we extend this nascent literature stream by providing causal evidence in contemporary settings for the role of different types of physical capital in research productivity.

The remainder of the paper is organized as follows: In the next section, we present the conceptual framework that will guide us through the empirical analysis. Thereafter, we introduce the data, followed by the empirical strategy and selected descriptive statistics. Finally, we present our empirical findings and conclude the paper with a brief discussion and future outlook.

I. Conceptual Framework

A. *Outline*

We model knowledge production as a maximization problem in continuous time over a scientist's life-cycle (Levin and Stephan 1991). In contrast to the prior literature (Jones 2009; McDowell 1982), yet in alignment with our empirical investigation, we develop a partial model that centers on physical capital rather than human capital.

Initially, the scientist is equipped with a new laboratory that includes infrastructure, basic equipment, and materials. This generic capital stock, denoted as K_{g_0}, is applicable to any research topic.[7] Due to technical progress, the generic capital stock is subject to obsolescence and depreciates at a rate $\theta > 0$:[8]

$$K_g(t) = K_{g_0} e^{-\theta t}. \tag{1}$$

To conduct research on a particular topic, scientists also need specialized capital, which differs from generic capital in two ways. First, because of its narrower and more uncertain use case, specialized capital is not available from commercial suppliers (Riggs and Von Hippel 1994). As a consequence, scientists often develop it themselves (Franzoni 2009; Von Hippel 1976). Second, because of its specificities, specialized capital is less applicable beyond its initial context (Rosenberg 1992). In other words, it is not easily transferable between scientists and across topics. This

[6] In contrast to Waldinger (2016), we do not investigate shocks to both physical and human capital. This prevents us from assessing the relative importance of these two input factors for research output within our context.

[7] At the start of their employment, scientists typically receive a so-called startup package, which includes their own laboratory with an initial setup of equipment and materials. The size of this initial capital stock can vary across time, disciplines, institutions, and laboratories.

[8] The pace of technological progress is evident from numerous examples in different fields. For instance, because of advancements in gene sequencing technologies, the productivity of sequencing machines doubled almost annually during the 1990s and early 2000s (Stephan 2010).

makes it difficult for scientists to liquidate their investments in specialized capital or to redeploy it elsewhere.

Accordingly, we model the accumulation of specialized capital as a function of generic capital and the scientist's time investment (Ben-Porath 1967; McDowell 1982). The scientist employs generic capital and invests a fraction $i(t)$ of their time to develop specialized capital, with $0 \leq i(t) \leq 1$. The remaining time is then spent on producing research output. For a given topic j, we express the change in the accumulated stock of specialized capital as[9]

$$\dot{K}_j(t) = i(t)\, K_g(t). \tag{2}$$

Specialized capital is subject to obsolescence as research opportunities on a given topic are exhausted over time, while new research topics emerge in parallel. Investments in specialized capital therefore differ in their value to research output over time and between topics. To reflect this, we associate $K_j(t)$ with the factor productivity $A_j(t)$, which is initially at level A_j and decays, for simplicity, at the same rate $\theta > 0$ as $K_g(t)$. We define the stock of specialized capital as obsolete when its factor productivity $A_j(t)$ becomes smaller than that of another available topic.[10]

With $A_j(t) = A_j e^{-\theta t}$, the research output can be represented as

$$R_j(t) = \big(1 - i(t)\big)\, A_j(t)\, K_j(t)^{\beta}, \tag{3}$$

where we assume for simplicity that the scientist works on one topic at a time.[11] The parameter β governs the relevance of specialized physical capital, which we assume to be constant across topics (although it likely varies between different research areas). Initially devoid of a specialized capital stock, the scientist starts working on the topic that has at the outset the highest factor productivity (topic 1).[12]

We make the following additional assumptions to reach a simple analytical solution (even though the results discussed in Section IB remain more general). First, the productivity of topic 1 and new emerging topics is such that topic 1 remains the optimal choice unless a shock occurs. Second, the scientist maximizes their research output without temporal preferences. Accordingly, their objective function is $J(R_1) = \int_0^T R_1(t)\,dt$.

[9] In a more general formulation, this equation could be defined as $\dot{K}_j(t) = i(t)\, K_g(t) - \delta K_j(t)$, where δ represents the rate at which specialized capital deteriorates. For simplicity, we assume δ is negligible relative to the rate of obsolescence of capital.

[10] The factor productivity may also capture the (academic or societal) importance of a topic and the availability of funding (Myers 2020).

[11] Note that for simplicity, research output does not directly depend on generic capital. In a more general formulation, the equation could be instead defined as $R_j(t) = \big(1 - i(t)\big)\, A_j(t)\, K_j(t)^{\beta} K_g(t)^{\gamma}$.

[12] The sequential selection of research topics resembles other models on research direction (e.g., Manso 2011).

The optimal solution $i(t)$ is a step function, that is, the scientist first invests in specialized capital up to time τ_1, and thereafter only produces research output.[13] The optimal length τ_1 of the investment phase is then

$$\tau_1^* = \frac{1}{\theta}\ln\left(\frac{K_{g_0}(\beta+1)}{K_{g_0}\left(\beta e^{-\theta T}+1\right)+K_{1_0}}\right), \tag{4}$$

where K_{1_0} represents the initial stock of specialized capital.[14] This period increases with the time horizon T but converges quickly to a constant. We assume that T is large, which simplifies the equations that follow. We comment on the implications of a finite time horizon and present related equations in Supplemental Appendix A.1.

B. *Physical Capital Shocks*

In line with our empirical strategy, we formulate predictions as to the consequences of unexpected negative shocks to the scientist's capital stock. We focus first on a shock to specialized capital. We consider a translation, where t_x indicates the time of the shock, and the parameters K_{g_x} and K_{1_x} indicate, respectively, the stocks of generic and specialized capital immediately before the shock. In the same way, A_{1_x} serves as a shorthand for $A_1 e^{-\theta t_x}$.

We first show that if the stock of specialized capital is not obsolete (i.e., no other topic with a higher factor productivity exists), a negative shock causes a permanent reduction in research output. The scientist extends (or returns to) the investment phase (see equation (4)), which reduces research output in the short term. However, even in the long term, the stock of specialized capital does not return to the counterfactual (no shock) level. As a result, the ratio of the derivative of the optimal level of research output with respect to K_{1_x} and that of the counterfactual level is a positive constant:

$$\frac{\partial R_{1_x}(t)^*/\partial K_{1_x}}{R_{1_x}(t)^*} = \frac{\theta\beta}{\theta K_{1_x}+K_{g_x}}. \tag{5}$$

This implies that a negative shock to the specialized capital stock can have a permanent negative effect on knowledge production. This result depends on the depreciation rate of generic capital ($\theta > 0$), with the scientist accumulating specialized capital less efficiently than before. In the more general formulation (with a finite time horizon T), it is also a consequence of the scientist having less time available than at the beginning of the period.

[13] In more general models with future discounting, investments are also concentrated at the beginning of the period, although the transition to production is not necessarily a step function (Ben-Porath 1967; McDowell, 1982). Our conclusions depend less on the specific functional form of the optimal solution for $i(t)$ than on the case that most investments are made at the beginning of the period.

[14] We maintain K_{1_0} in equation (4)—although it is assumed to be initially null—to help understand the consequences of capital shocks in Section IB.

The later in time the shock occurs, the more likely it is that the existing stock of specialized capital has become obsolete. We indicate with A_{2_x} the initial factor productivity of the best alternative topic. For our purpose, it is sufficient to imagine this value to be constant or increasing over time (as long as it does not warrant a change in topic on its own). Therefore, it becomes higher relative to A_{1_x} the later the shock occurs.

We compare the present value of future research at the time of the shock between switching to an alternative topic (topic 2) and sticking to topic 1—which we indicate with J_{2,t_x} and J_{1,t_x}, respectively. The scientist changes their topic if

$$(6) \qquad J_{2,t_x} > J_{1,t_x} \Longrightarrow A_{2_x} > A_{1_x}\left(\frac{\theta K_{1_x} + K_{g_x}}{K_{g_x}}\right)^{\beta+1}.$$

It becomes clear that even if the specialized capital has become obsolete (i.e., $A_{2_x} > A_{1_x}$), the scientist sticks to topic 1 as long as the stock of specialized capital K_{1_x} is sufficiently high relative to the stock of generic capital. A negative shock to K_{1_x} decreases the value of the ratio, making a switch to topic 2 more attractive. Interestingly, the depreciation of generic capital and, in the more general model, a finite time horizon each serve as a sufficient assumption for this result.[15]

If the scientist switches research topics after a shock to specialized capital, their research output may recover. The scientist returns to the investment phase and starts accumulating specialized capital for topic 2, $K_{2_x}(t)$ (initially null). Thereafter, the change in research output relative to the counterfactual is

$$(7) \qquad \frac{R_{2_x}(t)^* - R_{1_x}(t)^*}{R_{1_x}(t)^*} = \frac{A_{2_x}}{A_{1_x}}\left(\frac{K_{g_x}}{\theta K_{1_x} + K_{g_x}}\right)^{\beta} - 1.$$

The lower bound of this value is a negative constant and corresponds to the case in which the specialized capital is completely lost and $A_{2_x} = A_{1_x}$. The ratio increases and becomes positive for higher values of A_{2_x}. The upper bound is defined by the value of A_{2_x} that renders the scientist indifferent between topics in the absence of a shock. Recovery occurs because the scientist, in the absence of any shock, is better off avoiding the cost of investing in $K_{2_x}(t)$, even if changing their research topic was to come with an equal or even higher productivity in the long run.

We refrain from a detailed description of the consequences of generic capital shocks. In general, the model predicts that a generic capital shock aggravates the consequences of a specialized capital shock. If the scientist already holds specialized capital, a generic capital shock alone will have comparatively minor consequences on productivity, but will hamper future changes in research topic. We further understand that, in practice, generic capital shocks may be short-lived, because scientists can replenish their stock by purchasing generic capital from external sources or by drawing on the stock of colleagues and collaborators. Depending on the obsolescence

[15] Without these assumptions, the scientist would switch to the topic that guarantees the highest factor productivity immediately, independent of capital levels.

of the lost generic capital, this may amount to a renewal of the generic capital stock that actually increases the scientist's productivity relative to the counterfactual.[16]

In summary, we can formulate the following testable predictions derived from the model. First, the loss of specialized capital can lead to a permanent reduction in research output. Second, research output may recover if the loss relates to obsolete specialized capital, which is more likely for scientists with old laboratories. Third, such recovery results from a change in research direction. Supplemental Appendix Figure A-1 provides a graphical illustration of these predictions.

II. Data

A. *Collecting Adverse Events*

Our empirical strategy relies on a hand-assembled set of adverse events that led to the loss of physical capital in research laboratories (Baruffaldi and Gaessler 2026). We identify these events through a comprehensive search of news archives (NewsLibrary 2017; LexisNexis 2017; and Google News 2017) and other sources (i.e., the US FEMA Disaster Open Database (FEMA 2017a) and National Fire Incident Database (FEMA 2017b), incidence reports of the Office of Laboratory Animal Welfare (2017), the Global Terrorism Database (GTD 2017), and the diary of the Animal Liberation Front (Young 2010).[17] Altogether, we use almost 500 secondary sources (e.g., news articles, reports, and books). A detailed account of the data collection process (Supplemental Appendix B.1), several examples (Supplemental Appendix B.2), and the entire list of news sources (Supplemental Appendix B.3) are provided. This data collection effort results in an initial set of 296 adverse events.

We then process all available information and select those adverse events that caused nontrivial damage to research laboratories and appear plausibly exogenous. In particular, we exclude adverse events with only minimal loss of physical capital (e.g., shattered test tubes, fires under lab hoods) or with loss of physical capital unrelated to research (e.g., damage to classrooms). We further remove those that are linked to scientists' apparent carelessness or disregard of rules and regulations. Rather, we focus on adverse events with unanticipated and low-probability causes (e.g., accidents, natural disasters, and criminal acts). To isolate the effect of physical capital loss, we exclude a few cases in which the adverse event led to human casualties among the scientists. Finally, we disregard cases prior to 1980 to increase coverage in publications data, and after 2012 to reduce truncation in the post-event period. This reduces our dataset to 147 adverse events.

Because the collected secondary sources do not furnish complete information on all adverse events, we gather additional firsthand information through a targeted survey. For each event we seek to establish the affected departments, laboratories, and

[16] Relatedly, one aspect that we do not formalize or empirically capture is that generic capital may fall under both lab- and organization-level governance, thereby potentially alleviating some of the costs and risks for the individual scientist.

[17] 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).

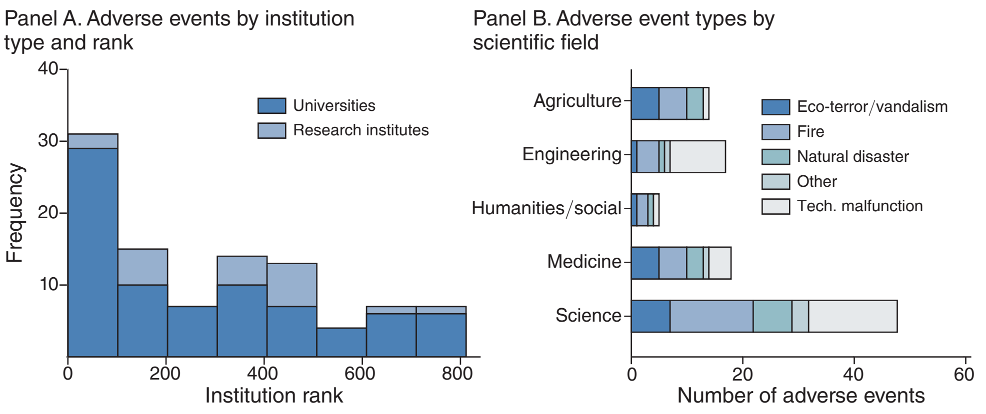

Figure 1. Research Institutions and Scientific Fields with Adverse Events

Notes: The left-hand figure presents the distribution of affected universities and research institutes by their position in the SCImago Institutions Ranking. The right-hand figure illustrates the distribution of different adverse event types by the main scientific field of the affected research department (OECD main research areas). In both graphs the unit of observation is the adverse event.

scientists (the lab head's name), the type of capital lost, and the extent of the damage in monetary terms. Where these details are missing from the secondary sources, we use the available information (research field, institution, year) to identify "likely informed" scientists. We design a brief online questionnaire with closed-ended questions to supplement and validate the information already gathered. We send the questionnaire via email to about 16,000 scientists and receive 1,475 (9 percent) responses, not only from scientists directly affected but also from spared scientists who witnessed the adverse event. On the basis of these responses, we gain sufficiently complete information for the majority of our adverse events. Following our collection efforts, we discard those events for which the identity of the affected scientists remains unknown. Eventually, we obtain a set of 102 adverse events with sufficiently complete information.[18]

B. *Adverse Event Characteristics*

The adverse events in our sample occurred at research institutions in the United States, Canada, Western Europe, and Australia. These institutions comprise not only universities but also public and private research institutes. Virtually all of them (98 percent) conduct research at a scale that places them among the top 1,000 research institutions worldwide (see Figure 1, panel A). A high proportion of cases involve top-ranked institutions. Although the sample covers adverse events from all of the main scientific fields, the events are concentrated in (natural) science, followed by medicine, engineering, and agriculture (see Figure 1, panel B).

[18] We provide further details of the survey and the survey questions in Supplemental Appendices B.4 and B.5, and a comparison of the different subsets of adverse events in Supplemental Appendix B.6.

These descriptive statistics suggest that our sample is not equally representative of all disciplines, institutions and countries. To discuss whether this threatens the external validity of our analysis, we examine the two main mechanisms that explain entry in our sample. The first of these relates to the chance of an adverse event and relevant damage. This probability varies between research fields and institutions. The low number of cases seen in humanities and social sciences can be attributed to the facts that some adverse event types are less likely in these fields and that the adverse events that do occur therein rarely involve loss of physical capital.[19] Similarly, top-ranked institutions are more research-oriented and hold larger stocks of physical capital, which explains why a relatively large proportion of events may involve such institutions.[20] Because we are primarily interested in the role of physical capital in empirical research, where it is an integral part of the research process, we deem this first mechanism to be in alignment with the objectives of our analysis.

The second mechanism concerns the probability of us being able to observe the adverse event and gain sufficient information about it. Thus, the high number of adverse events at US institutions in our sample likely reflects the geographical focus of our (English) news outlets. Likewise, top-ranked institutions may receive more media attention in general. This type of selection is less problematic and, if anything, facilitates the comparison with prior studies, which focus predominantly on highly productive scientists in the United States. However, it is possible that media coverage also depends on the degree of impact of the adverse event on the scientists affected. This would be of particular concern were our sample to omit cases in which the consequences for scientists in the long run were limited despite substantial physical capital loss. In practice this type of selection proves to be of minor significance. First, we find an almost perfect overlap when we cross-check our events with official incident records from the US Chemical Safety Board and the Occupational Safety and Health Administration, where such selectivity should not be a factor. Second, for more than 80 percent of the adverse events, the relevant news articles were published within the first ten days of the event. Finally, we find no statistically significant differences when comparing the characteristics (e.g., year, rank, research field) of adverse events included in the final dataset and those excluded because of missing information. Taken together, these results militate against the presence of serious selection effects that would compromise the external validity of our analysis.

C. *Affected Laboratories and Scientists*

Many adverse events involve multiple independent research laboratories and, hence, affect the physical capital stock of several different scientists. We therefore determine the damage caused by each adverse event at the laboratory level. We distinguish between different laboratories via the identity of the respective laboratory

[19] For instance, ecoterrorist attacks occur predominantly in the fields of life sciences and agriculture, where scientists work with living organisms. Similarly, adverse events caused by technical malfunctions are more frequent in engineering and physical sciences where researchers use complex machinery.

[20] Stephan (2012) exemplifies this by stating that the expenditures for research equipment of the leading five universities alone represent more than 10 percent of the total spent by all universities in the United States.

head.[21] While the focus of our analysis is on these directly affected laboratories, we also maintain a dataset of spared laboratories within the same department for which we can rule out any direct damage. Altogether, we identify 249 directly affected laboratories (and 178 spared laboratories) as linked to our 102 adverse events.

In each laboratory, we restrict our analysis to the laboratory head. This focus has both substantive and pragmatic reasons. First, the lab head is the scientist with the highest research autonomy and financial independence, whose publications best reflect the research carried out in the laboratory. Second, as the most productive and senior scientist, the lab head's career and research output can be more continuously observed both before and after the adverse event. Based on their full names and affiliations, we link these scientists to publication records. We further use curricula vitae and online information to describe their academic careers since they obtained their doctoral degree (or equivalent). Our dataset includes information on gender,[22] seniority, past and current affiliations, publications, and external funding from competitive research grants.[23] Previous and current affiliations are linked to the SCImago Institutions Ranking (SCImago 2022a) to capture the quality and prestige of the institutions involved, and to university research expenses to proxy the budget available to the scientist.[24]

D. *Control Group Construction*

Our empirical design demands the comparison of affected lab heads with a matched control group. The reasons for this are twofold. First, comparing lab heads with one another would ignore life cycle patterns and general time trends that affect research output but also correlate with treatment status. Second, comparing lab heads with a random draw of other scientists would be inappropriate given that inclusion in our sample correlates with a scientist's seniority and research activity in capital-intensive fields. In the absence of the counterfactual output path provided by properly matched control scientists, we would not be able to disentangle these effects from the actual treatment effect.

We therefore create a control group such that each lab head is uniquely matched to an unaffected scientist based on common productivity and career characteristics (see Supplemental Appendix C for further details). To this end we seek scientists who are active at different research institutions and have no coauthorship ties with

[21] Associating a laboratory with the name of its head scientist is common in science. The identification of the laboratory head is usually straightforward because the name is often mentioned in the news reports or the lab head responded to the questionnaire directly. Alternatively, we identify laboratory heads through the responses of (former) lab affiliates (e.g., postdocs, students). This approach minimizes possible survivorship bias that might arise if scientists still active today are more likely to respond to the survey.

[22] Gender information for the treated sample was obtained from CV. For the control group, we predict gender based on first names via (Namsor 2023).

[23] Funding data were obtained from the Australian Research Council (2022); the Canadian Institutes of Health Research (2022); the Natural Sciences and Engineering Research Council of Canada (2022);the National Institutes of Health (2022); the National Science Foundation (2022a); the Danish Council for Independent Research (2022); the European Research Council (2022); the Grant-in-Aid for Scientific Research (2022); Organisation for Scientific Research (2022) in the Netherlands; the Swedish Research Council (2022); Swiss National Science Foundation (2022); and the UK Research and Innovation (2022). Funding in foreign currencies was converted using historical exchange rates provided by the OECD (2022).

[24] Research expenses information was obtained from the National Science Foundation (2022b).

the affected scientist. Given that these control scientists remained unaffected by the adverse event but otherwise have a similar research profile and trajectory up to the year of the (inherited) adverse event, they should serve as a meaningful counterfactual in the posttreatment period.

We begin by extracting all publications listed in the Scopus database (Scopus 2023) and disambiguating author profiles. For this, we rely on data downloaded during the first six months of 2023 through the Scopus RestFUL API, using the pybliometrics library (Rose and Kitchin 2019). Given the diversity of the lab heads in our sample in terms of productivity, location, and research field, the pool of potential controls is immense. We thus disambiguate author profiles automatically, aggregating Scopus profiles with compatible names and sharing at least one coauthor. At this stage we remove authors with very common names and "accidental" researchers having fewer than three publications in their lifetime (Mohnen 2022; Oettl 2012).

We then define the pool of potential controls for each lab head and use Coarse Exact Matching (CEM) to balance their pre-event productivity based on bibliographic indicators (Azoulay, Graff Zivin, and Wang 2010). For each lab head, we define the pool of potential controls to authors who published prior to the adverse event year, were affiliated with a research institution located in a Western country, and worked in the same research area. We use CEM to pair treated lab heads to control candidates with a similar academic age (as proxied by the first year of publication), a similar overall pre-event publication count, a similar publication count in the two years preceding the adverse event, and a similarly ranked affiliation. To prevent contamination, we exclude both coauthors of the lab head and scientists from the lab head's location.

After narrowing the pool of potential controls to a tractable sample, we conduct a more thorough screening based on additional data to ensure affected lab heads and control scientists are similar also in their career trajectories. Most importantly, we automatically gather online CV information and process the unstructured text using a large language model (Korinek 2023). Based on the CV information, we prioritize control candidates in a comparable career position (i.e., we prioritize professors, principal investigators, and senior scientists over lab technicians, consultants, and research assistants) and those who engage in empirical research. In the frequent case of multiple control candidates meeting these criteria, we rank them through nearest-neighbor matching based on additional pre-event productivity indicators. Finally, we select the top-ranked candidate for the control group, ensuring that each control is uniquely matched to a single lab head.

We identify a control scientist for 98 percent of the initial sample of affected (and spared) lab heads and exclude the remaining from our analysis. Thus, the final sample consists of 244 affected (and 174 spared) lab heads and their respective controls.[25]

[25] In Supplemental Appendix F.5, we probe the robustness of our main result to the use of control group variants, each representing an alternative approach to a key methodological decision made in the outlined matching strategy.

III. Econometric Model, Variables, and Descriptive Statistics

A. *Econometric Specification*

We define a difference-in-differences estimation model in which the treatment group represents the lab heads affected by the adverse event, and the comparison group represents the matched lab head controls, who inherit the adverse event information from their respective treated counterpart. We perform our analysis for a period of 20 years before and up to 20 years after the adverse event and investigate the effect of the physical capital shock on research output and shifts in research trajectory.

We implement an event-study design to study the dynamic effects of adverse events on research output and direction, Y. To this end, we use a panel data model at the level of the individual scientist i in year t with the following elements. First, we include a full set of leads and lags specific to a given matched group, β_{mk}^{All}, where m denotes the matched group, and k, ranging from -20 to $+20$, denotes the year relative to the adverse event.[26] Note that each matched group m comprises one affected lab head and one control scientist. Second, we include binned sets of leads and lags for the affected lab heads, $\beta_k^{Affected}$: one binned lag for the years -20 to -9, two-year bins between -8 and $+11$ years, a four-year binned lead for years $+12$ to $+15$, and a five-year binned lead for years $+16$ to $+20$. We choose these broader leads to account for the fewer observations in those years due to right-hand truncation. Finally, we cluster errors, ϵ_{it}, at the adverse event level, which allows for correlation between the error terms of lab heads that were affected by the same adverse event and their respective controls. The specification is as follows:

$$Y_{it} = \sum_{k=-20}^{20} \beta_{mk}^{All} \mathbf{1}_{\{L_{it}^{All}=k\}} + \sum_{k=-20}^{20} \beta_{k}^{Affected} \mathbf{1}_{\{L_{it}^{Affected}=k\}} + \epsilon_{it}. \tag{8}$$

We normalize the coefficients $\beta_{k=-2}$ to zero and, hence, express the dynamic treatment effects relative to this pre-event year bin. The leads and lags specific to a matched group, L_{it}^{All}, capture mechanical effects that may emerge from our sample construction. Moreover, they subsume life cycle and calendar year fixed effects as the adverse event year and the academic age of affected and control lab heads are the same.[27] The leads and lags that are specific to the affected lab heads, $L_{it}^{Affected}$, capture the causal effect of the adverse event. We can examine the validity of our research design by testing for any significant differences between affected and control scientists in the pretreatment period.

In difference-in-differences frameworks with differential timing, the comparison is not only between treated and never treated but also between late and early treated

[26] Note that the full period restricts adverse events to those that occurred in 2002 or earlier. For scientists linked to the youngest adverse event in our sample (in 2012), we can only consider a lag of 10 years. We illustrate the observed time window by event cohort in Supplemental Appendix Figure D-4.

[27] Given that affected and control scientists are directly matched on pretreatment outcomes, we omit scientist fixed effects in our baseline specification (cf. Chabé-Ferret 2017). Adding (or using only) scientist fixed effects yields estimates similar to those of our baseline specification (see Supplemental Appendix F.1).

(Goodman-Bacon 2021). That is, the estimated coefficients on a given lead or lag can be contaminated by effects from other periods. We therefore compare the dynamic treatment effects of our baseline model to those of an "interaction-weighted" estimator that is free of contamination (Sun and Abraham 2021).[28] The dynamic treatment effects are highly consistent between both approaches.

In addition to the event-study specification (equation (8)), we discuss magnitudes and summarize additional results based on a second specification. In this, we replace the treatment-specific leads and lags with a binary variable that takes a value of 1 for affected lab heads in the post-event period, representing the static difference-in-differences estimator. Under our identification assumption, the coefficient $\beta^{Affected}$ gives the average causal effect of the physical capital shock in the post-event period. This second specification is as follows:

$$(9) \qquad Y_{it} = \sum_{k=-20}^{20} \beta_{mk}^{All} \mathbf{1}_{\{L_{it}^{All}=k\}} + \beta_k^{Affected} \mathbf{1}_{\{L_{it}^{Affected} \geq 0\}} + \epsilon_{it}.$$

To capture potential heterogeneity in the treatment effects, we expand the models above with interactions of the binary variables (indicating particular lab head subgroups) with the set of leads and lags specific to the group of treated lab heads. The modified version of equation (8) is then as follows:

$$(10) \qquad Y_{it} = \sum_{k=-20}^{20} \beta_{mk}^{All} \mathbf{1}_{\{L_{it}^{All}=k\}} + \sum_{k=-20}^{20} \beta_k^{Affected} \mathbf{1}_{\{L_{it}^{Affected}=k\}} + \sum_{k=-20}^{20} \beta_k^{Affected \times Subgroup} \mathbf{1}_{\{L_{it}^{Affected}=k\}} \times \mathbf{1}_{\{Subgroup=1\}} + \epsilon_{it}.$$

For count dependent variables, we estimate Poisson pseudo-maximum-likelihood (PPML) regressions with high-dimensional fixed effects; for continuous dependent variables, we run linear (OLS) regressions with high-dimensional fixed effects.[29]

B. *Dependent Variables*

We use simple and impact-weighted publication counts to measure research output, and rely on the share of new publication keywords to quantify changes in research direction.[30]

Publications.—We retrieve all publications of a scientist from the Scopus database and generate annual counts according to the year of publication. We focus on journal articles and conference proceedings, and exclude review articles, editorials, letters and books. Moreover, we exclude any article or conference proceeding with

[28] This estimator is available for linear regression, which is suboptimal given that our preferred model for count data is Poisson pseudo-maximum-likelihood. To ease comparison, we log-transform the dependent variables.

[29] We use, respectively, the *ppmlhdfe* and *reghdfe* Stata packages (Correia, Guimarães, and Zylkin 2020; Correia 2015).

[30] To ensure that extreme outliers and data errors do not skew our results, we winsorize all count variables at the ninety-ninth percentile.

more than 20 authors to focus on output that is directly attributable to the scientists concerned.

JIF-Weighted Publications.—We generate annual counts based on publications weighted by the respective journal's impact factor (JIF). For this, we draw on the annual SCImago Journal Rank (SCImago 2022b) indicator, which is based on the average number of citations received in the respective year by articles published in the journal in the three preceding years.[31] Unlike citation counts, this measure is not forward-looking and thus prevents contamination of the pretreatment period. We present additional results based on citation-weighted publication counts in Supplemental Appendix E.2.

Share of New Keywords.—We calculate a scientist's annual share of new keywords relative to all of the keywords in their publications in that year. Keywords summarize the themes of a publication and relate primarily to topics and not methods. This measure follows the intuition that scientists will be more likely to use new keywords in their publications if these cover different research topics to those in their publications before the adverse event. In line with prior literature (Azoulay, Graff Zivin, and Manso 2011; Murray et al. 2016), we use indexed keywords derived from standardized taxonomies to ensure comparability over time. Keyword information is not available for every publication. We therefore consider alternative measures of research direction in the form of the share of self-references and abstract similarity and present these additional results in Supplemental Appendix E.4.[32] These measures follow the same intuition but have the shortcoming that they are sensitive not just to topic-based change but also to method-related change.

C. *Lab Head Characteristics*

We present summary statistics on the pre-event characteristics of affected and control lab heads. In Table 1 we list the means, medians, and standard errors of a broad set of variables that exemplify the similarity of both groups in the year leading up to the adverse event.

We find that the average lab head in our sample is well-advanced in their scientific career and has considerable resources at hand. The mean seniority, which is measured as the time elapsed since first publication, is about 22 years. Lab heads are predominantly male (84 percent) and gained their PhD from a university with an average ranking of 228. On average, the lab head's PhD affiliation ranks substantially higher than their affiliation at the time of the adverse event (311). The high variance in both ranking variables reflects the heterogeneity of institutions in our sample. Because information on the lab heads' research budgets is scarce, we

[31] This information set goes back to the early 1990s; for earlier publications, we extrapolate the ranking.

[32] We calculate the scientist's annual share of references to their prior publications relative to all references. We calculate the maximum similarity of a publication's abstract to all abstracts of the scientist's previous publications. In the case of multiple publications in a year, we use the maximum throughout. Similarity of abstract text is measured as the cosine similarity of words used in abstracts, appropriately filtered by a dictionary of English stop words, and stemmed using *nltk* and *sklearn* Python libraries.

Table 1—Pre-event Characteristics of Affected Lab Heads with Matched Controls

	Affected ($N = 244$)			Controls ($N = 244$)				
	Mean	Median	Std. err.	Mean	Median	Std. err.	Diff.	p-value
Seniority	21.84	21.00	8.60	21.72	22.00	8.60	−0.12	0.875
Male	0.84	1.00	0.37	0.83	1.00	0.38	−0.01	0.716
PhD affiliation rank	227.58	171.00	213.74	221.45	148.50	206.81	−6.13	0.748
Affiliation rank	311.49	219.00	227.45	297.07	226.00	219.81	−14.42	0.477
Affiliation expenses ($ mio)	159.77	146.51	130.00	168.41	114.86	185.74	8.64	0.631
External funding ($ mio)	0.15	0.02	0.42	0.13	0.00	0.40	−0.03	0.492
Laboratory age	14.88	14.00	8.69	13.68	12.00	9.24	−1.20	0.140
Laboratory size	9.42	6.55	9.81	9.21	6.70	9.16	−0.21	0.805
Empirical publications (share)	0.42	0.40	0.20	0.43	0.41	0.22	0.01	0.774
Last author publications (share)	0.38	0.38	0.24	0.37	0.35	0.22	−0.01	0.505
Publications	3.83	3.00	3.21	3.75	2.85	2.89	−0.08	0.770
Publications (JIF-weighted)	8.85	4.88	10.71	8.75	5.30	11.01	−0.09	0.925
References	107.08	80.00	90.07	110.33	86.94	82.87	3.25	0.679
Self-references (prior pubs)	7.61	4.88	8.52	7.26	4.95	7.47	−0.36	0.623
Keywords	4.34	0.86	8.32	4.22	1.00	7.35	−0.12	0.863
New keywords	3.80	0.79	7.24	3.78	1.00	6.36	−0.02	0.978

Notes: This table presents summary statistics of pre-event characteristics of affected scientists and their matched control group. The unit of observation is at the scientist level. Information on affiliation expenses is only available for scientists at US affiliations. Reported p-values are based on an unpaired t-test.

approximate their available resources through several variables. First, we observe the annual research expenses of the lab heads' current affiliations, which are, on average, about $160 million. Second, we measure the lab heads' annual external funding, which averages about $156,000. The mean age of the labs is about 15 years old, calculated as the time since the lab head became the principal investigator at their current affiliation.[33] The mean lab size, measured as the number of unique coauthors of identical affiliation, is about 9.5.[34]

We use publication-based variables to measure the lab heads' reliance on empirical research and their contribution to research projects. First, we calculate the share of the lab head's publications that explicitly relate to empirical research.[35] The mean share of empirical publications is 0.42. Second, we calculate the share of publications in which the lab head is listed as the last author. In most research fields, the convention is that the last position in the author list is reserved for the scientist who has contributed most to the project in terms of funding, laboratory space, research material and equipment. We interpret this variable as a proxy for the share of research that is accredited to the lab head by virtue of their physical capital stock. On average this share is 0.38.

Finally, we look at the levels of our main measures of research output and direction. We report the annual averages for the ten years prior to the event. The average research output is relatively high, with about four publications in a simple

[33] Note that with this operationalization, we likely overestimate the actual age of the lab, as scientists may move to a new lab without changing their affiliations.

[34] These numbers are comparable with those in prior studies: The Science and Engineering PhD and Postdoc Survey reports a mean lab size of 10 (cf. Stephan 2012).

[35] To this end we search in each publication's title, abstract, and keywords for terms related to empirical research, such as "equipment," "experiment," "material," and "instruments." This method, borrowed from Franzoni (2009), likely understates the true number of publications related to empirical research.

count and about nine in an impact-weighted count. In these publications, lab heads list on average 107 references, of which around 7.6 refer to their own prior work (self-references). The average number of unique keywords is 4.3, with a relatively high number of these, 3.8, being keywords not previously used by the scientist.

We document a close resemblance in pre-event characteristics between affected and control lab heads.[36] The means of the two groups are statistically indistinguishable from each other for matched and unmatched variables: the t-test p-values are never below conventional significance thresholds, with most of them being well above 0.5. We also show that the characteristics of affected and control lab heads have similar distributions overall (see Supplemental Appendix Figure D-1). Altogether, this strongly suggests that affected and control lab heads have comparable profiles in terms of their educational background, career position, available resources, and research activities.

D. *Laboratory Damage*

There is substantial variation in physical capital loss between the laboratories in our sample. In the following, we detail the operationalization of our measures of physical capital loss and present relevant descriptive statistics (see Supplemental Appendix D.2 for further details).

Damage Extent.—We capture the damage extent in monetary terms with five ordinal categories (see Figure 2, panel A). Across the 244 affected laboratories, the extent of damage ranges from a few thousand dollars to more than ten million dollars. The majority of cases had damage between 100,000 and one million dollars. Given that the monetary value of a laboratory's equipment and material typically ranges between 250,000 and one million dollars (Stephan 2012), these damages are substantial.

Generic and Specialized Capital.—The damage descriptions in the news reports and the responses to our survey provide us with a detailed picture of the type of physical capital loss at each laboratory.[37] In line with our conceptual framework, we ultimately aggregate different types of physical capital loss to two groups: Generic capital incorporates laboratory space and infrastructure, equipment/material from multiple suppliers ("off-the-shelf"), and equipment/material from few suppliers; specialized capital represents equipment/material internally developed for specific research purposes.[38] Note that we make use of the nested case of "off-the-shelf" generic capital loss in the final part of our heterogeneity analysis.

About 40 percent of the affected laboratories lost only generic capital, while fewer than 10 percent lost only specialized capital (see Figure 2, panel B). Most often, laboratories lost both generic and specialized capital, especially where the damage was

[36] Supplemental Appendix Table D-1 presents the corresponding tests for the spared lab heads and their matched controls.

[37] The response options in our survey capture the following different categories of capital loss: laboratory space and infrastructure; equipment and material easily available from multiple sources ("off-the-shelf"); equipment and material available from few suppliers; equipment and material developed internally for specific research purposes.

[38] We also know about the loss of data and research notes, which we account for in robustness checks.

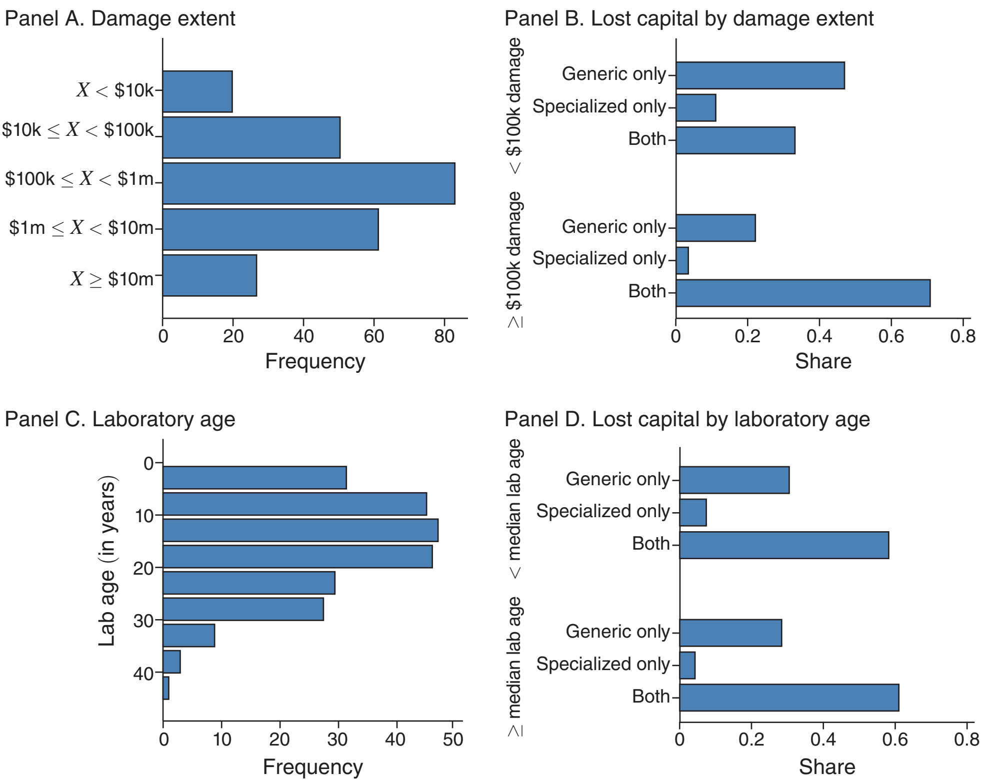

Figure 2. Laboratory Damage Caused by Adverse Events

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.

financially substantial. Therefore, we distinguish in our empirical analysis between laboratories with generic capital loss only and those with at least some specialized capital loss. There is a weak positive correlation between specialized capital loss and damage extent: The larger the monetary value of the physical capital loss, the more likely it is to involve both generic and specialized capital. Nevertheless, about 35 percent of the laboratories with damage of at least \$100,000 lost only generic capital.

Laboratory Age.—We use the age of the laboratory as a measure of the obsolescence of the lost capital. Because direct measures of capital obsolescence are hard to obtain, we capture this dimension using the time elapsed since the scientist started as a principal investigator at their respective research institution. Although it is an imperfect proxy, laboratory age is likely to correlate with the latent age of the physical capital stock. The recruitment of principal investigators is typically accompanied by "start-up packages" that are used to set up new laboratories; that is, most investment decisions in physical capital are made at that point. Although lab heads may upgrade their laboratory over time, it seems reasonable to assume that a younger laboratory is more likely to incorporate up-to-date physical capital than an older one.

At the time of its adverse event, most laboratories were between five and 20 years old (see Figure 2, panel C). Due to mid-career moves, in which a lab head establishes a new laboratory at a different research institution, laboratory age correlates with lab head seniority only moderately (see Supplemental Appendix Figure D-2). Notably, laboratory age shows little correlation with the type of lost capital: The share of cases in which only generic capital was lost is similar in laboratories below the median age and those above it (see Figure 2, panel D). This suggests that scientists start to accumulate specialized capital at a relatively early stage.

IV. Results

A. *Physical Capital Loss and Research Output*

Physical Capital Loss Has a Persistent Negative Effect on Research Output.—We examine the effect of physical capital loss due to adverse events on research output through multivariate analyses.[39] In Figure 3 we report Poisson pseudo-maximum likelihood regression estimates for the effect of adverse events on *Publications* and *Publications* (*JIF-weighted*) of affected lab heads relative to their matched controls over time. Both regressions are based on the event-study specification as outlined above (equation (8)). The dynamic treatment effects are normalized to the latest pre-event bin. All pre-event estimates are statistically insignificant and close to 0, bolstering the validity of the matched control group as counterfactual.

We find an immediate and persistent negative effect of adverse events on research output. The coefficients, which can be interpreted as semi-elasticities, all turn negative after the adverse event, with almost all being statistically significant (p-value < 0.05). Their magnitude ranges between -0.14 and -0.21 for simple publication counts and between -0.20 and -0.30 for quality-weighted publication counts. In both panels of the figure, we further report the average effect in the posttreatment period based on difference-in-differences estimators. The effect is -0.17 for simple publication counts and -0.20 for quality-weighted ones. These coefficients equate, respectively, to declines in research output of about 16 percent and 18 percent. In practical terms, this translates to the average affected lab head producing 0.62 fewer publications annually. The stable pattern of the dynamic effects around the average effect suggests that the reduction in research output is permanent. Even 15 years after the adverse event, the research output of affected lab heads has not moved substantially closer to the counterfactual level. The observed decline in research output is corroborated across different measures of research output, other model specifications, and alternative control groups.[40]

[39] We provide the results of a bivariate analysis in Supplemental Appendix E.1, where we plot the mean publication counts of affected and control lab heads over time. The publication counts of the two groups during the 10 years prior to the adverse event are balanced; afterwards, the affected lab heads' research outputs decrease relative to those of the control lab heads, with no subsequent reconvergence.

[40] We observe a similar decline in research output when weighting publications with their five-year citation count (see Supplemental Appendix Figure E-3). Additionally, models incorporating scientist and calendar year fixed

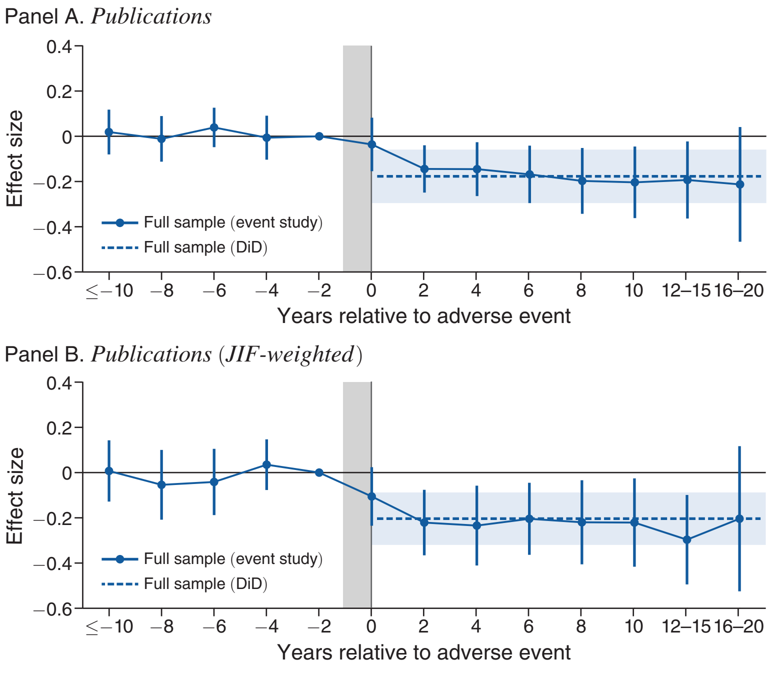

Figure 3. Impact of Adverse Events on Research Output—Event-Study and DiD Estimates

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 panel A is the simple publication count (*Publications*), and in panel B it is 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 Supplemental Appendix Table E-1 (Event study) and Supplemental Appendix Table E-2 (DiD). Confidence intervals are at the 95 percent level.

The negative effect on research output is strongest for high-impact publications (see Table 2). The average treatment effect for publications in the top 5 percent of the quality distribution (based on five-year citations) is about twice as large as for those in the bottom 50 percent (−0.32 versus −0.15). This result is a further indication that affected lab heads suffer after an adverse effect, particularly in terms of research quality.

The Effect Increases with the Scope of Physical Capital Loss.—Adverse events may reduce a lab head's research output through channels other than physical capital loss. We exclude from our sample all adverse events with human casualties to rule out the most obvious alternative channel. Nonetheless, to establish a more

effects yield similar results (see Supplemental Appendix F.1). The robustness of results extends to linear models with the dependent variable untransformed, log-transformed, or transformed using the inverse hyperbolic sine (see Supplemental Appendix F.2), and to models employing an interaction-weighted estimator (Sun and Abraham 2021) (see Supplemental Appendix F.3). Lastly comparing the affected lab heads to the "natural" control group of spared lab heads and to several differently matched control groups leads to results consistent with those from our preferred control group (see Supplemental Appendices F.4 and F.5).

Table 2—Impact of Adverse Events on Research Output—Scientific Impact

	Publications (*by scientific impact*)				
	Bottom 50% (1)	Top 50% (2)	Top 25% (3)	Top 10% (4)	Top 5% (5)
Affected × post	−0.154	−0.211	−0.258	−0.290	−0.324
	(0.078)	(0.067)	(0.079)	(0.105)	(0.132)
Matched group × event year FE	Yes	Yes	Yes	Yes	Yes
Observations	12,168	10,856	8,180	4,914	3,006
Scientists	488	486	474	426	376
Events	102	102	99	94	90
log likelihood	−20,096	−17,523	−11,179	−5,631	−3,139

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 (9). 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.

direct link between the loss of physical capital and the decline in research output, we examine whether the magnitude of the effect varies with the actual scope of the loss. For this purpose we create subsamples of affected lab heads according to the damage extent in monetary terms. We also draw on the sample of spared lab heads, who did not experience any physical capital loss themselves despite being part of the same department as the affected lab heads.

In Table 3, we report the effect of adverse events on impact-weighted publication counts for each subsample. Affected lab heads that suffer little damage (i.e., below $100,000) and spared lab heads experience no statistically significant change in their research output relative to their controls. However, for more substantial physical capital losses, the effects become negative and large in magnitude. For the groups of affected lab heads experiencing the largest amounts of damage, the effects on research output are statistically significant, with magnitudes (−0.23, −0.30, and −0.24) that surpass the previously estimated average effect for the full sample.

These results are informative in at least two ways. First, the estimated null effect for spared lab heads (and affected lab heads with little damage) assures us that the estimated effects in the full sample are not a methodological artifact; that is, they are not the result of our sample selection or control group construction. Second, given that the magnitude of the negative effect on research output increases with the scope of the physical capital loss, we conclude that it is not simply the *incidence* of an adverse event, but rather its *consequences* that explain the decline in research output.[41]

The Effect Concentrates on Research Output That Relies on the Lab Head's Physical Capital.—Not all of a lab head's research output relies to the same extent

[41] In line with this, the effect on research output does not hinge on a particular type of adverse event (e.g., ecoterrorism or natural disasters), type of institution, or geographical region (see Supplemental Appendix F.6).

TABLE 3—IMPACT OF ADVERSE EVENTS ON RESEARCH OUTPUT—DAMAGE EXTENT

	Publications (*JIF-weighted*)				
Damage:	None (spared)	X < \$100k	\$100k ≤X <\$1m	\$1m ≤X< \$10m	\$10m ≤ X
	(1)	(2)	(3)	(4)	(5)
Affected × post	0.075	−0.082	−0.226	−0.299	−0.235
	(0.082)	(0.126)	(0.110)	(0.099)	(0.125)
Matched group × event year FE	Yes	Yes	Yes	Yes	Yes
Observations	9,394	3,844	4,522	3,320	1,398
Scientists	348	142	168	124	54
Events	79	45	50	34	8
log likelihood	−30,009	−12,298	−13,503	−10,194	−4,556

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 (9). The dependent variable is the impact-weighted publication count (*Publications* (*JIF-weighted*)). 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).

on their physical capital. If physical capital loss is responsible for the reduction in research output, we would expect that the effect will be most pronounced for publications to which the lab head contributes the most physical capital. To explore this aspect, we leverage the fact that in most scientific fields, the positions of the authors signal their contributions to a publication. In particular, the last author position is usually reserved for the head of the laboratory in which the research project takes place, whereas the first author position is typically taken by the scientist who undertakes the project and makes the most significant intellectual contribution. Intermediary positions are assigned to scientists who make more marginal contributions of either kind. Last-author publications therefore represent the research output of the lab head that is most likely to rely on their physical capital stock.[42]

In Table 4 we separately report the effect of adverse events on first-, middle-, and last-author publication counts. The effect on first-author publications is small and statistically indistinguishable from zero (0.06). In contrast, the effect on last-author publications is considerably larger in magnitude and is statistically significant (−0.20). These effect differences are consistent with a 2.8 percentage-point decline in the share of last-author publications—a statistically insignificant yet economically substantial effect given the variable's average of about 35 percent. Indeed, Supplemental Appendix Figure E-4 illustrates that the share of last-author publications declines immediately after the adverse event and recovers gradually over time. These results demonstrate a direct link between a reduction in research output and the loss of physical capital as a relevant input factor. Furthermore, the results suggest that the effect is not a consequence of emotional stress or lack of motivation in

[42] Author ordering follows different conventions in social sciences and humanities. The following results become stronger when excluding lab heads active in these scientific fields.

Table 4—Impact of Adverse Events on Research Output—Author Position

	Publications (by author position)			
	First	Middle	Last	Last (share)
	(1)	(2)	(3)	(4)
Affected × post	0.068	−0.223	−0.200	−0.026
	(0.096)	(0.074)	(0.085)	(0.021)
Matched group × event year FE	Yes	Yes	Yes	Yes
Observations	6,886	10,844	10,780	9,730
Scientists	484	486	488	488
Events	102	102	102	102
log likelihood	−8,114	−16,868	−17,735	225

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 (9). 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 Supplemental Appendix Figure E-4.

the aftermath of the adverse event. If these psychological factors were the primary mechanism, we would expect to see the decline in research output extending to first-author publications, because these are the ones to which the lab head contributes most actively.

Alternative Explanations for the Effect's Persistence.—Temporary disruptions can have a lasting impact on research productivity if they alter a scientist's professional environment. In other words, it is conceivable that physical capital loss has a direct effect on research output in the short term (e.g., due to unrealized pending projects), but the long-term effect derives from conceptually different channels (e.g., career move, changes in human capital input, and reputational damage). In the following we summarize and discuss the results of additional analyses detailed in Supplemental Appendix E.3, which provide insights into whether any of these channels can explain the effect's persistence.

Career Move.—Adverse events may trigger exits from academia, retirement, or moves to institutions with inferior research conditions. Indeed, we find that affected lab heads are more likely to "retire" (i.e., stop publishing) and more likely to move to an affiliation with a worse rank than their previous one. To investigate whether such career changes explain 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. Furthermore, we estimate the intensive margin effect on research output in the full sample by setting all scientist-year observations with zero publications missing. In both cases, the resulting dynamic treatment effects resemble those of our main analysis. We take these results to indicate that career moves are not solely responsible for the long-term effect on research output.

Changes in Human Capital Input.—Adverse events may also affect the complementary human capital available to the lab head for research. For instance, repair costs and missed opportunities for research grants can strain the affected lab heads' budgets, forcing them to downsize their laboratories. Moreover, (potential) collaborators may be less inclined to work with a lab head who does not have the necessary physical capital to support their research ambitions. Overall, we find little evidence of such changes in human capital input: the average number of internal or external coauthors per publication remains practically unaffected. We further examine the effect of the adverse event on a human capital input-adjusted measure of research output by dividing each impact-weighted publication by its number of authors. The adverse events retain a significant negative effect on research output, which is slightly smaller in magnitude but equally stable over time.[43] These results suggest that labor input changes alone fall short when it comes to explaining the effect's persistence.

Reputational Damage.—It is conceivable that involvement in an adverse event lowers the reputation of affected lab heads in the scientific community, with negative implications for their (accredited) research output (cf. Merton 1968). If an adverse event lowers a lab head's reputation among their peers, we would expect to observe a "citation penalty" on their research output. In line with prior literature (Azoulay, Stuart, and Wang 2014), we focus on citations of publications from the pre-event period to isolate reputational effects from quality-related ones. 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. This renders reputational damage an unlikely driver of the long-term effect on research output.

All in all, we find no empirical evidence that would substantiate changes in the lab head's professional environment as being the main source of the effect's persistence. Taken together with the other findings in this section, we conclude that the physical capital loss itself explains the negative long-term consequences for research productivity. Evidently, lab heads fail to fully recover from physical capital loss even over the long term.

B. *Recovery from Physical Capital Loss*

Why do affected lab heads struggle to recover from physical capital loss? We seek an answer to this question by leveraging the heterogeneity in physical capital

[43] Note that these results come with the caveat that the observed human capital input is conditional on published research output. Furthermore, the null effect on the *quantity* of labor input does not rule out a decrease in the quality of labor input, for example, if the lab head cannot attract as talented PhD students as before. A related question concerns the effect of the adverse event on the lab affiliates' research output. In Supplemental Appendix E.3, we provide an initial examination of the impact on lab affiliates, finding only transient effects on their productivity, with junior affiliates taking longer to recover than their senior counterparts.

loss among our affected lab heads. To be more precise, we investigate whether the long-term effect on research productivity differs according to the specialization and obsolescence of the lost capital. Guided by our conceptual framework, we also consider under what circumstances physical capital loss affects research direction and how this relates to research output.

The following analysis needs to be put into perspective. Uncovering heterogeneity in the causal effects of physical capital loss does not itself permit a causal interpretation. That is, our estimations do not identify how treatment effects would change if the lost capital's obsolescence (or specialization) was exogenously altered. To obtain a valid interpretation, we therefore supplement our results with qualitative evidence derived from the personal statements of affected scientists.[44] Moreover, we show the general robustness of the empirical patterns using alternative measures of research output and direction in Supplemental Appendix E.5, and the inclusion of additional heterogeneity dimensions (i.e., research field, damage extent, laboratory size, lab head seniority, and affiliation rank) in Supplemental Appendix F.7.

The Loss of Specialized Physical Capital.—We first investigate whether physical capital loss affects our lab heads differently depending on its specialization. In our conceptual framework, we argue that specialized capital can only be accumulated through the lab head's own time investments. Consequently, the loss of specialized capital is hard to recoup in the short term, and makes a permanent reduction in research output more likely in comparison to generic capital loss. We test this empirically by distinguishing between lab heads that only lost generic capital and those that (also) lost specialized capital. To facilitate the comparison of the output paths between the two groups, we add up baseline and interaction coefficients and present only total effects.

We find that specialization of the lost physical capital moderates the effect of adverse events on research output (see Figure 4, panel A). The loss of specialized capital leads to a persistent negative effect on quality-weighted publication counts over the entire posttreatment period. The average posttreatment effect on research output for specialized capital loss is substantially larger in magnitude, -0.28, and is statistically significant. While the loss of generic capital has a more negative effect relative to the loss of specialized capital in the first two years after the adverse event, research output approaches the counterfactual level in subsequent years. Indeed, the average posttreatment effect on research output for generic capital loss is -0.06 and is statistically indistinguishable from zero. This underlines our initial assumption that the persistent effect on research output cannot be ascribed to a temporary interruption in the aftermath of the adverse event.

These results indicate that lab heads fail to recover in terms of research output if they lose their specialized capital. Specialized capital is created by the lab heads over time, which makes it hard to substitute (e.g., from external sources) and renders its loss practically irrecoverable. This interpretation finds qualitative support in the

[44] These statements originate from responses to our survey and direct quotes in the secondary sources.

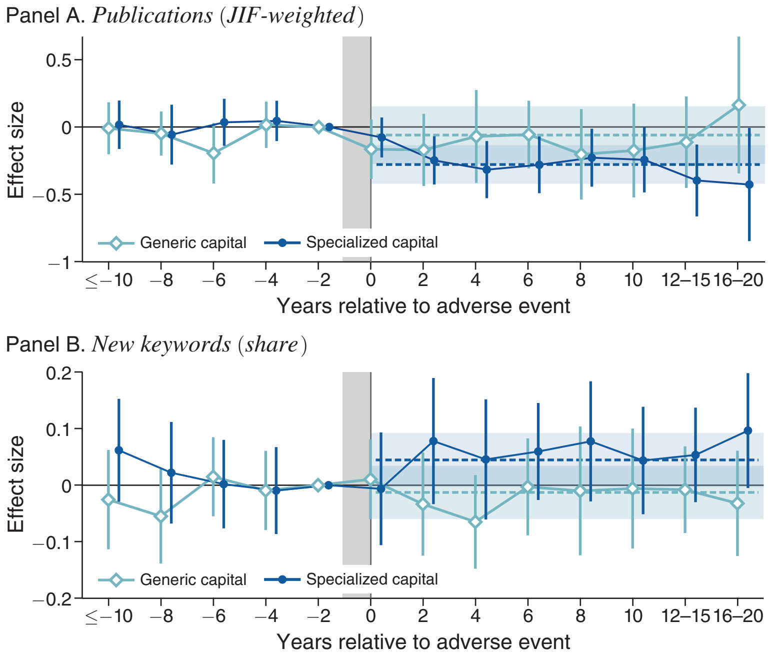

Figure 4. Impact of Adverse Events on Research Output and Direction by Capital Specialization

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). We introduce further interactions with a binary variable that indicates affected lab heads who lost specialized physical capital (see equation (10)). The dependent variable is the impact-weighted publication count (*Publications* (*JIF-weighted*)) in panel A, and the share of keywords that do not appear in the lab head's prior publications relative to all of the keywords in their publications (*New keywords* (*share*)) in panel B. The sample consists of all affected lab heads and their respective controls. The coefficients correspond to those reported in Supplemental Appendix Tables E-10 (event study) and E-11 (DiD). Confidence intervals are at the 95 percent level.

statements of affected scientists, which illustrate that specialized capital requires considerable time investment and is hard to recover once lost:[45]

> Research records and animal models that have been engineered to mimic human disease that have been five, ten years or more in creation have also been lost.

> Six pieces of equipment were one and only—ones we had developed from the ground up over six years. That kind of system is difficult to reproduce, or put a price tag on.

> In some cases, it's a total disaster […]. These animals were bred with unique characteristics for biomedical purposes. They will be hard to replace.

> [His] genetic research on the Drosophila goes back 35 years and some of it is irretrievably lost, he said. 'I have been studying that system for my entire career, since I was a graduate student.'

[45] The four quotations originate from the following four newspaper articles, in order: "Vital Research Records Lost in Flood," *The Miami Herald*, June 26, 2001; "Valuable Research Lost in Fire at UW Lab: Diagnostic Projects Were 'One-of-a-Kind'," *The Seattle Times*, April 26, 1989; "Four Surviving Pigs May Save Heart Disease Study," *St. Paul Pioneer Press* (MN), December 30, 1995; "Flood Decimates Building, Work at University of Hawaii," *USA Today*, January 11, 2004.

According to our conceptual framework, loss of specialized physical capital should also make lab heads more inclined to reorient themselves toward new research topics. We examine this in Figure 4, panel B, where we report linear regression estimates for the effect of adverse events on the share of new keywords in the lab heads' publications (*New keywords* (*share*)). The loss of specialized capital leads to a significant change in research direction: Affected lab heads become more likely to use keywords that they have not previously used in their publications. The average posttreatment effect is 0.05 and is statistically significant (p-value < 0.1).[46] For lab heads that only lost generic capital, the average posttreatment effect is -0.01 and is statistically indistinguishable from zero. Because the continuation of ongoing research is reliant on the lost specialized capital, affected lab heads seem more inclined to change their research direction and turn toward new projects, as reinforced by the personal testimonies of affected lab heads:[47]

> I had to change the scope and direction of my research because of the flood [that] totally destroyed my laboratory and my adjacent office in the same building. I lost DNA and RNA samples from critically endangered species.

> There were a lot of ongoing experiments that were destroyed […]. Many were short-term. Others were long-term where we lost five years. Those experiments likely will never be redone.

In summary, the evidence described above allows us to conclude that the permanent nature of specialized capital loss explains the lack of recovery in post-event research output.

The Loss of Obsolete Physical Capital.—We further investigate whether obsolescence also explains some of the heterogeneity in the effect of physical capital loss on research output. Conceptually, we argue that obsolescence is a relevant dimension for two main reasons: First, technical progress reduces the contribution made by old generic capital to new research output; Second, because the possibilities for research on a given topic become exhausted over time, old specialized capital is associated with a reduced research productivity. To explore this empirically, we proxy the obsolescence of a lab head's physical capital stock using the age of their laboratory at the time of the adverse event. We distinguish between the heads of laboratories that are below (*Modern lab*) and above (*Old lab*) the median laboratory age.

We find that physical capital loss leads to a larger reduction in research output for lab heads in modern laboratories (see Figure 5, panel A). Although both groups of lab heads experience very similar declines in research output in the first post-event years, the trends subsequently diverge, with lab heads in old labs achieving a partial return to the counterfactual level. Thus, the average posttreatment effect is more than twice as large in magnitude for lab heads in modern labs (-0.30 versus -0.13). These differences imply that the loss of obsolete physical capital permits a recovery path that is not otherwise available.

[46] The observed changes in research direction are not driven by a shift from empirical to theoretical research: The share of empirical publications does not decrease after the adverse event (see Supplemental Appendix Figure E-15).

[47] The first quotation is a response to our lab damage survey; for further details see Baruffaldi and Gaessler (2026). The second quotation originates from the newspaper article: "Heat Destroys USU Research," *The Herald Journal* (Logan, UT), April 6, 2000.

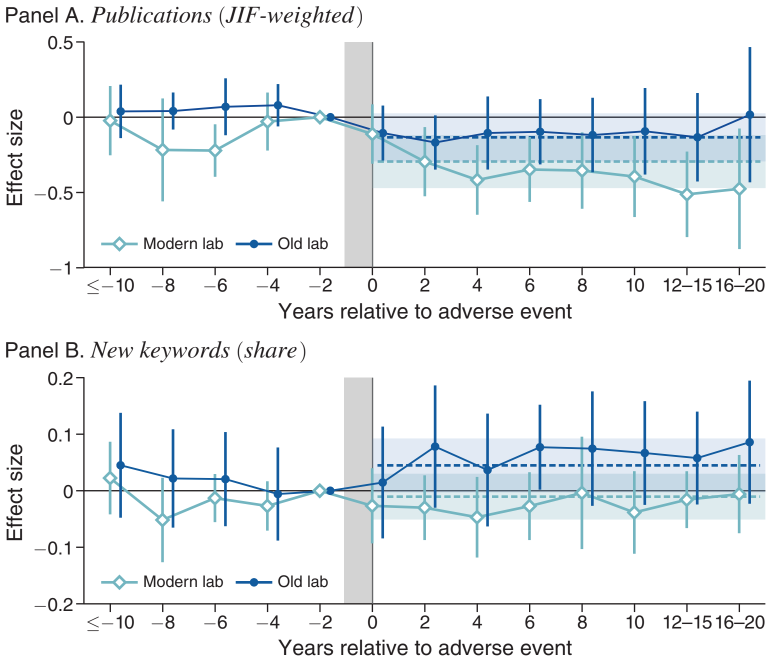

FIGURE 5. IMPACT OF ADVERSE EVENTS ON RESEARCH OUTPUT AND DIRECTION BY LABORATORY AGE

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). We introduce further interactions with a binary variable that indicates affected lab heads who worked in a laboratory older than the median age (see equation (10)). The dependent variable is the impact-weighted publication count (*Publications* (*JIF-weighted*)) in panel A, and the share of keywords that do not appear in the lab head's prior publications relative to all of the keywords in their publications (*New keywords* (*share*)) in panel B. The sample consists of all affected lab heads and their respective controls. The coefficients correspond to those reported in Supplemental Appendix Tables E-10 (event study) and E-11 (DiD). Confidence intervals are at the 95 percent level.

At the same time, affected lab heads in old laboratories undertake a significant and permanent shift in research direction following physical capital loss (see Figure 5, panel B). By contrast, affected lab heads in modern labs do not change their research direction (0.05 versus −0.01) despite their larger decline in research output. Taken together, the more obsolete the lost physical capital, the more likely the affected lab heads are to conduct research on new topics and recover their research productivity.

The positive association between a change in research direction and recovery in research output is consistent with the idea that the loss of obsolete physical capital reduces path dependence. Because the lab head can no longer live off the previously accumulated capital stock, abandoning their previous research projects and turning toward new topics becomes relatively more attractive. At this point, due to obsolescence, it is more likely that the lab head can now choose a research topic that offers a much better return on their time investment than the existing one. Consequently, for lab heads that suffer the loss of obsolete physical capital, a change in research direction can lead to subsequent productivity gains, which alleviate the long-term negative impact on research output.

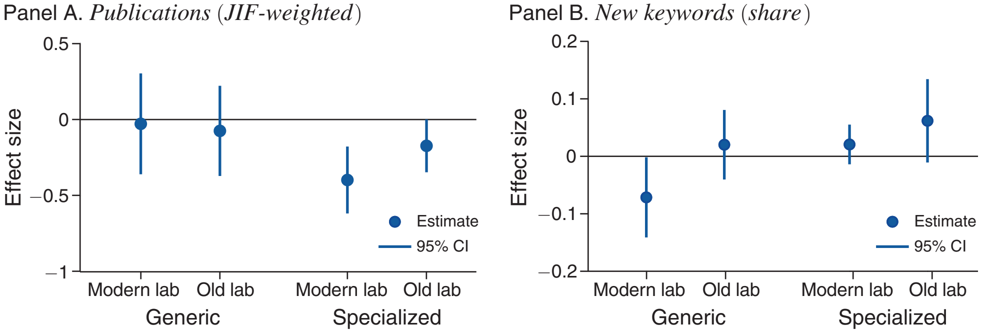

Figure 6. Impact of Adverse Events on Research Output and Direction by Capital Specialization and Laboratory Age

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 who lost specialized physical capital. The second one indicates affected lab heads who worked at the time of the adverse event in a laboratory older than the median age. The dependent variable in panel A is the impact-weighted publication count (*Publications* (*JIF-weighted*)), and in panel B it is the share of keywords that do not appear in the lab head's prior publications relative to all of the keywords in their publications (*New keywords* (*share*)). The coefficients correspond to those reported in Supplemental Appendix Table E-13. The sample consists of all affected lab heads and their respective controls. Confidence intervals are at the 95 percent level.

The following statements of affected lab heads provide qualitative evidence that physical capital loss can indeed reduce path dependence and reorient lab heads to new and more worthwhile research topics:[48]

> The silver lining of the whole storm […] is the fact that it allows me to refocus myself. Now, I can go after what is interesting to me now, not what was interesting to me two years ago.

> My former research in physiological ecology of woody plants was ended and a whole new career direction at age 59+ unfolded. This new direction turned out to be vastly rewarding.

We find additional support for this mechanism in Figure 6, in which we plot the total average treatment effects on research output and research direction for four subgroups of affected lab heads, delineated by specialization *and* obsolescence. Lab heads experiencing specialized capital loss and with an old laboratory exhibit the strongest positive reaction in terms of research direction (0.06), but show a smaller reduction in research output than lab heads experiencing specialized capital loss and with a modern laboratory (−0.40 versus −0.17). If we focus instead on the two subgroups of lab heads experiencing only generic capital loss, the reductions in research output do not differ substantially between old and modern laboratories (−0.07 versus −0.03).[49] This implies that the necessity for new specialized capital

[48] The first quotation originates from the newspaper article: "Scientists Focus on Another Sandy Loss, Lab Mice," *Associated Press Archive*, March 6, 2013. The second quotation is a response to our lab damage survey; for further details see Baruffaldi and Gaessler (2026).

[49] It is noteworthy that affected lab heads in modern laboratories who only experience generic capital loss are actually significantly *less* likely to change research direction relative to their counterfactual. This attachment to pre-event research topics aligns with our model, in which generic capital is a prerequisite for creating new specialized capital.

deters scientists from changing their research trajectories, even if their physical capital stocks have become obsolete and more attractive research topics are available.

The heterogeneity results and qualitative evidence presented above lend support to our theoretical predictions on how obsolescence moderates the effects of physical capital losses on both research output *and* research direction. Specifically, the model predicts a smaller reduction in research output for lab heads in older labs and a more likely change in their research direction. This prediction does not apply to other lab characteristics that likely correlate with lab age. For instance, while the model also predicts a smaller reduction in research output for lab heads in well-equipped labs, it does not predict a more likely change in their research direction.[50] Nonetheless, we cannot rule out the influence of other relevant factors, such as the lab head's access to funding, age, human capital, and social capital—all of which could be contributing to the patterns of heterogeneity we observe.

Physical Capital Renewal.—The heterogeneity results thus far suggest that loss of generic capital has only minor effects on research output. This is consistent with the idea that generic capital becomes a less crucial input to knowledge production once a scientist has accumulated specialized capital. However, a competing explanation lies in the possibility that lab heads can quickly reestablish their generic capital stock given its transferability and commercial availability. In other words, the results above leave open the question of whether generic capital is, indeed, less relevant to knowledge production in the long run or whether its loss is simply more transient.

To shed light on this question, we first investigate whether affected lab heads obtained compensation after their adverse events that would enable them to restock their generic capital. While such information is only partially available from our data, it does appear that lab heads typically received some post-event financial or material support.[51] This enabled lab heads to quickly replenish their generic capital stock, as exemplified by the following quotes:[52]

> The fire was in a facility that performed DNA sequencing tasks. It slowed down research, because we had to send the material to an outside company for sequencing. But new machines were installed soon, and the insurance paid for the replacements.
>
> It won't set us back more than a few months […]. As soon as we get the incubators, we'll be back on line.
>
> This tornado destroyed a storage building filled with older beekeeping equipment. The insurance payout allowed us to purchase new beekeeping equipment and construct a new storage facility.

[50] Lab heads in well-equipped laboratories, characterized by a high level of generic capital (K_g) and a low rate of depreciation θ, are more likely to already work on the optimal topic. Hence, the physical capital shock has a smaller effect on research output *as well as* on the probability of a change in research direction.

[51] The funding sources involved are quite diverse and differ according to institution and adverse event type: Some lab heads received money either by filing insurance claims or directly from a self-insured university/research institute; others received help from disaster relief funds and/or donations.

[52] The first and third quotations are responses to our lab damage survey; for further details see Baruffaldi and Gaessler (2026). The second quotation originates from the newspaper article: "Fire Ruins Gypsy Moth Experiment," *The Columbus Dispatch* (OH), February 8, 1995.

Against this backdrop, physical capital loss actually provides an opportunity for lab heads to *renew* their generic capital, which may have a countervailing (i.e., positive) effect on research productivity depending on the obsolescence of the replaced capital. Whereas replacement of the lost generic capital is likely to result in a modernization of the capital stock in the case of old laboratories, for modern laboratories it corresponds at best to a return to the status quo. We look for evidence of this countervailing effect in a particular subgroup of lab heads: those that *only* lost "off-the-shelf" generic capital. Such "off-the-shelf" generic capital is a subset of all generic capital and reportedly available from multiple vendors, meaning that lab heads should, indeed, be able to reacquire it following the adverse event.

We find that lab heads that only lost "off-the-shelf" generic capital experience on average a slightly positive but insignificant effect on their research output in the posttreatment period (see Figure 7). Examining the effect formation along the obsolescence dimension reveals that this positive effect is driven by laboratories that—from a theoretical viewpoint—should benefit most from physical capital renewal. More specifically, the positive effect on research output is large in size and significant for affected lab heads with laboratories in the upper tertile of the age distribution (0.49), while lab heads with more modern laboratories experience no statistically significant effect on their research output. In our sources we find qualitative evidence that substantiates capital renewal as a mechanism for an increase in productivity and, hence, a recovery in research output following physical capital loss:[53]

> […] all equipment was replaced on a new-for-old basis […]. I was also relocated in a well-equipped lab. So basically my group came out of it very well.
>
> This event led to the replacement of the original building, but with a building co-designed by staff, students, and faculty, as well as outside consultants and university operations, to a high standard of sustainability. […] it was transformative.

This evidence further substantiates the fundamental difference between generic and specialized capital. It also suggests that, while specialized capital is an irreplaceable input to knowledge production, up-to-date generic capital embodies productivity gains.

V. Conclusion

We investigate the nature and relevance of physical capital as an input to knowledge production. The unexpected loss of physical capital following adverse events in research laboratories serves as a natural experiment by which to assess its contribution to the research outputs and trajectories of scientists. We find that physical capital loss leads to a permanent reduction in research output. This result echoes a previous finding that researchers fail to recover from the loss of collaborators as a unique knowledge source (Azoulay, Graff Zivin, and Wang 2010). We demonstrate

[53] Both quotations are responses to our lab damage survey; for further details see Baruffaldi and Gaessler (2026).

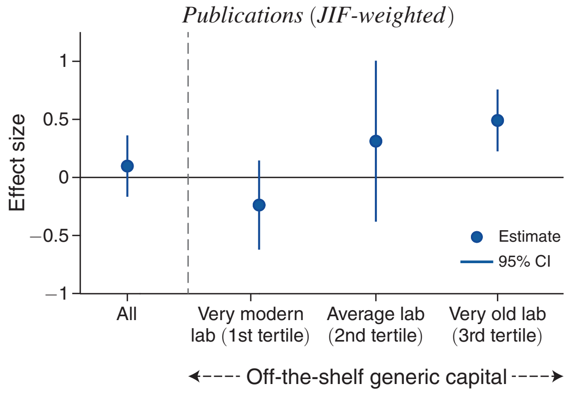

Figure 7. Impact of Adverse Events on Research Output by Laboratory Age (Generic Capital Renewal)

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 Supplemental Appendix Table E-15. The sample consists of all affected lab heads and their respective controls. Confidence intervals are at the 95 percent level.

that research productivity rests upon specialized physical capital, which represents a unique and irreplaceable input and whose loss cannot be compensated because of its singular development process. In this sense, if specialized physical capital is lost, some knowledge will be lost with it.[54]

We also find that physical capital influences a scientist's research trajectory. The loss of specialized and obsolete physical capital renders a scientist more inclined to change research direction. This suggests that such loss reduces a scientist's path dependence because they can no longer live off their previous investments. The scientist has to create new capital, but at this juncture will opt for the research topic that now offers the best return. This implies that the necessity for new specialized capital deters scientists from changing their research trajectories, even if their physical capital stock has become obsolete. Hence, the accumulation of physical capital constitutes one explanation for the observed reluctance of scientists to change research direction (Myers 2020).

Whereas the prior literature has largely focused on human capital, our study indicates that physical capital plays a critical role in the production of knowledge. Because a crucial type of this physical capital appears to be the product of a scientist's effort and vision, this result does not call into question the relevance of human capital. Rather, we suggest that there are important complementarities between the human and physical spheres, especially at the knowledge frontier: Here, new discoveries rely not just on specialized human capital (Jones 2009) but also on specialized equipment and material. As noted by Rosenberg (1992), these can mature into standardized and transferable goods that increase research productivity for many

[54] Indeed, historical case studies suggest that physical capital can embody knowledge that is not otherwise attainable (cf. Mokyr 2002).

scientists. However, as we argue, this type of physical capital exhibits in its genesis economic features commonly associated with human capital. In particular, specialized physical capital results from a scientist's individual investment decisions, which are likely influenced by other factors not fully explored in our study, such as the scientist's ability. Indeed, a closer examination of the interplay between specialized human *and* physical capital presents a valuable direction for future research.

This perspective suggests that science and innovation policy should give more consideration to the role of physical capital in knowledge production. Notably, specialized physical capital may not be within the reach of direct interventions such as increased research funding. Instead, indirect measures, such as the provision of state-of-the-art laboratories and funding schemes with longer time horizons, may serve to increase scientists' investments in specialized physical capital. Moreover, promoting standardization and sharing between scientists seems desirable when it comes to improving the (re)allocation of existing physical capital (Furman and Stern 2011; Agrawal and Goldfarb 2008). Such initiatives, however, must involve incentives that compensate scientists to forego private returns to their investments (cf. Walsh, Cohen, and Cho 2007). A promising area for future research involves examining how different governance levels—from labs to governments—can promote the efficient development of physical capital.

The evaluation of policies targeting physical capital may, however, be challenging because of the difficulty in measuring physical capital inputs and linking this to research output.[55] The costs of self-created physical capital do not enter official statistics, and the scientific value of physical capital can greatly exceed its commercial value, making it often impossible to assign a dollar price to a scientist's most valuable physical capital. Even more so, it is important to understand this aspect of the research process and its relevance to knowledge creation so as to optimize the accumulation of physical capital and its allocation. Overall, our study constitutes a significant first step toward a more comprehensive analysis of the variety of resources that influence knowledge production (cf. Azoulay et al. 2018).

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[55] Research output is most commonly quantified via scientific articles and patents. Existing bibliographic databases provide decent proxies for human capital (i.e., author/inventor information) and knowledge inputs (i.e., references to prior publications). By contrast, structured information on physical capital inputs is rarely available, although recent projects offer significant promise in overcoming some of the limitations in this regard (cf. Lane et al. 2015).

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