Strategic Idea Revival:
How Scientists Leverage Evaluator Turnover to Resubmit Rejected Ideas

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Abstract

Idea rejection is a common yet often overlooked aspect of the creative process. While prior research emphasizes the benefits of revising ideas after rejection, we propose an alternative strategy: strategic idea revival. Rather than modifying their ideas, creators may choose to resubmit rejected proposals when the evaluators responsible for rejection have departed. Using data from the Novo Nordisk Foundation's proposal review process, we find that applicants are more likely to resubmit rejected ideas when a greater share of intellectually close evaluators have left the committee. Moreover, evaluator turnover increases the likelihood of resubmitting "boomerang" proposals—those nearly identical to the original rejection. Strategic idea revival yields funding success rates comparable to idea revision, challenging the dominant view that creators should pivot after rejection. We contribute by shedding light on how the interaction between evaluators and creators shapes the evolution of ideas over time.

Keywords: Idea Rejection, Idea Evaluation, Creative Revision, Evaluator Turnover

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1 Introduction

In 1935, Albert Einstein and his co-authors published a paper on quantum entanglement, challenging the dominant interpretation of quantum mechanics. Initially overlooked, the paper gained recognition decades later, ultimately reshaping quantum theory (Ke et al., 2015). A similar example comes from the computer industry: In the 1970s, engineers at Xerox developed the graphical user interface (GUI), but management dismissed its potential. Only when Steve Jobs saw and adopted the idea did it revolutionize personal computing through the Apple Lisa and Macintosh. Likewise, in 1907, Pablo Picasso painted *Les Demoiselles d'Avignon*, which was first met with harsh criticism and dismissed as crude and jarring. Yet, in 1939, the Museum of Modern Art acquired the painting, now considered one of the most influential of the 20th century (Sgourev, 2013).

These examples illustrate a broader pattern in science, innovation, and the arts: ideas rejected by some evaluators—whether managers, experts, or entire scientific communities—are later embraced and even celebrated by others. Scholars have long sought to explain why evaluations of the very same idea often vary across evaluators and time, identifying organizational inertia (Criscuolo et al., 2014; Mainemelis, 2010; Vinokurova and Kapoor, 2020), differences in evaluators' backgrounds and experiences (Boudreau et al., 2016; D Li, 2017), and random contextual factors (Dushnitsky and Sarkar, 2022; Kovács, 2017) as key drivers. While this research has deepened our understanding of the sources of heterogeneity in judgment, much less is known about how creators—those generating ideas—account for it when navigating their creative careers, especially when they face initial rejection of their ideas.

Rejection is a near-universal experience for those engaged in generating novel ideas (Deichmann and van den Ende, 2014; Piezunka and Dahlander, 2019; Wang et al., 2019). Many innovation scholars (Camuffo et al., 2020; Camuffo et al., 2024; Cornelius and Gokpinar, 2020; Wilhelm et al., 2024) and practitioners (Ries, 2011) have argued that creators should respond by revising their ideas or shifting their efforts toward entirely new ones. Yet, the examples above suggest an alternative response that has received little attention in the literature: instead of revising or abandoning a rejected idea, creators may choose to wait—holding on to their idea in anticipation of a more favorable future evaluation.

This paper examines this alternative strategy. We propose that, following the rejection of an idea, creators may temporarily shelve their rejected ideas, only to revive them when the evaluators responsible for the rejection have left and been replaced by new ones. Such evaluator turnover is common in science and innovation: managers climb corporate ladders and are succeeded by new ones, reviewers serve limited terms on funding panels, and members of prize juries rotate out. When incumbents are replaced, they bring in new preferences that may better align with previously rejected ideas. This creates an opportunity for creators to revive their ideas in the hope of selection, while avoiding the costs of revision. We refer to this practice as *strategic idea revival*.

The Novo Nordisk Foundation (NNF) is a major philanthropic research funder, investing DKK 9.1 billion (≈ $1.27 billion) in 2023—more than any other Danish research foundation

and even surpassing the Danish government's RD budget. Globally, it ranks third in terms of endowment behind the Bill Melinda Gates Foundation and the Wellcome Trust. Its financial strength is closely tied to Novo Nordisk's success with Ozempic, a drug originally developed for type 2 diabetes that gained worldwide recognition as a weight-loss treatment. Proposals submitted to the NNF are evaluated through peer review by dedicated scientific committees, each focusing on a distinct scientific area. These committees comprise 4 to 14 evaluators, each serving a term of typically 2 to 3 years before being replaced by new members. A key feature of this review process is that the composition of the committees is publicly announced in the call for submissions, providing applicants with prior knowledge of who will evaluate their proposals. Consequently, applicants also know, in retrospect, which evaluators were responsible for rejecting their proposal.

Our findings suggest that strategic idea revival is widely practiced. First, while evaluator turnover in general does not affect applicants' likelihood of resubmission, the departure of close evaluators—those with expertise closely related to the rejected idea and likely influential in the rejection decision—increases resubmission likelihood. Cox Proportional Hazard models indicate a 95.94% increase in the hazard of resubmission when all close evaluators have left the panel compared to when none have left. By contrast, the turnover of distant evaluators—those with little expertise in the rejected idea's field—has no effect. This result remains robust across alternative model specifications and when including a large set of applicant, idea, and panel controls.

Second, using natural language processing methods to measure the similarity between rejected and resubmission, we find that applicants have a 484.75%% higher likelihood of submitting proposals that are (nearly) identical to the rejected one, so-called 'boomerang proposals', when all close evaluators have left the committee compared to when none have left. This effect is exclusive to the turnover of close evaluators; the departure of distant evaluators has no impact.

We also examine whether *strategic idea revival* benefits applicants. Our analysis shows that boomerang proposals achieve funding likelihoods comparable to modified proposals, indicating that resubmission can be a viable strategy. However, we find no evidence that targeting new evaluators specifically improves funding chances compared to resubmitting to incumbent evaluators. In other words, while applicants adjust their resubmission decisions based on evaluator turnover, this strategic timing does not enhance funding outcomes. Instead, the relative success of boomerang versus modified proposals hinges primarily—and intuitively—on the quality of the original rejected proposal.

Our study makes three contributions. First, we challenge the dominant view that creators should always pivot away from rejected ideas. While research in entrepreneurship and creativity often emphasizes revising or abandoning ideas, we identify conditions under which persistence can be beneficial, offering a more nuanced perspective on idea rejection. Second, we introduce the concept of 'boomerang ideas'—rejected ideas that creators later resubmit ('revive'). Our findings show that boomerang ideas account for a substantial share of submissions (5–10% in our context), underscoring their practical relevance. Third, we shed new light on the evolution of ideas over time. While prior work has highlighted the role of creator-evaluator interaction

in shaping ideas, how this interaction unfolds and its implications for organizations remain underexplored.

2 Theory and Hypotheses

In the following, we develop a theory of strategic idea revival. We first outline the dominant view in the literature according to which creators respond to rejection by revising their ideas. We then challenge this view and propose that creators respond to rejection with strategic idea revival—waiting for incumbent evaluators to be replaced by new ones to resubmit their rejected ideas.

2.1 Idea Rejection and Revision

Idea rejections result from evaluation processes designed to allocate scarce resources across competing ideas (Boudreau et al., 2016). Given resource constraints, organizations must prioritize investments and cannot support all proposed ideas. To guide these decisions, they rely on evaluators with domain-specific expertise, such as managers and senior scientists. These evaluators often convene in panels to discuss proposal strengths and weaknesses, exchange information, and assess ideas (Criscuolo et al., 2017; Csaszar and Eggers, 2013; Lane et al., 2022; D Li, 2017). Evaluations typically follow pre-specified criteria intended to capture idea quality, including prospective commercial, technological, or scientific value, as well as feasibility (Franzoni and Stephan, 2023; Lane et al., 2024). Resources are then allocated in rank order until they are depleted, leaving the remaining ideas rejected.

Ideally, selected ideas should stand out for their high quality. Indeed, research suggests that evaluators can reliably distinguish between ideas based on quality, with selected ideas generally outperforming rejected ones. For example, D Li and Agha (2015) find that grant proposals receiving more favorable reviewer scores tend to yield more publications and citations. Similarly, Scott et al. (2020) and NL Wright et al. (2023) show that experts effectively differentiate between high- and low-quality venture ideas, with higher-rated ventures more likely to secure VC funding and reach commercialization. Further, Mollick (2012) attributes firms' innovation success to middle managers' ability to identify valuable employee ideas.

Extensive research shows that idea evaluations, even when reflecting idea quality, are also shaped by the preferences and backgrounds of those in the evaluator role at a given time. For example, some research suggests that an idea's likelihood of receiving a favorable evaluation depends on its proximity to the evaluator's field of expertise or intellectual tradition. Evaluators may favor close ideas because they view the field as important (Laband and Piette, 1994; Travis and Collins, 1991) or expect that attention to such ideas will benefit their own work (D Li, 2017). Conversely, they may downgrade close ideas because their expertise enables them to identify more weaknesses (Boudreau et al., 2016) or because endorsing close ideas could invite accusations of favoritism (Aadland et al., 2019). As a result, ideas may be rejected not due to low quality but because they do not align with the preferences of particular evaluators.

Most research suggests that for initially rejected ideas to be selected, creators must revise

them to better align with evaluator preferences (Cornelius and Gokpinar, 2020; Wilhelm et al., 2024). That is, they must improve the fit between their idea and these preferences (Cattani et al., 2017; Falchetti et al., 2022; Orazi and Mannucci, 2024). This can be particularly challenging in the early stages of the idea journey, when creators face significant uncertainty about evaluators' preferences—one reason many ideas are initially rejected (Fernandez-Mateo and Coh, 2015; Piezunka and Dahlander, 2019; Terwiesch and Xu, 2008). Over time, as creators interact with evaluators and observe which ideas are favored or dismissed, they can refine their initially rejected ideas or develop new ones that better align with evaluator preferences (Mannucci and Perry-Smith, 2022; Park et al., 2024; Perry-Smith and Mannucci, 2017).

Revising ideas in response to (negative) feedback is widely recognized as crucial for increasing the likelihood of idea selection. For example, founders improve their chances of securing funding on crowdfunding platforms by refining their business ideas based on feedback from the 'crowd' (Cornelius and Gokpinar, 2020). Similarly, founders can reduce the risk of investing in 'false-positive' ideas and enhance commercialization prospects by incorporating feedback from accelerators (Hallen et al., 2020; Yu, 2020) and following a 'scientific' approach to entrepreneurship, where feedback plays a central role (Camuffo et al., 2020; Camuffo et al., 2024; Gagliardi and Novelli, forthcoming). In academia, revising ideas in response to evaluator feedback is fundamental to the scientific revision process, increasing the chances of manuscript acceptance.

In sum, the above research suggests that creators will and should modify their ideas in response to rejection to improve the fit between idea and evaluator preferences.

2.2 Strategic Idea Revival

We challenge this prevailing view, arguing that creators may choose an alternative strategy to improve the fit between their ideas and evaluator preferences, namely by waiting for those evaluators who rejected their ideas to be replaced by new evaluators. Evaluator turnover is pervasive across domains: Managers responsible for evaluating product ideas leave firms or transition to new roles, reviewers of research proposals serve limited terms, and partners in venture capital firms overseeing investment decisions exit and are replaced. Turnover has various reasons. In corporate settings, evaluators may be promoted within the hierarchy (Bidwell and Mollick, 2015). In science and politics, turnover is often institutionalized to ensure diversity in perspectives and prevent favoritism (Chang and Kirgios, 2024). In some cases, turnover occurs naturally as evaluators retire or pass away (Azoulay et al., 2019). The entry of new evaluators brings fresh preferences that may diverge significantly from those of their predecessors. Such heterogeneity in judgment is evident in the consistently low interrater reliability documented across evaluation contexts, where evaluators frequently disagree on the merits of the same idea (Marsh et al., 2008). These shifting preferences create opportunities for previously rejected ideas to find more favorable reception. We argue that creators recognize this possibility and respond by delaying resubmission until evaluators turn over—a behavior we term strategic idea revival.

Strategic idea revival does not guarantee success. New evaluators may prove even less receptive, leading to repeated rejection. However, we posit that creators perceive the potential

for a more favorable reception as sufficiently high to justify postponing resubmission rather than incurring the costs of revision. Revising a rejected idea is both emotionally and materially demanding. Creators develop psychological ownership over their ideas (Baer, 2012; Staw and Ross, 1989), making revisions feel like an affront to their sense of identity (Grimes, 2018). Idea revision entails significant cognitive and emotional strain (Toivonen et al., 2023) and can trigger 'psychological, social, and financial turmoil' (Ucbasaran et al., 2013). Beyond emotional costs, revision carries opportunity costs. Time and cognitive resources spent refining a rejected idea are diverted from generating new ideas or advancing other projects. Many creators manage an 'idea portfolio,' balancing multiple projects simultaneously (Ananth and Harvey, 2023). Scientists routinely juggle several manuscripts, while entrepreneurs often pursue multiple ventures at once (Westhead and M Wright, 1998; Wiklund and Shepherd, 2008). Investing in revision means sacrificing other opportunities for innovation.

In sum, we argue that creators, recognizing the potential for more favorable future evaluation outcomes, strategically delay resubmission until evaluator turnover occurs. Thus, we hypothesize:

H1: Evaluator turnover increases creators' likelihood to resubmit ideas following rejection.

H2: Evaluator turnover increases creators' likelihood to resubmit rejected ideas.

Idea selection typically rests with groups of evaluators, or evaluation *panels*, rather than individual evaluators. The strength of panels lies in their diverse expertise, ensuring the collective knowledge needed for effective evaluation (Criscuolo et al., 2017; Csaszar and Eggers, 2013). Less knowledgeable evaluators can rely on the assessments of intellectually closer colleagues. Research suggests that this division of labor—where intellectually closer evaluators exert greater influence—emerges when evaluators are aware of each other's expertise (Stasser et al., 1995).

We propose that creators' likelihood of reviving rejected ideas depends on the intellectual proximity of the departing evaluator. Although creators do not know individual evaluators' positions or who was primarily responsible for the rejection, they likely assume that intellectually closer evaluators had greater influence. Whether this assumption is correct is irrelevant—what matters is that creators believe it. As a result, creators are especially likely to resubmit their idea when intellectually proximate evaluators leave the panel. Thus, we hypothesize:

H3: Creators' likelihood of resubmitting rejected ideas in response to evaluator turnover increases with evaluators' intellectual proximity.

3 Empirical Context

The Organization. The context of our study is the proposal evaluation process at the Novo Nordisk Foundation (NNF). Established in 1926 by the Danish pharmaceutical company Novo Nordisk, the NNF's mission is to "invest in scientific research, education, and innovation to enable a world-class life science ecosystem." In 2023, the NNF allocated DKK 9.1 billion (≈ 1.27

billion) to research—more than any other Danish research foundation and surpassing the Danish government's RD budget of DKK 7 billion ($\approx$ 1 billion) that same year. Globally, the NNF ranks third among philanthropic research funders, behind the Bill Melinda Gates Foundation and the Wellcome Trust. Its financial strength is closely tied to Novo Nordisk's recent success with Ozempic, a blockbuster drug originally developed for type 2 diabetes that gained worldwide recognition as a weight-loss treatment.

The NNF funds research through three main instruments: project grants, fellowships, and research leader programs.

- **Project grants** support basic research. They are awarded to Principal Investigators (PIs) for three years.
- **Fellowships** support the careers of PhD candidates and postdoctoral researchers, covering salaries and international research stays for three years.
- **Research leader programs** support the career development of junior, mid-career, and senior researchers. Awarded for up to five years.

Despite their different objectives, all instruments require applicants to propose a research project ('idea'). Eligibility requires employment at or collaboration with a Danish research institution. **Proposal Submission**. To apply for funding, applicants submit proposals in response to specific calls. Most calls are recurring, typically issued annually, with some released twice per year. For example, *Project Grants in Endocrinology and Metabolism* have been issued annually since 2016.

Proposals consist of the following sections: (1) title, (2) project description in both scientific and lay language, (3) summary of the applicant's past research and its relevance to the proposed project, (4) list of relevant publications, including the applicant's own, and (5) the applicant's CV.

Panels and Evaluators. Proposals are evaluated by scientific committees ("panels") composed of internationally recognized scientists ("evaluators"), who are appointed by the NNF Board of Directors. Evaluators often have national and international experience as members of research councils and academic assessment committees. Our data covers the activity of ... distinct panels across various scientific areas.[1] Panel sizes range from 4 to 14 evaluators, with larger panels handling higher evaluation workloads. Panels are led by a chair, who is one of its members. Each call falls under the responsibility of a specific committee, which typically oversees multiple calls within its scientific domain. For instance, the *Committee on Endocrinology and Metabolism* evaluates proposals for *Project Grants in Endocrinology and Metabolism* and *Emerging (Ascending/Distinguished) Investigator Grants in Endocrinology and Metabolism.*

[1] These include: The Committee on Society in the Green Transition, Science Education and Outreach, Science Communication and Debate, Research in Art and Art History, Plant Science, Agriculture and Food Biotechnology, Interdisciplinary Research, Industrial Biotechnology and Environmental Biotechnology, Endocrinology and Metabolism, Clinical and Translational Medicine, Bioscience and Basic Biomedicine, Inequity in Health, Natural and Technical Sciences, Data Science, and Nursing Research.

The NNF website lists each committee's call responsibilities, and every call for proposals specifies the responsible committee on its first page (see Figure 2 for an example).

Evaluators serve for two to four years, before being replaced by new ones. Evaluator turnover ensures a manageable workload and prevents long-term commitments. While the Board of Directors formally appoints new evaluators, selections often reflect recommendations from current committee members or grant officers overseeing the process. Evaluators receive a honorarium for their contributions, along with reimbursement for expenses incurred in their review activities.

Evaluation Process. Evaluators must reach a unanimous decision on whether to select or reject proposals through discussion. Evaluators are tasked to assess proposals based on the following set of criteria: Quality, novelty, state-of-the-art and feasibility of the project, and commitment and merits of the applicant relative to age and career stage. Before the discussion, each proposal is assigned to a subset of evaluators—typically those with the most relevant expertise—who grade it on a scale from 1 to 6, with 1 being the highest. They also provide brief comments justifying their assessments, but neither grades nor comments are shared with applicants. Grant officers match proposals to evaluators based on expertise. For some calls, every evaluator grades every proposal. In rare cases, a proposal is sent to external reviewers if no committee member has the necessary expertise. Some calls follow different decision-making processes. In certain cases, the Board of Directors or the panel chair makes the selection/rejection decision. Our data does not cover these cases—we focus on calls where the decision is made collectively by all committee members.
The call for proposals specifies the available budget and individual grant sizes, making it clear ex ante how many proposals can be funded at most. If evaluators determine that few proposals meet the evaluation criteria, they may fund fewer projects than budgeted.

Feedback. Applicants are notified of the funding decision approximately four months after submission. The foundation does not provide feedback on the decision, proposal grades, or rankings. Funded projects and their recipients are publicly listed on the website.

Resubmissions. Applicants who receive funding cannot submit another application to the same call while their grant is active. They must complete the ongoing project before reapplying. However, they may apply to other calls, provided they describe how the proposed project differs from and/or aligns with their existing grant(s) and briefly outline the progress of ongoing projects. Active grants from other public or private funders do not disadvantage applicants, but they must explain how the proposed project relates to prior funding.
Applicants who receive a rejection may reapply to the same call in future cycles or submit proposals to other calls. They are not required to indicate a previous rejection, but continuity in evaluation panels means evaluators may recall past submissions. Call descriptions remain largely consistent over time, targeting the same scientific fields. This consistency allows applicants to resubmit previously rejected proposals with little or no modification.
In recent years, some calls have introduced funding earmarked for specific scientific areas. For

example, within the call for *Project Grants in Clinical and Translational Medicine*, 15% of the budget was allocated to 'Innovative Therapies' in 2021 and 'Precision Medicine in Cardiovascular Diseases' in 2022. However, these targeted priorities do not prevent resubmissions of (nearly) identical proposals.

Restrictions on Cross-Call Submissions. Strategic switching between calls is not possible. Calls focus on distinct research areas with minimal overlap. For example, a proposal rejected in *Project Grants in Clinical and Translational Medicine* cannot be resubmitted to *Project Grants in Endocrinology and Metabolism* without substantial revision. Such a shift would require significant modifications to align with the new topic and could raise concerns about the applicant's research identity. An applicant with a track record in clinical and translational medicine who suddenly applies for endocrinology and metabolism funding would face scrutiny.

The entire process, from submission to decision communication, spans approximately six months. Figure 3 illustrates this process.

4 Data and Methods

Our data comprises 10,943 proposals submitted by 5,498 Principal Investigators (PIs) between 2017 and 2022, evaluated by 154 evaluators on 22 panels. 8,609 (18.74%) proposals were rejected. Below, we describe the variables and outline the construction of a panel dataset tracking applicants after rejection.

4.1 Variables

Dependent Variables

Proposal Resubmission. This variable indicates whether applicants submit another proposal after their previous one was rejected (=1) or not (=0). A submission qualifies as a resubmission only if it is to the same call type as the rejected proposal; submissions to different call types do not qualify. For example, if a proposal to the call type *Project Grants in Endocrinology and Metabolism* is rejected, a future submission by the same applicant to the call type *Interdisciplinary Synergy Programme* does not qualify as a resubmission.

Applicants may submit multiple proposals and receive multiple rejections within the same call type. For instance, an applicant may submit to the call type *Project Grants in Endocrinology and Metabolism* in 2019, 2020, and 2021, with the first two proposals rejected. In such cases, a resubmission is defined as the first proposal submitted following a rejection. Thus, the proposal submitted in 2020 is considered a resubmission of the one rejected in 2019, while the 2021 submission is a resubmission of the proposal rejected in 2020 but not of the one rejected in 2019.

Proposal Similarity. This variable captures the textual resemblance between a rejected

proposal and a resubmission. Following common practice in innovation research (Arts et al., 2023; Guzman and A Li, 2023; Hoberg and Phillips, 2018), we measure this variable using the cosine similarity of word embedding vectors, computed as the dot product of the vectors divided by the product of their magnitudes. The resulting value ranges from 0 to 1, where 1 indicates that the rejected proposal and resubmission are identical, and 0 indicates that they are completely dissimilar. Unless otherwise noted, we calculate *Proposal Similarity* based on all proposal sections, excluding applicants' CVs. The CV is excluded because it is not part of the proposal's 'idea' and can be modified only minimally.

We derive word embedding vectors from the SciBERT algorithm, a pre-trained language model specifically designed for processing scientific text (Beltagy et al., 2019). Unlike general-purpose models, it captures the contextual meaning of words and is particularly well-suited for analyzing text with scientific terminology. Its performance advantages over alternative algorithms have been demonstrated by, e.g., Miric et al. (2023).

Identical Resubmission. We are particularly interested in nearly identical resubmissions, where applicants make minimal changes to their rejected ideas. We capture such resubmissions with *Similarity 99* and *Similarity 95*, which take the value of 1 if *Proposal Similarity* exceeds 0.99 or 0.95, respectively, which is the case for 3.52% and 15.78% of all resubmissions.

Independent Variables

Share Turnover. This variable measures the share of evaluators who were on the panel when an applicant's proposal was rejected and who have since exited. It ranges from 0 (no evaluator has left) to 1 (all evaluators have left). We calculate *Share Turnover* by dividing the number of evaluators who have exited by the number of evaluators on the panel at the time of rejection, not by the current panel size. As a result, *Share Turnover* remains 0 until at least one incumbent evaluator exits, even if new evaluators join the panel.

Share Turnover Close. This variable is constructed similarly to *Share Turnover*, but focuses on the turnover of intellectually close evaluators. Evaluators are considered intellectually close if they were assigned to grade the rejected proposal. Thus, we calculate *Share Turnover Close* by dividing the number of evaluators who graded the rejected proposal and have since exited by the total number of evaluators who graded the rejected proposal.

Share Turnover Distant. This variable is constructed in the same way as *Share Turnover Close*, but focuses on the turnover of intellectually distant evaluators. Evaluators are considered intellectually distant if they were on the panel at the time of rejection but were not assigned the rejected proposal for grading. Thus, we calculate *Share Turnover Distant* by dividing the number of distant evaluators who have since exited by the total number of distant evaluators. The sum of *Share Turnover Close* and *Share Turnover Distant* equals *Share Turnover*.

Control Variables

To mitigate the effect of potential confounders on applicants' resubmission behavior, we include control variables at the level of the applicant, rejected proposal, and panel.

Applicant Controls. Recent research indicates that females are more likely to resubmit rejected ideas than males (Aneja et al., 2024). Gender may also influence the likelihood of modifying ideas, with females being more likely to modify because they attribute rejection to the (poor) quality of their idea rather than external factors including idiosyncratic evaluator preferences. Therefore, we control for applicants' *Gender* (0 = Male, 1 = Female).

Junior applicants may depend on funding from the organization for tenure and promotion and may leave academia if rejected. Consequently, they may be less likely to resubmit than senior applicants. Additionally, junior applicants may exhibit greater cognitive flexibility and have a less established research identity, making them more likely to modify their rejected proposals. To account for these effects, we control for applicants' biological age (*Age*).

Drafting and modifying proposals, especially after rejection, may become easier as applicants gain submission experience. Therefore, we control for the total number of proposals previously submitted to the organization (*# Previous Proposals*). Additionally, past success in applying may increase applicants' confidence in the quality of their work, making them more likely to resubmit following rejection and less likely to modify rejected proposals (Audia and Goncalo, 2007; Bayus, 2013). Therefore, we also control for the number of successful past proposals with the organization (*# Previous Successful Proposals*).

Proposal Controls. Applicants' resubmission strategy may depend on the characteristics of the rejected proposal.

First, the quality of the rejected proposal may affect the likelihood of resubmission. Applicants whose proposal was of reasonable quality but was rejected due to strong competition may be more likely to resubmit than those whose proposals were of lower quality. Similarly, applicants will be less likely to modify higher-quality proposals upon resubmission. We approximate quality using the average grade of the rejected proposal, *Proposal Grade Rejected*, which ranges from 1 (best) to 5 (worst).

The likelihood of resubmission may decrease as more time passes since rejection, as applicants may secure alternative funding or leave academia (Bol et al., 2018; Wang et al., 2019). Meanwhile, those who do resubmit may modify their proposals more extensively over time as their research focus evolves. To account for this, we control for the number of periods since rejection (*# Periods Since Rejection*).

Call types likely differ in terms of resubmission ease. Applicants will find it more difficult to resubmit for calls in fast- than slow-evolving scientific fields. In addition, they will find it more difficult to resubmit to call types that earmark funding for varying areas in each period. For example, the call *Project Grants in Clinical and Translational Medicine* allocated approximately 15

Finally, applicants' resubmission likelihood likely increases with total funding available for a given call as a larger funding pool raises selection chances. In addition, applicants' resubmission likelihood likely increases with the individual grant since larger grants make resubmission more attractive. Both total available funding and individual grant size are advertised in the call for proposals and known to applicants. Thus, we control for *Total Funding* and *Grant Size*.

Panel Controls. Applicants' resubmission likelihood may depend on the panel size at the

time of rejection. If the panel was small, with each evaluator playing a significant role in the decision, the departure of an evaluator may be seen as a greater opportunity for resubmission than in a larger panel. Thus, we control for *Panel Size Rejection*. Additionally, resubmission likelihood may depend on the panel size in the current period. A larger current panel, particularly due to new evaluators joining, may encourage resubmission by introducing fresh perspectives on the applicant's proposal. Thus, we control for *Panel Size Current*.

4.2 Construction of Dataset

To estimate the effect of evaluator turnover on applicants' resubmission strategy, we construct a dataset at the level of the applicant, rejected proposal, and period since rejection. We identify proposal rejections and track applicants for all periods following rejection until they resubmit a proposal or until the end of our observation period. For example, consider an applicant who submitted a proposal to the call *Project Grants in Clinical and Translational Medicine* in 2019, which was rejected. If she resubmits in 2022, we follow her through 2020, 2021, and 2022. Some applicants never resubmit following rejection within our observation period, in which case they remain in the dataset for all periods since rejection until our data coverage ends in 2022. Applicants may enter the dataset with multiple rejections, either within the same call type or across different call types. As outlined in the previous section, a submission qualifies as a resubmission only if it is to the same call type. Consequently, we exclude submissions to one-off calls, which typically address urgent topics, such as those related to the COVID-19 pandemic. Our final dataset consists of ... observations at the applicant, rejected proposal, and period since rejection level. Summary and correlational statistics are presented in Tables 1 and 2.

4.3 Data Description

The number of proposals received for recurring calls by the NNF increased from 738 in 2017 to 2,021 in 2020 before declining to 1,509 in 2022 (Figure 4). Rejection rates have fluctuated between 79.81% and 83.77%, with rejection rates increasing with the number of proposals received (Figure 5). Applicants have a 25.43%, 6.66%, 2.65%, and 1.05% probability of resubmitting one, two, three, and four periods after rejection, conditional on not having resubmitted before (Figure 6). 35.26% of the applicants are female. At the time of submission, applicants are, on average, 47.15 years old and have previously submitted 1.60 proposals to the NNF, with 0.23 of them being successful.

Resubmitted proposals vary widely in similarity to the rejected ones. As shown in Figure 7, the thick right tail of the *Proposal Similarity* distribution indicates that many applicants resubmit proposals closely resembling their rejected ones, while the thin left tail suggests that few applicants make substantial changes. Notably, the spike at *Proposal Similarity* = 0.99 reveals that over 5% of resubmitted proposals are identical to the rejected ones.

To further assess this similarity distribution, we compare it in Figure 7 with that of proposals submitted by *different* applicants within the same call. This latter distribution exhibits a substantial left shift, which further underlines that applicants tend to base their resubmissions

strongly on their rejected proposals.

We also find, as expected, that the similarity between rejected and resubmitted proposals declines over time. Figure **??** shows that proposals resubmitted one period after rejection are more similar to the rejected one than those submitted two or three periods after rejection.

Panel size ranges from 3 to 14, with an average panel size of 7.97 members. Panels slightly grew in size over time, with an average panel size of 7.20 in 2017 and 7.93 in 2022. 15.64% of evaluators leave a panel from one period to the next. As shown in Figure 10, applicants find that 17.93%, 35.32%, 52.73%, and 66.58% of evaluators who rejected their proposal have left the panel one, two, and three periods after rejection. When decomposed into close and distant evaluators, these figures are 5.50%, 11.09%, 15.72%, and 19.20% for close and 12.43%, 24.23%, 37.11% and 47.37% for distant evaluators.

4.4 Empirical Specification

Our goal is to examine how evaluator turnover affects applicants' resubmission behavior—specifically, whether and when they submit new proposals and how these proposals compare to their rejected ones. To this end, we exploit quasi-random evaluator turnover over time: Evaluators exit the panel based on their tenure, a factor exogenous to applicants. Since applicants have no control over panel composition changes, evaluator turnover is uncorrelated with other factors that likely shape resubmission strategies, such as alternative funding opportunities or current funding status.

Our baseline specification reads as follows:

$$y_{ijt} = \alpha Share\ Turnover_{jt} + \beta \boldsymbol{X}_{it} + \gamma \boldsymbol{Z}_j + \delta_t + \epsilon_{ijrt} \tag{1}$$

where i denotes the applicant, j the rejected proposal, and t the number of periods since the proposal was rejected. The dependent variables, *Proposal Submission* and *Proposal Similarity*, and key independent variable, *Share Turnover*, are specified as above. Notably, *Proposal Similarity* is defined only when *Proposal Submission* equals 1.

Our primary interest is in estimating α, which captures whether and how applicants adjust their resubmission strategy in response to evaluator turnover. δ_t represents fixed effects for the number of periods since rejection, controlling for the declining likelihood of resubmission and decreasing proposal similarity over time. V_{it} is a vector of time-varying applicant characteristics, W_{it} a vector of time-varying panel characteristics, and X_j a vector of rejected proposal characteristics. ϵ_{ijrt} is the error term.

5 Results

5.1 The Effect of Evaluator Turnover on Proposal Resubmission

We begin by examining how evaluator turnover affects applicants' decisions on whether and when to resubmit proposals after rejection. To do so, we estimate discrete-time survival models, which have been widely used in innovation and strategy research to account for time-varying

independent variables in survival analyses (Krieger, 2021; Nanda and Sørensen, 2010; Yang et al., 2024). In this context, applicants 'survive' as long as they have not resubmitted a proposal following rejection. These models are particularly well suited to our study because they accommodate right-censoring—a key feature of our dataset: Since our observation period ends in 2022, we cannot determine whether applicants who have not resubmitted by then will do so later or never.

We estimate discrete-time survival models using Cox Proportional Hazard regression, stratifying by call types to account for variation in baseline submission hazard rates. We present results in Table 3. Column 1 shows statistically insignificant coefficient estimates, suggesting that evaluator turnover does not, on average, affect applicants' resubmission likelihood. However, distinguishing between the turnover of close versus distant evaluators reveals a more nuanced pattern. Column 2 indicates a statistically significant increase in the likelihood of resubmission following the departure of close evaluators. Specifically, the hazard of resubmission increases by 95.94% when all close evaluators involved in the rejection have left compared to when none have left. By contrast, Column 3 shows that the turnover of distant evaluators has no significant effect. This pattern remains consistent when considering both types of turnover jointly (Column 4) and when including the full set of control variables (Column 5). In the Appendix, we replicate Table 3 using logistic regression and obtain similar results (Table 4). These findings indicate that while evaluator turnover in general does not influence resubmission decisions, the departure of close and presumably more influential evaluators increases the likelihood of resubmission, suggesting that applicants engage in strategic resubmission in response to changes in the evaluation audience.

5.2 The Effect of Evaluator Turnover on Proposal Similarity

In the previous section, we showed that evaluator turnover increases applicant's post-rejection resubmission likelihood. Next, we examine how turnover influences the extent to which applicants modify their rejected proposals, provided that they do resubmit. We begin by descriptively analyzing the relationship between *Share Evaluator Turnover* and *Proposal Similarity*. In Figure 11, we compare the distribution of *Proposal Similarity* for when at least one evaluator who rejected an applicant's proposal has left the panel (solid line) with the distribution for when none has left (dashed line). The solid line is slightly shifted to the right compared to the dashed one, suggesting that evaluator turnover makes applicants less likely to modify their rejected proposal, providing preliminary support for H2.

Next, we examine how the patterns in Figure 11 differ between the turnover of close versus distant evaluators. In Figure 12, we decompose the solid line from Figure 11 into cases where at least one close evaluator has left the panel versus cases where at least one distant evaluator has left. The similarity distribution for the turnover of close evaluators (green line) is noticeably more right-skewed than that for distant evaluators (blue line). In particular, the turnover of at least one close evaluator is associated with a substantially higher share of identical resubmissions (12.5%) than the turnover of at least one distant evaluator (8%). This is strong preliminary support for H3, according to which strategic idea revival is driven by the turnover

of intellectually closer and arguably more influential evaluators.

We now use regression analysis to estimate the effect of evaluator turnover on the extent to which applicants modify their rejected proposals. We begin by running OLS regressions of *Proposal Similarity* on our key independent variables. We report results in Table 5. Column 1 indicates that evaluator turnover does not affect proposal modification on average. However, distinguishing between the turnover of close versus distant evaluators reveals a more nuanced pattern. Column 2 suggests that resubmissions are on average 5.86% more similar to the rejected proposal when all close evaluators have exited the panel compared to when no close evaluators have exited. In the meanwhile, the turnover of distant evaluators has no effect on applicants' modification decisions (Colum 3). These findings remain very similar once we consider the turnover of close and distant evaluators jointly (Column 4), and include call fixed effects as well as a battery of control variables (Columns 5-7).

Our primary focus lies on 'boomerang' proposals—cases where applicants resubmit virtually unchanged proposals. Thus, we estimate the effect of evaluator turnover on the likelihood of applicants submitting such boomerang proposals. We replicate Table 5, replacing the dependent variable *Proposal Similarity* with *Resubmission 99* and *Resubmission 95*. Recall that *Resubmission 99* and *Resubmission 95* take the value 1 if *Proposal Similarity* exceeds the value of 0.99 and 0.95, respectively, and 0 otherwise.

Tables 6 and 7 show a marked increase in the likelihood of boomerang proposals when close evaluator turnover is high. Our preferred specification, which includes call fixed effects and the full set of control variables, predicts that applicants are 484.75% (189.19%) more likely to resubmit proposals with a cosine similarity of 0.99 (0.95) or higher to their rejected proposal when all close evaluators have exited the panel, compared to when none have exited. In contrast, the departure of distant evaluators has no statistically significant effect on the likelihood of submitting boomerang proposals. This strongly supports H3, which posits that applicants' decision to resubmit boomerang proposals is driven by the turnover of intellectually closer evaluators, who likely played a greater role in the initial rejection.

6 Does Strategic Idea Revival Pay Off?

Above, we documented that applicants engage in strategic idea revival as they resubmit their previously rejected idea to new evaluators. Here, we examine whether this strategy pays off for applicants. We say that it does if those who resubmit their rejected proposal to new evaluators—and thus avoid the costs of modification—have at least the same likelihood of selection as those who submit a modified proposal to new evaluators.

We begin by analyzing whether and how funding likelihoods vary with the similarity between rejected proposals and resubmissions. Intuitively, since rejections indicate low quality, we would expect funding likelihoods to decrease with increasing similarity. Strikingly, this is not what we find (Table 8). Regressing *Funded*—which equals 1 if a proposal was funded and 0 otherwise—on *Proposal Similarity* as well as *Resubmission 99* and *Resubmission 95* yields statistically insignificant results. This result remains robust when we include fixed effects for

the call type and year, and control for applicant and proposal characteristics, in particular the grade of the rejected proposal. In other words, whether applicants resubmit their rejected proposal or submit a modified version makes no difference in terms of funding likelihood on average.

Next, we examine whether applicants improve their selection likelihood by applying idea revival selectively—resubmitting rejected proposals to new evaluators while submitting modified proposals to incumbent ones. To test this, we extend the models in Table 8, interacting our similarity measures with *Share Turnover*. If idea revival were more effective with new evaluators than with incumbents, the interaction term coefficient should be positive and statistically significant. However, as shown in Table 9, this is not what we find. Additionally, we find no evidence that the effectiveness of idea revival depends on the turnover of close versus distant evaluators (Tables 11 and 10). Thus, *strategic* idea revival—where resubmission is contingent on evaluator turnover—does not provide any additional advantage in terms of funding likelihood.

This finding suggests that applicants may overestimate the influence of panel composition on funding outcomes. Instead, funding success may ultimately depend more on the inherent quality of the proposal than applicants assume. To examine this, we analyze how the effectiveness of idea revival varies with the quality of the rejected proposal, using its grade, *Grade Rejected*, as a proxy, where lower grades indicate higher quality. Intuitively, resubmitting proposals that—despite being rejected—received relatively high grades should lead to greater funding success compared to resubmitting proposals that received poor grades.

We regress *Funded* on an interaction between our proposal similarity measures and *Grade Rejected* (Table 12). The negative and statistically significant coefficients for *Grade Rejected* $\times$ *Proposal Similarity* and *Grade Rejected* $\times$ *Resubmission 95* provide suggestive evidence that resubmitting rejected proposals is more effective when the original proposal received a better grade. For instance, Column 6 of Table 12 indicates that resubmitting a proposal with at least a 0.95 cosine similarity to the rejected proposal decreases the likelihood of funding by 41.18% for each one-point increase in the grade of the rejected proposal.

7 Conclusion

7.1 Contributions

Recently, scholars and practitioners have intensely debated whether individuals should persist with or abandon their rejected ideas. The dominant view strongly favors pivoting away, often portraying pivots as essential for success. This perspective is reinforced by celebrated business stories, such as Instagram or Netflix, where abandoning initial ideas led to breakthrough innovations. Entrepreneurship research aligns with this narrative, with several scholars attributing the performance advantages of a 'scientific' approach to entrepreneurship to the ability to pivot quickly. Similarly, creativity research often assumes that creators should revise their ideas in response to negative feedback, focusing on psychological barriers such as identity-based attachment that hinder effective revision. Our work challenges this prevailing consensus by identifying conditions under which creators benefit from persisting with rejected ideas. We thus offer a more

balanced framework that counters the assumption that pivoting is always the superior choice, thereby enriching the discussion on how to navigate idea rejection.

We contribute to the growing body of research on the role of feedback in the creative revision process. The journey from the inception of an idea to its final implementation is often long, as creators repeatedly seek and incorporate feedback from diverse stakeholders (Amabile, 1996; Ananth and Harvey, 2023; Perry-Smith and Mannucci, 2017). For instance, Herbold (2002) describes how product proposals at Procter & Gamble underwent "30 to 40 revisions as they were exposed to the various 'layers of wisdom' in product development, sales, finance, and top management." Although recent scholarship has made some progress in understanding the role of feedback in shaping ideas over time (Baer, 2012; Grimes, 2018), the evolution of ideas remains poorly understood. This gap arises partly from the challenges of tracing how ideas move through organizations and receive feedback from multiple evaluators. Additionally, until recently, limitations in the analysis of large-scale textual data made it hard to reconstruct their evolution. Our study addresses these challenges by leveraging an empirical context that enables us to trace how ideas move back and forth between creators and evaluators and by employing advanced natural language processing techniques to examine their evolution over time. This enables us to produce novel insights into the creative revision process, showing how creators refine their ideas in response to rejections and, equally importantly, how they sometimes choose to ignore feedback and persist with their original ideas.

We contribute by introducing the concept of boomerang ideas, an underexplored yet significant phenomenon in organizational innovation. While it is almost a cliché to claim that organizations need novel ideas to stay competitive, we argue and show that organizations often encounter old ideas—ideas they have previously seen and rejected. We call these "boomerang ideas," drawing inspiration from the term "boomerang employees," which refers to employees who leave an organization only to return later. Boomerang ideas result from creators seeking to revive their rejected ideas with different evaluators, avoiding the costs and effort required to modify their proposals. To the best of our knowledge, evidence of such ideas has been largely anecdotal. A classic example is the post-it note, initially proposed by an M3 employee and rejected by management, only to be re-proposed years later to different management, who then selected the idea—leading to one of M3's most successful products. Our findings go beyond anecdotal examples, showing that boomerang ideas constitute a substantial share of the ideas organizations receive. In our context, they represent roughly 14% of the idea pool. This highlights that boomerang ideas are not only theoretically intriguing but also practically relevant, deserving greater attention in both research and practice.

7.2 Implications

Our study holds important implications for both creators and organizations. For creators, our study has two key implications. First, resubmitting ('reviving') rejected proposals is generally a sound strategy, as it results in no lower funding likelihoods than proposal modification while saving on revision costs. Rather than spending time and cognitive efforts on modifying ideas or coming up with entirely new ones, creators should not hesitate to hold on to their rejected

ideas. Second, creators should base their decision to revive rejected ideas on the quality of their proposals rather than on changes in the evaluating audience. Our findings demonstrate that the success of idea revival does not depend on changes in audience composition; proposals resubmitted to incumbent audiences are as likely to secure funding as those submitted to new audiences. Instead, and perhaps unsurprisingly, the primary determinant of revival success is the quality of the rejected proposal. High-quality ideas, even when initially rejected, have a significantly better chance of success in subsequent rounds. Therefore, applicants should hone their skills of self-assessment, rather than relying on external factors such as audience shifts.

Organizations tasked with selecting ideas should carefully consider the information they disclose about their evaluation processes and outcomes. A first central question is whether they should reveal the identity of evaluators before eliciting ideas. Many organizations disclose evaluator identities to enhance the transparency of their decision-making processes and to signal credibility by showcasing the expertise of their evaluators. While these goals are valid, our findings suggest that such transparency has unintended consequences: it incentivizes creators to resubmit previously rejected ideas, or 'boomerang ideas,' when there is a turnover among evaluators. Boomerang ideas are not inherently problematic. In fact, reevaluating previously rejected ideas with a new audience may allow organizations to identify false negatives–ideas that were unfairly dismissed the first time. However, 'boomerang ideas' also have a downside. They can conflict with the goal of fostering a steady influx of diverse and novel ideas (Piezunka and Dahlander, 2015). If too many resources are allocated to reevaluating old ideas, organizations may inadvertently limit their exposure to new ones. Thus, organizations may consider keeping evaluator identities anonymous or revealing their identity only after the evaluation process has concluded.

Organizations should consider providing creators with more than a simple rejection notification by offering insights into the absolute quality of their ideas. Sharing an assessment—such as a grade or quality score—can encourage the resubmission of high-quality ideas that might otherwise be lost. Rejections often reflect strong competition in a particular round rather than a lack of merit, and such ideas may perform well in future rounds when evaluated against a different set of submissions. Our findings show that resubmitted high-quality boomerang ideas are particularly likely to succeed, emphasizing the importance of signaling their potential value. By offering an absolute quality assessment, organizations can help creators recognize the merit of their ideas independently of the competition and encourage resubmissions. If detailed feedback for all submissions is impractical, organizations could signal quality for ideas surpassing a specific threshold. Even a simple acknowledgment that an idea exceeded a benchmark can guide creators toward resubmission, ensuring promising ideas are not lost and remain in the pipeline.

7.3 Boundary Conditions and Limitations

Our findings are likely bounded to contexts where rejections offer little to no detailed feedback on the idea, whether in absolute terms (e.g., grades), relative terms (e.g., ranks), or specific suggestions for improvement. Without clear guidance, creators face uncertainty about how

modifications might enhance selection likelihood, making the benefits of revision ambiguous and increasing the appeal of strategic idea revival. This lack of feedback is common in settings such as funding agencies and academic journals, where rejections are typically accompanied by generic statements due to the high costs and risks associated with providing detailed feedback. In contrast, settings like online communities or crowdfunding platforms often provide creators with more specific reasons for rejection, offering clearer pathways for improvement and reducing the appeal of strategic idea revival. We encourage future research to examine how the type and extent of information provided with rejections shape the likelihood and effectiveness of strategic idea revival.

Strategic idea revival is more likely in settings where creators have prior knowledge of the evaluating audience, including whether evaluators who rejected their idea are no longer involved. When creators are uncertain about audience composition and rejecting evaluators may still be present, strategic idea revival is less effective, as these evaluators are likely to reject the idea again. In some contexts, creators know the evaluating audience, such as employees aware of the managers reviewing their ideas, scientists familiar with the editors assessing their manuscripts, or open-source developers who know their code reviewers. In other contexts, audience composition is deliberately kept confidential to protect evaluators from external pressures, as in grant reviews by the National Science Foundation or European Research Council. In these cases, strategic idea revival is less likely because creators do not know the extent of evaluator rotation. However, time works in their favor—if they wait long enough, they can be reasonably certain that evaluator turnover has occurred, allowing them to resubmit their ideas.

References

Aadland E, Cattani G, Ferriani S (2019) Friends, Gifts, and Cliques: Social Proximity and Recognition in Peer-Based Tournament Rituals. *Academy of Management Journal*, *62*(3):883–917.

Amabile T (1996) Creativity in Context (Westview Press, Boulder, CO).

Ananth P, Harvey S (2023) Ideas in the Space Between: Stockpiling and Processes for Managing Ideas in Developing a Creative Portfolio. *Administrative Science Quarterly*, *68*(2):465–507.

Aneja A, Reshef O, Subramani G (2024) Attrition and the Gender Patenting Gap. *The Review of Economics and Statistics*:1–31.

Arts S, Cassiman B, Hou J (2023) Position and Differentiation of Firms in Technology Space. *Management Science*, *69*(12):7253–7265.

Audia PG, Goncalo JA (2007) Past Success and Creativity over Time: A Study of Inventors in the Hard Disk Drive Industry. *Management Science*, *53*(1):1–15.

Azoulay P, Fons-Rosen C, Graff Zivin JS (2019) Does Science Advance One Funeral at a Time? *American Economic Review*, *109*(8):2889–2920.

Baer M (2012) Putting Creativity to Work: The Implementation of Creative Ideas in Organizations. *Academy of Management Journal*, *55*(5):1102–1119.

Bayus BL (2013) Crowdsourcing New Product Ideas over Time: An Analysis of the Dell IdeaStorm Community. *Management Science*, *59*(1):226–244.

Beltagy I, Lo K, Cohan A (2019) Scibert: A pretrained language model for scientific text.

Bidwell M, Mollick E (2015) Shifts and Ladders: Comparing the Role of Internal and External Mobility in Managerial Careers. *Organization Science*, *26*(6):1629–1645.

Boudreau KJ, Guinan EC, Lakhani KR, Riedl C (2016) Looking Across and Looking Beyond the Knowledge Frontier: Intellectual Distance, Novelty, and Resource Allocation in Science. *Management Science*, *62*(10):2765–2783.

Camuffo A, Cordova A, Gambardella A, Spina C (2020) A Scientific Approach to Entrepreneurial Decision Making: Evidence from a Randomized Control Trial. *Management Science*, *66*(2):564–586.

Camuffo A, Gambardella A, Messinese D, Novelli E, Paolucci E, Spina C (2024) A scientific approach to entrepreneurial decision-making: Large-scale replication and extension. *Strategic Management Journal*, *45*(6):1209–1237.

Cattani G, Ferriani S, Lanza A (2017) Deconstructing the Outsider Puzzle: The Legitimation Journey of Novelty. *Organization Science*, *28*(6):965–992.

Chang EH, Kirgios EL (2024) Demographic "Stickiness": The Demographic Identity of Departing Group Members Influences Who Is Chosen to Replace Them. *Management Science*, *70*(7):4236–4259.

Cornelius PB, Gokpinar B (2020) The Role of Customer Investor Involvement in Crowdfunding Success. *Management Science*, *66*(1):452–472.

Criscuolo P, Dahlander L, Grohsjean T, Salter A (2017) Evaluating Novelty: The Role of Panels in the Selection of R&D Projects. *Academy of Management Journal*, *60*(2):433–460.

Criscuolo P, Salter A, Ter Wal ALJ (2014) Going Underground: Bootlegging and Individual Innovative Performance. *Organization Science*, *25*(5):1287–1305.

Csaszar FA, Eggers JP (2013) Organizational Decision Making: An Information Aggregation View. *Management Science*, *59*(10):2257–2277.

Deichmann D, van den Ende J (2014) Rising from Failure and Learning from Success: The Role of Past Experience in Radical Initiative Taking. *Organization Science*, *25*(3):670–690.

Dushnitsky G, Sarkar S (2022) Here Comes the Sun: The Impact of Incidental Contextual Factors on Entrepreneurial Resource Acquisition. *Academy of Management Journal*, *65*(1):66–92.

Falchetti D, Cattani G, Ferriani S (2022) Start with "Why," but only if you have to: The strategic framing of novel ideas across different audiences. *Strategic Management Journal*, *43*(1):130–159.

Fernandez-Mateo I, Coh M (2015) Coming with Baggage: Past Rejections and the Evolution of Market Relationships. *Organization Science*, *26*(5):1381–1399.

Franzoni C, Stephan PE (2023) Uncertainty and risk-taking in science: Meaning, measurement and management in peer review of research proposals. *Research Policy*, *52*(3):104706.

Gagliardi L, Novelli E (forthcoming) Female Entrepreneurs Targeting Women: Strategic Redirection Under Scientific Decision-Making. *Organization Science*, *0*(0):null.

Grimes MG (2018) The Pivot: How Founders Respond to Feedback through Idea and Identity Work. *Academy of Management Journal*, *61*(5):1692–1717.

Guzman J, Li A (2023) Measuring Founding Strategy. *Management Science*, *69*(1):101–118.

Hallen BL, Cohen SL, Bingham CB (2020) Do Accelerators Work? If So, How? *Organization Science*, *31*(2):378–414.

Herbold RJ (2002) Inside Microsoft: Balancing Creativity and Discipline. *Harvard Business Review*.

Hoberg G, Phillips G (2018) Conglomerate Industry Choice and Product Language. *Management Science*, *64*(8):3735–3755.

Ke Q, Ferrara E, Radicchi F, Flammini A (2015) Defining and identifying Sleeping Beauties in Science. *Proceedings of the National Academy of Sciences*, *112*(24):7426–7431.

Kovács B (2017) Too hot to reject: The effect of weather variations on the patent examination process at the United States Patent and Trademark Office. *Research Policy*, *46*(10):1824–1835.

Krieger JL (2021) Trials and Terminations: Learning from Competitors' R&D Failures. *Management Science*, *67*(9):5525–5548.

Laband DN, Piette MJ (1994) Favoritism versus Search for Good Papers: Empirical Evidence Regarding the Behavior of Journal Editors. *Journal of Political Economy*, *102*(1):194–203.

Lane JN, Cai T, Menietti M, Weber G, Guinan E (2024) *Greenlighting Innovative Projects: How Evaluation Format Shapes the Perceived Feasibility of Novel Ideas* (tech. rep. No. 24-064).

Lane JN, Teplitskiy M, Gray G, Ranu H, Menietti M, Guinan EC, Lakhani KR (2022) Conservatism Gets Funded? A Field Experiment on the Role of Negative Information in Novel Project Evaluation. *Management Science*, *68*(6):4478–4495.

Li D (2017) Expertise versus bias in evaluation: Evidence from the NIH. *Am. Econ. J. Appl. Econ.*, *9*(2):60–92.

Li D, Agha L (2015) Big names or big ideas: Do peer-review panels select the best science proposals? *Science*, *348*(6233):434–438.

Mainemelis C (2010) Stealing Fire: Creative Deviance in the Evolution of New Ideas. *Academy of Management Review*, *35*(4):558–578.

Mannucci PV, Perry-Smith JE (2022) "Who Are You Going to Call?" Network Activation in Creative Idea Generation and Elaboration. *Academy of Management Journal*, *65*(4):1192–1217.

Marsh HW, Jayasinghe UW, Bond NW (2008) Improving the peer-review process for grant applications: Reliability, validity, bias, and generalizability. *The American psychologist*, *63*(3):160–168.

Miric M, Jia N, Huang KG (2023) Using supervised machine learning for large-scale classification in management research: The case for identifying artificial intelligence patents. *Strategic Management Journal*, *44*(2):491–519.

Mollick E (2012) People and process, suits and innovators: The role of individuals in firm performance. *Strategic Management Journal*, *33*(9):1001–1015.

Nanda R, Sørensen JB (2010) Workplace Peers and Entrepreneurship. *Management Science*, *56*(7):1116–1126.

Orazi DC, Mannucci PV (2024) Disentangling audiences' reactions to creative content and creative packaging. *Strategic Management Journal*, *45*(13):2763–2790.

Park S, Piezunka H, Dahlander L (2024) Coevolutionary Lock-In in External Search. *Academy of Management Journal*, *67*(1):262–288.

Perry-Smith JE, Mannucci PV (2017) From Creativity to Innovation: The Social Network Drivers of the Four Phases of the Idea Journey. *Academy of Management Review*, *42*(1):53–79.

Piezunka H, Dahlander L (2015) Distant Search, Narrow Attention: How Crowding Alters Organizations' Filtering of Suggestions in Crowdsourcing. *Academy of Management Journal*, *58*(3):856–880.

Piezunka H, Dahlander L (2019) Idea Rejected, Tie Formed: Organizations' Feedback on Crowdsourced Ideas. *Academy of Management Journal*, *62*(2):503–530.

Ries E (2011) The Lean Startup: How Today's Entrepreneurs Use Continuous Innovation to Create Radically Successful Businesses (Crown Business, New York, NY).

Scott EL, Shu P, Lubynsky RM (2020) Entrepreneurial Uncertainty and Expert Evaluation: An Empirical Analysis. *Management Science*, *66*(3):1278–1299.

Sgourev SV (2013) How Paris Gave Rise to Cubism (and Picasso): Ambiguity and Fragmentation in Radical Innovation. *Organization Science*, *24*(6):1601–1617.

Stasser G, Stewart DD, Wittenbaum GM (1995) Expert Roles and Information Exchange during Discussion: The Importance of Knowing Who Knows What. *Journal of Experimental Social Psychology*, *31*(3):244–265.

Staw BM, Ross J (1989) Understanding Behavior in Escalation Situations. *Science*, *246*(4927):216–220.

Terwiesch C, Xu Y (2008) Innovation Contests, Open Innovation, and Multiagent Problem Solving. *Management Science*, *54*(9):1529–1543.

Toivonen T, Idoko O, Jha HK, Harvey S (2023) Creative Jolts: Exploring How Entrepreneurs Let Go of Ideas During Creative Revision. *Academy of Management Journal*, *66*(3):829–858.

Travis GDL, Collins HM (1991) New Light on Old Boys: Cognitive and Institutional Particularism in the Peer Review System. *Science, Technology, & Human Values*, *16*(3):322–341.

Ucbasaran D, Shepherd DA, Lockett A, Lyon SJ (2013) Life After Business Failure: The Process and Consequences of Business Failure for Entrepreneurs. *Journal of Management*, *39*(1):163–202.

Vinokurova N, Kapoor R (2020) Converting inventions into innovations in large firms: How inventors at Xerox navigated the innovation process to commercialize their ideas. *Strategic Management Journal*, *41*(13):2372–2399.

Wang Y, Jones BF, Wang D (2019) Early-career setback and future career impact. *Nature Communications*.

Westhead P, Wright M (1998) Novice, portfolio, and serial founders: Are they different? *Journal of Business Venturing*, *13*(3):173–204.

Wiklund J, Shepherd DA (2008) Portfolio Entrepreneurship: Habitual and Novice Founders, New Entry, and Mode of Organizing. *Entrepreneurship Theory and Practice*, *32*(4):701–725.

Wilhelm H, Steigenberger N, Weber CE, Juntunen JK, Ebers M (2024) (No) Time for Change: When and Why Entrepreneurs Act During Underperforming Fundraising Attempts. *Organization Science*, *35*(4):1299–1321.

Wright NL, Koning R, Khanna T (2023) Judging foreign startups. *Strategic Management Journal*, *44*(9):2195–2225.

Yang T, Kacperczyk A(, Naldi L (2024) The Motherhood Wage Penalty and Female Entrepreneurship. *Organization Science*, *35*(1):27–51.

Yu S (2020) How Do Accelerators Impact the Performance of High-Technology Ventures? *Management Science*, *66*(2):530–552.

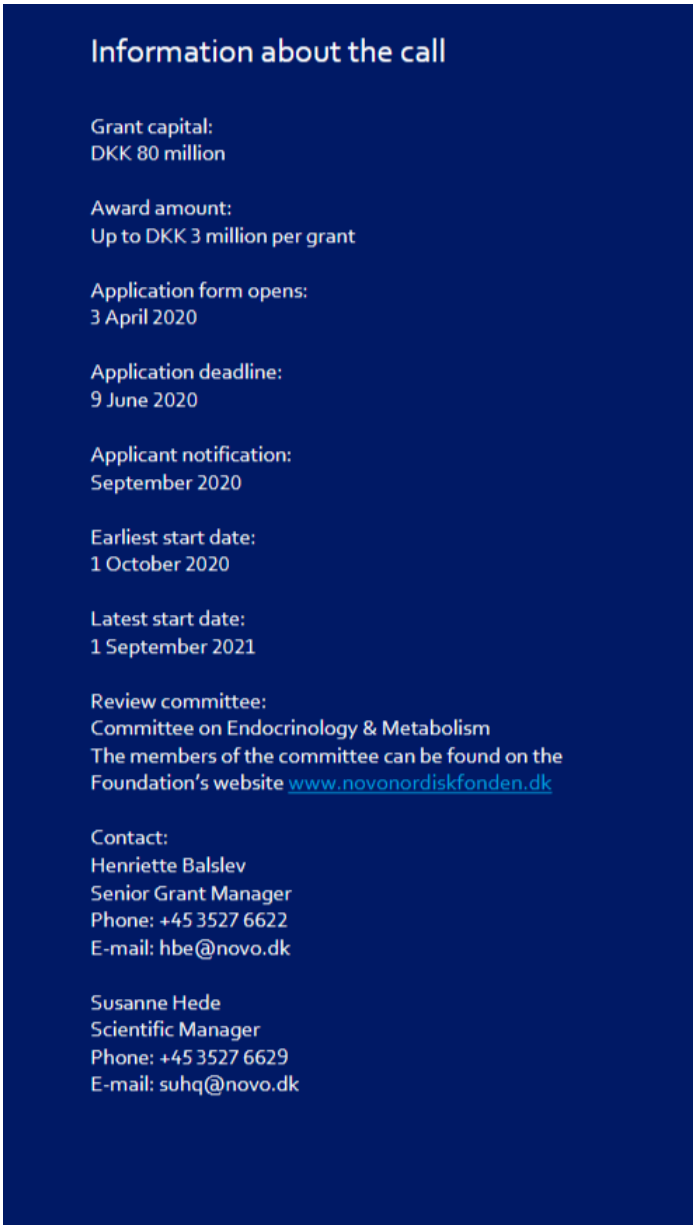
8 Tables and Figures

Figure 1:



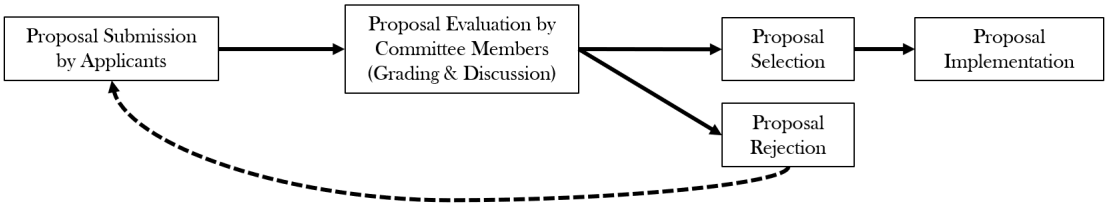
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Figure 2:



Notes:

Figure 3:



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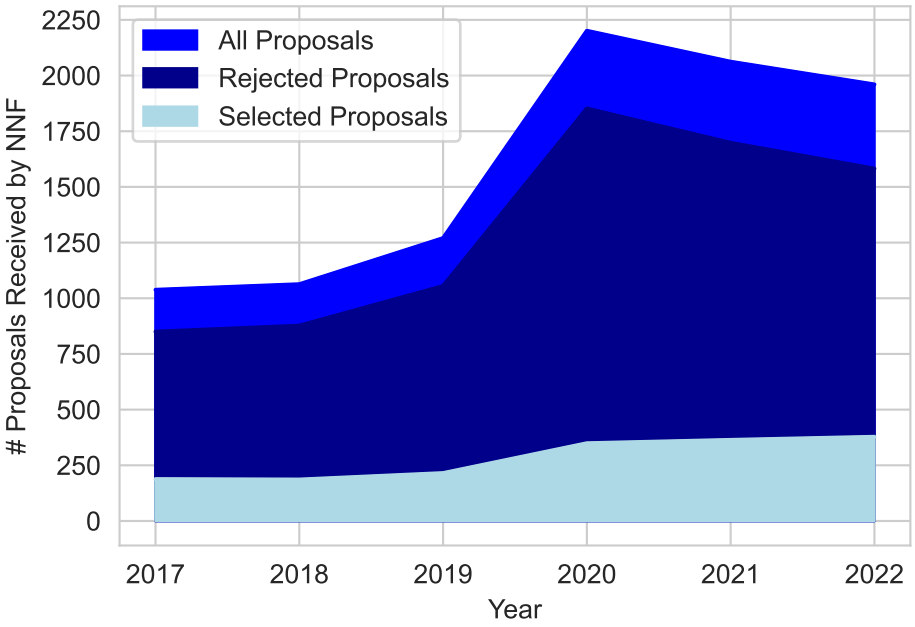
Table 1: Summary Statistics, Level: Applicant/Rejected Proposal/Periods Since Rejection

Variable	N	Mean	Std.	Min.	Median	Max.
Proposal Submission	9,215	0.18	0.39	0.00	0.00	1.00
Proposal Similarity	1,578	0.90	0.05	0.62	0.90	1.00
Resubmission 99	1,578	0.04	0.19	0.00	0.00	1.00
Resubmission 95	1,578	0.16	0.36	0.00	0.00	1.00
Share Turnover	9,215	0.31	0.20	0.00	0.29	1.00
Share Turnover Close	9,215	0.10	0.10	0.00	0.09	0.86
Share Turnover Distant	9,215	0.22	0.17	0.00	0.20	0.82
Gender	9,215	0.35	0.48	0.00	0.00	1.00
Age	9,215	49.47	9.63	26.00	48.00	81.00
# Previous Appl.	9,215	2.16	2.65	0.00	1.00	22.00
# Previous Successful Appl.	9,215	0.13	0.53	0.00	0.00	10.00
Proposal Grade Rejected	9,215	3.25	0.67	1.00	3.20	6.00
Periods Since Rejection	9,215	1.78	0.94	1.00	1.00	4.00
Total Funding (in USD)	9,215	8,414,999	3,626,647	94,104	9,204,351	18,159,022
Grant Size (in USD)	9,215	581,445	523,673	41,514	356,835	6,747,460
Panel Size Rejection	9,215	9.43	1.44	4.00	10.00	14.00
Panel Size Current	9,215	9.44	1.42	4.00	10.00	14.00

Table 2: Correlations

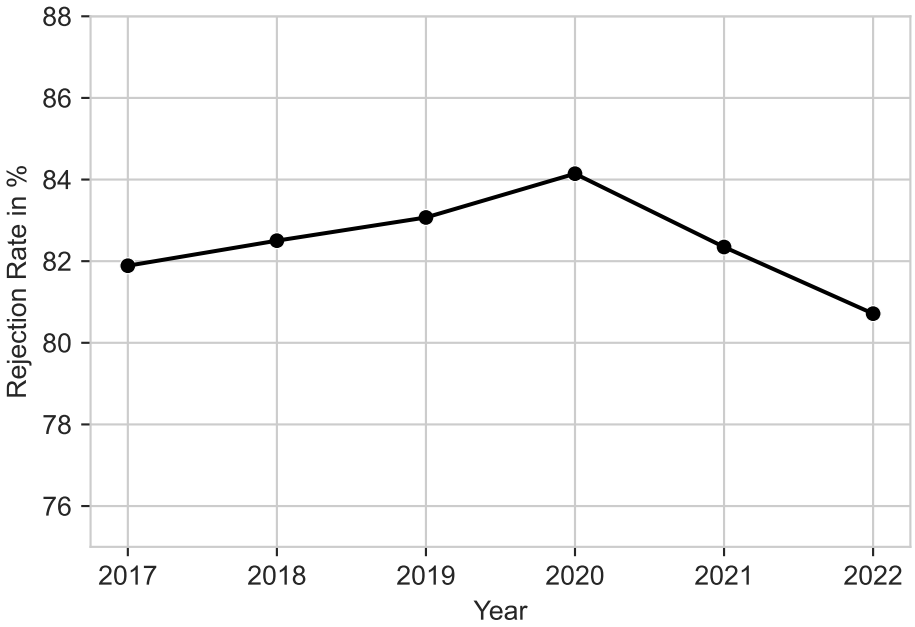
	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	Proposal Submission	1.00																
2	Proposal Similarity	-	1.00															
3	Resubmission 99	-	0.36	1.00														
4	Resubmission 95	-	0.64	0.44	1.00													
5	Share Turnover	-0.14	-0.10	-0.03	-0.05	1.00												
6	Share Turnover Close	-0.10	0.06	0.05	0.11	0.56	1.00											
7	Share Turnover Distant	-0.10	-0.16	-0.06	-0.13	0.86	0.06	1.00										
8	Gender	-0.00	-0.00	-0.06	-0.04	0.02	0.06	-0.01	1.00									
9	Age	-0.01	-0.07	-0.00	-0.01	0.12	0.04	0.11	-0.10	1.00								
10	# Previous Appl.	0.22	-0.07	0.00	-0.07	0.05	0.02	0.05	-0.05	0.11	1.00							
11	# Previous Successful Appl.	0.09	-0.01	0.05	-0.01	0.02	0.02	0.01	-0.03	0.09	0.49	1.00						
12	Proposal Grade Rejected	-0.10	-0.06	-0.07	-0.06	0.01	-0.01	0.02	0.04	-0.06	-0.12	-0.13	1.00					
13	Periods Since Rejection	-0.20	-0.18	-0.08	-0.11	0.78	0.44	0.67	0.01	0.09	-0.04	-0.02	0.05	1.00				
14	Total Funding (in USD)	0.11	-0.02	-0.08	-0.09	0.16	-0.10	0.25	-0.09	0.07	0.05	-0.03	-0.01	0.06	1.00			
15	Grant Size (in USD)	-0.04	0.07	0.05	0.04	-0.03	0.15	-0.13	-0.07	0.01	0.15	0.10	-0.09	-0.10	0.04	1.00		
16	Panel Size Rejection	0.05	-0.04	0.00	-0.09	0.14	-0.12	0.25	-0.13	0.01	0.12	0.00	-0.04	-0.08	0.39	0.18	1.00	
17	Panel Size Current	0.05	-0.04	0.00	-0.09	0.14	-0.12	0.24	-0.13	0.01	0.11	-0.00	-0.05	-0.07	0.39	0.18	1.00	1.00

Figure 4:



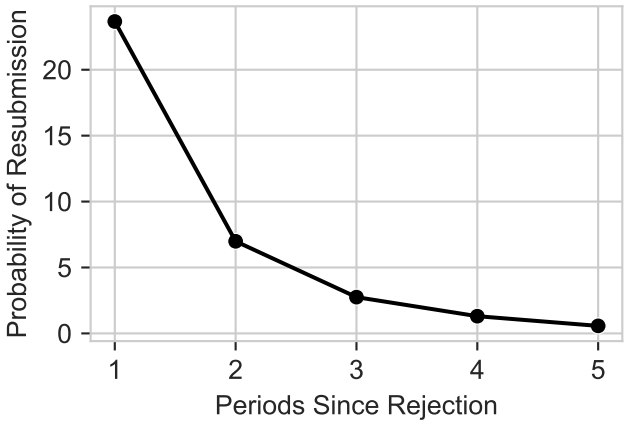
Notes: This figure plots the number of proposals submitted to the NNF during the observation period (2017–2022). $N = \ldots$.

Figure 5:



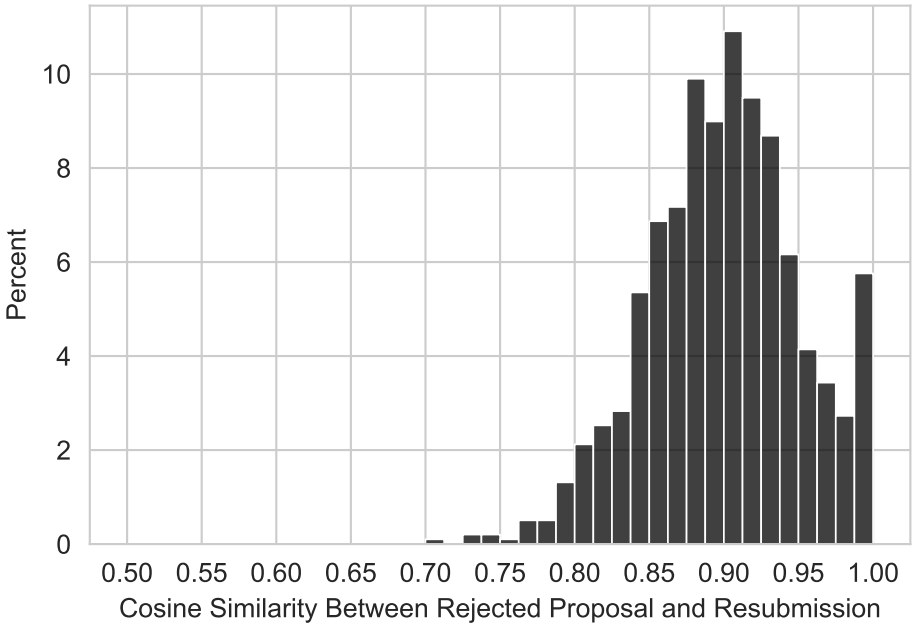
Notes: This figure plots the average proposal rejection rate from 2017 to 2022. The shaded area represents the standard deviation. $N = \ldots$.

Figure 6:



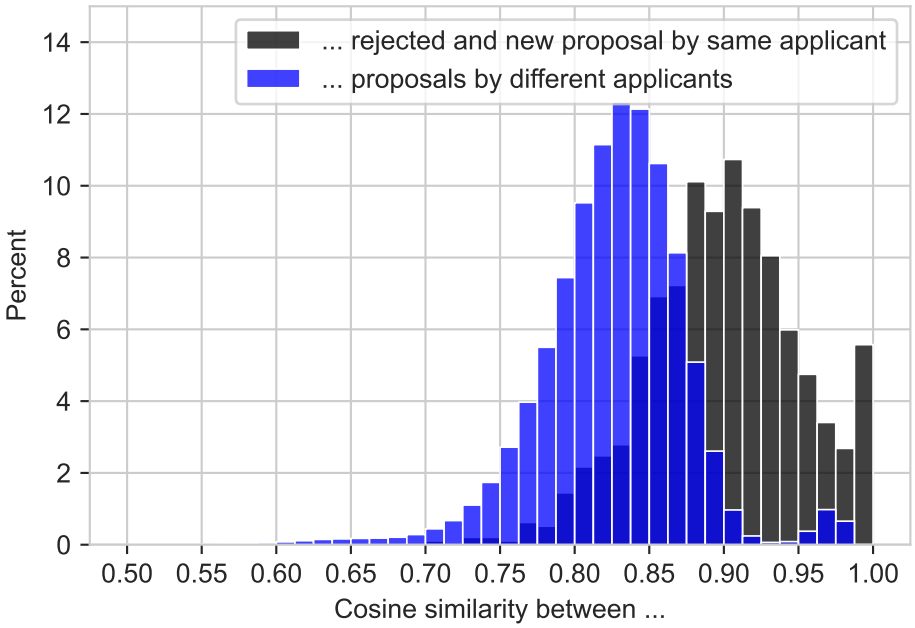
Notes: This figure plots the average probability of proposal resubmission following rejection. For instance, applicants have a 7% probability of resubmitting their proposal two periods after rejection, conditional on not having resubmitted in the first period. $N = \ldots$.

Figure 7:



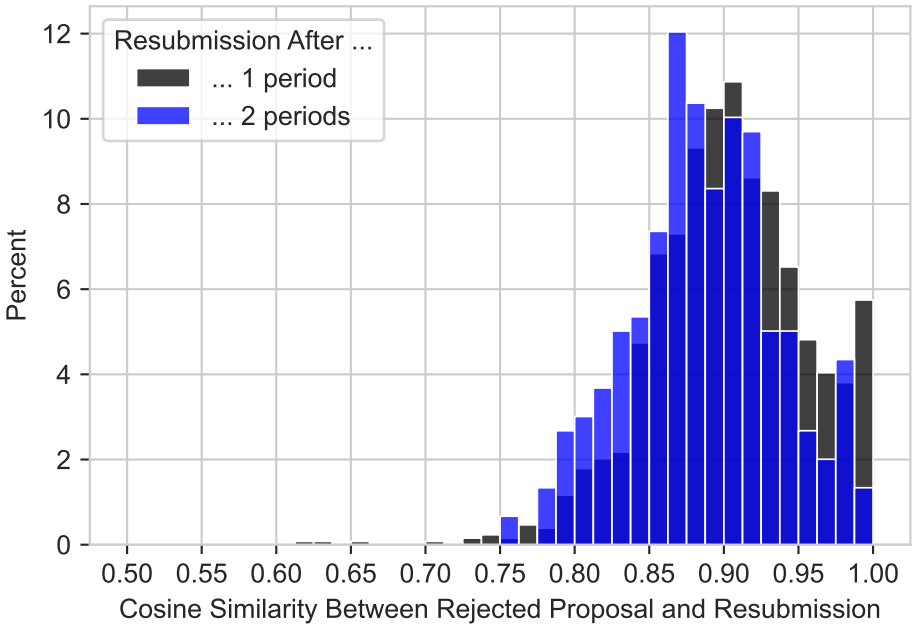
Notes: This figure plots the distribution of cosine similarity between rejected proposals and their resubmissions, where a value of 1 indicates an identical resubmission. $N = \ldots$.

Figure 8:



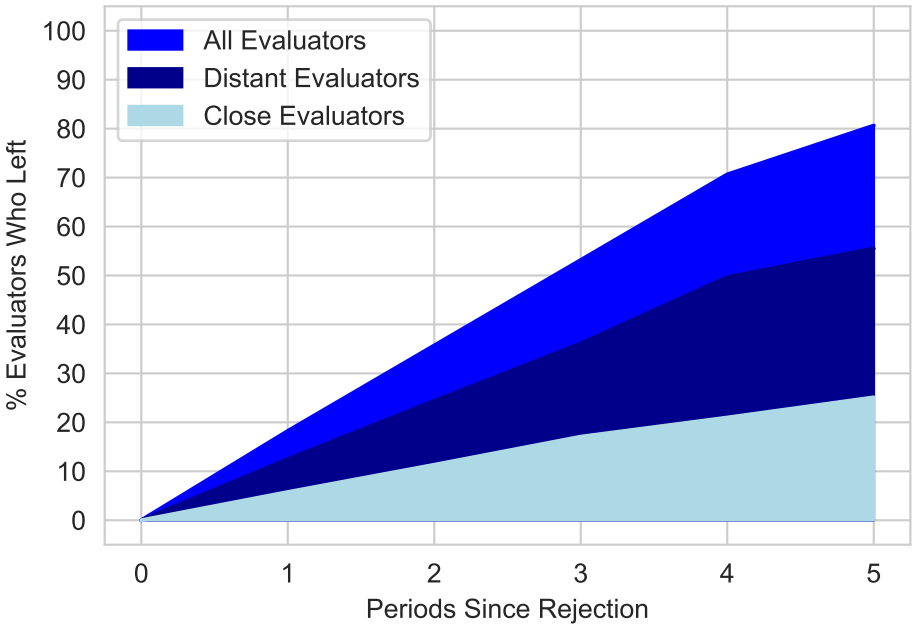
Notes: This figure plots the distribution of cosine similarity between rejected proposals and their resubmissions by the same applicant (black, also shown in Figure 7) alongside the distribution of cosine similarity between rejected proposals and submissions by different applicants within the same call (blue). The pronounced leftward shift of the black distribution suggests that applicants rely heavily on their rejected proposals when preparing resubmissions. $N = \ldots$.

Figure 9:



Notes: This figure plots the distribution of cosine similarity between rejected proposals and resubmissions for cases where the resubmission occurs one period after rejection (black) alongside the distribution for cases where the resubmission occurs two periods after rejection (blue). The pronounced leftward shift of the black distribution suggests that applicants who resubmit one period after rejection build more directly on their rejected proposal than those who resubmit two periods after rejection. $N = \ldots$.

Figure 10:



Notes: This figure plots the average share of evaluators responsible for rejection who have left the panel t periods after rejection. The light blue area represents the share of close evaluators, the dark blue area the share of distant evaluators who have exited the panel. The total share of evaluators who have left the panel is given by the sum of the light blue and dark blue areas. For example, five periods after rejection, on average, 25% of close evaluators, 55% of distant evaluators, and a total of 80% of evaluators have left the panel.

Table 3:

DV	Cox PH Models				
	Proposal Submission				
	(1)	(2)	(3)	(4)	(5)
Share Turnover	0.36				
	[42.62]				
	(0.22)				
Share Turnover Close		0.67**		0.75**	1.02***
		[95.94]**		[112.26]**	[176.13]***
		(0.31)		(0.33)	(0.37)
Share Turnover Distant			0.02	0.19	0.03
			[2.48]	[21.22]	[3.54]
			(0.23)	(0.24)	(0.33)
Controls					X
# Applicants	3,021	3,021	3,021	3,021	3,021
# Rejections	5,172	5,172	5,172	5,172	5,172
# Obs.	10,358	10,358	10,358	10,358	10,358
Log Likelihood	−10,364.16	−10,363.14	−10,365.44	−10,362.83	−10,111.23

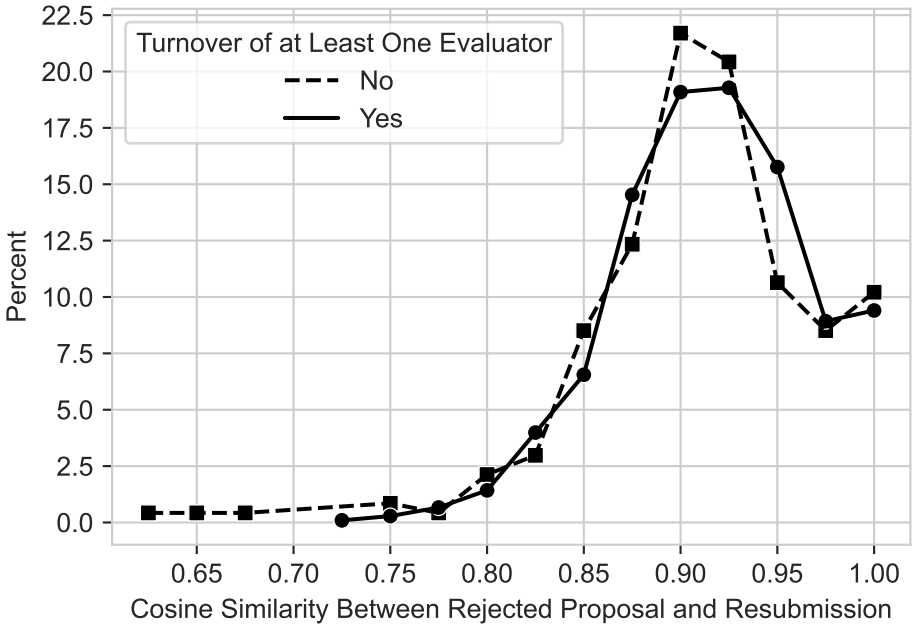
Notes: This table presents results from Cox Proportional Hazard models. The dependent variable indicates whether an applicant resubmits a proposal t periods after receiving a rejection. Independent variables capture the share of (close/distant) evaluators responsible for the rejection who are no longer on the panel in the current period. All models stratify estimates by call type. Coefficient estimates indicate changes in the log of the hazard of resubmission; values in square brackets indicate percentage changes in the hazard of resubmission. Controls are as usual. Robust standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 4:

DV	Logistic Regression				
	Proposal Submission				
	(1)	(2)	(3)	(4)	(5)
Share Turnover	0.49**				
	[1.62]**				
	(0.20)				
Share Turnover Close		0.95**		1.07***	1.36***
		[2.59]**		[2.91]***	[3.91]***
		(0.37)		(0.39)	(0.48)
Share Turnover Distant			−0.01	0.26	0.12
			[0.99]	[1.29]	[1.13]
			(0.23)	(0.20)	(0.43)
Call FE	X	X	X	X	X
Controls					X
# Applicants	3,021	3,021	3,021	3,021	3,021
# Rejections	5,172	5,172	5,172	5,172	5,172
# Obs.	10,358	10,358	10,358	10,358	10,358
Pseudo R^2	0.09	0.09	0.09	0.09	0.15

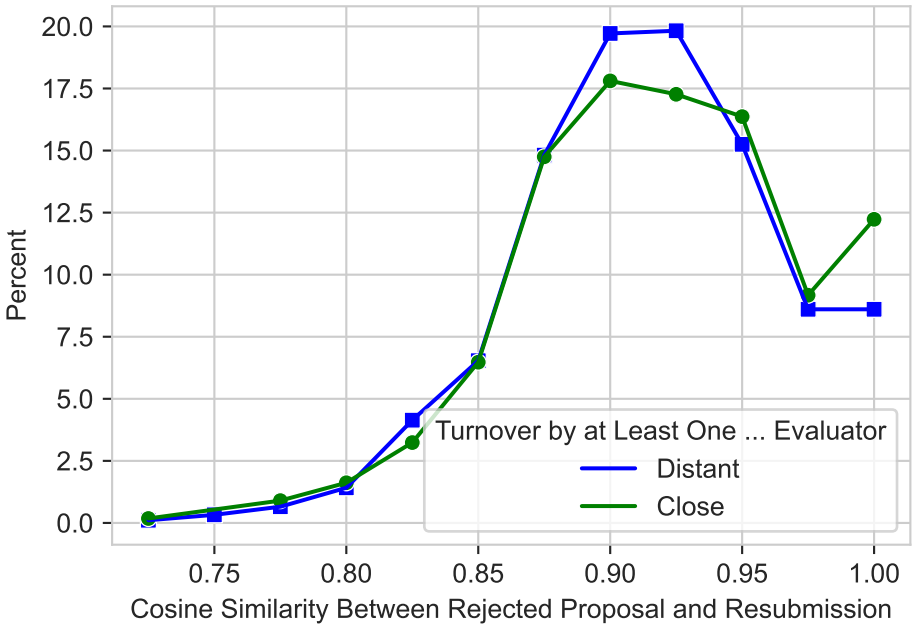
Notes: This table replicates Table 3 using logistic regression. Coefficient estimates indicate changes in the log odds of proposal resubmission; values in square brackets indicate changes in the odds of proposal resubmission. Controls are as usual. Robust standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Figure 11:



Notes: This figure plots the distribution of cosine similarity between rejected proposals and resubmissions for cases where at least one evaluator has exited the panel (solid line) alongside the distribution for cases where no evaluator has exited the panel (dashed line). The analysis is restricted to resubmissions occurring one period after rejection to account for the influence of time since rejection on both evaluator turnover and the similarity between rejected proposals and the resubmissions. $N = \ldots$.

Figure 12:



Notes: This figure decomposes the solid line from Figure 11 into cases where at least one close evaluator has exited the panel (green line) and cases where at least one distant evaluator has exited the panel (blue line). $N = \ldots$.

Table 5:

DV	OLS Regression					
	Proposal Similarity					
	(1)	(2)	(3)	(4)	(5)	(6)
Share Turnover	0.01					
	[1.10]					
	(0.01)					
Share Turnover Close		0.05***		0.05***	0.03*	0.03*
		[5.86]***		[5.61]***	[3.52]*	[3.63]*
		(0.01)		(0.01)	(0.01)	(0.01)
Share Turnover Distant			−0.02+	−0.01	0.01	0.01
			[−1.86]+	[−0.58]	[1.27]	[1.30]
			(0.01)	(0.01)	(0.01)	(0.01)
Periods Since Rej.	X	X	X	X	X	X
Call FE					X	X
Controls						X
DV Mean	0.90	0.90	0.90	0.90	0.90	0.90
# Applicants	1,061	1,061	1,061	1,061	1,061	1,061
# Obs. (=# Rej.)	1,725	1,725	1,725	1,725	1,725	1,725
R^2	0.04	0.05	0.04	0.05	0.11	0.11

Notes: This table presents results from OLS regression of the similarity between rejected proposals and resubmissions on evaluator turnover. The dependent variable measures the extent to which the resubmission builds on the rejected proposal, with 1 indicating identical resubmissions. Independent variables capture the share of (close/distant) evaluators responsible for the rejection who are no longer on the panel in the current period. Values in square brackets indicate percentage changes in *Proposal Similarity*. Controls are as usual. Robust standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 6:

DV	OLS Regression					
	Resubmission 99					
	(1)	(2)	(3)	(4)	(5)	(6)
Share Turnover	0.01					
	[33.53]					
	(0.03)					
Share Turnover Close		0.14**		0.13*	0.19**	0.18**
		[374.20]**		[338.83]*	[523.03]**	[484.75]**
		(0.05)		(0.05)	(0.06)	(0.06)
Share Turnover Distant			−0.06	−0.03	0.02	−0.01
			[−157.05]	[−79.61]	[48.44]	[−20.50]
			(0.04)	(0.04)	(0.04)	(0.04)
Periods Since Rej.	X	X	X	X	X	X
Call FE					X	X
Controls						X
DV Mean	0.90	0.90	0.90	0.90	0.90	0.90
# Applicants	1,061	1,061	1,061	1,061	1,061	1,061
# Obs. (=# Rej.)	1,725	1,725	1,725	1,725	1,725	1,725
R^2	0.04	0.05	0.04	0.05	0.11	0.11

Notes: This table replicates Table 5 using *Resubmission 99* as the dependent variable. * p < 0.05, ** p < 0.01, *** p < 0.001.

Table 7:

DV	OLS Regression					
	Resubmission 95					
	(1)	(2)	(3)	(4)	(5)	(6)
Share Turnover	0.00					
	[−1.69]					
	(0.07)					
Share Turnover Close		0.47***		0.40***	0.30***	0.30***
		[296.26]***		[253.50]***	[192.03]***	[189.19]***
		(0.09)		(0.10)	(0.08)	(0.08)
Share Turnover Distant			−0.25***	−0.15*	0.05	0.04
			[−157.17]***	[−96.26]*	[29.32]	[28.17]
			(0.07)	(0.07)	(0.07)	(0.07)
Periods Since Rej.	X	X	X	X	X	X
Call FE					X	X
Controls						X
DV Mean	0.90	0.90	0.90	0.90	0.90	0.90
# Applicants	1,061	1,061	1,061	1,061	1,061	1,061
# Obs. (=# Rej.)	1,725	1,725	1,725	1,725	1,725	1,725
R^2	0.04	0.05	0.04	0.05	0.11	0.11

Notes: This table replicates Table 5 using *Resubmission 95* as the dependent variable. * p < 0.05, ** p < 0.01, *** p < 0.001.

Table 8:

DV	OLS Regression					
	Funded					
	(1)	(2)	(3)	(4)	(5)	(6)
Proposal Similiarity	0.13			−0.04		
	(0.17)			(0.09)		
Resub. 99		0.01			0.02	
		(0.05)			(0.06)	
Resub. 95			0.01			0.01
			(0.02)			(0.02)
Call FE				X	X	X
Year FE				X	X	X
Controls				X	X	X
DV Mean	0.17	0.17	0.17	0.17	0.17	0.17
# Applicants	1,059	1,059	1,059	1,059	1,059	1,059
# Obs.	1,722	1,722	1,722	1,722	1,722	1,722
R^2	0.00	0.00	0.00	0.15	0.02	0.02

Notes: This table presents results from OLS regression of the funding outcome of a resubmission on its similarity to the initially rejected proposal. Controls are as usual. Robust standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 9:

DV	OLS Regression					
	Funded					
	(1)	(2)	(3)	(4)	(5)	(6)
Proposal Similiarity	0.03			−0.02		
	(0.28)			(0.20)		
Resub. 99		−0.02			−0.03	
		(0.09)			(0.06)	
Resub. 95			0.01			0.02
			(0.04)			(0.01)
Proposal Sim. x Share Turnover	0.51			−0.12		
	(0.96)			(0.80)		
Resub. 99 x Share Turnover		0.12			0.23	
		(0.38)			(0.28)	
Resub. 95 x Share Turnover			0.02			−0.06
			(0.17)			(0.09)
Call FE				X	X	X
Year FE				X	X	X
Controls				X	X	X
DV Mean	0.17	0.17	0.17	0.17	0.17	0.17
# Applicants	1,059	1,059	1,059	1,059	1,059	1,059
# Obs.	1,722	1,722	1,722	1,722	1,722	1,722
R^2	0.00	0.00	0.00	0.15	0.02	0.02

Notes: This table replicates Table 8 but extends all models by incorporating an interaction term between the respective similarity measure and the share of evaluators who left the panel, *Share Turnover*. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 10:

DV	OLS Regression					
	Funded					
	(1)	(2)	(3)	(4)	(5)	(6)
Proposal Similiarity	0.02			0.02		
	(0.22)			(0.16)		
Resub. 99		−0.05			−0.05	
		(0.07)			(0.08)	
Resub. 95			0.00			0.01
			(0.03)			(0.02)
Proposal Sim. x Share Turnover Close	1.28			−0.84		
	(1.56)			(1.49)		
Resub. 99 x Share Turnover Close		0.57			0.74	
		(0.55)			(0.55)	
Resub. 95 x Share Turnover Close			0.16			−0.07
			(0.24)			(0.25)
Call FE				X	X	X
Year FE				X	X	X
Controls				X	X	X
DV Mean	0.17	0.17	0.17	0.17	0.17	0.17
# Applicants	1,059	1,059	1,059	1,059	1,059	1,059
# Obs.	1,722	1,722	1,722	1,722	1,722	1,722
R^2	0.00	0.00	0.00	0.15	0.02	0.02

Notes: This table replicates Table 8 but extends all models by incorporating an interaction term between the respective similarity measure and the share of close evaluators who left the panel, *Share Turnover Close*. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 11:

DV	OLS Regression					
	Funded					
	(1)	(2)	(3)	(4)	(5)	(6)
Proposal Similiarity	0.16			−0.09		
	(0.25)			(0.15)		
Resub. 99		0.03			0.04	
		(0.07)			(0.05)	
Resub. 95			0.02			0.01
			(0.04)			(0.02)
Proposal Sim. x Share Turnover Distant	0.09			0.28		
	(1.17)			(0.93)		
Resub. 99 x Share Turnover Distant		−0.20			−0.14	
		(0.44)			(0.32)	
Resub. 95 x Share Turnover Distant			−0.05			−0.02
			(0.21)			(0.10)
Call FE				X	X	X
Year FE				X	X	X
Controls				X	X	X
DV Mean	0.17	0.17	0.17	0.17	0.17	0.17
# Applicants	1,059	1,059	1,059	1,059	1,059	1,059
# Obs.	1,722	1,722	1,722	1,722	1,722	1,722
R^2	0.00	0.00	0.00	0.15	0.02	0.02

Notes: This table replicates Table 8 but extends all models by incorporating an interaction term between the respective similarity measure and the share of distant evaluators who left the panel, *Share Turnover Distant*. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 12:

DV	OLS Regression					
	Funded					
	(1)	(2)	(3)	(4)	(5)	(6)
Proposal Similiarity	2.53**			2.41*		
	(0.81)			(1.09)		
Resub. 99		0.19			0.24	
		(0.19)			(0.17)	
Resub. 95			0.23+			0.22*
			(0.12)			(0.09)
Proposal Sim. x Grade Rejected	−0.81**			−0.79*		
	(0.26)			(0.32)		
Resub. 99 x Grade Rejected		−0.07			−0.08	
		(0.06)			(0.05)	
Resub. 95 x Grade Rejected			−0.08*			−0.07*
			(0.04)			(0.03)
Call FE				X	X	X
Year FE				X	X	X
Controls				X	X	X
DV Mean	0.17	0.17	0.17	0.17	0.17	0.17
# Applicants	1,059	1,059	1,059	1,059	1,059	1,059
# Obs.	1,722	1,722	1,722	1,722	1,722	1,722
R^2	0.05	0.05	0.05	0.07	0.07	0.07

Notes: This table replicates Table 8 but extends all models by incorporating an interaction term between the respective similarity measure and the grade of the rejected proposal, *Grade Rejected*. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.