The State's Flight to Safety: Innovation Financing under Crisis

ABSTRACT

Crises strengthen the case for counter-cyclical public intervention in innovation markets. When private investors retreat from early-stage risk, government funding agencies are expected to act as a countervailing force. Yet whether state funding systems expand risk-taking under systemic shock remains largely unexplored. Leveraging the onset of COVID-19 as an exogenous disruption, we examine SBIR allocation decisions at the NIH, NSF, and DOE. We uncover an unexpected and uneven pattern: public innovation funding shifted toward older, larger, investor-backed firms pursuing less novel innovation. This effect was strongest at NIH, moderate at DOE, and not at all at NSF. These compositional changes occurred despite stable budgets and unchanged evaluation criteria. Analysis of the mechanism indicate that crisis conditions amplified the influence of reviewer human capital: panels with greater commercial expertise disproportionately favored mature, revenue-generating firms, while panels with stronger scientific capital preferred ventures already validated by external investors. Rather than altering formal rules, uncertainty activated evaluative tendencies that privileged visible signals of viability and legitimacy. Together, these findings reveal crisis-induced evaluative conservatism within the state and suggest that public innovation funding can become pro-cyclical under systemic uncertainty.

Keywords: public innovation decision-making, crisis decision-making, risk-taking, funding agency behavior

INTRODUCTION

Periods of systemic shock intensify the market frictions that constrain financing for risky innovation. Private investors retreat from early-stage, high-risk ventures and redirect capital toward safer, more established firms when uncertainty spikes. This pattern described as a *flight to safety* finds that venture capital investment is strongly pro-cyclical, with downturns not only reducing overall funding but also shifting capital toward later-stage and less experimental ventures (Gompers & Lerner, 2004; Nanda & Rhodes-Kropf, 2013; Howell et al., 2020). During periods of crisis and a retreat in private financing, the rationale for public intervention becomes stronger. If governments fund innovation to correct private underinvestment in risky entrepreneurial activity, then crises should represent moments of intensified public risk-taking. The state, in principle, should move counter-cyclically. Consequently, public intervention becomes even more critical during crises to sustain innovation and support entrepreneurial activity.

Over the past few decades, a series of shocks, including the dot-com collapse (2000), the economic consequences of the September 11 attacks (2001), the global financial crisis (2008), and multiple public health emergencies such as SARS, H1N1, Ebola, Zika, and most recently the COVID-19 pandemic—demonstrate the recurring and varied nature of such disruptions. Despite the frequency and scale of these crises, surprisingly little is known about how government programs that support innovation and entrepreneurship operate during such periods of heightened uncertainty. Yet, it remains an open empirical question whether existing government programs are sufficiently responsive and effective in mitigating the impact during times when market failure is amplified and if public programs support entrepreneurial resilience and innovation continuity during crises.

We investigate how three major U.S. federal agencies—the National Institutes of Health (NIH), National Science Foundation (NSF), and Department of Energy (DOE)—allocated early-stage innovation funding during the onset of the COVID-19 pandemic. The SBIR program provides an ideal setting: it funds small, technology-oriented firms at the frontier of commercialization, and its mission explicitly emphasizes high-risk, high-reward innovation. Importantly, federal budget allocations for these programs were not reduced at the onset of COVID-19, and agencies reported no formal changes in review criteria or procedures.

Against theoretical expectations, we uncover a striking pattern. During the onset of COVID-19, grant recipients at the NIH were significantly older, larger, higher-revenue firms, more likely to be investor-backed, and pursuing less novel innovation compared to pre-pandemic awardees. In other words, public innovation funding mirrored the private market's flight to safety. Rather than expanding support for young, high-risk ventures, agencies shifted toward more mature and commercially validated firms. This shift was not uniform across agencies. NSF maintained relative stability in their profile of funded firms. The DOE displayed an intermediate pattern. The NIH showed a striking shift in the attributes of funded firms. These differences suggest that crisis responses are not mechanically determined by macro conditions alone but depend on organizational design and evaluation structure.

To better understand the mechanisms underlying this shift, we examine the composition and human capital of NIH peer review panels. Although reviewer demographics and professional backgrounds did not change substantially during COVID-19, we find that reviewer human capital interacted with crisis conditions in consequential ways. Panels with greater commercial human capital were more likely, during COVID-19, to select older, larger, and higher-revenue firms. Panels with greater scientific human capital were more likely to select firms that were

already investor-backed. These findings suggest that crisis conditions may activate evaluative heuristics that privilege observable signals of viability and stability.

Together, our findings surface a previously undocumented phenomenon: crisis-induced conservatism within public innovation agencies. This challenges a core assumption in theories of market failure and the entrepreneurial state—that public funding automatically expands or stabilizes risk-taking when private markets contract. Instead, public evaluators may be subject to similar cognitive and institutional pressures as private investors, leading the state to mirror, rather than counteract, market retrenchment. By uncovering this pattern and identifying micro-level mechanisms within peer review processes, this study opens a new line of inquiry into how state institutions behave under systemic shock. More broadly, it invites management scholars to treat governments not as static policy instruments, but as organizations whose decision processes, risk preferences, and evaluative routines are themselves shaped by crisis conditions.

PUBLIC RISK-TAKING UNDER SYSTEMIC UNCERTAINTY

Public innovation programs are designed to support ventures that private capital markets are unlikely to fund. The economic rationale is well established: early-stage innovation is characterized by uncertainty, long time horizons, and information asymmetries that discourage private investment (Arrow, 1962; Nelson, 1959; Hall & Lerner, 2010). When macroeconomic uncertainty intensifies, these frictions deepen. Venture capital becomes more selective and reallocates toward later-stage, lower-variance investments (Gompers & Lerner, 2004; Nanda & Rhodes-Kropf, 2013). In such periods, the justification for public intervention strengthens. If public agencies exist to offset private underinvestment in exploratory entrepreneurship, systemic crises should represent moments of counter-cyclical support.

This counter-cyclical expectation implies stability—or even expansion—in the funding of young, small, commercially unproven, and technologically novel ventures during crisis. These firms are most exposed to capital market retrenchment and most aligned with exploratory innovation. Implicit in this logic, however, is the assumption that public evaluation systems are insulated from the cognitive and organizational consequences of heightened uncertainty. Organizational theory suggests a competing possibility.

Systemic crises increase environmental volatility and widen outcome distributions, making it more difficult to forecast which projects will succeed (Knight, 1921; Bloom, 2009). Under such conditions, evaluators face uncertainty not only about the intrinsic quality of proposals but also about the broader environment in which funded ventures must survive. Research on bounded rationality suggests that as ambiguity rises, decision-makers rely more heavily on observable cues that simplify inference (March & Simon, 1958; Tversky & Kahneman, 1974). This shift need not involve formal changes to evaluation criteria or mandates. Review rubrics may remain stable, yet the relative weighting of signals within those rubrics may change.

Public innovation reviews typically assess technical merit, feasibility, and commercialization potential, creating space to balance novelty against viability. Under stable conditions, novelty and exploratory potential may carry substantial weight. Under heightened uncertainty, however, signals that indicate resilience and organizational stability may become more salient. Firm age signals survival through prior uncertainty. Organizational size suggests execution capacity. Prior sales indicate market validation. External investor backing provides third-party endorsement. By contrast, highly novel innovations that span distant technological domains introduce variance and ambiguity. When uncertainty increases, evaluators may

implicitly privilege ventures that display visible markers of viability over those that maximize exploratory potential.

We refer to this process as crisis-induced evaluative conservatism: a shift in the composition of selected ventures toward attributes associated with organizational stability and commercial validation, even in the absence of policy change or budget contraction. If such reweighting occurs, awardees during crisis periods should be older, larger, more likely to have prior revenues, more likely to have external investor backing, and less technologically novel than awardees selected under more stable conditions.

Evaluation systems, however, are enacted by individuals whose professional backgrounds shape how signals are interpreted. Human capital influences the perception of the attributes as credible indicators of quality and feasibility (Daft & Weick, 1984; Haveman, 1992). Review panels with substantial commercial experience may be particularly attentive to revenue generation, operational scale, and prior market validation when uncertainty heightens perceived downside risk. Panels with strong scientific backgrounds may continue to value intellectual merit but rely more heavily on legitimacy signals—such as prior investor endorsement—when assessing commercialization prospects under ambiguous conditions. Crisis-induced conservatism should therefore manifest not only as aggregate shifts in funded venture characteristics, but also as interactions between systemic shock and reviewer human capital.

Although federal innovation programs operate under a shared statutory mandate, agencies differ in review structure, panel composition, and the relative emphasis placed on commercialization. If crisis-induced signal reweighting operates within existing evaluative architectures, its magnitude should vary across agencies depending on these organizational features. Comparing allocation patterns across agencies during the onset of COVID-19 therefore

allows us to assess whether public innovation funding behaves counter-cyclically or whether evaluative processes contract toward lower-variance selections under systemic uncertainty.

These arguments yield competing expectations. The counter-cyclical logic predicts sustained or expanded support for younger, smaller, non–investor-backed, and more novel ventures during crisis. The evaluative conservatism logic predicts compositional shifts toward older, larger, revenue-generating, investor-backed, and less novel ventures, with the magnitude of the shift conditioned by reviewer human capital and organizational design. By examining changes in awardee characteristics before and during the onset of COVID-19, and by analyzing how reviewer composition interacts with crisis conditions, we assess which logic governs public innovation funding under systemic uncertainty.

SBIR/STTR PROGRAM

Our empirical context is The SBIR program, a congressionally mandated public/private partnership grant program to stimulate technological innovation in U.S. small businesses.[1] The program provides three phases of funding. Phase I awards provide approximately are generally $50,000 - $250,000 of funding distributed over 6-12 months, with the aim of establishing the technical merit, feasibility, and commercial potential of the proposed research and to determine the preliminary performance quality of the associated small business prior to providing further monetary support. Overall, the funding rate of SBIR Phase 1 applications is less than 20%. Phase II funding determinations are based on the results achieved in Phase I and on the scientific merit, technical merit, and commercialization potential of the project proposed in Phase II. Phase III

[1] SBIR is used as shorthand for the SBIR/STTR program. Federal agencies with external research programs exceeding $100 million are mandated to dedicate a minimum 3.2 % of their external research budgets to the SBIR program. The STTR program guidelines are like SBIR directives, with a requirement that federal agencies whose budgets exceed $1 billion allocate a minimum 0.45% to small businesses formally collaborating with non-profit research institutions.

awards are targeted towards advanced pursuit of commercialization objectives after the completion of Phase I and II awards.

Eleven federal agencies participate in the program, the DOD, NASA and NIH, NSF, and DOE accounting for 98% of all award dollars between 2019-2021. NASA and DOD are distinct in that the SBIR/STTR program is coupled with a procurement objective. The NIH, NSF, and DOE all fund small businesses with the objective of facilitating commercialization. We compare the Phase I grants awarded through the Omnibus solicitations in the pre-COVID-19 and COVID-19 period, spanning 2019-2021. There are slight differences between the ways the program is operationalized at each agency that reflect the agency of the specific mission. Next, we consider each of the agencies we examine. The devil is in the details.

SBIR/STTR Program at the NIH

As the largest funder of biomedical research in the world, the SBIR/STTR program at the NIH facilitate the translation of scientific findings that advances public health innovations to enhance health, lengthen life, and reduce illness and disability. NIH releases omnibus solicitations with three application cycles per fiscal year: September, January, and April.[2] Omnibus solicitations are general solicitations pertaining to all twenty-four NIH sub-agencies plus the Food and Drug Administration and Center for Disease Control.

Applications are reviewed by the Center for Scientific Review (CSR), which has Review Branches (RBs) (also known as Integrated Review Groups) representing a general scientific area. Each RB has a cluster of Study Sections. Applications are assigned first to an RB, and then to a

[2] About 75 percent of all SBIR/STTR funds dispersed through the NIH is through the Omnibus solicitation. The other 25 percent of funds is distributed through the RFA (Request for Application), where solicitations are administered by sub-agencies, and specialized to their needs. The relevant omnibus solicitation covering both the pre-COVID-19 and COVID-19 periods are PHS 2019-02 (PA-19-270; PA-19-271; PA-19-272; PA-19-273) and PHS 2020 (PA-20-260; PA-20-261; PA-20-262; PA-20-265).

specific Study Section within the RB for evaluation of scientific merit. A full schedule of the grant solicitation and award distribution is detailed in Appendix A.

SBIR/STTR Program at NSF

The SBIR/STTR program at NSF funds small business innovation projects in a broad spectrum of technologies that show promise of commercial and/or societal impact, and involve a level of technical risk, which can be alleviated by NSF support. Managed by the Directorate for Technology, Innovation and Partnerships (TIP), the submission window at NSF is on a rolling basis as opposed to specific deadlines, moving from December to March, March to June, June to September, and September to December.[3] A panel of at least three technical and commercial experts reviews the application along with the Program Director. A full schedule of the grant solicitation and award distribution is detailed in Appendix B.

SBIR/STTR Program at DOE

The SBIR/STTR program administered at DOE funds early-stage high-risk innovation projects aligned to DOE's mission to secure the nation's energy future. A central program office manages the funding opportunity announcements and administers the review process. Within DOE, there are 12 different program offices focused on specific research topics, who are responsible for identifying the reviewers and ranking the awardees, from which the final awardees are determined by the central program office.

There are two Phase I solicitations per year with submission deadlines in mid-October and end-February.[4] The two solicitations differ in the topics covered. The program requires a letter of intent to be submitted by the applicants, and DOE provides feedback before the full

[3] The relevant omnibus solicitation covering both the pre-COVID-19 and COVID-19 periods are NSF 19-554 and NSF 20-527.
[4] The relevant omnibus solicitation covering both the pre-COVID-19 and COVID-19 periods are DE-FOA-0001941, DE-FOA-0002145, DE-FOA-0002146, DE-FOA-0002359, and DE-FOA-0002360.

application is submitted. A full schedule of the grant solicitation and award distribution is detailed in Appendix C.

EMPIRICAL APPROACH

As an exploratory study, the objective of this paper is to determine the differences in the attributes of the awardees in the pre-COVID-19 and COVID-19 periods. This method is appropriate for articulating new insights into an unexplored topic of government funding during crises, and can serve as a useful basis for future empirical research on entrepreneurial policies spurring innovation and theory-building around best practices and capabilities of the government as an organization. In so doing, we highlight the differences in the review process at the NIH, NSF, and DOE. The empirical approach in this paper starts with a descriptive analysis followed by a multivariate analysis comparing the key differences in the grant recipients awarded through the NIH, NSF, and DOE during the pre-COVID-19 and COVID-19 periods in terms of the quality and novelty of the innovation pursued by the ventures.

There are several attractive features of the COVID-19 pandemic and the SBIR grant program as an empirical context. First, the COVID-19 pandemic offers a crisper delineation to ascertain how the agencies responded and managed their regular processes and routines. Second, the sudden onset of the pandemic makes it exogenous to the supply of funding opportunities, which offers an interesting "out of sample" analysis to evaluate government funding in the immediate aftermath of the pandemic. Third, the SBIR grant program provides relatively more transparency compared to other federal initiatives in sharing information related to the grant awardees, grant solicitation, and the general selection processes and routines, that allows us to identify awardees in the pre- and during the onset of COVID-19. Finally, the SBIR program is unique in funding small business entities unlike other federal grants that are typically given to

individual researchers. The kind of innovations funded by the NIH, NSF, and DOE through the SBIR program covers a broad spectrum of technologies including healthcare, semiconductors, climate technology, and information technology that represents broader set of technology intensive industries targeted by the private market.

Data

***NIH Sample*:** All awardees were identified from the NIH RePORTER database, which includes data on the grant date, firm identity (name and location), grant amount ($), and the study section that conducted the peer review of the grant application. The sample includes 496 recipients: 249 grant recipients in the pre-COVID-19 and 247 grant recipients in the COVID-19 period.[5]

***NSF Sample*:** All awardees were identified from NSF website and www.SBIR.gov, which includes data detailing the grant date, firm identity (name and location), grant amount ($), and project description. The sample includes 476 recipients: 263 grant recipients in the pre-COVID-19 period and 213 grant recipients in the COVID-19 period.[6]

***DOE Sample*:** All awardees were identified from DOE website, Portfolio Analysis and Management System (PAMS), and www.SBIR.gov.[7] The sample includes 618 recipients: 307 grant recipients in the pre-COVID-19 period and 311 grant recipients in the COVID-19 period.[8]

The grant recipients' information was augmented with firm-level data on patents awarded, revenues, employees, external funding investments, founding year, industry

[5] To assess the comparison, we eliminated 10 firms in the COVID-19 period that received the grant specifically in response to COVID-19.
[6] To assess the comparison, we eliminated 100 firms in the COVID-19 period that received the grant specifically in response to the COVID-19 pandemic.
[7] https://science.osti.gov/sbir/Award; https://pamspublic.science.energy.gov/WebPAMSExternal/interface/awards/AwardSearchExternal.aspx
[8] To assess the comparison, we eliminated one firm in the COVID-19 period that received the grant specifically in response to the COVID-19 pandemic.

classification, and prior grants at the time of receiving the focal grant gathered from USPTO patent database, Crunchbase, PitchBook, Privco, Dun & Bradstreet, and company websites.[9]

Variables of Interest

The variables for the comparative analyses of the grant recipients include performance metrics related to firm growth, innovation, and commercialization potential, which correspond to the stated objectives of the grant program.

Three variables approximate the maturity and stability of the recipient prior to receiving the grant and have been used in prior research (e.g., Coad et al., 2016; Sørensen & Stuart, 2000). Higher values of these variables coincide with more maturity. *Firm age* is the number of years from founding year until the time of receiving the grant. *Firm size* is the number of active employees in the firm in the year before receiving the grant. *Sales* is the annual revenue generated in the year before receiving the grant.

Commercialization potential is approximated using *Investor-backed*, which is a dummy variable equal to "1" if the recipient received private equity investment before receiving the focal grant, and "0" otherwise. Private equity investment reflects commercialization potential and empirical evidence shows venture that attract private equity funding have a higher likelihood of commercialization (Hellmann & Puri, 2002; Stuart et al., 1999).

To ascertain innovation related metrics, we identify patents associated with each recipient from the annual USPTO patent database *Patent count* is measured as the number of patents filed (and eventually granted) before receiving the grant. Patent filing date is used because it closely approximates the innovation date (Griliches et al., 1987). The riskiness of the innovation is

[9] CrunchBase along with PitchBook and PrivCo provide comprehensive coverage of U.S. private companies. These databases provide data on new ventures, entrepreneurs, and investors in the U.S., including funding histories for both small private firms and large publicly listed corporations.

approximated with a measure of *Innovation Novelty*. Following precedent, we use patent citations (i.e., prior art referenced by the patent) to operationalize the riskiness of the innovation (e.g., Jaffe et al., 1993; Hall et al., 2005). The extent to which patents cite previous patents in a broader array of technology classes outside of its own technological domain is indicative of novel innovation, moving beyond technology boundaries that is considered riskier (Rosenkopf & Nerkar, 2001). A patent's originality is calculated as in Hall et al. (2005) - a Herfindahl index of the patent classes associated with the patents that a focal patent cites. A higher value suggests that a patent builds on a broader set of technological areas. A firm-level value of *Innovation novelty* is the maximum originality score of the patents in the recipient's patent portfolio filed in the 3-year window prior to receiving the grant.[10]

FINDINGS

Comparison of Grant Recipients Pre-COVID-19 and during COVID-19

COVID-19 and pre-COVID-19 grant recipients are compared along the parameters identified above. Table 1 presents the univariate analysis comparing the means of the variables across the sample of recipients awarded the grant in the pre-COVID-19 and during COVID-19 through the NIH, NSF, and DOE.

The analysis reveals several interesting patterns. First, focusing on the NIH (Table 1; cols. 1-2), the most striking is that recipients in the COVID-19 period tend to be significantly older and larger in size (more employees), have higher sales, are more likely to be already investor-backed, and tend to pursue less novel innovation. Recipients during COVID-19 are, on average, over one year older, have nearly twice the number of employees, over three times the

[10] As a robustness, we also measured innovation novelty in a 5-year window. The findings are similar to those reported.

revenues, are twice as likely to be investor-backed, have nearly twice the number of patents, and are less novel. These are substantive differences.

Looking into the NSF sample (Table 1; cols. 3-4), except for the COVID-19 recipients more likely to be investor-backed compared to pre-COVID-19 recipients, we do not observe any significant differences in firm age, sales, firm size, innovation output, and innovation novelty. Unlike the NIH, the differences between pre-COVID-19 and COVID-19 recipients in NSF are marginal, suggesting that NSF continued to award grants in a consistent fashion during the COVID-19 crisis, focusing on younger small businesses pursuing risky innovation.

Examining the DOE sample (Table 1; cols. 5-6), the recipients in COVID-19 period tend to be significantly older, with higher sales, and are more likely to be already backed by investors. We do not observe any significant difference in the innovation output and novelty of the innovation. Recipients during COVID-19 are, on average, over two years older, have nearly 70% more revenues, and are more than twice as likely to be investor-backed. These differences follow a similar pattern to the NIH grant recipients, albeit the differences are substantive for the NIH. On a related note, it is interesting to observe that the DOE grant recipients are significantly older, larger in firm size, and have higher sales compared to the NIH and NSF grant recipients.

---------- Insert Table 1 ----------

In Figures 1-5, we show the differences in the grant recipients over time in the pre- and during COVID-19 periods for firm age, firm size, sales, investor-backed, and innovation novelty. In the figures, the triangle point on the x-axis (t) is March 2020 when the US was shut down by COVID-19.[11] The time intervals on the x-axis (t-2; t+3) reflect the review periods pre- and

[11] On March 11, 2020, the World Health Organization declared Covid-19 to be a global pandemic, schools and workplaces shut by the end of the week.

during COVID-19 between 2019-2020.[12] Figure 1a plots the firm age of the grant recipients for the three agencies. For all the three agencies, the average firm age of the recipients shows an upward trend in the periods *t*+1 and *t*+2, at the onset of COVID-19. Likewise, in Figure 1b, the average firm size of the recipients of NIH and DOE varies over time with an upward trend during the COVID-19 periods, but the NSF grant recipients' firm size remains stable in the pre- and during COVID-19. Looking at the average sales, in Figure 1c, the grant recipients of the NIH and DOE show a significant jump in sales during the COVID-19 period but the average sales of the NSF grant recipients remain stable in pre- and during COVID-19. In Figure 2a, for all the three agencies, the percentage of recipients being investor-backed jumps significantly immediately at the onset of COVID-19 and continues to show an upward trend for the NIH and DOE. The innovation novelty plot (Figure 2b) shows a significant downward trend for the NIH grant recipients during the COVID-19 period. For NSF and DOE, the recipients' innovation novelty remains stable with a marginal dip in the COVID-19 period.

---------- Insert Figures 1 (a, b, c) and 2 (a, b) ----------

Next, we compare the recipient attributes just around the advent of COVID-19, i.e., comparing the recipients reviewed in the *t*-1 (pre-COVID-19) and *t*+1 (during COVID-19) intervals. Note that the recipients reviewed in the *t*+1 period during COVID-19 submitted the grant application before the onset of COVID-19, i.e., before March 2020. In Table 2, the findings are consistent with those reported in Tables 1, with significant differences shown for the NIH grant recipients in the COVID-19 period for all the parameters of firm age, firm size, sales, investor-backed and innovation novelty.

[12] For the NIH, *t*-2 is Oct/Nov 2019, *t*-1 is Feb/Mar 2020, *t*+1 is Jun/Jul 2020, and *t*+2 is Nov/Dec 2020. For the NSF, *t*-2 is Jun-Sept 2019, *t*-1 is Dec 2019-Feb 2020, *t*+1 is Mar-May 2020, *t*+2 is Jun-Aug 2020, and *t*+3 is Sept-Dec 2020. For the DOE, *t*-2 is Mar-May 2019, *t*-1 is Oct-Dec 2019, *t*+1 is Mar-May 2020, and *t*+2 is Oct-Dec 2020.

---------- Insert Table 2 ----------

Multivariate Analysis

We also investigate whether these differences obtain in a multivariate setting. A number of recipient-level variables are regressed on the outcome variables – firm age, firm size, firm sales, investor-backed firm, and innovation novelty, and test the following model:

$$Y_i = \alpha + \beta(Covid) + \nu(X_i) + \mu + \varepsilon_i \quad (1)$$

Y denotes the outcome variables of recipient *i* at the time of receiving the grant, *COVID* is a binary variable equal to 1 if the recipient was awarded the grant during the COVID-19 period, and 0 otherwise, vector *X* includes the recipient control variables (prior patents, prior grants, grant amount, grant type- SBIR or STTR, minority-owned, women-owned, industry, location), μ captures the time effects, and ε is the error term. We employed an ordinary least squares (OLS) estimation to analyze the impact of COVID-19 on firm age, firm size, firm sales, and innovation novelty, and a logit model to test whether the firm is investor-backed.

---------- Insert Table 3 ----------

In Table 3 (cols.1-5), assessing the NIH sample, across all models, the coefficient of the COVID variable is significant, which shows that recipients of the grant during COVID-19 were 23 percentage points older in age (col. 1), 57 percentage points larger in size (col. 2), 45 percentage points higher in sales (col. 3), and the patent portfolio is 15 percentage points less novel (col. 5) than the recipients in the pre-COVID-19 period. Related to whether the recipient is investor-backed, the odds are 409% higher in the COVID-19 period than in the pre-COVID-19 period (exponentiating 1.409; col 4). Overall, the results confirm the univariate analysis highlighted earlier, showing that the attributes of NIH's grant recipients were different during COVID-19, reflecting the recipients to be safer bets by funding mature firms that have more

employees, have higher sales, are already investor-backed, and are pursuing less novel innovation.

In Table 3 (cols. 6-10), assessing the NSF sample, the coefficient of the COVID variable is not significant for any of the models, suggesting that the attributes of the NSF grant recipients did not change significantly in the pre- and during COVID-19. Analyzing the DOE sample, in Table 3 (cols. 11-15), the coefficient of the COVID variable is significant for some of the models, showing the COVID-19 recipients were 6 percentage points older in age (col. 11), 24 percentage points larger in size (col. 12), 7 percentage points higher in sales (col. 13), and 310% higher odds to be investor-backed (col. 14) than the recipients in the pre-COVID-19 period. The results are generally in line with the descriptive findings.

Venture Capital Response to Crisis

As a comparison, we examine how private capital responded to the onset of COVID-19. Using PitchBook data, we construct a biweekly panel of U.S. venture capital (VC) investments from January 1, 2019 through December 31, 2021. Each observation corresponds to the week identified on the x-axis. We define the onset of the COVID-19 crisis as the third week of March 2020, when confirmed U.S. cases surpassed 1,000, most states reported initial infections, schools and public venues closed, and federal agencies shifted to virtual operations.

We focus on VC investments in U.S.-based ventures operating in Healthcare, Energy, and Information Technology—sectors that overlap with SBIR/STTR awardees from NIH, DOE, and NSF. The sample is restricted to transactions classified as VC in PitchBook, excluding angel investments, buyouts, and other non-VC financing. We further distinguish between seed/early-stage and late-stage investments using PitchBook's stage classifications.

---------- Insert Figures 3 (a, b, c) ----------

Figure 3a presents biweekly seed/early-stage deal counts and the year-over-year percentage difference relative to the same biweek in the prior year. Seed/early-stage investment declines sharply following the crisis onset, falling from an average of 125 deals per biweek in the two months preceding March 2020 to 87 deals in the subsequent two months—a 30% reduction. Figure 3b reports the analogous series for late-stage investments. In contrast to early-stage activity, late-stage deal volume remains stable, averaging 98 deals per biweek both before and after the crisis onset.

Figure 3c displays the mean age of VC-backed firms by biweek and its year-over-year variance. Consistent with the compositional shift toward more mature ventures, average firm age increases from 5.7 years in the two months prior to the crisis to 6.1 years afterward, with a continued upward trend through 2020 and 2021.

Taken together, these patterns indicate that the aggregate resilience of the VC market during COVID-19 masks a pronounced contraction in financing for younger ventures and early-stage entrepreneurial opportunities. The apparent robustness of overall deal flow is driven primarily by sustained late-stage investments in more mature portfolio companies, consistent with contemporaneous reports (PitchBook, 2020) and prior evidence (Howell et al., 2020).

Key Takeaways

In summarizing the findings across the three agencies, the following takeaways are important. The onset of COVID-19 altered the characteristics of the grant recipients, albeit the differences varied across the agencies. In the NIH, the differences between the grant recipients pre- and during COVID-19 is substantial across all the parameters. DOE grant recipients show a similar pattern with COVID-19 grant recipients being more mature and commercially stable, and more likely to be investor-backed. NSF grant recipients, unlike the NIH and DOE, showed no

difference between pre-COVID-19 and COVID-19 recipients, which suggests NSF maintained consistency in awarding grants to young small businesses pursuing risky innovation. Overall, the shift in recipient attributes during the COVID-19 crisis is dramatic for the NIH with the DOE reflecting similar pattern, but the differences are muted for NSF.

Of course, our ability to show causal evidence of shifts in agencies' grant selection is limited by the lack of access to the application pool, in which shifts in the application pool, if any, may be endogenous to agencies' selection choices. Nevertheless, we are comforted by the fact that the comparison of the recipients who applied for the grant just before COVID-19 but were reviewed after the immediate onset of the COVID-19 pandemic showed a similar pattern – they were relatively older, larger in size, with higher sales, and more likely to be investor-backed (see Table 2), and these differences are prominent for the NIH grant recipients. Moreover, the COVID-19 crisis occurred too immediately and discontinuously to plausibly reflect changes in application pool seeking grant money, it is also arguably exogenous to the supply of entrepreneurial startups, particularly in the short term. In addition, there is only a slight uptick in the Phase I applicant pool from 2019 to 2020 across the three agencies (see Appendix Figure E). We also do not observe much difference in the distribution of the applicant pool across major states within the past four years.

To further corroborate our findings and to better understand the agencies' response to COVID-19, we reached out to the SBIR program directors at the NIH, NSF, and DOE. We were able to interview the directors at the NIH and NSF to understand whether any policy directives or selection criteria were changed during COVID-19.[13] The interviews with both the directors confirmed that there were no changes in the selection criteria, processes, or policy directives in

[13] The interviews were conducted face-to-face via zoom on July 2021, September 2021, and September 2024.

the SBIR program related to COVID-19 crisis. As the director at the NIH noted, "… while there was lot of uncertainty during Covid, those were interesting times, there were no changes in the review process and solicitation calls … in fact majority of our grants went to non-Covid related projects." Similarly, the NSF director emphasized that "our review policies and structure did not change because of Covid except for the meetings moving to virtual."

Exploring Possible Explanations

While we cannot infer the causal factors that may explain the shift in agencies' grant choices, we investigate some possible explanatory factors below. Given the opacity of the data shared by federal agencies, we are able to do so for the NIH sample, as the NIH is relatively more transparent in sharing information about the reviewer panels evaluating grant applications. As our findings highlight a substantial difference for the NIH grant recipients pre- and during COVID-19, this effort helps to shed some light in this direction.

Reviewer attributes changed. The disruption during the onset of COVID-19 may have changed the composition of the reviewer committee, which perhaps altered the types of entities receiving the grant. Several factors may alter the reviewer committee's composition. For instance, moving to virtual meetings made it easier for some individuals to accept a reviewer invitation. It may also be that COVID-19 inhibited the involvement of certain types of reviewers (e.g., medical practitioners may be less able to participate).

Federal agencies generally face challenges in getting reviewers with adequate technical expertise while ensuring they do not have a conflict of interest (NASEM, 2020). With the shock of COVID-19 pandemic disrupting individuals' personal and professional lives, people in academia were struggling to switch to online teaching formats, practitioners in the medical field were stretched thin with long hours in attending patients, and individuals in the corporate sector

were burdened with the shift to remote work. These disruptions may further aggravate the challenge to get the right mix of experts to commit their time to the review process.

In recruiting reviewers, the Center for Scientific Review (CSR) at the NIH responsible for the peer review process attempts to maintain a balance between reviewers from academia and from the commercial sector.[14] To investigate whether review teams changed during COVID-19, we identified the reviewers involved in the peer review process associated with the grants in our sample, and traced the relevant study sections, meeting dates, and meeting rosters from the CSR website and web archives.[15, 16] The reviewer-level data was augmented with information on reviewers' work experience, which includes experience in academia, corporate experience, and entrepreneurial experience, along with information on education history. Information was gathered from LinkedIn using web-scraping algorithms, individuals' resume, bio sketches, and web profiles. For each reviewer, we reconstruct their careers from the time they obtained their highest level of education (typically after a PhD) until the year they reviewed for the focal SBIR/STTR grants. Our dataset includes employment history, degrees held, year of undergraduate degree obtained, gender, minority race, and affiliations, as well as a complete list of publications, patents, and funding obtained by each reviewer.[17, 18]

[14] The review committee is generally composed of 75% reviewers from academia and 25% from the commercial sector.
[15] https://public.csr.nih.gov/StudySections/SmallBusinessAndTechnologyTransfer. For each study section, the CSR website makes three recent meeting rosters open to public view. The recent rosters were obtained from the CSR website and the older rosters for year 2019 were collected from web archives.
[16] We verified the meeting dates and meeting format (in-person/virtual) from the Federal Register (www.federalregister.gov) that documents all meetings conducted by federal agencies.
[17] The source of the publication data is PubMed, an online resource from the National Library of Medicine that provides reliable access to the biomedical research literature. PubMed indexes more than 40,000 journals within the life sciences. The source of patent data is USPTO. The source of NIH/NSF funding is NIH Reporter and NSF website corroborated with www.grantome.com. Information about gender was obtained from WIPO gender name dictionary (WGND 2.0) supported with manually identifying the reviewers. Information about minority race (includes African Americans, Hispanics, Latinos, and Asian Americans) was sourced from the R package "predictrace" developed from U.S. Census data, which says how many people of each race has a certain surname and supported with manually identifying the reviewers.
[18] Appendix D details the steps taken to ensure that the list of patents, publications, and funding is complete and accurate.

There are 2,063 unique reviewers in the meeting rosters associated with the NIH awards, with 1,424 reviewers having reviewed in the COVID-19 period and 1,165 reviewers having reviewed in the pre-COVID-19 period.[19] Table 4 presents the descriptive statistics comparing the means of the variables across the sample of reviewers in the pre-COVID-19 and during the COVID-19 periods. We did not find much evidence that the attributes of the reviewers differed across the pre- and during COVID-19 periods. Across the periods, the NIH maintained a similar balance in gender and minority representation, and the average academic and corporate experience was similar in both cohorts. It is interesting that although the number of reviewers with doctorate and medical degrees was significantly higher in the COVID-19 period, the average experience of practicing medicine was significantly lower than the pre-COVID-19 period. This makes sense given the unprecedented need for medical practitioners to be in the field during COVID-19 reduced their availability to serve as peer reviewers. Consequently, we conclude that changes in reviewer committees across the periods are not substantive to account for the differences in NIH grant recipients pre- and during COVID-19.

---------- Insert Table 4 here ----------

Behavioral changes in reviewers. Crisis conditions invoke behavioral changes in individuals' decision-making process. Organizational theorists have acknowledged that individuals employ a variety of heuristics and cognitive simplifications to circumvent the ambiguities of the environment in the decision-making process (Haveman, 1992; March & Simon, 1958; Tversky & Kahneman, 1974), and such heuristics can influence (sometimes deleterious) their evaluations and perceptions (Benartzi & Thaler, 2007; Hallen & Pahnke, 2016). It is not that the crisis disruptions per se make them hard to handle, but rather that

[19] 531 reviewers reviewed in both pre-COVID-19 and COVID-19 periods.

individuals are limited cognitively in their ability to process complex information cues (Daft & Weick, 1984; Lant et al., 1992). As Knight (1921: 235) noted: "The problem of the human attitude to uncertainty … is as beset with difficulties as that of uncertainty itself. Not merely is the human reaction to situations of this character apt to be erratic and extremely various from one individual to another, but the 'normal' reaction is subject to well-recognized deviations from the conduct which sound logic would dictate."

Little attention has been devoted to understanding the decision-making challenges in crises—where the turbulence is more widespread and systematic, impacting the economic and social welfare (Bloom, 2009)—like COVID-19. The decision-making processes that occur when individuals are forced to act under conditions of crisis are far more complex and perhaps call for different resources and mechanisms to navigate through the crisis (Lampel et al., 2009).

Based on the premise that behavior changes under crises, one might expect peer reviewers' experience to have different effects in the pre- and during COVID-19 crisis. We test whether reviewers' behavioral changes are driving the differences in NIH grant recipients pre- and during COVID-19. To facilitate the multivariate analysis described below, we used principal component factor analysis to reduce the human capital attributes (i.e., academic experience, corporate experience, medical experience, patent count, publication count, SBIR grant count, and research grant count) to a manageable number of dimensions. These attributes loaded on two factors, where factor 1 loadings were dominated by academic experience, publication count, and research grant count, and factor 2 loadings included corporate experience, patent count, and SBIR grant count.[20] The two factors were standardized, termed as *scientific human capital* (factor 1) and *commercial human capital* (factor 2), to test the following model:

[20] Appendix Table D.1 reports the factor loadings and Appendix Figure D.1 shows the scree plot of the Eigen values.

$$Y_i = \alpha + \beta_1(Covid) + \beta_2\left(H_{i,j}\right) + \beta_3\left(H_{i,j}\right) * (Covid) + \nu(X_i) + \mu + \gamma + \delta + \varepsilon_i \quad (3)$$

Y denotes the outcome variables of recipient *i* at the time of receiving the grant, *COVID* is a binary variable equal to 1 if the recipient was awarded the grant during the COVID-19 period, and 0 otherwise, vector *H* includes average scientific and corporate human capital of the reviewer committee roster *j*, vector *X* includes the recipient control variables, μ captures the time effects, γ captures the study section fixed effects, δ captures the funding institute fixed effects, and ε is the error term.

---------- Insert Tables 5a and 5b here ----------

In Tables 5a and 5b, across all the models, the coefficient of the *COVID* variable remains significant. Interestingly, the coefficient of the interaction term *covid*commercial human capital* is positive and significant for firm age (table 5a; col. 3), firm size (table 5a; col. 7) and firm sales (table 5a; col. 11), which suggests that during COVID-19, reviewers with high commercial human capital were more likely to select mature and stable recipients - older, larger in size, and with more sales. Similarly, the coefficient of the interaction term *covid*scientific human capital* is positive and significant for the likelihood of selecting investor-backed recipient (table 5b; col. 2), indicating that during COVID-19, reviewers with high scientific human capital were more likely to select recipients that are already investor-backed. Figure 4 plots the significant interaction curves.

---------- Insert Figure 4 here ----------

Change in meeting format. At the onset of COVID-19, all reviewer panel meetings immediately switched to virtual format, whereas during the pre-COVID-19, only a small portion of the reviewer meetings were conducted virtually. The sudden switch to virtual meeting format may alter the decision process in some way, potentially influencing the shift in grant recipients.

To investigate the possibility that meeting format changes are driving the differences in NIH grant recipients, we identified all study sections that used virtual meeting formats in the pre-COVID-19 period. Three study sections in our NIH sample (i.e., OTC11-Radiation Therapy and Biology, VH10-Vascular and Hematology, and DKUS11Renal and Urological Sciences) conducted virtual review meetings in the pre-COVID-19 period. A dummy variable, *format changed,* equals to "0" for any firms evaluated by these study sections, and "1" for those evaluated by all other study sections. The dummy variable was interacted with the *COVID* variable in the multivariate analyses, and a significant positive interaction would suggest that differences in NIH grant recipients across the periods were accentuated when reviewer meeting format were altered. However, the interaction coefficient is insignificant across all but one outcome variable. In the regression on Sales, the interaction was negative, not positive. Overall, results (available on request) do not support the explanation that meeting format changes are driving the differences in grant recipients across the periods.

Change in the applicant pool. Crisis periods altered the composition of the applicant pool. If different types of firms applied during crises, observed award patterns could reflect selection into the pool rather than changes in public support.

We cannot directly assess this possibility because agencies do not provide data on unsuccessful applicants. However, we have no reason to believe that the applicant pool shifted in ways that would mechanically generate our findings. If anything, contractions in venture capital during crises should increase applications from younger, capital-constrained firms seeking non-dilutive government funding. Such a substitution effect would likely introduce more early-stage and riskier ventures into the pool, which would attenuate rather than exaggerate the patterns we observe. To further assuage the concern, the sub-sample analysis of the awardees who applied

for the grant before COVID-19 but were reviewed after the onset of the COVID-19 showed similar attributes as the main findings – they were relatively more mature and investor-backed (see Table 2). Thus, while we cannot completely rule out compositional change, plausible selection dynamics run counter to the explanation that the findings are driven solely by shifts in application pool.

DISCUSSION

Our findings identify a mechanism through which systemic shocks reshape public investment behavior. We characterize this mechanism as crisis-induced evaluative conservatism, a process whereby heightened environmental uncertainty alters how evaluators weight information within existing decision frameworks. Rather than reflecting formal policy change, budget contraction, or explicit mandate revision, the shift operates through micro-level evaluation dynamics. Under crisis conditions, observable signals of viability and stability gain salience relative to exploratory potential.

Organizational theory has long argued that uncertainty increases reliance on simplifying heuristics and reduces tolerance for variance (March & Simon, 1958; Tversky & Kahneman, 1974). When future states become more difficult to anticipate, the perceived costs of error rise. In such environments, decision-makers may narrow the range of acceptable alternatives and privilege options that appear more resilient or externally validated. In the context of innovation funding, this translates into greater emphasis on firm age, prior revenue, organizational scale, and investor backing—signals that reduce perceived downside risk—even if such attributes do not maximize technological novelty or exploratory scope.

Importantly, crisis-induced evaluative conservatism does not imply a change in formal criteria. Agencies did not alter review rubrics or stated priorities. Instead, the relative weighting

of signals within those criteria appears to have shifted. The interaction between reviewer human capital and crisis conditions supports this interpretation. Panels with greater commercial expertise were more likely, during crisis, to select older, larger, and higher-revenue firms. Panels with stronger scientific capital were more likely to favor ventures that had already secured external investor endorsement. Crisis conditions appear to activate evaluative tendencies rooted in reviewers' professional backgrounds, amplifying reliance on signals aligned with their domain-specific logics.

This mechanism helps explain how public innovation systems can become effectively pro-cyclical even in the absence of explicit retrenchment. When uncertainty heightens sensitivity to downside risk, selection processes may contract toward lower-variance ventures, mirroring private-sector "flight to safety" dynamics. The fact that this shift was pronounced at the NIH, more moderate at the DOE, and largely absent at the NSF suggests that organizational design conditions the extent of evaluative conservatism. Differences in panel composition, review structure, and the institutionalization of commercialization criteria may moderate how strongly uncertainty reweights signals.

Conceptually, these findings extend theories of bounded rationality and exploration–exploitation tradeoffs into the domain of public investment decision-making. Much of the literature on the entrepreneurial state assumes that public agencies are structurally positioned to act counter-cyclically when markets retreat. Our results suggest that risk posture is not determined solely by mandate or mission. It is shaped by how uncertainty interacts with micro-level evaluative processes. The state, like private actors, may exhibit context-dependent shifts in signal weighting when ambiguity intensifies.

More broadly, this study invites greater attention to government agencies as organizations whose decision processes merit the same analytical scrutiny applied to firms and investors. Selection systems inside public institutions are not neutral conduits for policy objectives; they are interpretive arenas in which signals are assessed, weighted, and enacted. Systemic shocks may therefore influence public investment not through changes in formal rules, but through shifts in how evaluators interpret evidence of quality and viability.

At the same time, our investigation is exploratory. We observe funded ventures but lack systematic data on unsuccessful applicants, limiting our ability to fully disentangle changes in evaluation from potential shifts in the applicant pool. Although the timing of the crisis and the stability of formal procedures mitigate some concerns, we cannot directly observe how the distribution of submitted proposals evolved. Future research with access to applicant-level and scoring data would allow more precise identification of how uncertainty reshapes evaluation.

Further work could also examine whether similar dynamics arise in other public funding domains or under different types of shocks, including positive funding expansions. Understanding when public systems sustain exploratory risk and when they contract toward safer selections is central to theories of innovation policy and organizational adaptation. By identifying crisis-induced evaluative conservatism as a candidate mechanism, this study opens a line of inquiry into how systemic shocks reweight signals within organizations and how institutional design shapes the capacity of public systems to maintain risk tolerance under uncertainty.

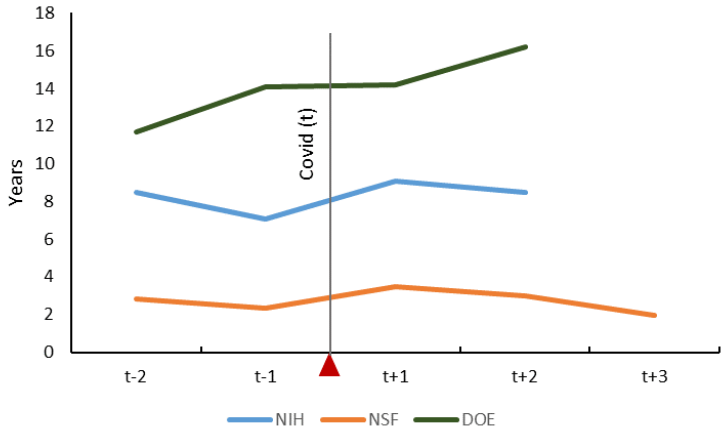
REFERENCES

Arrow, K. (1962). Economic welfare and the allocation of resources for invention. In Universities National Bureau Committee for Economic Research, Committee on Economic Growth of the Social Science Research Council (Eds.),***The rate and direction of inventive activity: Economic and social factors***: 609–626. Princeton Press.

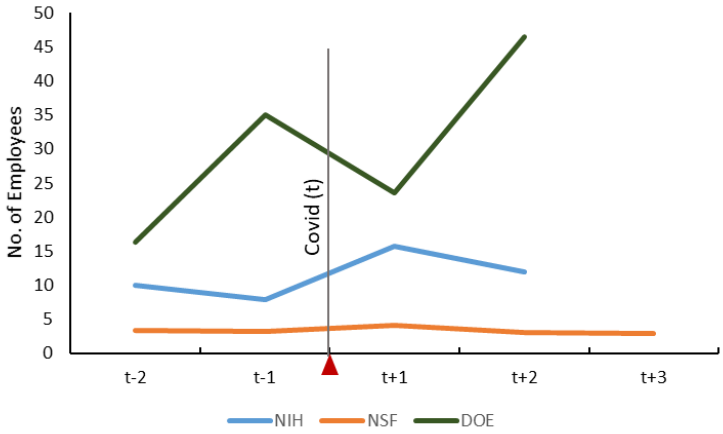
Benartzi, S., & Thaler, R. H. (2007). Heuristics and biases in retirement savings behavior. ***Journal of Economic Perspectives***, 21(3), 81-104.
Bloom, N. (2009). The impact of uncertainty shocks. ***Econometrica***, 77(3), 623-685.
Coad, A., Segarra, A., & Teruel, M. (2016). Innovation and firm growth: does firm age play a role?. ***Research Policy***, 45(2), 387-400.
Daft, R. L., & Weick, K. E. (1984). Toward a model of organizations as interpretation systems. ***Academy of Management Review***, *9*(2), 284-295.
Gompers, P. A., & Lerner, J. (2004). ***The venture capital cycle***. MIT press.
Griliches, Z., Hall, B. H., & Pakes, A. (1987). The value of patents as indicators of inventive activity. In P. Dasgupta & P.Stoneman(Eds.), ***Economic policy and technological performance***:97–124.Cambridge University Press: UK.
Hall, B., Jaffe, A., & Trajtenberg, M. (2005). Market value and patent citations. ***RAND Journal of Economics***, 16-38.
Hall, B. H., & Lerner, J. (2010). ***The financing of R&D and innovation***. In: Hall, B.H., Rosenberg, N. (Eds.), The Handbook of the Economics of Innovation, vol. I. Elsevier, Amsterdam, NL, pp. 609–639.
Hallen, B. L., & Pahnke, E. C. (2016). When do entrepreneurs accurately evaluate venture capital firms' track records? A bounded rationality perspective. ***Academy of Management Journal***, 59(5), 1535-1560.
Haveman, H. A. (1992). Between a rock and a hard place: Organizational change and performance under conditions of fundamental environmental transformation. ***Administrative Science Quarterly***, 48-75.
Hellmann, T., & Puri, M. (2002). Venture capital and the professionalization of start-up firms: Empirical evidence. ***Journal of Finance***, 57(1), 169-197.
Howell, S. T., Lerner, J., Nanda, R., & Townsend, R. R. (2020). How resilient is venture-backed innovation? Evidence from four decades of US patenting. ***NBER Working paper***.
Jaffe, A. B., Trajtenberg, M., Henderson, R. (1993). Geographic localization of knowledge spillovers as evidenced by patent citations. ***Quarterly Journal of Economics,*** 108(3): 577-598.
Knight, F. H. (1921). Risk, uncertainty and profit (Vol. 31). Houghton Mifflin.
Lampel, J., Shamsie, J., & Shapira, Z. (2009). Experiencing the improbable: Rare events and organizational learning. ***Organization Science***, *20*(5), 835-845.
Lant, T. K., Milliken, F. J., & Batra, B. (1992). The role of managerial learning and interpretation in strategic persistence and reorientation: An empirical exploration. ***Strategic Management Journal***, *13*(8), 585-608.
March, J., & H. Simon. (1958). ***Organizations***. John Wiley, New York.
Nanda, R., & Rhodes-Kropf, M. (2013). Investment cycles and startup innovation. ***Journal of Financial Economics***, *110*(2), 403-418.
National Academies of Sciences, Engineering, and Medicine. (2020). ***Review of the SBIR and STTR Programs at the Department of Energy***. Washington, DC: The National Academies Press.
Nelson, R. R. (1959). The economics of invention: A survey of the literature. ***Journal of Business***, 32: 101–127.
Pitchbook. (2020). "Venture Capital Fundraising and Investment Dollars Remained Healthy Through 1H 2020 Amid Slowdown in Exits and Deal Count Due to Impacts of COVID-19." Pitchbook Press.
Rosenkopf, L., & Nerkar, A. (2001). Beyond local search: boundary-spanning, exploration, and impact in the optical disk industry. ***Strategic Management Journal***, *22*(4), 287-306.
Sørensen, J. B., & Stuart, T. E. (2000). Aging, obsolescence, and organizational innovation. ***Administrative Science Quarterly***, 45(1), 81-112.
Stuart, T. E., Hoang, H., & Hybels, R. C. (1999). Interorganizational endorsements and the performance of entrepreneurial ventures. ***Administrative Science Quarterly***, 44(2): 315-349.
Tversky, A., & Kahneman, D. (1974). Judgment under Uncertainty: Heuristics and Biases: Biases in judgments reveal some heuristics of thinking under uncertainty. ***Science***, 185(4157), 1124-1131.

FIGURE 1. Grant Recipient Attributes (pre- and during COVID-19)

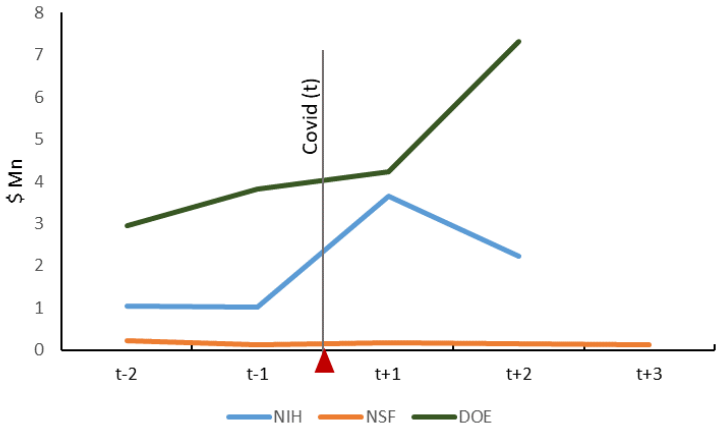
(a) Firm Age



(b) Firm Size



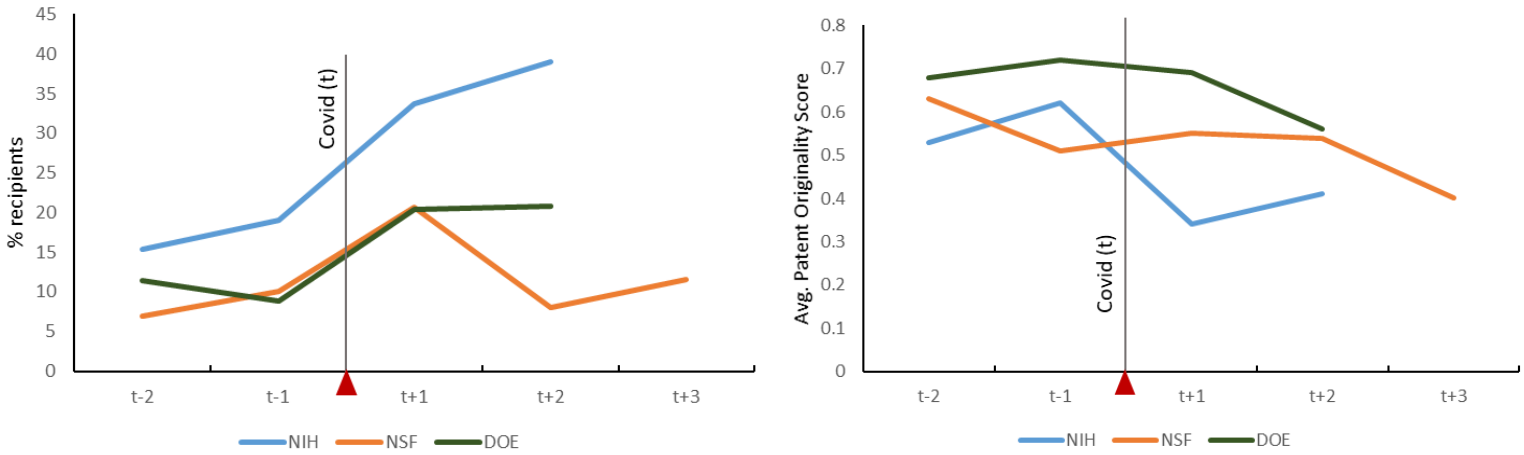
(c) Firm Sales



Note: The figures show the comparison of the grant recipient reviewed in pre- and during COVID-19 for average (a) firm age, (b) firm size, and (c) firm sales. The triangle point on the x-axis (*t*) is mid-March 2020 when the US was shut down by COVID-19. The time intervals on the x-axis (*t*-2; *t*+3) reflect the review periods between 2019-2020. For the NIH, *t*-2 is Oct/Nov 2019, *t*-1 is Feb/Mar 2020, *t*+1 is Jun/Jul 2020, and *t*+2 is Nov/Dec 2020. For the NSF, *t*-2 is Jun-Sept 2019, *t*-1 is Dec 2019-Feb 2020, *t*+1 is Mar-May 2020, *t*+2 is Jun-Aug 2020, and *t*+3 is Sept-Dec 2020. For the DOE, *t*-2 is Mar-May 2019, *t*-1 is Oct-Dec 2019, *t*+1 is Mar-May 2020, and *t*+2 is Oct-Dec 2020.

FIGURE 2. Grant Recipient Investment and Innovation (pre- and during COVID-19)

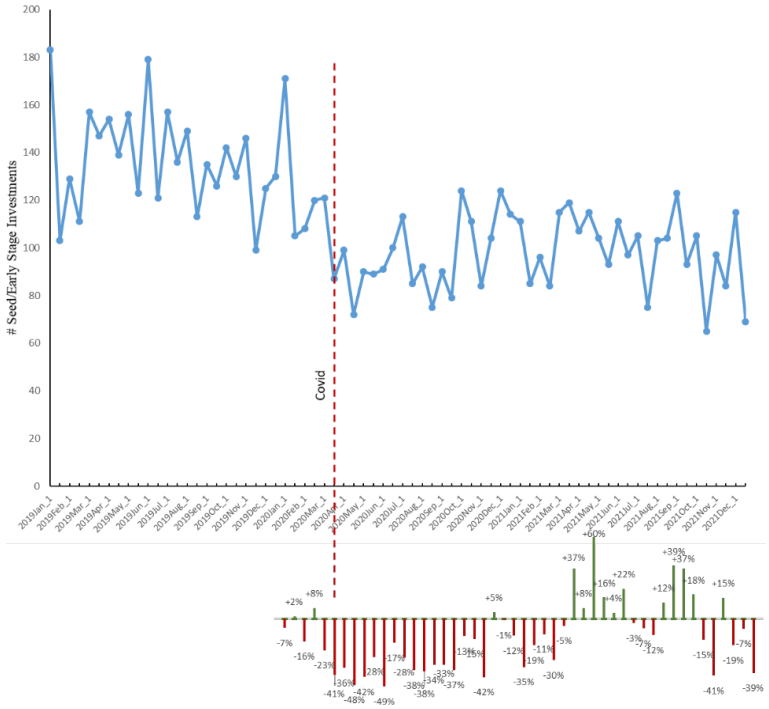
(a) Investor-backed **(b) Innovation novelty**



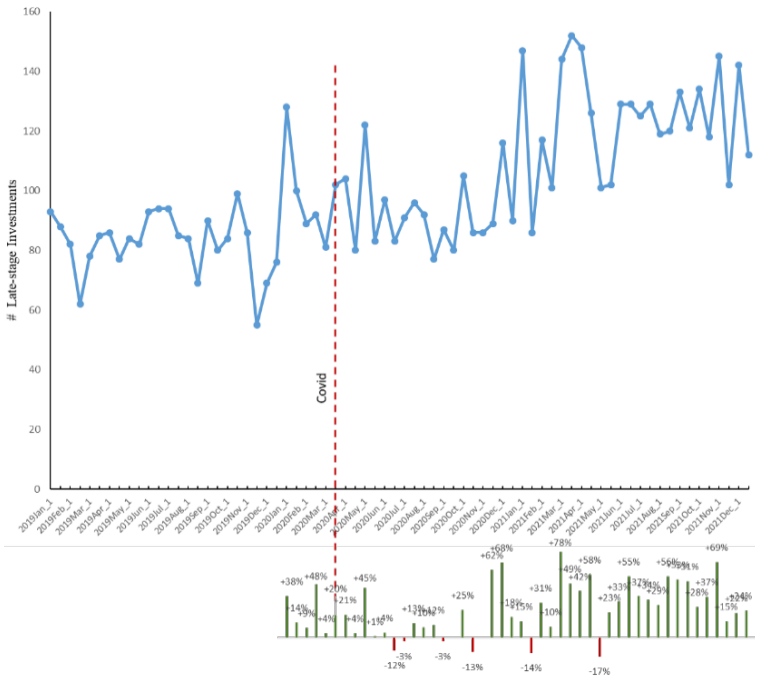
Note: Figures show (a) the percentage grant recipients that were investor-backed before receiving grant reviewed in pre- and during COVID-19, and (b) the average innovation novelty of the patents filed in the 3-yr before receiving grant for the recipients reviewed in pre- and during COVID-19. The triangle point on the x-axis (*t*) is mid-March 2020 when the US was shut down by COVID-19. The time intervals on the x-axis (*t*-2; *t*+3) reflect the review periods between 2019-2020. For the NIH, t-2 is Oct/Nov 2019, *t*-1 is Feb/Mar 2020, *t*+1 is Jun/Jul 2020, and *t*+2 is Nov/Dec 2020. For the NSF, *t*-2 is Jun-Sept 2019, *t*-1 is Dec 2019-Feb 2020, *t*+1 is Mar-May 2020, *t*+2 is Jun-Aug 2020, and t+3 is Sept-Dec 2020. For the DOE, t-2 is Mar-May 2019, *t*-1 is Oct-Dec 2019, *t*+1 is Mar-May 2020, and *t*+2 is Oct-Dec 2020.

FIGURE 3. Distribution of VC Investments (pre- and during COVID-19)

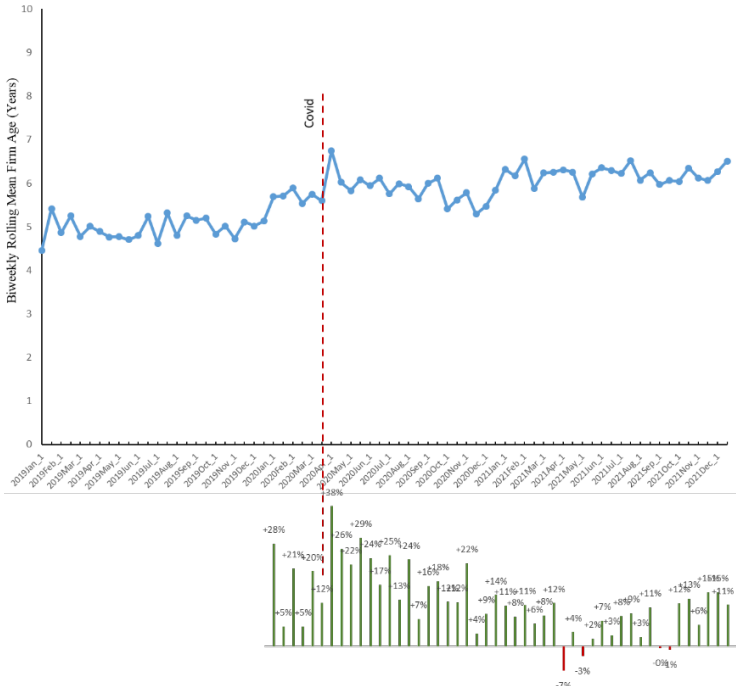
(a) Seed/Early Stage



(b) Late Stage

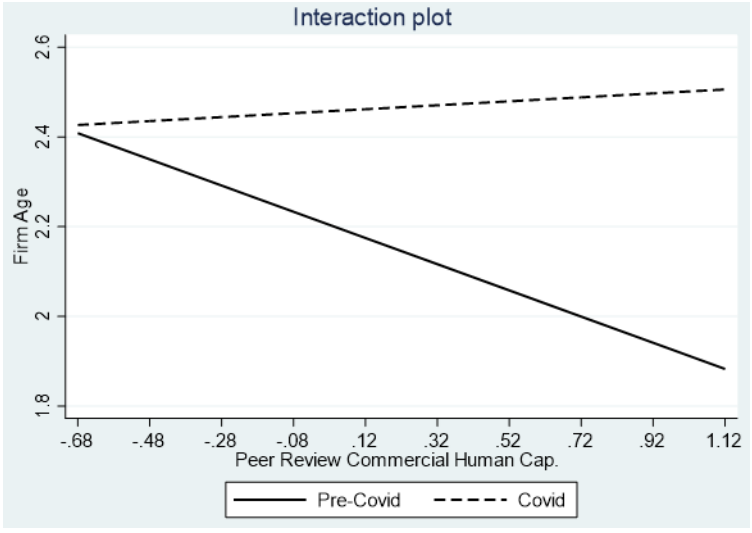


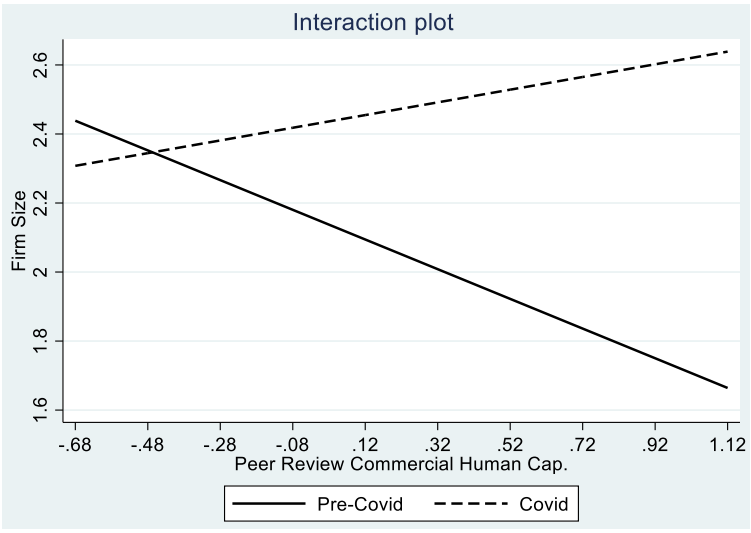
(c) Firm Age

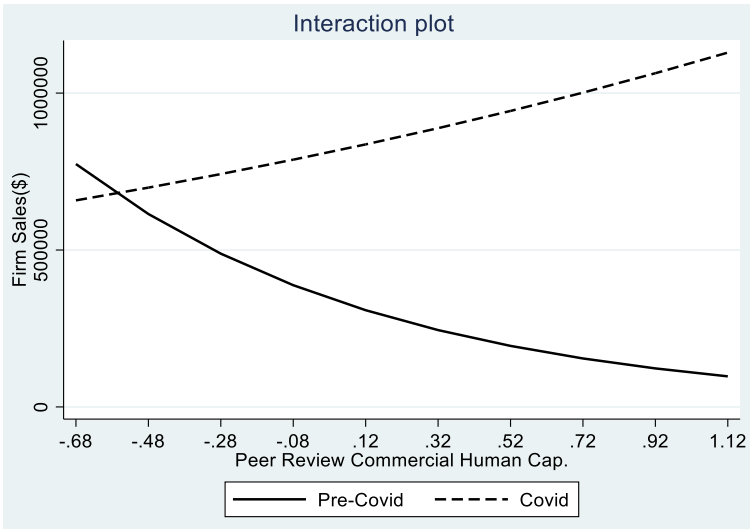


Note: Figures 3a and 3b show the biweekly number of VC investments by investment stage. Figure 3c shows the bi-weekly mean firm age of the investments. The bar lines show the variance, i.e., the percentage difference in the same bi-week of previous year (green>0; red <0). The dashed line is mid-March 2020 when the US was shut down by COVID-19.

FIGURE 4. NIH Interactions Plots: Reviewer Human Capital and COVID







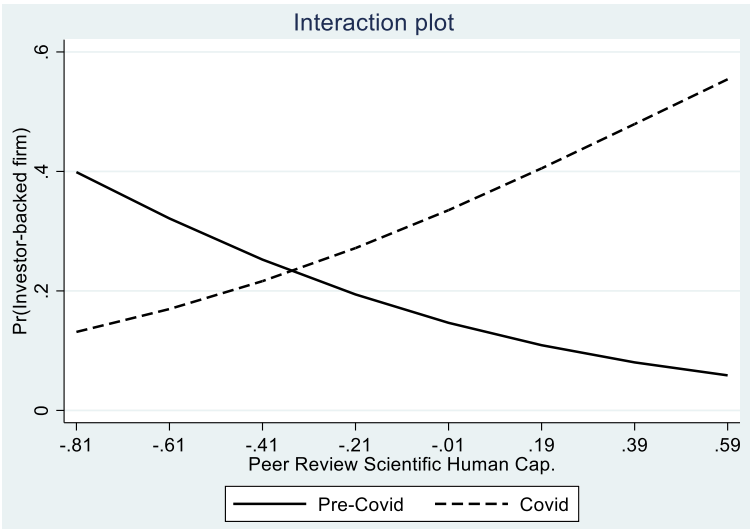


TABLE 1
Comparing Pre-COVID-19 & COVID-19: NIH, NSF, DOE Grant Recipients

			NIH		NSF		DOE	
			(1)	(2)	(3)	(4)	(5)	(6)
VARIABLE	DEFINITION		Pre-Covid	Covid	Pre-Covid	Covid	Pre-Covid	Covid
Firm age	Age in years of firm as of year of the award.		7.68	8.87†	2.53	2.57	12.62	14.99**
Firm size	No. of employees in the year of the award.		8.72	14.35*	3.25	3.25	23.31	32.74
Sales	Sales in ($ Mn) in the year of the award.		1.03	3.15**	0.16	0.13	3.27	5.50**
Investor-backed	Dummy = 1 if the firm previously received investment from external investors (VCs, angels, accelerators).		0.18	0.36***	0.09	0.14*	0.10	0.21***
Patent count	No. of patents filed (and ultimately granted) before receiving the grant.		2.24	4.13	0.55	0.47	34.84	26.96
Innovation Novelty	1- Herfindahl concentration of patent class assignments associated with patents cited by the focal patent, adjusted for bias correction associated with small numbers of backward citation counts. Measured as the max value for the portfolio of patents filed in the 3-year period before receiving the award.		0.58	0.37**	0.34	0.34	0.69	0.64
Grant Amount	Amount of money received by firm for the grant ($ Mn).		0.26	0.29***	0.22	0.25***	0.20	0.22***
Prior SBIR award	Dummy= 1 if the firm has received prior SBIR/STTR awards before receiving the focal award.		0.72	0.60**	0.19	0.17	0.77	0.78
Women-owned	Dummy= 1 if the firm is women-owned.		0.21	0.15*	0.12	0.23**	0.13	0.14
Minority-owned	Dummy= 1 if the firm is minority-owned.		0.20	0.17	0.23	0.22	0.22	0.22
SBIR	Dummy= 1 if the grant was SBIR and 0 if it was STTR.		0.73	0.75	0.83	0.85	0.85	0.85
Location	Indicator variable for firm headquarter location.	CA	0.19	0.22	0.22	0.85	0.19	0.21
		MA	0.09	0.07	0.07	0.14**	0.09	0.07
		NY	0.08	0.07	0.07	0.09	0.04	0.06
		PA	0.06	0.04	0.04	0.05	0.03	0.03
Industry	Indicator variable for firm's 2-digit SIC industry classification.	SIC87	0.60	0.28	0.28	0.31	0.43	0.40
		SIC28	0.12	0.08	0.08	0.05†	0.13	0.14
		SIC38	0.13	0.10	0.10	0.12	0.09	0.09
		SIC73	0.07	0.30	0.30	0.23*	0.15	0.16
No. of firms			249	247	263	213	307	311

Note: The sample includes SBIR/STTR Phase-I grant recipients awarded during the pre-COVID-19 and COVID-19 period under the NIH omnibus grant solicitation PHS 2019 and PHS 2020, NSF omnibus grant solicitations NSF 19-554 and NSF 20-527, and DOE omnibus grant solicitations DE-FOA-0001941, DE-FOA-0002145, DE-FOA-0002146, and DE-FOA-0002359. ***, **, *, † indicates difference is significant at $p < 0.001$, $p < 0.01$, $p < 0.05$, and $p < 0.1$ respectively.

TABLE 2
Comparing Pre-COVID-19 & during COVID-19: t-1/t+1 time period

		NIH		NSF		DOE	
		(1)	(2)	(3)	(4)	(5)	(6)
VARIABLE	DEFINITION	Pre-Covid	Covid	Pre-Covid	Covid	Pre-Covid	Covid
Firm age	Age in years of firm as of year of the award.	7.08	9.09*	2.34	3.46*	14.12	14.16
Firm size	No. of employees in the year of the award.	7.85	15.72*	3.20	4.03*	35.07	23.54
Sales	Sales in ($ Mn) in the year of the award.	1.01	3.65*	0.11	0.16	3.81	4.24
Investor-backed	Dummy = 1 if the firm previously received investment from external investors (VCs, angels, accelerators).	0.21	0.34**	0.11	0.21*	0.08	0.20**
Patent count	No. of patents filed (and ultimately granted) before receiving the grant.	2.09	1.42†	0.36	0.22	30.54	33.18
Innovation Novelty	1- Herfindahl concentration of patent class assignments associated with patents cited by the focal patent, adjusted for bias correction associated with small numbers of backward citation counts. Measured as the max value for the portfolio of patents filed in the 3-year period before receiving the award.	0.62	0.34**	0.51	0.54	0.72	0.69
Grant Amount	Amount of money received by firm for the grant ($ Mn).	2.63	2.87**	0.22	0.25***	0.20	0.21***
Prior SBIR award	Dummy= 1 if the firm has received prior SBIR/STTR awards before receiving the focal award.	0.66	0.59†	0.18	0.21	0.89	0.74**
Women-owned	Dummy= 1 if the firm is women-owned.	0.24	0.15*	0.11	0.32***	0.18	0.12†
Minority-owned	Dummy= 1 if the firm is minority-owned.	0.22	0.17	0.21	0.24	0.22	0.21
SBIR	Dummy= 1 if the grant was SBIR and 0 if it was STTR.	0.72	0.76	0.77	0.89*	0.86	0.85
No. of firms		144	160	149	63	114	186

Note: The sample includes SBIR/STTR Phase-I grant recipients awarded during the pre-COVID (i.e., just before start of Covid-19; t-1) and COVID period (i.e., just during the advent of Covid-19; t+1). The recipients in the Covid-19 period applied for the grant on or before March 2020 but reviewed during COVID-19. ***, **, *, † indicates difference is significant at $p < 0.001$, $p < 0.01$, $p < 0.05$, and $p < 0.1$ respectively.

TABLE 3
Multivariate Analysis Comparing Pre-COVID-19 & COVID-19 Grant Recipients

	NIH					NSF					DOE				
Estimation	OLS			Logit	OLS	OLS			Logit	OLS	OLS			Logit	OLS
	Firm age	Firm size	Firm sales	Investor-backed	Innov. novelty	Firm age	Firm size	Firm sales	Investor-backed	Innov. novelty	Firm age	Firm size	Firm sales	Investor-backed	Innov. novelty
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
COVID	0.236** (0.032)	0.530*** (0.034)	0.454** (0.057)	1.409*** (0.093)	-0.155* (0.038)	0.495 (0.250)	0.074 (0.294)	0.133 (0.171)	0.496 (0.489)	0.049 (0.203)	0.064* (0.018)	0.244** (0.034)	0.077* (0.025)	1.132*** (0.105)	-0.035 (0.016)
(Log) Grant Amount	-1.368 (0.841)	-1.486* (0.351)	-1.358* (0.327)	-2.222† (1.304)	0.018 (0.822)	-18.927 (9.170)	-4.079 (10.126)	-6.220 (6.685)	-5.057 (8.375)	-5.953 (4.384)	-1.802 (1.707)	3.337 (2.162)	1.490 (0.764)	-8.452 (13.411)	0.931 (0.637)
(Log) Prior Patents	0.271* (0.057)	0.251*** (0.008)	0.200** (0.035)	0.284** (0.106)	0.104* (0.031)	0.394** (0.061)	0.165 (0.087)	0.073* (0.018)	0.289 (0.270)	0.103 (0.085)	0.233*** (0.011)	0.299*** (0.023)	0.260** (0.028)	0.147 (0.125)	0.038** (0.006)
Prior Grants	0.329*** (0.025)	0.279** (0.040)	0.254* (0.048)	-0.133*** (0.042)	0.027* (0.008)	0.663*** (0.051)	0.117 (0.106)	0.073* (0.024)	0.320 (0.329)	-0.015 (0.114)	0.544*** (0.041)	0.361 (0.169)	0.293** (0.050)	0.102 (0.319)	-0.072 (0.115)
SBIR	0.068 (0.087)	0.056 (0.048)	-0.051 (0.049)	0.186† (0.113)	-0.014 (0.032)	-0.144 (0.101)	-0.041 (0.029)	0.005 (0.024)	1.625*** (0.349)	0.143† (0.065)	-0.021 (0.103)	0.199* (0.055)	0.091 (0.054)	0.334 (0.269)	0.065* (0.019)
Minority-owned	-0.148* (0.035)	-0.068 (0.136)	0.052 (0.153)	0.284 (0.272)	-0.044 (0.023)	-0.038 (0.086)	-0.037 (0.040)	0.001 (0.013)	-0.394 (0.262)	-0.085* (0.050)	-0.188* (0.056)	-0.183† (0.065)	-0.299** (0.026)	0.469** (0.179)	0.015 (0.043)
Women-owned	0.223* (0.045)	-0.102 (0.137)	-0.037 (0.081)	-0.060 (0.287)	-0.001 (0.057)	0.063 (0.062)	0.031 (0.056)	0.008 (0.017)	-0.557 (0.461)	-0.063 (0.127)	0.125 (0.101)	-0.059 (0.140)	0.049 (0.050)	0.211 (0.156)	-0.074 (0.107)
Constant	1.671** (0.219)	1.581*** (0.055)	0.235** (0.040)	-1.951 (1.266)	0.522 (0.291)	4.850* (1.788)	2.186 (2.026)	1.363 (1.355)	-2.427 (1.768)	1.397† (0.664)	1.784** (0.263)	0.972† (0.411)	0.049 (0.100)	-1.321 (2.361)	0.299 (0.193)
Location effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fiscal Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# obs.	496	493	481	496	88	476	473	408	476	37	618	614	591	618	177
R-squared	0.5255	0.3805	0.3764	0.0807	0.3402	0.2707	0.0781	0.1473	0.1050	0.4501	0.4332	0.3470	0.3491	0.0680	0.1919

Note: The variables firm age, firm size (i.e., no. of employees), firm sales, and innovation novelty log transformed. The main independent variable *COVID* is a dummy variable equal to one for firms reviewed for grant during COVID-19 period, and zero otherwise. The no. of observation is less for firm size and firm sales because we did not find information for all the recipients in the sample. Heteroskedasticity-adjusted robust standard errors clustered at the review period level are reported in parenthesis. ***, **, *, † indicates significance at $p < 0.001$, $p < 0.01$, $p < 0.05$, and $p < 0.1$ respectively; two-tailed test.

TABLE 4
NIH Reviewer Descriptive Statistics (Pre-COVID-19 & During COVID-19)

VARIABLE	DEFINITION	Pre-Covid	Covid
Doctorate degree	Dummy= 1 if the reviewer has a doctorate degree.	0.91	0.94**
Medical degree	Dummy= 1 if the reviewer has a medical degree.	0.53	0.77***
Engineering degree	Dummy= 1 if the reviewer has an engineering degree.	0.18	0.17
Business degree	Dummy= 1 if the reviewer has a business degree.	0.05	0.03**
Entrepreneur	Dummy= 1 if the reviewer has been a founder/co-founder of a firm.	0.18	0.18
Academic experience	No. of years the reviewer is associated with academic/research institutions.	15.40	15.00
Corporate experience	No. of years the reviewer is associated with corporate organizations.	6.53	6.56
Medical experience	For reviewer with medical degree, the no. of years the reviewer is consulting patients.	6.49	4.21***
Patent count	No. of granted patents invented by the inventor.	3.00	3.10
Publication count	No. of journal publications authored the reviewer.	77.83	72.42
Research grant count	No. of NIH/NSF research grants awarded to the reviewer.	12.45	11.92
SBIR grant count	No. of NIH/NSF SBIR/STTR grants awarded to the reviewer.	1.78	1.93
Scientific human capital	Standardized value of reviewer's scientific human capital (calculated using principle component factor analysis of academic experience, corporate experience, medical experience, patent count, publication count, research and SBIR grant count)	0.02	-0.02
Commercial human capital	Standardized value of reviewer's commercial human capital (calculated using principle component factor analysis of academic experience, corporate experience, medical experience, patent count, publication count, research and SBIR grant count)	-0.02	-0.01
Female	Dummy= 1 if the reviewer gender is female.	0.29	0.29
Minority	Dummy= 1 if the reviewer belongs to minority (minority includes African American, Asian American, Hispanics, and Latino).	0.35	0.35
No. of reviewers		1165	1424

Note: The sample includes reviewers of the study sections that reviewed SBIR/STTR phase-I grants during the pre-COVID-19 (Oct/Nov 2019 and Feb/Mar 2020) and COVID-19 period (Jun/Jul 2020 and Oct/Nov 2020), awarded under the NIH omnibus grant solicitation PHS 2019 and PHS 2020. ***, **, *, † indicates difference is significant at $p < 0.001$, $p < 0.01$, $p < 0.05$, and $p < 0.1$ respectively.

TABLE 5a
NIH Multivariate Analysis Evaluating Impact of Reviewer Human Capital

Estimation model	OLS								ZINB			
	Firm age				Firm size				Firm sales			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	
COVID	**0.264** (0.090)**	**0.256** (0.085)**	**0.245** (0.081)**	**0.247** (0.082)**	**0.558*** (0.132)**	**0.521*** (0.145)**	**0.540*** (0.135)**	**0.538*** (0.141)**	**0.754*** (0.225)**	**0.713** (0.225)**	**0.603** (0.226)**	**0.635** (0.228)**
Peer Review Scientific Human Cap.	-0.265 (0.242)	-0.205 (0.303)	-0.261 (0.238)	-0.301 (0.343)	-0.094 (0.343)	0.105 (0.387)	-0.076 (0.324)	-0.070 (0.440)	-1.138† (0.610)	-0.961 (0.650)	-0.876 (0.638)	-1.227† (0.659)
Peer Review Commercial Human Cap.	-0.177 (0.237)	-0.174 (0.230)	-0.323 (0.219)	-0.354 (0.254)	-0.029 (0.330)	-0.025 (0.309)	-0.355 (0.306)	-0.351 (0.361)	-0.647 (0.560)	-0.628 (0.558)	-1.151* (0.571)	-1.479* (0.645)
COVID x Peer Review Scientific Human Cap.		-0.146 (0.267)		0.097 (0.395)		-0.462 (0.389)		-0.014 (0.517)		-0.373 (0.639)		1.020 (0.893)
COVID x Peer Review Commercial Human Cap.			**0.325* (0.157)**	0.390 (0.291)			**0.715* (0.274)**	**0.706† (0.390)**			**1.451* (0.750)**	**2.227* (1.029)**
COVID (logistic ZINB)									-0.521** (0.187)	-0.521** (0.187)	-0.521** (0.187)	-0.521** (0.187)
Firm level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Study Section effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Funding IC effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fiscal Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# observations	489	489	489	489	486	486	486	486	474	474	474	474
R-squared/log likelihood	0.5614	0.5617	0.5629	0.5630	0.4575	0.4604	0.4641	0.4641	-4443.46	-4443.31	-4441.55	-4440.94

Note: The variables firm age (cols. 1 - 4) and firm size (i.e., no. of employees) (cols. 5 – 8) are inverse hyperbolic sine transformed. The main independent variable *COVID* is a dummy variable equal to one for firms reviewed for grant during COVID-19, and zero otherwise. Firm level controls include: Grant Amount, Prior Patents, Prior Grants, SBIR, Minority-owned, and Women-owned. Heteroskedasticity-adjusted robust standard errors clustered at the study section level are reported in parenthesis. ***, **, *, † indicates significance at $p < 0.001$, $p < 0.01$, $p < 0.05$, and $p < 0.1$ respectively; two-tailed tests.

TABLE 5b
NIH Multivariate Analysis Evaluating Impact of Reviewer Human Capital

Estimation model	Logit				OLS			
	Investor-backed				Innovation novelty-5yr			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
COVID-19	**0.852** (0.356)**	**1.109*** (0.317)**	**0.999** (0.320)**	**1.085*** (0.318)**	**-0.212*** (0.057)**	**-0.214*** (0.059)**	**-0.211*** (0.062)**	**-0.209** (0.064)**
Peer Review Scientific Human Cap.	-0.302 (1.054)	-1.696 (1.196)	-0.323 (1.074)	-1.895† (1.089)	0.172 (0.243)	0.254 (0.269)	0.171 (0.243)	0.290 (0.265)
Peer Review Commercial Human Cap.	0.212 (0.616)	0.140 (0.561)	1.067 (1.152)	-0.231 (1.047)	-0.223 (0.184)	-0.203 (0.176)	-0.219 (0.203)	-0.136 (0.174)
COVID x Peer Review Scientific Human Cap.		**3.205** (1.086)**		**3.714** (1.351)**		-0.147 (0.206)		-0.262 (0.218)
COVID x Peer Review Commercial Human Cap.			-1.805 (1.258)	0.786 (1.344)			-0.012 (0.187)	-0.192 (0.201)
COVID (logistic ZINB)								
Firm level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Study Section effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Funding IC effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fiscal Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# observations	489	489	489	489	172	172	172	172
R-squared/log likelihood	0.1691	0.1894	0.1753	0.1901	0.4098	0.4118	0.4101	0.4133

Note: The variables innovation novelty (cols. 5 - 8) is inverse hyperbolic sine transformed. The main independent variable *COVID* is a dummy variable equal to one for firms reviewed for grant during COVID-19, and zero otherwise. Firm level controls include: Grant Amount, Prior Patents, Prior Grants, SBIR, Minority-owned, and Women-owned. Heteroskedasticity-adjusted robust standard errors clustered at the study section level are reported in parenthesis. ***, **, *, † indicates significance at $p < 0.001$, $p < 0.01$, $p < 0.05$, and $p < 0.1$ respectively; two-tailed tests.

APPENDIX A
SBIR Grant Process at the NIH

When an application is submitted to Phase I of the National Institutes of Health (NIH) SBIR grant program, the application must move through two stages of review prior to being deemed meritorious for the potential receipt of funding. Appendix Figure A.1 shows the timeline of events in the selection process In the first phase of the review process, an application is sent to NIH's Center for Scientific Review (CSR), where a referral officer assigns the application to a small business study section (detailed in Appendix Table A.1) and to the appropriate Institute or Center within the National Institutes of Health.[21, 22] Within the assigned study section, the application is assigned a scientific review officer who builds the peer review committee.

Prior to the next peer review meeting, all applications being considered for full discussion at the meeting are assigned a preliminary overall impact score on a scale of (1-9), with 9 being the maximum potential score received. Only a subset of all applications is discussed in full at each peer review meeting, which is determined by the preliminary overall impact scores granted.[23] The subset of applications elected for full discussion at the meeting are then assigned a final impact score by each eligible committee member based on the score review criteria in Appendix Table A.2. The overall impact score granted by each individual reviewer captures the perceived likelihood that the project will have a sustained and powerful influence on involved research fields.

Every reviewer assigns a score to each of the five categories to comprehensively assess the scientific merit of a project, which are then aggregated to determine the overall impact score granted by the respective reviewer. Reviewers consider both innovativeness and importance when determining the scientific merit (and the respective overall impact score for a project), so a project can have a high likelihood of scientific impact without gaining high scores in all of the five categories. In addition to the five standardized categories, reviewers may include additional criteria to better determine the scientific and technical merit of the project on a project-by-project basis. Separate scores will not be given for any additional criteria the reviewer considers, but subjective assessment of additional criteria may contribute to the overall impact score.

The final impact score is determined in accordance with the equation below through calculating the mean score of all eligible members' total impact scores and multiplying that number by 10. Final overall impact scores of projects discussed in full at the peer review meeting range from 10-90 and are reported on the summary statement.

Final Overall Impact Score Calculation (Stage 1 Review)

$$\text{Final Overall Impact Score} = 10 * \left[\frac{\Sigma (X_1 + X_2 + X_3 + \dots X_N)}{N} \right]$$

[21] https://sbir.nih.gov/review/selection-process
[22] https://public.csr.nih.gov/StudySections/SmallBusinessTechnologyTransfer/Pages/default.aspx
[23] https://grants.nih.gov/grants/peer-review.htm#scoring2

Applications not discussed in full at the meeting are not awarded a final impact score at the meeting and are instead marked with (++) on the summary statement, typically ranked in the bottom half of applications but moving on to stage 2 of review. Only applications deemed 'Not Recommended for Further Consideration' (NRFC) due to lack of merit or serious ethical issues do not move on to stage 2 of peer review.

A subset of applications (with the number varying by NIH Institute) are tagged with an overall percentile on their statement, indicating the percentage of applicants who received a better overall impact score from the respective study section in the past year. Therefore, applications assigned a low percentile are deemed more meritorious at this stage in the application process.[24] The impact score is used as the indicator of assessment in the absence of percentile rank. The designated scientific review officer provides a summary statement to the applicant and the respective NIH Institute or Center. After receiving stage 1 peer review summary statements, applicants can seek reconsideration of the initial review results if they believe for some reason the stage 1 peer review process was flawed.

The applications selected to move on to stage 2 of review (all but NRFC applications) will be reviewed by the advisory board of the respective NIH Institute which would be directly granting the award. Board members are a) chosen by the respective Institute or Center within the NIH or b) directly appointed by the President, consisting of extramural scientists and public representatives approved by the Department of Health and Human Services.

At this stage, the respective advisory board examines the overall impact scores given during the stage 1 peer review meeting, the summary statement in relation to the Institute's respective priorities, and the assigned percentile rank. Stage 2 funding decisions are primarily driven by three criteria: (1) scientific and technical merit (determined by stage 1 peer review), (2) availability of funds in the respective Institute, and (3) relevance of the proposed projects to the Institute's program priorities.

Advisors conduct a Special Council Review of applications submitted by investigators who currently receive at least $1M in NIH funding to determine if additional funds should be provided. The advisory board provides funding recommendations to the respective Institute's Director, who ultimately makes the final decision concerning which projects get funded. Applicants whose projects are selected for funding work closely with the program official of the respective funding Institute and a Grants Management Officer.

[24] Rockey, S. (2011, February 15). Paylines, Percentiles and Success Rates. https://nexus.od.nih.gov/all/2011/02/15/paylines-percentiles-success-rates/

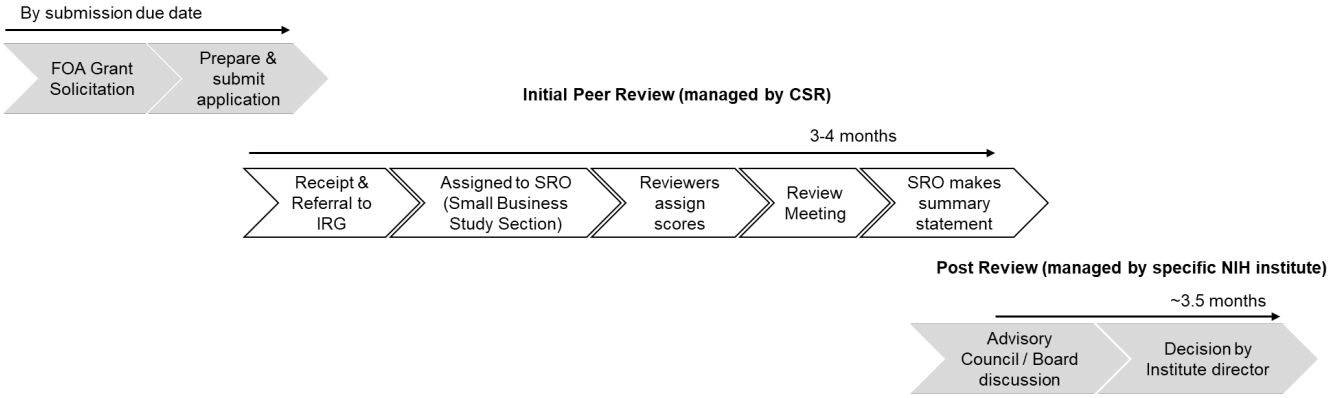
APPENDIX TABLE A.1
Study Section Descriptions

Study Section	Study Section Description
AIDC (10)	Small Business: Innovative Immunology Research
AIDC (11)	Small Business: Microbial Vaccine Development
AIDC (12)	Small Business: Anti-Infective Therapeutics
AIDC (13)	Small Business: Microbial Diagnostics and Detection of Infectious Agents, Food and Waterborne Pathogens, and Methods in Microbial Sterilization, Disinfection, and Bioremediation
BCMB (10)	Small Business: Drug Discovery and Development
BST (10)	Small Business: Biomaterials, Delivery, and Nanotechnology
CVRS (10)	Small Business: Cardiovascular Sciences Activities SEP
CVRS (11)	Small Business: Respiratory Sciences
DKUS (10)	Small Business: Digestive Sciences
DKUS (11)	Small Business: Renal and Urological Sciences
EMNR (10)	Small Business: Diabetes, Metabolism, Nutrition and Obesity
ETTN (10)	Small Business: Clinical Neurophysiology, Devices, Neuroprosthetics and Biosensors
ETTN (11)	Small Business: Drug Discovery for Aging, Neuropsychiatric and Neurologic Disorders
ETTN (12)	Small Business: Aging, Auditory, Vision and Low Vision Technologies
ETTN (13)	Small Businesses: Neuroscience Assays, Diagnostics, Instrumentation and Interventions
ETTN (14)	Small Business: Drug Discovery for Aging, Neuropsychiatric and Neurologic Disorders
HDM (11)	Small Business: Health Informatics
IMST (10)	Small Business: Biological Chemistry, Biophysics, and Assay Development
IMST (12)	Small Business: Instrumentation, Environmental, and Occupational Safety
IMST (14)	Small Business: Computational, Modeling, and Biodata Management
IMST (15)	Small Business: Cell and Molecular Biology
IMST (19)	Small Business: SBIR/STTR Commercialization Readiness Pilot (CRP) Program
MOSS (10)	Small Business: Musculoskeletal, Oral and Skin Sciences
OTC (12)	Cancer Biotherapeutics Development (CBD) SBIR/STTR SEP
OTC (13)	Cancer Diagnostics and Treatments (CDT) SBIR/STTR SEP
OTC1 (10)	Cancer Drug Development and Therapeutics (CDDT) SBIR/STTR SEP
OTC1 (11)	Radiation Therapy and Biology (RTB) SBIR/STTR SEP
RPHB (10)	Small Business: Risk, Prevention and Health Behavior
RPHB (11)	Small Business: Health Informatics
RPHB (12)	Small Business: Psycho/Neuropathology, Life Span Development, and STEM Education
RPHB (13)	Small Business: Psycho/Neuropathology Lifespan Development, STEM Education
RPHB (14)	Small Business: Disease Prevention and Management, Risk Reduction and Health Behavior Change
RPHB (16)	Small Business: Psychopathology, Substance Abuse, and Community-Based Interventions Across the Lifespan
SBIB (10)	Small Business: Medical Imaging
SBIB (11)	Small Business: Biomedical Sensing, Measurement and Instrumentation
SBIB (12)	Small Business: Cardiovascular and Surgical Devices
VH (10)	Small Business: Vascular and Hematology

APPENDIX TABLE A.2
NIH Evaluation Criteria

Selection Criteria	Characteristics of Selection Criteria
Significance	Scientific premise of project, importance of the problem, degree to which scientific knowledge, technical capability, and clinical practice will be improved by the project's success, commercial potential
Investigator(s)	Suitability of PIs to project, experience/training, past accomplishments, team dynamics
Innovation	Novel theoretical concepts, methodologies, instrumentation, or interventions
Approach	Strategies to ensure robust and unbiased approach, proposed benchmarks, tactics to mitigate potential problems, risk management, measurable milestones to Phase II
Environment	Suitability of project to scientific environment, institutional support, resources, and equipment

APPENDIX FIGURE A.1
Timeline of Events in the SBIR Process at the NIH



APPENDIX B
SBIR Grant Process at the NSF

When an application is submitted to Phase I of the National Science Foundation (NSF) SBIR grant program, it is typically placed into a group of 4-18 similar proposals called a panel following initial administrative review.[25] Program Directors assign three to ten experts in the proposed topic area to a panel, with a minimum of three reviewers assigned to confidentially review each proposal. These reviewers are primarily technical experts in the respective research field or proposed markets, while some reviewers have a mix of commercial and technical expertise.[26] Once the assigned reviewers provide feedback, all external reviewers meet in person or engage in virtual conversations to discuss the proposals in the given panel. If the application is competitive for funding, the Program Director may conduct additional diligence through asking follow-up questions to the applicant via email.

SBIR Program Directors assigned technical reviewers, and any additional commercial reviewers asked to sit on the Phase I panel help to evaluate the technical and commercial merit of each proposal. Reviews are based on two basic criteria in accordance with the National Science Board (intellectual merit and the broader impacts of the proposed effort) consistent across all NSF grant reviews and one additional criterion in accordance with the SBIR mission (technical and commercial merit). Proposals are evaluated individually, where no exact score is assigned to each proposal. There is no score-based cutoff within each panel, and it is possible that all proposals within a given panel of applications could be funded. The Program Director has significant discretion in terms of which projects get funded, and his or her opinion may not always be aligned with that of the expert reviewers on the panel. This process stands in contrast to the SBIR selection processes of several other agencies who rank applications and fund only the proposals with scores that fall above a certain threshold.

NSF's SBIR program goal is to encourage firms to conduct cutting-edge, high-risk, high-quality research and derive social and economic benefit from scientific discovery through private sector-commercialization. In order to select projects that advance this program goal, NSF reviews applications in accordance with selection criteria detailed in Appendix Table B.1. All NSF proposals are evaluated for intellectual merit and broader impact, with SBIR proposals additionally evaluated for commercial impact. While NSF keeps the agency priorities in mind, there is no top-down prioritization of goals when evaluating individual applications. Rather, the agency relies heavily on the personal experience of Program Directors and gut instinct to ensure that each batch of proposals selected for funding is aligned with program and agency objectives at large. [27]

If applications do not pass the initial administrative review, they do not move on to the panel review stage and are returned to the applicant without review. In 2-4 months after the application deadline, Program Directors conduct due diligence on proposals and may contact applicants with any questions. In 4-6 months after the application deadline, official funding notifications will be given out to the applicants. Applicants with proposals that went through the entirety of the merit

[25] https://www.nsf.gov/pubs/2017/nsf17071/nsf17071.jsp#q44
[26] https://seedfund.nsf.gov/resources/review/
[27] Interview with NSF Senior Program Director. Personal phone interview. September 2024.

review process will be notified of this decision and receive anonymous written reviews detailing how the proposal could be improved. These applicants can contact the Program Director with any questions that arise concerning their review in order to improve their application for the next funding cycle. In 6-7 months following the application deadline, Phase I awards will begin to be dispersed to the winning applicants. A summary of the timeline is detailed in Appendix Table B.2.

APPENDIX TABLE B.1
NSF Evaluation Criteria

Criteria	Criteria Category	Criteria Characteristics
Intellectual Merit of Proposed Activity	**All NSF Proposals**	Technical and commercial feasibility, unique/ingenious concepts or applications, qualifications of technical team, access to resources, likelihood of state-of-the-art advancements
Broader Impact of Proposed Activity	**All NSF Proposals**	Potential commercial and societal benefits, propensity to lead to a marketable product/process, balance of team's technical and business skills, prior success at commercializing technology with or without SBIR support, competitive advantage of technology, innovation potential, ability to attract further funding
High Degree of Technical Risk	**Specific to SBIR**	Never previously successfully attempted, still facing technical hurdles
Significant Commercial Impact/Societal Benefit	**Specific to SBIR**	Potential to disrupt target market segment, strong product-market fit, barriers to entry, potential for societal benefit

APPENDIX TABLE B.2
SBIR– NSF Review Timeline

Time After Application Deadline	Characteristics of Time Period
2-4 Months	Program Director conducts due diligence, applicants may be contacted with questions
4-6 Months	Funding decisions and written reviews for full merit review process proposals sent to applicants
6-7 Months	Phase I awards initiated

Note: Information sourced from National Science Foundation.

APPENDIX C
SBIR Grant Process at the DOE

Each year the Department of Energy (DOE) issues Funding Opportunity Announcements (FOAs), inviting small businesses to apply for SBIR/STTR grants. DOE's SBIR program, housed within its Office of Science (SC), organizes the solicitation of applications for grants into two distinct activity periods: Release 1 and Release 2. Release 1 includes topics in the areas of Basic Science and Engineering and Nuclear Security. Release 2 includes topics in the areas of Clean Energy and Environmental Management. Within the DOE, six program offices and six research programs located administratively in the Office of Science participate in the SBIR/STTR grant program. Each participating office or division has authority or obligation to develop topics for solicitations and suggest individuals who could serve as application reviewers. The process of topic and sub-topic formation is consistent across program offices. The technical topic managers (TTMs) from each participating office gather input from the scientific community on their funding priorities. Stakeholders are usually research scientists in academia, industry, and the affiliated national research laboratories.

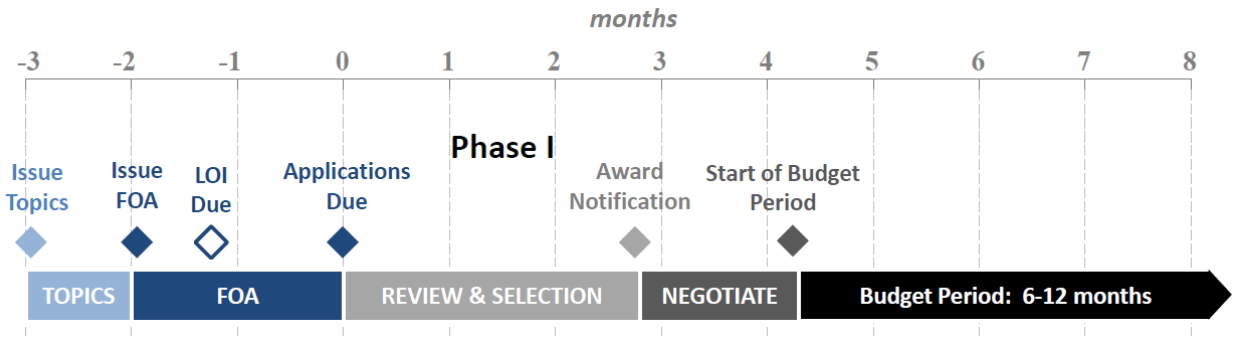
The SBIR program is operated in alignment with the DOE's mission to "to advance the national, economic, and energy security of the United States; to promote scientific and technological innovation in support of that mission; and to ensure the environmental cleanup of the national nuclear weapons complex." SBIR awards are selected primarily on the basis of their potential to contribute to the field of energy. Applications are due about two months after FOAs are released, and letters of intent are required one month prior to the application due date. Appendix Table C.1 shows a typical program schedule of the SBIR Phase-I program at DOE. Letters of intent allow TTMs to anticipate the numbers and types of reviewers that will be needed. In the review process, each proposal is reviewed by three technical merit reviewers, who are generally recruited by the TTM. The applications are reviewed in accordance with selection criteria, which includes (1) strength of the scientific approach, (2) ability to carry out the project, and (3) project impact, all equally weighted. Once the reviews are received, the meritorious applications are rank-ordered based on these reviews and office priorities. The review and award selection process must be completed within 90 days of the application deadline. Appendix Figure C.1 shows the timeline of events in the review and selection process. The Program offices adhere consistently to the administrative process structure established by the DOE's SBIR/STTR Programs Office.

APPENDIX TABLE C.1
SBIR– DOE Program Schedule

	Phase I	
	Release 1	**Release 2**
Topics Issued	Mid-July	Late October
FOA Issued	Mid-August	Late November
LOI Due	Early September	Mid-December
Applications Due	Mid-October	Early February
Award Notification	Early January	Late April
Grant Start Date	Mid-February	Early June

Note: Information sourced from Department of Energy and National Academies of Sciences, Engineering, and Medicine. 2020. Review of the SBIR and STTR Programs at the Department of Energy. Washington, DC: The National Academies Press.
FOA: Funding Opportunity Announcement; LOI: Letter of Intent.

APPENDIX FIGURE C.1
Timeline of Events in the SBIR Process at the DOE



Note: Information sourced from Department of Energy and National Academies of Sciences, Engineering, and Medicine. 2020. Review of the SBIR and STTR Programs at the Department of Energy. Washington, DC: The National Academies Press.
FOA: Funding Opportunity Announcement; LOI: Letter of Intent.

APPENDIX D
Reviewer Patent, Publication, Grant

***Publication Information*:** The main source of publication information is PubMED - an online resource from the National Library of Medicine that provides fast, free, and reliable access to more than 34 million publications in the biomedical research literature. In a first step, we downloaded the entire baseline dataset, which includes 1114 XML format data files (https://ftp.ncbi.nlm.nih.gov/pubmed/baseline/). Next, using a PYTHON program we converted the data files into TXT format. The data includes author last name, author first name, author middle name, date of publication, publication type,[28] journal name, and in some cases authors' institute affiliation is also provided. In many cases, the author first name is just the first alphabet of the name. For example, the name Lawrence A. Tabak (director of NIH) PubMED query could include "L A Tabak" or "L Tabak." Lawrence Tabak's PubMED information accounts for his inconsistent use of the middle initial, but is otherwise quite simple. For other author names, information might factor in their inconsistent use of the suffix "Jr.," or other name variations. Using a SAS name matching algorithm, we first matched on last name and first alphabet of first name. To guard against spurious author matching, we devoted hundreds of person-hours to identify accurate publication match of our 2,063 reviewers using information from reviewer CV, google scholar profile, research gate profile, ORCID profile, and faculty institution profile (e.g., Harvard catalyst profile).

***Patent Information*:** The source for patent information was obtained from USPTO database (https://patentsview.org/download/data-download-tables), which includes disambiguated inventor level data for granted patents. The reviewer last and first names were matched with inventor names using a name matching algorithm. We crosschecked the patent match in cases where patent information was also available in reviewers' CV, ORCID profile, and faculty institution profile.

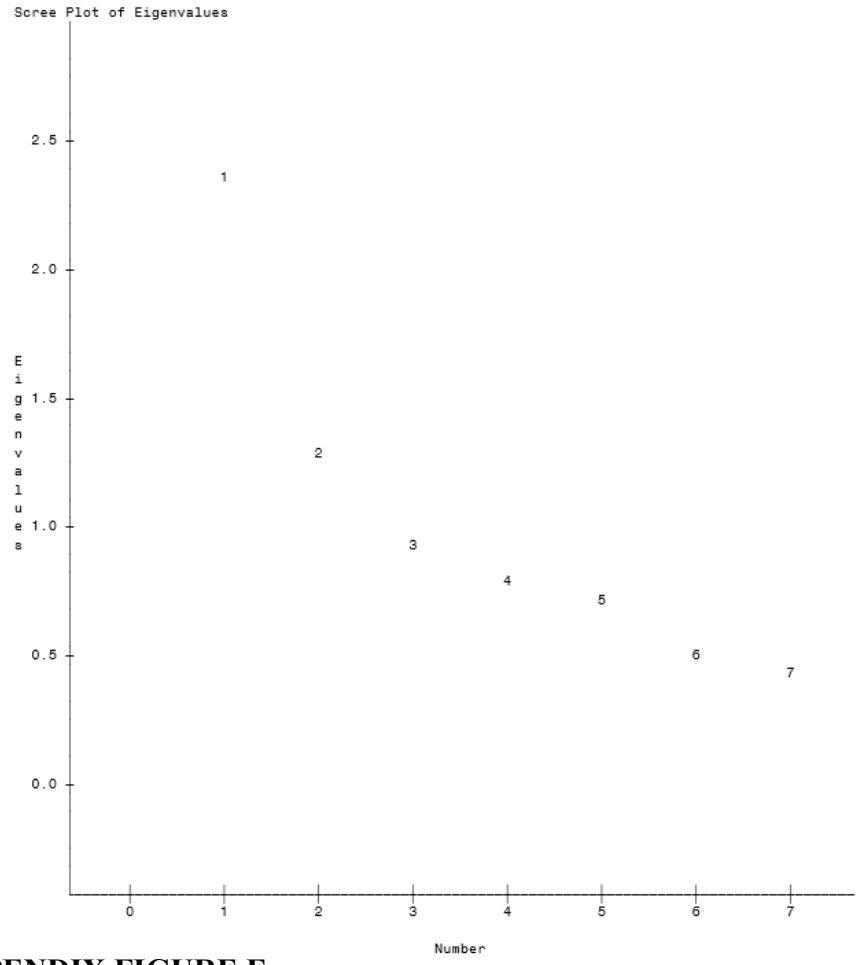
***Grant Information*:** The information on grants (NIH/NSF) including SBIR/STTR grants awarded to each reviewer was sourced from NIH RePORTER and NSF websites, and from www.grantome.com (https://grantome.com/search)

[28] Publication types like letters to the editor, comments, or other "atypical" articles are not considered.

APPENDIX Table D.1
Factor Loadings

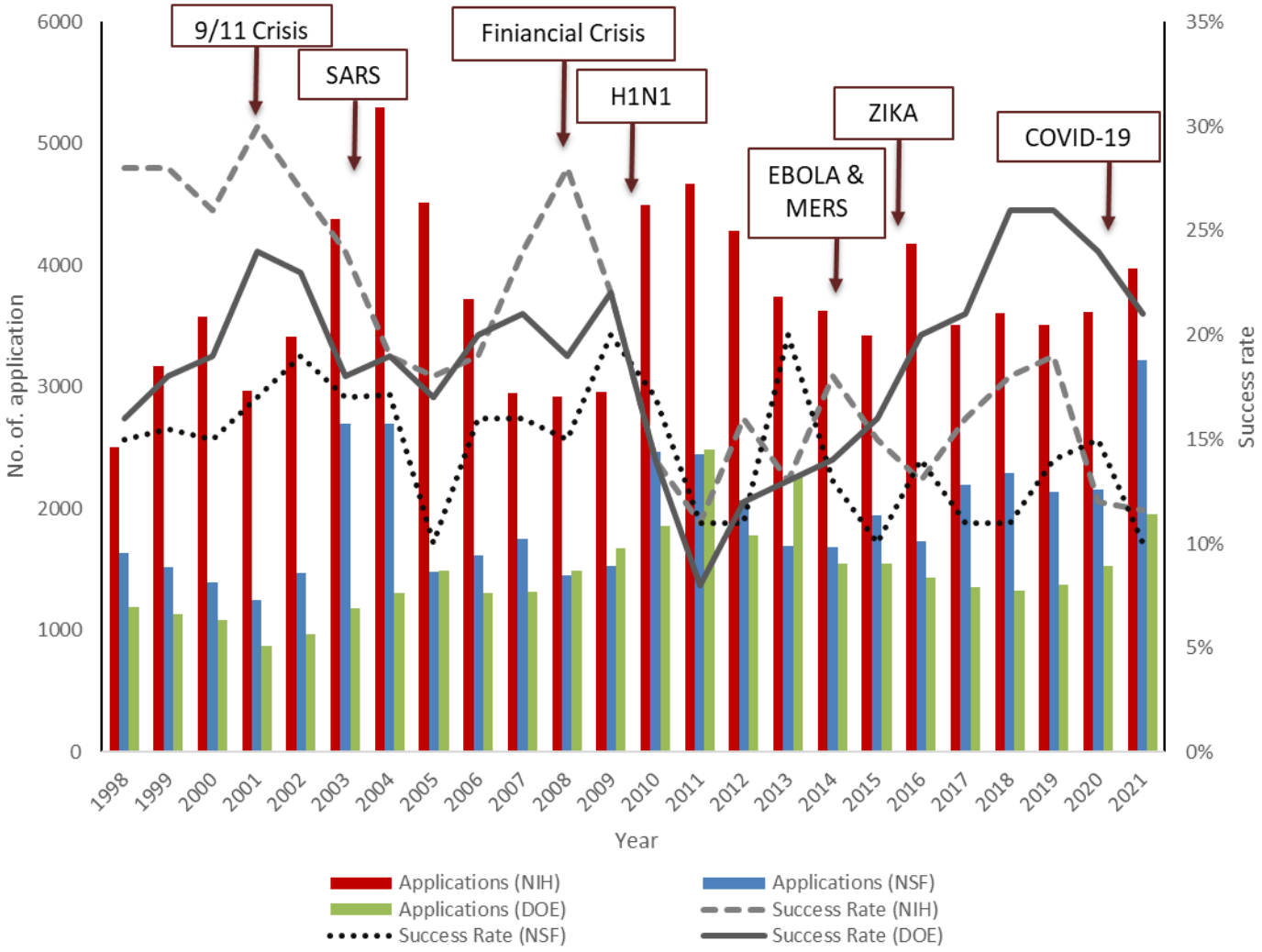
Standardized Scoring Coefficients		
	Factor1	**Factor2**
Academic Experience	0.37105	-0.07609
Corporate Experience	-0.04917	0.42558
Medical Experience	0.11605	-0.12606
Patent Count	0.23193	0.46473
Publication Count	0.40422	0.16317
Research Grant Count	0.45467	0.10324
SBIR Grant Count	0.04373	0.41404

APPENDIX FIGURE D.1
Scree Plot of Eigen Values



APPENDIX FIGURE E

SBIR Phase I Application and Success Rate at the NIH, NSF, and DOE



Note: Information sourced from Annual SBIR/STTR program reports.

Appendix Table: Review Process Differences across Agencies

	NIH	NSF	DOE	Notes
Evaluation Criteria	• Technical merit weightage: High • Commercial merit weightage: Low	•Technical merit weightage: High •Commercial merit weightage: High	•Technical merit weightage: High •Commercial merit weightage: High	• While all the three agencies emphasize technical merit in reviewing the applications, NIH appears to provide less emphasis on the commercial merit compared to the NSF and DOE, as highlighted in their evaluation criteria. • NSF posts the commercial review form on its website for transparency with the applicants. • NSF overtly emphasizes funding high-risk research as a key program objective, stating: "*By increasing the incentive and opportunity for small firms to undertake cutting-edge, high-risk, high-quality scientific, engineering, or science and engineering education research, the NSF SBIR/STTR program seeks to transform scientific discovery into both social and economic benefit by emphasizing private sector commercialization*."[1] • DOE emphasizes the technical/economic benefits, the potential for developing a marketable product, and the ability to attract post-SBIR/STTR funding. • DOE evaluates the qualifications of the applicant's team members to assess whether they have the ability to carry out the project.
Review panel composition	• Academia: 75% • Commercial sector: 25%	•Academia: 50% •Commercial sector: 50%	•Academia: 30% •Commercial sector: 10% •Government: 10% •DOE labs: 50%	• Inclusion of external reviewers in the application process may decrease internal reviewer (Li, 2012), political (Hedge and Mowery, 2008), and applicant-induced biases (Bhattacharjee, 2012; Ginther et al., 2011). • NSF review panels has a balanced representation of academicians and entrepreneurs, and puts more emphasis in bringing external reviewers with commercial expertise to evaluate the commercial impact of the innovation.[2] • The NIH and DOE reviewer panel composition is skewed towards individuals from academia and research institutions.
Review Structure	• Decentralized	•Centralized	•Decentralized	• At the NIH, while the initial review process is handled by the center of scientific review (CSR), the advisory board of the respective NIH institutes (27

	NIH	NSF	DOE	Notes
				institutes) manage the final grant decisions separately. • At the NSF, the SBIR program is centralized was housed under the Division of Innovation and Partnerships within the Directorate of Engineering. The program is now located within the newly created Directorate for Technology, Innovation and Partnerships (TIP).[2] • At the DOE, a central program office manages the funding announcement, but the 12 program offices are responsible for the selection of funding opportunities, the review process, and ranking the potential awardees.[3]
Repeat Grant Recipients	• High • Sizeable fraction of funding goes to repeat grant recipients.	• Low • Program directors rarely fund previous grant recipients and existence of prior grants do not influence subsequent grant support.[2]	•High •Approximately 80-90% of the Phase-I grants go to repeat recipients.[3]	• Policy researchers have highlighted the controversy with awarding grants to repeated applicants identified as "SBIR Mills" because of the concerns about the underlying quality and commercial potential of the recipients with multiple grants (Lerner, 1999; Link and Scott, 2009; Howell, 2017; Wessner, 2008). • Recent assessment reports, however, argue that repeat grant recipients often serve critical research and procurement needs that fits the agency's objectives.[3] • At the NSF, the review process has the checks and balances to reduce the percentage of repeat recipients.

Note: Information sources:
[1]https://seedfund.nsf.gov/resources/review/peer-review/
[2]National Academies of Sciences, Engineering, and Medicine. (2023). Review of the SBIR and STTR Programs at the National Science Foundation. Washington, DC: The National Academies Press.
[3]National Academies of Sciences, Engineering, and Medicine. (2020). Review of the SBIR and STTR Programs at the Department of Energy. Washington, DC: The National Academies Press.