R&D grants and the novelty of innovation*

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Abstract

The paper examines whether competitive R&D grants incentivize private firms to pursue innovation in unexplored directions or more conventional ones. We use applicant-level data from the largest ever European program awarding R&D grants to individual small and medium-sized enterprises. We do not find any evidence of systematic bias against novelty in grant allocation, as firms with more unconventional patents before the program are not ranked lower than firms with more conventional patents. We then exploit the discontinuity in the program design to infer the effects of grants and find that: i) they induce firms to innovate in domains that are new and distant from their past technological trajectories; ii) they increase the likelihood of introducing unconventional patents without increasing the chances of filing conventional ones. These results are driven by firms that are cash-constrained, which is consistent with the idea that financial frictions hinder more risky and experimental research endeavors.

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1 Introduction

Competitive research and development (R&D) grants are one of the most widely used policy instruments to promote innovation in the private sector. As a result, extant literature in the field has primarily focused on whether grants increase the quantity of R&D. Firms, however, do not just decide how much R&D to conduct; they also choose how to direct their resources across R&D projects that may be relatively conventional and safe, or atypical and risky. To understand how grants affect the direction of innovative activities it is then important to study these policies across two dimensions. The first concerns how funding agencies allocate grants. Do these institutions systematically favor projects that explore uncharted territory or safer and more conventional ones? This is important as potential biases towards more exploratory projects may impede or delay breakthroughs. The second dimension has to do with the effects of grants on the nature of subsequent innovations. Do grants allow firms to explore technological areas that are similar or different from their past technological trajectory? Are grants responsible for the emergence of safe and conventional inventions or risky and unconventional ones? Addressing how R&D policy affects the novelty of innovation bears particular relevance in light of recent evidence documenting a secular decline in the degree of novelty embedded in inventions (Park et al., 2023; Kalyani, 2022). Moreover, these questions are important as the market frictions characterizing private R&D investments (Nelson, 1959; Arrow, 1962) may be more severe when R&D efforts pursue unexplored and riskier pathways (Kamien and Schwartz, 1978) and that inventions departing from established technological paradigms and taking explorative routes can have deep long-term impacts on the economy and society as a whole (Dosi, 1982).[1] Finally, investigating whether public grants affect the nature of inventive activities amounts to take into account their impact on the direction of technological change, which is arguably one of the central intended goal of these programs.[2]

In this paper we provide evidence on the effects of direct public R&D support on the novelty

[1]There is increasing evidence documenting that innovations combining together disparate pre-existing ideas tend to be particularly impactful (see, e.g. Fleming 2001; Uzzi et al. 2013; Arts and Veugelers 2015; Kim et al. 2016; Berkes and Gaetani 2021). Also, innovations stemming from more radical R&D projects generate more spillovers than those created by incremental R&D efforts (see, e.g., Frankel et al. (2022)).

[2]In contrast with other innovation policies (e.g. R&D tax credits) which are considered 'technology neutral', grants are supposed to influence both the rate and the direction of technological change. In fact, they are employed to prioritize technological areas characterized by heavier market failures, featuring potentially large positive externalities or high societal returns (Bloom et al., 2019). Understanding if different types of policies have different effects in terms of the *nature* - and not only the *quantity* - of innovations is essential to design the optimal policy mix.

of innovation. To that end, we examine the SME Instrument, a European grant program explicitly designed to provide financial support to small and medium-sized enterprises (SMEs) aiming to commercialize breakthrough innovations. We link data on applicants with ORBIS Intellectual Property and PATSTAT to retrieve information about their patent applications. Based on these data, we measure the degree of unconventionality embedded in those inventions by defining two different indicators of patent novelty, as developed by Uzzi et al. (2013) and Stirling (2007). Those indicators identify innovations that are based on an unusual combination of knowledge (i.e. patents' technology classes) and deviate from more standard patterns of knowledge generation.

Motivated by recent concerns about research and innovation funding agencies' bias against the most novel ideas, we start by providing evidence on the patterns of grants allocation. In particular, we examine whether there is any bias against applicants with an *ex-ante* record of atypical innovations. By leveraging confidential information on competition rankings and awards, we show that firms featuring prior atypical innovations do have a higher chance of being ranked higher and securing a grant. Yet, these positive associations disappear when controlling for a number of observable characteristics. Hence, these results indicate the absence of any systematic bias against novelty in grant allocation to private firms.

We then exploit the discontinuity in grant assignment and adopt a regression discontinuity design (RDD) to study whether grants have an impact on the nature of *ex-post* innovations. First, we address whether R&D grants increase the novelty of innovation in relative terms. That is, we investigate if they induce firms to introduce innovations in domains that are novel relative to their past technological capabilities. Results indicate that grants increase the likelihood of patenting in technology classes that are new to the firm. Moreover, these technology classes are distant from those already used by the firm before the competition. This evidence supports the conjecture that grants allow firms to explore novel avenues rather than following their previous technological paths.

Second, we investigate if R&D grants trigger the introduction of innovations that are the result of unconventional combinations of knowledge in absolute terms (i.e. with respect to the combinations carried out in the universe of patent applications). Results show that grants induce an increase in the probability of filing very unconventional patents. On the contrary, we do not find any evidence that grants lead to the filing of conventional patents. In sum, these findings document that, absent direct public support for private R&D, we would miss out on innovations that are particularly novel and unconventional.

We also investigate heterogeneous treatment effects in order to uncover potential underlying mechanisms. The baseline results show that grants increase the chances to produce novel, and arguably riskier, patents both in relative and absolute terms, while leaving unaffected the probability of producing conventional and safer patents. This finding already provides some support for the idea that financial frictions affect innovative investments in heterogeneous ways depending on the degree of risk and uncertainty (Kamien and Schwartz, 1978). To directly corroborate this hypothesis, we test whether treatment is sensitive to the availability of internal financial resources before the competition. Results confirm this conjecture as we find that firms with lower cash-holdings before the competition drive the overall results.

This paper contributes to several strands of literature. It speaks to the growing literature on grant allocation processes in research and innovation funding (see, e.g. Li 2017; Myers 2020; Azoulay and Li 2022; Lane et al. 2022). In particular, several studies have documented that researchers with a track-record of novel research tend to be evaluated less favorably by funding agencies.[3] Against this backdrop, there is increasing concern that competitive research grants prioritize relatively safe, conventional projects over risky, novel ones (Wang et al., 2018; Franzoni and Stephan, 2023). Beyond the potential biases against *ex-ante* novelty, there is only limited and mixed evidence on whether competitive grants stimulate high-risk, high-reward innovations *ex-post* (Azoulay et al., 2011; Veugelers et al., 2022).[4] A common feature of this literature is that it largely focuses on scientific funding to researchers. To the best of our knowledge, this is the first study addressing these issues in the context of a competitive program assigning innovation grants to private firms.[5]

The paper also contributes to the R&D evaluation literature. Most empirical work in this field

[3] For instance, Boudreau et al. (2016) find in an experimental setting that evaluators assign lower scores to highly novel proposals. Ayoubi et al. (2021), based on applications data to Swiss National Science Foundation's SINERGIA program, document that novel scientists receive lower scores by evaluators and have lower likelihood of being awarded a grant. Veugelers et al. (2022) examine the selection procedure of the European Research Council (ERC) and show that applicants with a track-record of risky research are less likely to be awarded funding. In contrast with these findings, Packalen and Bhattacharya (2020) show that the NIH funds edge science more often than less novel science, but with a delay.

[4] Azoulay et al. (2011) compare the research output of HHMI funded researchers with that of a matched sample of NIH-funded researchers. The program influences a shift in their research direction towards exploring novel avenues of investigation. Veugelers et al. (2022) find no clear evidence that ERC grants induce researchers to conduct more novel and riskier research.

[5] One of the few studies assessing bias against novelty in the private sector is Krieger et al. (2022). Based on an internal start-up program of a pharmaceutical company, they show that R&D projects perceived as more risky tend to be penalized more.

looks at whether grants have an impact on terms of the quantity of innovation (see, e.g., Bronzini and Piselli 2016; Howell 2017; Santoleri et al. 2022). On the contrary, very few studies address the relationship between R&D subsidies and the nature of innovation. Bérubé and Mohnen (2009) use survey data from Canadian firms and find that subsidized firms introduced more world-first innovations. Beck et al. (2016), using firm-level Swiss CIS data, find that R&D subsidies increase the introduction of radical innovations (i.e. the sales percentage of products being radically new to the firm or to the market) as opposed to incremental innovations (i.e. the sales share of products that are significantly improved compared to already existing ones).[6] Yet, these studies have generally two main drawbacks. The first is the use of self-reported measures of novelty. The second is the lack of applicant data and the reliance on matching on observables to build control groups. Hence, unobserved characteristics of firms that have applied for R&D support may be systematically different from those of firms that may not even be willing to commit to R&D, which makes the treatment-control comparison misleading. Differently from such studies, we combine patents – which we use to define the type of innovation produced by firms – with applicant-level data, and employ a clearer identification strategy to infer the effect of grants on the direction of innovation.

Our work also adds to the literature on financial frictions and firms' R&D investments (see, e.g., Bond et al. 2005; Brown et al. 2009; Hall and Lerner 2010; Kerr and Nanda 2015) and on whether financial frictions have a differential impact depending on the degree of novelty embodied in innovative efforts (Kamien and Schwartz, 1978; Czarnitzki and Hottenrott, 2011). Recently, two papers have dealt with financing frictions and firm investment in novel, risky projects. Krieger et al. (2022) show that exogenous cash flow shocks to pharmaceutical companies affect their decisions to develop more novel drugs, while leaving unaffected the chances to develop marginal "me-too" drugs. Widmann (2022) finds that R&D grants in Austria lead firms to file more unconventional patents. Differently from Krieger et al. (2022) and Widmann (2022), whose contributions focus respectively on the US pharmaceutical sector and on Austria, we leverage a much broader setting spanning various countries and sectors. Moreover, they focus on relatively larger firms, whereas

[6]Other studies focus on public R&D funding in general, that is, not confined to private firms. Corredoira et al. (2018) find that patents stemming from US federally funded R&D tend to have more influence on subsequent innovations and are in technological areas that private corporations eschew. Fleming et al. (2019) provide descriptive evidence that patents relying on federal research are more likely to introduce words not seen in previous patents, suggesting they are more novel and foundational.

our context encompasses small, young, and mainly high-tech firms,[7] which play a crucial role for aggregate economic dynamism (Haltiwanger et al., 2016).

2 Empirical setting

2.1 Institutional framework

In this paper we examine the SME Instrument, a program established in 2014 and managed by the Executive Agency for Small and Medium-sized Enterprises (EASME) of the European Commission.[8] The policy was explicitly designed to provide support for companies conducting high-risk, high-reward innovations. The scheme is in fact "the first ever attempt of EU research and innovation funding programmes to invest in high potential and high risk, disruptive innovation in single SMEs" (European Commission and Executive Agency for Small and Medium-sized Enterprises, 2017, p.6).

The program awards grants that can be worth between €0.5 and €2.5 million to fund R&D activities.[9] Firms have four deadlines every year by which to submit their proposals. They apply to topic-specific contests that are divided into 13 categories. Proposals submitted by eligible SMEs[10] are then evaluated by four independent experts appointed by EASME. The evaluation is carried out remotely. Experts work independently from one another, they are unaware of each other's assessments and the final number of grants to be awarded. Evaluators are required to rate proposals on three criteria (impact, excellence, and quality & efficiency of implementation), on a scale from 0 to 5. Each project receives a final score that ranges from 0 to 15 by summing the median scores for each of the three categories. Based on these scores, the projects are then ranked. Proposals that score higher than the minimum quality threshold (i.e. 12 points) can be awarded the grant. Yet, not all of them will receive it as the budget allocated to each competition is limited and this ultimately determines the number of grants to be disbursed.[11] Projects deemed worthy of funding

[7]Our sample is composed by firms that, on average, have 20 employees. In Widmann (2022), firms have 119 employees on average.

[8]Both the agency and the program were recently re-branded. Since 2019, the SME Instrument is known as European Innovation Council (EIC) Accelerator. In 2021, EASME became EISMEA (i.e. European Innovation Council and SMEs Executive Agency).

[9]Grants cover 70% of all project costs for a 12-24 month period.

[10]A proposal will be evaluated if all three of the following conditions are met: i) the applicant is a for-profit SME; ii) the applicant is established in a EU Member State or a Horizon2020-associated country; iii) the applicant does not have concurrent submissions or executions of another SME Instrument proposals.

[11]It is important to note that the funding amount for each competition is set beforehand and does not change based on the number of applicants or eligible firms. Grants will be awarded to firms above the minimum quality standard

but that are not awarded a grant due to budgetary constraints receive the "Seal of Excellence" (SOE). The SOE serves as a recognition of the proposal's high value and it is intended to help companies increase their visibility and access alternative funding from private or public sources.

We use data from all competitions organized by EASME throughout 2014-2017. We have information on the applicant's company name, address, funded status, and award notice date. While the identity of beneficiaries is publicly disclosed, information on ranks and unsuccessful applicants is not. Descriptive statistics on competitions are reported in the top panel of Table 1. The average competition features around 81 applicants and four winners. The average grant size is €1.6 million.[12]

2.2 Measuring the novelty of innovation

New inventions are often the result of the recombination of pre-existing bits of knowledge (see, e.g., Schumpeter 1939; Fleming 2001). This process can lead to relatively safe and conventional innovations when it involves pieces of knowledge that are frequently recombined together. Riskier and unconventional projects, instead, usually propose atypical combinations of previous knowledge. Following this idea, existing literature has measured the nature of innovation and its degree of novelty by looking at the type of recombination carried out in scientific research or inventions. For instance, Uzzi et al. (2013) define the novelty of scientific articles by identifying the relevance of atypical combinations of knowledge (i.e. journals in articles' references) in each paper. The higher the importance of combinations that deviate from what is observed in the past, the higher the article's novelty. Kim et al. (2016) follow this methodology to measure novelty in patents by considering technological classes as the bits of knowledge recombined in the inventive process.[13]

In the same vein, we use similar indicators to detect the degree of novelty associated with the inventions of SME Instrument applicants by analyzing the presence of unconventional and risky combinations of previous knowledge in their patent portfolio. Since we aim to study how the grants deviate firms' R&D activities from pre-existing paths at the firm and global level and open

until all competition funds run out.

[12] For additional details and summary statistics about the institutional context and evaluation procedures, see Santoleri et al. (2022).

[13] Technological (sub)classes represent the standard classification of technology embedded in a patent and are assigned, and continuously updated, by intellectual property offices to each patent application. They are widely used in the literature to represent the units of technological knowledge that are recombined to generate new inventions (see, among others, Fleming 2001).

up unprecedented research trajectories, our approach focuses on the detection of atypical or distant knowledge (i.e. technology classes) combinations.[14] To that end, we link applicant data with ORBIS Intellectual Property and PATSTAT databases, which allow us to retrieve information on firms' patent applications at the patent offices of all countries participating to the SME Instrument.[15] We then include each invention only once (even if it has been patented in multiple patent offices) by considering data at the patent-family level (i.e. DOCDB families). For each patent family we retrieve the earliest application date and the list of associated technology classes at the 4-digit level according to the Cooperative Patent Classification (CPC). Exploiting this information, we can establish the degree of unconventionality and novelty of the knowledge produced by SME Instrument applicants before and after the competition. To assess this novelty, we consider a four-year time window for each period (pre- and post-competition), and we introduce a one-year lag between the competition and the patent application dates to properly select inventions developed in the post-competition phase.

Specifically, we introduce two different categories of novelty indicator for each applicant-competition pair:

- Absolute novelty, that measures the nature of innovation produced by the applicant before and after the competition compared to the novelty of patents filed in all considered patent offices in the same period and assigned to same technology classes (i.e., novelty relative to the universe of inventions).

- Relative novelty, that detects how different and atypical is the knowledge produced in the post-competition phase compared to the one generated before the competition by the same applicant (i.e., novelty with respect to applicants' past trajectories).

[14] While we are observing an increasing number of novelty indicators in science and technology based on text analysis (see, e.g., Arts et al. 2021; Balsmeier et al. 2018; Fleming et al. 2019; Kelly et al. 2021), the use of patent technology classes allows a simpler representation of the technological knowledge space and an easier detection of deviations from standard technological trajectories. Firstly, technology classes represent a standardized and well-established map of technologies, while there is no agreement on text-mining indicators and their ability to represent a technological space. Secondly, technology classes allow the analysis of patents independently of the language of their texts. This aspect is particularly relevant in our setting since we study patents in different languages from different patent offices and we work at the patent-family level. Text-mining measures are usually tested on patents written in a single language (mostly English) and their application to a multi-language setting would create issues in the interpretability of results. Indicators based on technology classes are, therefore, a better choice for our purpose.

[15] These encompass all patent offices of the EU-28 Member States and Horizon2020-associated countries, including the European Patent Office (EPO).

Both indicators are based on the definition of atypical combinations of technologies and the detection of the relevance of these atypical combinations in the inventions produced by SME Instrument applicants. Therefore, we are interested in detecting the degree of unconventionality of knowledge recombination in absolute and general terms. To this purpose, we define a knowledge space in which the location of each technology class is based on its proximity to all other technologies. This proximity is computed on the universe of patents filed in all patent offices in order to obtain an indicator of similarity among technology classes that is as objective as possible. From this perspective, atypical combinations of technology are those that are distantly located in the knowledge space.

While our measures of novelty are grounded on the literature that detect atypical combinations of knowledge in science and technology (Uzzi et al. 2013, Kim et al. 2016, Berkes and Gaetani 2021, among others), they differ from previous indicators for two crucial reasons. Firstly, we define indicators at the applicant level instead of considering only the micro perspective (scientific article or patent levels). Secondly, previous measures focus on what we call 'absolute novelty'. Instead, in this paper we introduce a generalization of atypical-combinations indicators in dynamic terms to detect the relative novelty produced by applicants.

In what follows, we detail the construction of the novelty measures and the knowledge space that we use to detect atypical combinations.

Knowledge space Since novelty indicators are based on the detection of atypical (distant) combinations of technology classes, we first assess the technology-class proximity, intended as the normalized frequency of co-occurrence between two different classes (CPC codes). Atypical and unconventional combinations of knowledge are those that are distant in this knowledge space. In this respect, we define technological spaces for each time period by computing the normalized co-occurrence of the technology classes that are assigned to the universe of patent families in all considered patent offices. Since larger technological classes will occur more frequently, these co-occurrences are normalized by the size of the various classes across time by introducing a null model that estimates the number of co-occurrences if the CPC codes were randomly assigned to each patent family. The obtained technology-class proximity is equal to the ratio between the observed and the estimated CPC co-occurrences (as in Berkes and Gaetani 2021), re-scaled by the arctangent function to obtain a number between 0 and 1 and, most importantly, to ensure the symmetry in the distribution of typical and atypical combinations in proximity values:[16]

$$p_{jk} = \arctan \frac{C_{jk}^{Observed}}{C_{jk}^{Expected}}, \tag{1}$$

where j and k are two CPC codes at the 4-digit level, p_{jk} is their proximity and $C_{jk}^{Observed}$ ($C_{jk}^{Expected}$) is the observed (expected) number of co-occurrence between j and k.[17]

Absolute novelty The first novelty indicator addresses whether firms with R&D grants present a higher likelihood of filing patents that are the result of unconventional combinations of technology classes in absolute terms (i.e. relative to the universe of patent families). Based on this definition, we have firstly to asses the novelty of patent families filed by SME Instrument applicants.

We can detect patent novelty in terms of the unconventionality of their knowledge recombination by considering the previously defined knowledge space. Specifically, following Uzzi et al. (2013), we introduce an indicator that detects the relevance of atypical (distant) combinations of knowledge in patents' technology classes. For each patent family f, we define an indicator of novelty as:

$$\text{Patent Novelty}_f = 1 - \text{10th percentile}\left(F_f(p_{jk})\right), \tag{2}$$

where $F_f(p_{jk})$ is the cumulative distribution of proximity among pairs of CPC codes associated to the patent family f.[18]

We also provide an alternative definition of patent novelty, i.e. the disparity index (Stirling, 2007). This indicator is equal to the average distance among CPC codes associated to each patent family and grows with the degree of unconventionality of CPC combinations.[19] The disparity of a

[16]With this re-scaling, the value 0.5 discerns between typical and atypical combinations. Strongly atypical combinations are close to 0, while common ones are close to 1. Without the arctangent function, a value between 0 and 1 would correspond to atypical combinations (observed value lower than the expected one) while a value between 1 and infinity would indicate typical combinations (observed value greater than the expected one).

[17]It is worth noticing that we consider rolling windows of four years to define these knowledge spaces for what concerns absolute novelty measures (pre- or post-competition periods) and rolling windows of eight years for relative novelty indicators (since these measures are related to both the periods before and after the competition). This approach allows us to consider the evolution of technology proximity and provide a more precise measure of novelty.

[18]Following Uzzi et al. (2013) and Berkes and Gaetani (2021), we selected the 10^{th} percentile of the proximity distribution to detect highly atypical (distant) combinations of CPC pairs. To obtain a value that grows with the degree of unconventionality we define our index as 1 minus this percentile.

[19]This indicator is widely applied in the interdisciplinarity literature (see, for instance, Stirling 2007). However, it can also be interpreted as a measure of novelty as atypical combinations. Fontana et al. (2020), indeed, show that

patent family f is equal to:

$$\text{Patent Disparity}_f = \frac{\sum_{j,k \in T_f;\, j \neq k} (1 - p_{jk})}{n_f(n_f - 1)}, \tag{3}$$

where T_f and n_f are, respectively, the set and the number of technology classes in the patent family f and p_{jk} is the proximity between these technology classes.

To control for novelty heterogeneity in different technology classes over time, we compute the patent novelty and patent disparity for the universe of patent families filed in all considered patent offices, and we assign to each patent family in our sample the corresponding percentile of the novelty distribution of patents filed in the same year and same technology classes.

We then use those indicators to define dummy variables that capture applicants' absolute novelty and disparity in the pre- and post-competition periods. Specifically, for each period, we identify a firm as novel (non-novel) in absolute terms if its best patent in terms of novelty belongs to the top (bottom) tercile of the novelty distribution. The same procedure is applied to the disparity index. Specifically, for each firm-competition pair ic, we define:

$$\text{Top Absolute Novelty}_{ic}^{Pre(Post)} = \mathbb{1} \Big| \left[\exists f \text{ for } f \in \left(PP_i^{Pre(Post)} \cap P_{top33}^{N} \right) \right], \tag{4}$$

where $PP_i^{Pre(Post)}$ is the firm's patent portfolio in the pre (post) competition period and P_{top33}^{N} is the top tercile of the patent novelty distribution. To better assess the novelty of each patent independently of the year and field of the invention, we define novelty distributions that are normalized by year and technology class.[20] Analogously, we define *Bottom Absolute Novelty*$_{ic}^{Pre(Post)}$ as a dummy variable equal to 1 for firms with their best patent in term of novelty in the bottom tercile of the patent novelty distribution.

Similarly, the absolute disparity of firms is:

$$\text{Top Absolute Disparity}_{ic}^{Pre(Post)} = \mathbb{1} \Big| \left[\exists f \text{ for } f \in \left(PP_i^{Pre(Post)} \cap P_{top33}^{D} \right) \right], \tag{5}$$

it is highly correlated to the novelty indicator presented by Uzzi et al. (2013) and that the two measures provide similar information. Moreover, Yang et al. (2022) use a generalized version of the disparity index, i.e. the Rao-Stirling diversity, as an alternative indicator of novelty. Results using this indicator are very similar and they are reported in the Appendix.

[20] We consider novelty distributions for each application year and technology class. Since patents are usually assigned to more than one technology class, we associate to each patent the weighted average of the its percentiles in the patent novelty distributions of the technology classes of the patent itself.

where P^{D}_{top33} is the top tercile of the patent disparity distribution. The *Bottom Absolute Disparity*$^{Pre(Post)}_{ic}$ is instead a dummy variable equal to 1 for firms with their best patent in term of disparity in the bottom tercile of the patent disparity distribution.

Descriptive statistics on absolute novelty indicators are reported in the bottom panel of Table 1. Around 30% (20%) of all applicants filed for at least one patent before (after) the competition. Both novelty measures indicate that approximately 12% (9%) has an unconventional (conventional) patent before the program. After the program, around 7% (7%) has an unconventional (conventional) patent.

[Table 1 here]

Relative novelty The second set of novelty measures examines the impact of R&D grants on exploring technological domains that are novel to a given firm, relative to its prior patenting behavior. To do so, we restrict the analysis to firms with at least one patent filed before the competition. We then consider several measures by comparing the technology classes assigned to patent families of the same firm between the pre-competition and the post-competition period. Before moving to novelty indicators based on typical and atypical combinations, we assess whether the firm introduces new technological knowledge in the post-competition period. For each firm-competition pair, we record all distinct technology classes that are assigned to any patent family filed by the firm during the post-competition period. Then we count how many of these technology classes had not been assigned to any patent family filed by the same firm in the pre-competition period. We compute i) whether firms have introduced new technology classes, ii) the number of new technology classes, and iii) the number of new technology classes over the number of patent families filed in the post-competition period. These measures are then employed to test whether grants induce firms to patent in new technology areas. Yet, they are not informative as to whether firms keep patenting in areas that are close or distant to what the firm has done in the past. To that end, we consider indices that capture the technological distance, as defined in the knowledge space, between firms' patenting behavior before and after the competition. In particular, we propose a dynamic version, at the firm-competition level, of the novelty indicator proposed in Eq. 2. This measure captures the novelty of newly introduced technology classes with respect to the pre-competition ones, i.e. the relevance of atypical combinations in pairs of pre-competition/newly introduced technology classes. For each firm i and competition c, we define the relative novelty as:

$$\text{Relative Novelty}_{ic} = 1 - \text{10th percentile}\left(F_i(p_{rs})\right), \tag{6}$$

where $F(p_{rs})$ is the cumulative distribution of proximity (as defined in equation 1) among pairs of pre-competition CPC codes (r) in the firm's patent families and CPC codes (s) introduced in the period after the competition by the same firm.

As for the absolute novelty indicators, we introduce an alternative measure of relative novelty, which is defined as the average distance between old and new CPC codes for each firm-competition pair. This indicator is a dynamic generalization of the disparity index introduced in Eq. 3. The relative disparity of a firm i in competition c is equal to:

$$\text{Relative Disparity}_{ic} = \frac{\sum_{r \in T_i^{old},\, s \in T_i^{new}} (1 - p_{rs})}{n_i^{old} \cdot n_i^{new}}, \tag{7}$$

where T_i^{old} is the set of technology classes in the firm's patent families before the competition, T_i^{new} is the set of newly introduced CPC codes, n_i^{old} and n_i^{new} are the number of old and new CPC codes, and p_{rs} is the proximity between old and new technology classes.

We then define dummy variables indicating whether the firm-competition pair is in the top (bottom) tercile of the relative novelty (*Top (Bottom) Relative Novelty*$_{ic}$) and relative disparity (*Top (Bottom) Relative Disparity*$_{ic}$) distributions.

3 Estimation strategy

Our first goal is to understand whether firms with a track record of atypical innovations before the program have higher (lower) likelihood of being ranked higher and win a given competition. To that end we estimate the following regression by means of ordinary least squares (OLS):

$$Grant_{ic} = \alpha + \beta Y_{ic}^{Pre} + \gamma X_{ic}^{Pre} + \delta_c + \varepsilon_{ic} \tag{8}$$

where the dependent variable is a dummy variable indicating whether applicant i has received a grant or not in competition c. Alternatively, we use the (log) raw ranking assigned to applicant

i in competition c on the left hand side. Our variable of interest is Y_{ic}^{Pre}, which proxies the innovation novelty of applicant i in the period preceding the competition (see Eq. (4) and (5)). We always include competition fixed effects (δ_c), while some specifications also feature a set of control variables (X_{ic}^{Pre}) encompassing a dummy for patents, number of patent citations, amount of funding requested, proposal duration, 2-digit (NACE rev.2) sector fixed effects, country fixed effects, age fixed effects, consortium fixed effects and first applicant fixed effects. Standard errors are robust and clustered at the competition level to adjust for potential serial correlation in errors.

After assessing whether grant and ranking assignment are biased against novelty, we move on to examine the causal effects of grants in terms of the direction of innovation. The identification strategy exploits the policy's assignment mechanism: firms' proposals are ranked according to experts' evaluation and funding availability ultimately determines the number of grants awarded in each competition. We leverage this discontinuity and employ a sharp RDD comparing firms around the threshold. The RDD approach is based on the idea that treatment assignment around the threshold is approximately random. In this context, firms that are close to the threshold on either side are supposed to be very similar, and potential differences in the post-treatment performance of beneficiaries and non-beneficiaries can be attributable to the grant. In light of this, we estimate the following equation by means of OLS:

$$\begin{aligned} Y_{ic}^{Post} = &\alpha + \beta Grant_{ic} + f\left(Rank_{ic}\right) + \gamma Y_{ic}^{Pre} + \delta_c + \varepsilon_{ic} \\ &\text{where } -r \leq Rank_{ic} \leq r \end{aligned} \tag{9}$$

Y_i^{Post} is one of the unconventionality measures during the post-treatment period for firm i in competition c; $Rank_{ic}$ is the centered rank assigned by experts to firm i in competition c, $Grant$ is an indicator for firm i winning the competition c (i.e. $Rank_{ic} > 0$); $f\left(Rank_{ic}\right)$ is a polynomial control for centered ranks. All regressions feature the pre-assignment dependent variable (Y_i^{Pre}) to reduce variability (Lee and Lemieux, 2010) and competition fixed effects (δ_c). The latter effectively restrict the comparison to applicants on either side of the threshold, but within the same competition, thus controlling for time and topic specific factors.[21] Finally, r is the bandwidth, ε_{ic} is the idiosyncratic error term and standard errors are robust and clustered at the competition-level.

[21] Competitions have a thematic nature as detailed in Santoleri et al. (2022).

We use variants of Eq. (9) to address two potential effects stemming from grants. The first one relates to the possibility that grants allow firms to deviate in terms of their pre-existing technological trajectory. In this case, we limit the analysis to applicants that have already patented in the period preceding the competition. The second case concerns the possibility that grants induce a higher chance to produce patents that are novel not only with respect to the previous activity of a given firm, but in relation with the universe of patent applications. In other words, the first approach examines whether grants increase relative novelty (i.e. relative to the firm's past), whereas the second approach investigates whether they induce absolute novelty (i.e. relative to the entire technological space).

The validity of the research design hinges on the absence of manipulation of the running variable and of discontinuity in pre-competition observables between firms on either sides of the threshold. Santoleri et al. (2022) discuss manipulation and provide evidence of continuity of baseline co-variates around the threshold. In the Appendix we provide additional evidence focusing on the pre-intervention dependent variables considered in this paper (see Table A2). Graphical evidence of local continuity in pre-intervention dependent variable is reported in Figure 1. Results confirm that before applying, grantees and non-grantees do not differ in terms of having filed for patents that are either typical or atypical, which reassures on the validity of the research design.

4 Results

This section presents the main results. Section 4.1 examines whether there is any evidence of bias against novelty in grant allocation. Section 4.2 describes the effects grants have on the novelty of innovation. Finally, section 4.2 tests for heterogeneous effects to uncover potential mechanisms.

4.1 Bias against novelty?

Table 2 contains the results from Eq. (8), where we regress the $Grant_{ic}$ or the (log) raw ranks against a dummy indicating whether a firm has filed atypical (typical) patents before the competition. Odd columns report regression results controlling for competition fixed effects only. They indicate that firms with unconventional innovations enjoy a 3 p.p. higher chance of securing the grant. In line with this, having an unconventional innovation before the competition decreases by around 23%

the raw ranking obtained by a given applicant (i.e. a higher position in the final ranking). We then test whether these findings hold when accounting for a host of additional observable characteristics. Even columns in Table 2 report regression results controlling for a dummy for patents, number of patent citations, amount of funding requested, proposal duration, 2-digit (NACE rev.2) sector fixed effects, country fixed effects, age fixed effects, consortium fixed effects and first applicant fixed effects. The inclusion of these covariates substantially reduces the size of the coefficient which loses statistical significance. When estimating regressions using a dummy indicating whether a firm has filed for a typical innovation before the competition, we find similar results with grants increasing the likelihood of securing a grant (1.5-2 p.p) and ranking higher (16-18%). This suggests that what matters in terms of achieving a higher ranking or being awarded a grant is actually having patented before the competition, irrespective of the degree of novelty of that innovation. In Appendix Table A1 we restrict the sample to those applicants that filed at least one patent before the competition. Results seem to suggest that there is some positive discrimination in favor of unconventional innovators: having an unconventional (conventional) patent increases (decreases) the chances to secure the grant and rank higher in a competition, though point estimates are never statistically significant when controlling for the additional covariates.

In sum, these findings do not provide support for the the idea that having a track-record of atypical innovations leads applicants to be discriminated against in terms of winning or being ranked higher in a grant competition.

[Table 2 here]

4.2 The effects of grants on the novelty of innovation

Do grants induce firms that have patented in the past to introduce patents in new technological domains? Table 3 answers this question by estimating our baseline RDD Eq.(9). As we are interested in learning whether grants affect the behavior of firms with patents prior to the competition, we only include applicants with at least one filed patent before participating. Regression results using different bandwidths around the threshold indicate that grants increase the likelihood of patenting in new technology classes by around 12-15 p.p. Similar findings are obtained when using different dependent variables: grants induce a 17-24% increase in the the (log) number of new technology classes plus one, and a 20-25% increase in the number of new technology classes divided by the number of patent families. This evidence combined suggests that grants lead firms to patent in novel areas in terms of both intensive and extensive margins.

[Table 3 here]

While these estimates suggest that grants induce firms to explore new technological domains, they are not informative of how new and unexplored these technological domains are relative to firms' past trajectories. In fact, firms may just innovate in new fields that are extremely close to those of prior inventions. To examine whether this is the case, we use our proxies for innovation novelty which measure the distance between what the firm has produced prior and after the competition. In particular, we create two dummy variables that take the value of 1 if the patent is in the top (bottom) tercile of the novelty distribution, and 0 otherwise. Results in Table 4 indicate that grants increase by 8-15 p.p. the chances to produce innovations that are distant from previous ones. On the contrary, we find a negative effect of grants on the production of patents that are closer to what the firm produced in the past, though point estimates are generally not statistically significant.

[Table 4 here]

We now move to assess whether grants induce firms to produce patents that are unconventional with respect to the entire technological space. Here we consider the full sample of applicants, regardless of whether they have already applied for a patent before the competition takes place.

Table 5 reports our main results. Effects for patents that pertain to the top tercile unconventionality score distribution are positive, around 5-11 p.p., and generally statistically significant at the 0.05 level. On the contrary, estimation results for the effect of the grant on the propensity to file a conventional patent tend to be considerably smaller (between 0-3 p.p.) and statistically insignificant. These results suggest that grants helps firms push the technological frontier by building on more disparate ideas to introduce novel technologies.

[Table 5 here]

4.3 Heterogeneous effects and potential channels

In this section we explore heterogeneous effects which speak to potential mechanisms. Prior literature has shown that financial frictions represent a significant hurdle for innovative firms in general (see, e.g., Hall and Lerner 2010), and that they are especially binding for firms with radical R&D projects as opposed to those firms doing routine R&D (Kamien and Schwartz, 1978).[22] The evidence reported so far already provides partial support for this conjecture: grants lead firms to produce unconventional patents, whereas they do not affect the production of conventional ones. Absent frictions, we would not observe the effects on unconventional patents. One possibility behind these findings is exactly the presence of financial frictions, which hinder firms' investments in novel and risky projects. As a result, we expect firms that have lower availability of internal finance, to be more responsive to treatment. To provide evidence on this point, we re-run all of our main specifications by splitting the sample across firms that before the competition have an above (below) median level of cash holdings over total assets. Results reported in Tables 6, 7, and 8 indicate that the coefficient on the treatment effect is positive and statistically significant for the firms with lower cash-holdings. For those with higher cash-holdings, point estimates are considerably smaller and never statistically significant. Though the difference between the two sub-groups is not always statistically significant, firms with lower cash-holdings clearly drive the overall results.

[Tables 6, 7, 8 here]

5 Robustness

We test the sensitivity of our results in the following ways, as reported in Appendix. Figure A2 displays estimates using a variety of bandwidths around the threshold. Tables A3, A4, and A5 report results obtained by augmenting our baseline equations with a number of additional controls. Estimates using robust standard errors are in Tables A6, A7, and A8. Table A9 contains placebo tests. Table A10 reports results using a local randomization inference approach, while Tables A13, A14, A11, and A12 display results with a non-parametric approach. Tables A15, A16, A17 contain results obtained using different measures of innovation novelty. Tables A18, A19, A20 report

[22] Santoleri et al. (2022) documented that grants indeed have a positive effect on the quantity of innovation by alleviating financial frictions.

estimates with alternative thresholds that define what is considered conventional vs unconventional.

6 Conclusions

The paper investigates whether government intervention through competitive R&D grants affects the novelty of innovation. Based on the European SME Instrument, we find that grant allocation is not biased towards applicants with a track-record of unconventional and arguably riskier innovations. Leveraging the discontinuity in the assignment mechanism of the policy, the paper also documents that grants induce firms to undertake innovations in new and distant technological fields compared to their prior technological trajectories. Grants also trigger the emergence of innovations that are unconventional with respect to the universe of patent applications. These results tend to be stronger for firms that are more prone to suffering from financial frictions. Overall, these findings suggests that competitive R&D grants help directing innovation efforts towards the exploration of more novel and original technologies whose emergence, development and diffusion might arguably be prevented, or slowed down, if left to pure market selection mechanisms.

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Figures and Tables

Table 1: Descriptives on competitions and applicants

	(1) Mean	SD	Median	Max	Count
# competitions	179.01				176
# applicants per competition	81.23	71.37	66	438	14296
# winning applicants per competition	3.99	2.96	3	15	703
Grant amount (€1,000)	1646.33	610.31	1530	4115	703
	Mean	**SD**	**Median**	**Max**	**N**
$\mathbb{1}\vert Patent_i^{Pre}$	0.304	0.460	0	1	14296
$\mathbb{1}\vert Patent_i^{Post}$	0.194	0.396	0	1	14296
$Top\ Absolute\ Disparity_i^{Pre}$	0.130	0.336	0	1	14296
$Bottom\ Absolute\ Disparity_i^{Pre}$	0.086	0.280	0	1	14296
$Top\ Absolute\ Disparity_i^{Post}$	0.072	0.258	0	1	14296
$Bottom\ Absolute\ Disparity_i^{Post}$	0.065	0.246	0	1	14296
$Top\ Absolute\ Novelty_i^{Pre}$	0.120	0.325	0	1	14296
$Bottom\ Absolute\ Novelty_i^{Pre}$	0.095	0.293	0	1	14296
$Top\ Absolute\ Novelty_i^{Post}$	0.068	0.252	0	1	14296
$Bottom\ Absolute\ Novelty_i^{Post}$	0.069	0.253	0	1	14296

Notes: summary statistics for competitions and applicants participating to the SME Instrument during 2014-2017. The top panel reports summary statistics at the competition-level for the estimation sample. The last column (i.e. Count) reports the total number of competitions, applicants, and winning applicants contained in the samples. The remaining columns in the top panel report the mean, standard deviation and median of the number of (winning) applicants per competition. The bottom presents summary statistics at the firm-level for different patent outcomes before and after the competitions

Table 2: Bias against novelty?

	(1) Grant	(2) Grant	(3) log(Ranks)	(4) log(Ranks)
Top Absolute Disparity$_{ic}^{Pre}$	0.030***	0.009	-0.232***	-0.009
	(0.007)	(0.008)	(0.028)	(0.033)
Controls	No	Yes	No	Yes
N	14296	13757	14296	13757
R^2	0.03	0.06	0.37	0.43
AIC	-3640.92	-3670.40	38297.19	35632.42
Top Absolute Novelty$_{ic}^{Pre}$	0.029***	0.007	-0.236***	-0.018
	(0.007)	(0.008)	(0.026)	(0.030)
Controls	No	Yes	No	Yes
N	14296	13757	14296	13757
R^2	0.03	0.06	0.37	0.43
AIC	-3635.40	-3669.69	38299.63	35632.12
Bottom Absolute Disparity$_{ic}^{Pre}$	0.019***	-0.001	-0.162***	0.008
	(0.007)	(0.008)	(0.028)	(0.034)
Controls	No	Yes	No	Yes
N	14296	13757	14296	13757
R^2	0.03	0.06	0.37	0.43
AIC	-3617.75	-3668.75	38360.86	35632.45
Bottom Absolute Novelty$_{ic}^{Pre}$	0.015**	-0.008	-0.182***	0.002
	(0.006)	(0.008)	(0.025)	(0.029)
Controls	No	Yes	No	Yes
N	14296	13757	14296	13757
R^2	0.03	0.06	0.37	0.43
AIC	-3615.44	-3669.99	38348.10	35632.51

Notes: results obtained by means of OLS estimating variants of the following equation: $Y_{ic} = \alpha + \beta Y_{ic}^{Pre} + \gamma X + \delta_c + \varepsilon_{ic}$. Dependent variable in columns 1 and 2 is a dummy variable indicating whether a firm has received a grant. In columns 3 and 4 the dependent variable is the log of uncentered rankings. All regressions include competition fixed effects. Even columns add the following controls: a dummy for patents, number of citations, amount of funding requested, proposal duration, 2-digit sector fixed effects, country fixed effects, age fixed effects, consortium fixed effects and first applicant fixed effects. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Effects on introduction of new technological classes

	(1) All	(2) ±15	(3) ±10
LHS: $\mathbb{1}\lvert new\ classes^{Post}_{ic}$			
Grant	0.132**	0.148***	0.121*
	(0.051)	(0.056)	(0.063)
N	4364	1151	861
R^2	0.13	0.25	0.29
AIC	4935.62	1227.63	875.27
LHS: $log(new\ classes{+}1)^{Post}_{ic}$			
Grant	0.198***	0.235***	0.169*
	(0.072)	(0.078)	(0.088)
N	4364	1151	861
R^2	0.14	0.25	0.29
AIC	7479.60	1922.30	1412.84
LHS: $(new\ classes/families)^{Post}_{ic}$			
Grant	0.223***	0.251***	0.195*
	(0.083)	(0.094)	(0.103)
N	4364	1151	861
R^2	0.05	0.17	0.21
AIC	9781.66	2400.42	1723.75

Notes: results obtained estimating our baseline RDD equation by means of OLS with pre-determined observables as dependent variables: $Y^{Post}_{ic} = \alpha + \beta Grant_{ic} + f\left(Rank_{ic}\right) + \delta_c + \varepsilon_{ic}$. Estimates are obtained using different bandwidths around the threshold (i.e. an infinite one, ±10 or ±5 centered ranks). The sample includes only applicants that have filed a patent before the competition. All regressions include linear polynomials of the running variable on both sides of the threshold, competition fixed effects and the pre-competition number of patents. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Effects on relative novelty

	(1) All	(2) ±15	(3) ±10
LHS: Top Relative Disparity$_{ic}^{Post}$			
Grant	0.091**	0.139***	0.111**
	(0.043)	(0.048)	(0.055)
N	4364	1151	861
R^2	0.14	0.21	0.26
AIC	2657.71	747.20	507.42
LHS: Top Relative Novelty$_{ic}^{Post}$			
Grant	0.080*	0.145***	0.112*
	(0.045)	(0.054)	(0.059)
N	4364	1151	861
R^2	0.12	0.20	0.24
AIC	2759.05	743.52	493.92
LHS: Bottom Relative Disparity$_{ic}^{Post}$			
Grant	-0.002	-0.045	-0.094*
	(0.038)	(0.047)	(0.056)
N	4364	1151	861
R^2	0.05	0.12	0.19
AIC	3027.48	797.76	533.79
LHS: Bottom Relative Novelty$_{ic}^{Post}$			
Grant	-0.003	-0.035	-0.080
	(0.036)	(0.046)	(0.054)
N	4364	1151	861
R^2	0.05	0.12	0.18
AIC	2962.71	772.29	512.23

Notes: results obtained estimating our baseline RDD equation by means of OLS with pre-determined observables as dependent variables: $Y_{ic}^{Post} = \alpha + \beta Grant_{ic} + f\left(Rank_{ic}\right) + \delta_c + \varepsilon_{ic}$. Estimates are obtained using different bandwidths around the threshold (i.e. an infinite one, ±10 or ±5 centered ranks). The sample includes only applicants that have filed a patent before the competition. All regressions include linear polynomials of the running variable on both sides of the threshold, competition fixed effects and the pre-competition number of patents. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Effects on absolute novelty

	(1) All	(2) ±10	(3) ±5
LHS: Top Absolute Disparity$_{ic}^{Post}$			
Grant	0.067***	0.057**	0.108***
	(0.020)	(0.027)	(0.036)
N	14296	2338	1378
R^2	0.11	0.20	0.24
AIC	194.23	467.51	322.68
LHS: Top Absolute Novelty$_{ic}^{Post}$			
Grant	0.069***	0.047*	0.095***
	(0.020)	(0.025)	(0.034)
N	14296	2338	1378
R^2	0.11	0.18	0.24
AIC	-557.09	457.30	307.79
LHS: Bottom Absolute Disparity$_{ic}^{Post}$			
Grant	0.016	-0.017	0.000
	(0.019)	(0.024)	(0.033)
N	14296	2338	1378
R^2	0.04	0.10	0.15
AIC	-96.59	551.69	300.95
LHS: Bottom Absolute Novelty$_{ic}^{Post}$			
Grant	0.030	-0.018	-0.013
	(0.020)	(0.025)	(0.034)
N	14296	2338	1378
R^2	0.04	0.10	0.14
AIC	612.07	756.60	465.87

Notes: results obtained estimating our baseline RDD equation by means of OLS with post-competition outcomes as dependent variables: $Y_{ic}^{Post} = \alpha + \beta Grant_{ic} + f\left(Rank_{ic}\right) + \theta Y_{ic}^{Pre} + \delta_c + \varepsilon_{ic}$. Estimates are obtained using different bandwidths around the threshold (i.e. an infinite one, ±10 or ±5 centered ranks). All regressions include linear polynomials of the running variable on both sides of the threshold, the pre-grant dependent variable and competition fixed effects. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Effects on the introduction of new technology classes (high vs low cash)

	Low-cash			High-cash		
	All	±15	±10	All	±15	±10
LHS: $\mathbb{1}\|new\ classes_{ic}^{Post}$						
Grant	0.184*	0.127	0.153	0.088	0.153	0.106
	(0.094)	(0.136)	(0.166)	(0.087)	(0.098)	(0.115)
N	1367	327	221	1555	426	313
R^2	0.21	0.46	0.56	0.19	0.39	0.42
AIC	1347.40	256.29	120.19	1696.25	366.33	260.24
LHS: $log(new\ classes{+}1)_{ic}^{Post}$						
Grant	0.310**	0.303*	0.325	0.132	0.204	0.136
	(0.126)	(0.182)	(0.226)	(0.124)	(0.132)	(0.159)
N	1367	327	221	1555	426	313
R^2	0.21	0.46	0.52	0.20	0.39	0.41
AIC	2116.10	452.26	267.77	2583.12	618.24	471.53
LHS: $(new\ classes/families)_{ic}^{Post}$						
Grant	0.397**	0.403*	0.410	0.043	0.094	0.090
	(0.176)	(0.225)	(0.249)	(0.125)	(0.151)	(0.183)
N	1367	327	221	1555	426	313
R^2	0.16	0.43	0.48	0.11	0.25	0.28
AIC	2606.29	551.94	286.97	3565.04	878.18	663.34

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Effects on relative novelty (high vs low-cash)

	Low-cash			High-cash		
	All	±15	±10	All	±15	±10
LHS: Top Relative Disparity$_{ic}^{Post}$						
Grant	0.175**	0.223*	0.299*	-0.013	0.029	-0.031
	(0.082)	(0.119)	(0.151)	(0.063)	(0.074)	(0.082)
N	1367	327	221	1555	426	313
R^2	0.22	0.38	0.48	0.16	0.35	0.41
AIC	622.37	179.58	68.72	861.74	134.67	92.76
LHS: Top Relative Novelty$_{ic}^{Post}$						
Grant	0.153**	0.260**	0.314**	0.012	0.089	0.038
	(0.075)	(0.106)	(0.127)	(0.069)	(0.082)	(0.092)
N	1367	327	221	1555	426	313
R^2	0.20	0.36	0.45	0.15	0.30	0.36
AIC	611.35	153.69	48.26	976.54	193.71	130.22
LHS: Bottom Relative Disparity$_{ic}^{Post}$						
Grant	-0.067	-0.150	-0.192	0.020	-0.074	-0.108
	(0.073)	(0.108)	(0.124)	(0.068)	(0.080)	(0.094)
N	1367	327	221	1555	426	313
R^2	0.11	0.31	0.40	0.12	0.33	0.42
AIC	795.10	124.37	71.32	1093.27	239.95	119.13
LHS: Bottom Relative Novelty$_{ic}^{Post}$						
Grant	-0.082	-0.132	-0.147	0.017	-0.074	-0.108
	(0.071)	(0.110)	(0.128)	(0.068)	(0.080)	(0.094)
N	1367	327	221	1555	426	313
R^2	0.10	0.29	0.38	0.12	0.33	0.42
AIC	769.65	112.30	66.14	1106.55	239.95	119.13

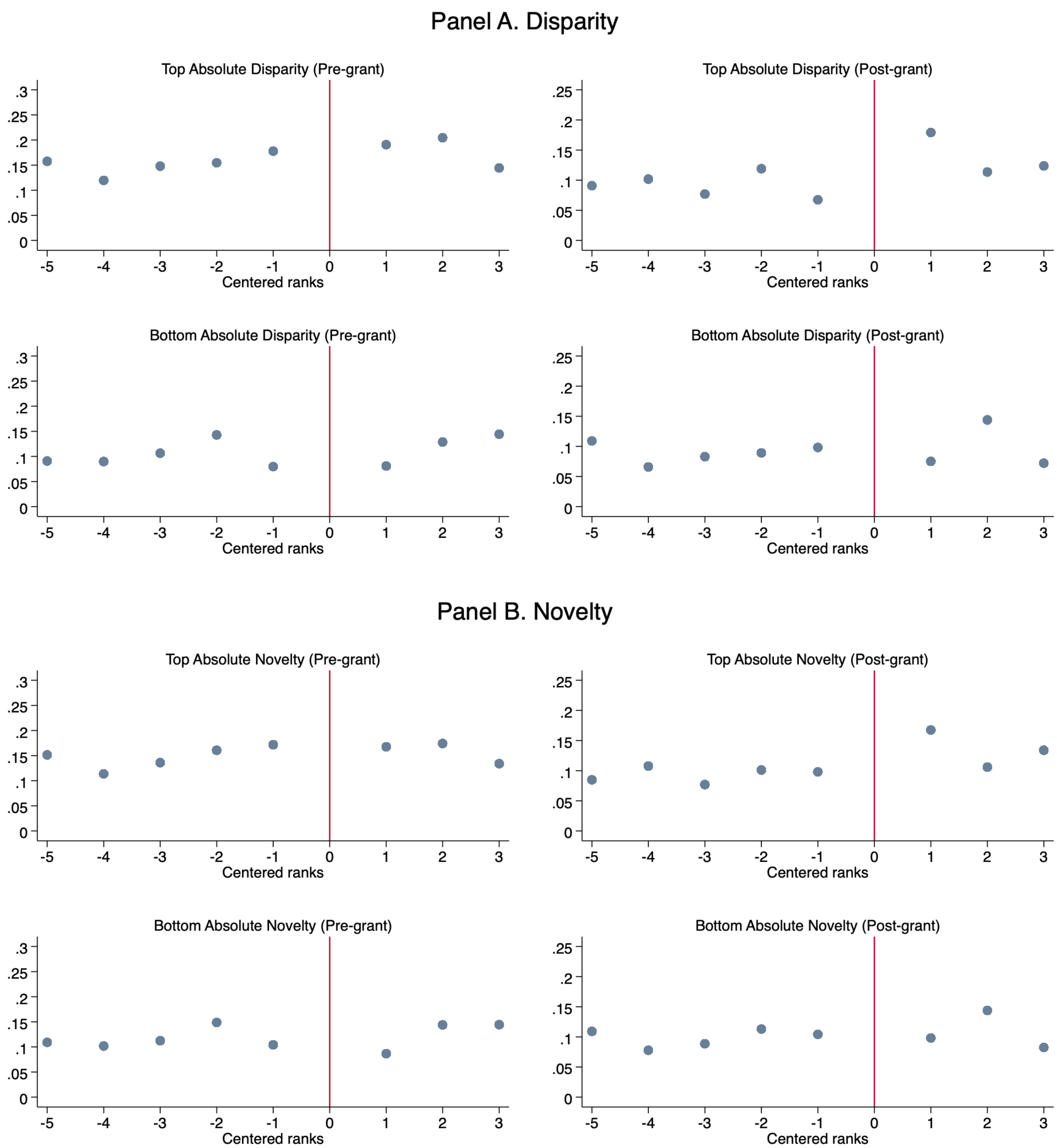
Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Effects on absolute novelty (high vs low-cash)

	Low-cash			High-cash		
	All	±10	±5	All	±10	±5
LHS: Top Absolute $Disparity_{ic}^{Post}$						
Grant	0.088**	0.106**	0.190***	0.044	0.032	0.055
	(0.038)	(0.050)	(0.071)	(0.030)	(0.039)	(0.056)
N	4701	734	399	4704	871	494
R^2	0.11	0.27	0.34	0.16	0.27	0.34
AIC	-1137.34	20.03	25.35	370.36	83.07	43.48
LHS: Top Absolute $Novelty_{ic}^{Post}$						
Grant	0.099***	0.090*	0.181**	0.044	0.049	0.063
	(0.037)	(0.047)	(0.075)	(0.029)	(0.039)	(0.052)
N	4701	734	399	4704	871	494
R^2	0.12	0.27	0.37	0.16	0.24	0.32
AIC	-1190.78	4.58	24.48	-6.11	63.06	26.95
LHS: Bottom Absolute $Disparity_{ic}^{Post}$						
Grant	-0.026	-0.060	-0.015	0.026	-0.029	0.000
	(0.028)	(0.040)	(0.059)	(0.036)	(0.048)	(0.066)
N	4701	734	399	4704	871	494
R^2	0.07	0.26	0.37	0.05	0.23	0.28
AIC	-376.09	22.65	-64.95	602.19	139.92	97.75
LHS: Bottom Absolute $Novelty_{ic}^{Post}$						
Grant	0.013	-0.032	-0.003	0.024	-0.027	0.010
	(0.034)	(0.044)	(0.064)	(0.036)	(0.049)	(0.067)
N	4701	734	399	4704	871	494
R^2	0.08	0.25	0.37	0.05	0.22	0.28
AIC	-236.59	104.98	-5.33	763.11	196.92	122.69

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure 1: RDD plots



Notes: Circles represent centered rank-level means of the pre-competition (left) and post-competition (right) firm-level outcomes. The sample includes firms with centered ranks between -5 and 3.

Online Appendix

Additional tables

Table A1: Bias against novelty? (only patent-active firms)

	(1) Grant	(2) Grant	(3) log(Ranks)	(4) log(Ranks)
Top Absolute Disparity$_{ic}^{Pre}$	0.012	0.010	-0.046	-0.033
	(0.008)	(0.009)	(0.029)	(0.035)
Controls	No	Yes	No	Yes
N	4333	4203	4333	4203
R^2	0.06	0.10	0.30	0.35
AIC	131.05	1.12	12089.50	11432.02
Top Absolute Novelty$_{ic}^{Pre}$	0.008	0.007	-0.053*	-0.042
	(0.008)	(0.009)	(0.027)	(0.032)
Controls	No	Yes	No	Yes
N	4333	4203	4333	4203
R^2	0.06	0.10	0.30	0.35
AIC	132.38	1.87	12088.77	11431.46
Bottom Absolute Disparity$_{ic}^{Pre}$	-0.004	0.000	0.049	0.024
	(0.008)	(0.009)	(0.032)	(0.034)
Controls	No	Yes	No	Yes
N	4333	4203	4333	4203
R^2	0.06	0.10	0.30	0.35
AIC	133.31	2.49	12089.60	11432.65
Bottom Absolute Novelty$_{ic}^{Pre}$	-0.009	-0.007	0.031	0.023
	(0.008)	(0.009)	(0.029)	(0.031)
Controls	No	Yes	No	Yes
N	4333	4203	4333	4203
R^2	0.06	0.10	0.30	0.35
AIC	132.35	1.77	12090.81	11432.67

Notes: results obtained by means of OLS estimating variants of the following equation: $Y_{ic} = \alpha + \beta Y_{ic}^{Pre} + \gamma X + \delta_c + \varepsilon_{ic}$. Dependent variable in columns 1 and 2 is a dummy variable indicating whether a firm has received a grant. In columns 3 and 4 the dependent variable is the log of uncentered rankings. All regressions include competition fixed effects. Even columns add the following controls: a dummy for patents, number of citations, amount of funding requested, proposal duration, 2-digit sector fixed effects, country fixed effects, age fixed effects, consortium fixed effects and first applicant fixed effects. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A2: Balancing tests

	(1) All	(2) ± 10	(3) ± 5
LHS: $\mathbb{1}\vert Patent_{ic}^{Pre}$			
Grant	0.032	-0.041	-0.047
	(0.034)	(0.040)	(0.060)
N	14296	2338	1378
R^2	0.08	0.14	0.20
LHS: log(Patents+1)$_{ic}^{Pre}$			
Grant	0.020	-0.074	-0.100
	(0.042)	(0.051)	(0.073)
N	14296	2338	1378
R^2	0.08	0.15	0.21
LHS: log(Fwd citations+1)$_{ic}^{Pre}$			
Grant	0.049	-0.142	-0.171
	(0.082)	(0.100)	(0.151)
N	14296	2338	1378
R^2	0.08	0.15	0.21
LHS: Bottom Absolute Disparity$_{ic}^{Pre}$			
Grant	-0.005	-0.031	-0.014
	(0.020)	(0.027)	(0.036)
N	14296	2338	1378
R^2	0.02	0.08	0.13
LHS: Top Absolute Disparity$_{ic}^{Pre}$			
Grant	0.048**	0.033	0.016
	(0.023)	(0.031)	(0.047)
N	14296	2338	1378
R^2	0.04	0.10	0.15
LHS: Bottom Absolute Novelty$_{ic}^{Pre}$			
Grant	-0.011	-0.030	-0.015
	(0.021)	(0.027)	(0.038)
N	14296	2338	1378
R^2	0.02	0.08	0.12
LHS: Top Absolute Novelty$_{ic}^{Pre}$			
Grant	0.030	0.012	-0.024
	(0.023)	(0.031)	(0.047)
N	14296	2338	1378
R^2	0.04	0.09	0.15

Notes: results obtained estimating our baseline RDD equation by means of OLS with pre-determined observables as dependent variables: $Y_{ic}^{Pre} = \alpha + \beta Grant_{ic} + f\left(Rank_{ic}\right) + \delta_c + \varepsilon_{ic}$. Estimates are obtained using different bandwidths around the threshold (i.e. an infinite one, ± 10 or ± 5 centered ranks). All regressions include linear polynomials of the running variable on both sides of the threshold and competition fixed effects. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Additional controls

Table A3: Effects on new technology classes

	(1) All	(2) ± 15	(3) ± 10
LHS: $\mathbb{1}\|new\ classes_{ic}^{Post}$			
Grant	0.100**	0.148**	0.171***
	(0.050)	(0.058)	(0.065)
N	4234	1113	818
R^2	0.22	0.39	0.46
AIC	4363.22	967.28	619.70
LHS: $log(new\ classes{+}1)_{ic}^{Post}$			
Grant	0.167**	0.251***	0.251***
	(0.071)	(0.078)	(0.093)
N	4234	1113	818
R^2	0.22	0.38	0.43
AIC	6865.56	1660.44	1167.23
LHS: $(new\ classes/families)_{ic}^{Post}$			
Grant	0.189**	0.192**	0.227*
	(0.079)	(0.096)	(0.116)
N	4234	1113	818
R^2	0.13	0.32	0.37
AIC	9169.27	2110.45	1454.94

Notes: results obtained estimating our baseline RDD equation by means of OLS with pre-determined observables as dependent variables: $Y_{ic}^{Post} = \alpha + \beta Grant_{ic} + f\left(Rank_{ic}\right) + \delta_c + \varepsilon_{ic}$. Estimates are obtained using different bandwidths around the threshold (i.e. an infinite one, ± 10 or ± 5 centered ranks). The sample includes only applicants that have filed a patent before the competition. All regressions include linear polynomials of the running variable on both sides of the threshold, competition fixed effects, pre-competition number of patents, a dummy for patents, number of citations, amount of funding requested, proposal duration, 2-digit sector fixed effects, country fixed effects, age fixed effects, consortium fixed effects and first applicant fixed effects. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Effects on relative novelty

	(1) All	(2) ±15	(3) ±10
LHS: Top Relative Disparity$_{ic}^{Post}$			
Grant	0.073*	0.137***	0.139**
	(0.038)	(0.047)	(0.054)
N	4234	1113	818
R^2	0.21	0.36	0.41
AIC	2183.17	510.07	304.13
LHS: Top Relative Novelty$_{ic}^{Post}$			
Grant	0.059	0.146***	0.136**
	(0.042)	(0.053)	(0.061)
N	4234	1113	818
R^2	0.20	0.36	0.41
AIC	2212.62	480.09	267.82
LHS: Bottom Relative Disparity$_{ic}^{Post}$			
Grant	0.011	-0.058	-0.133**
	(0.038)	(0.051)	(0.058)
N	4234	1113	818
R^2	0.14	0.28	0.34
AIC	2536.08	564.03	359.86
LHS: Bottom Relative Novelty$_{ic}^{Post}$			
Grant	0.011	-0.041	-0.119**
	(0.036)	(0.050)	(0.057)
N	4234	1113	818
R^2	0.14	0.28	0.35
AIC	2466.92	532.40	332.58

Notes: results obtained estimating our baseline RDD equation by means of OLS with pre-determined observables as dependent variables: $Y_{ic}^{Post} = \alpha + \beta Grant_{ic} + f\left(Rank_{ic}\right) + \delta_c + \varepsilon_{ic}$. Estimates are obtained using different bandwidths around the threshold (i.e. an infinite one, ±10 or ±5 centered ranks). The sample includes only applicants that have filed a patent before the competition. All regressions include linear polynomials of the running variable on both sides of the threshold, competition fixed effects, pre-competition number of patents, a dummy for patents, number of citations, amount of funding requested, proposal duration, 2-digit sector fixed effects, country fixed effects, age fixed effects, consortium fixed effects and first applicant fixed effects. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Effects on absolute novelty

	(1) All	(2) ± 10	(3) ± 5
LHS: Top Absolute Disparity $_{ic}^{Post}$			
Grant	0.061***	0.053**	0.118***
	(0.019)	(0.026)	(0.036)
N	13757	2247	1305
R^2	0.16	0.28	0.35
AIC	-594.90	237.11	128.45
LHS: Top Absolute Novelty $_{ic}^{Post}$			
Grant	0.062***	0.042*	0.098***
	(0.019)	(0.023)	(0.033)
N	13757	2247	1305
R^2	0.16	0.27	0.36
AIC	-1198.60	218.72	90.59
LHS: Bottom Absolute Disparity $_{ic}^{Post}$			
Grant	0.013	-0.013	-0.002
	(0.019)	(0.026)	(0.037)
N	13757	2247	1305
R^2	0.08	0.21	0.28
AIC	-559.40	272.90	74.28
LHS: Bottom Absolute Novelty $_{ic}^{Post}$			
Grant	0.024	-0.015	-0.024
	(0.020)	(0.027)	(0.039)
N	13757	2247	1305
R^2	0.09	0.21	0.29
AIC	89.45	484.71	224.96

Notes: results obtained estimating our baseline RDD equation by means of OLS with post-competition outcomes as dependent variables: $Y_{ic}^{Post} = \alpha + \beta Grant_{ic} + f\left(Rank_{ic}\right) + \theta Y_{ic}^{Pre} + \delta_c + \varepsilon_{ic}$. Estimates are obtained using different bandwidths around the threshold (i.e. an infinite one, ± 10 or ± 5 centered ranks). All regressions include linear polynomials of the running variable on both sides of the threshold, competition fixed effects, pre-competition number of patents, a dummy for patents, number of citations, amount of funding requested, proposal duration, 2-digit sector fixed effects, country fixed effects, age fixed effects, consortium fixed effects and first applicant fixed effects. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Alternative standard error adjustment

Table A6: Effects on new technology classes

	(1) All	(2) ±15	(3) ±10
LHS: $\mathbb{1}\vert new\ classes_{ic}^{Post}$			
Grant	0.132***	0.148***	0.121*
	(0.047)	(0.057)	(0.066)
N	4364	1151	861
R^2	0.13	0.25	0.29
AIC	4937.62	1229.63	877.27
LHS: $log(new\ classes{+}1)_{ic}^{Post}$			
Grant	0.198***	0.235***	0.169*
	(0.067)	(0.081)	(0.095)
N	4364	1151	861
R^2	0.14	0.25	0.29
AIC	7481.60	1924.30	1414.84
LHS: $(new\ classes/families)_{ic}^{Post}$			
Grant	0.223***	0.251**	0.195*
	(0.079)	(0.098)	(0.111)
N	4364	1151	861
R^2	0.05	0.17	0.21
AIC	9783.66	2402.42	1725.75

Notes: results obtained estimating our baseline RDD equation by means of OLS with pre-determined observables as dependent variables: $Y_{ic}^{Post} = \alpha + \beta Grant_{ic} + f\left(Rank_{ic}\right) + \delta_c + \varepsilon_{ic}$. Estimates are obtained using different bandwidths around the threshold (i.e. an infinite one, ±10 or ±5 centered ranks). The sample includes only applicants that have filed a patent before the competition. All regressions include linear polynomials of the running variable on both sides of the threshold, competition fixed effects, and pre-competition number of patents. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: Effects on relative novelty

	(1) All	(2) ±15	(3) ±10
LHS: Top Relative Disparity$_{ic}^{Post}$			
Grant	0.091**	0.139***	0.111**
	(0.040)	(0.048)	(0.055)
N	4364	1151	861
R^2	0.14	0.21	0.26
AIC	2659.71	749.20	509.42
LHS: Top Relative Novelty$_{ic}^{Post}$			
Grant	0.080**	0.145***	0.112**
	(0.040)	(0.048)	(0.055)
N	4364	1151	861
R^2	0.12	0.20	0.24
AIC	2761.05	745.52	495.92
LHS: Bottom Relative Disparity$_{ic}^{Post}$			
Grant	-0.002	-0.045	-0.094
	(0.037)	(0.048)	(0.058)
N	4364	1151	861
R^2	0.05	0.12	0.19
AIC	3029.48	799.76	535.79
LHS: Bottom Relative Novelty$_{ic}^{Post}$			
Grant	-0.003	-0.035	-0.080
	(0.036)	(0.047)	(0.057)
N	4364	1151	861
R^2	0.05	0.12	0.18
AIC	2964.71	774.29	514.23

Notes: results obtained estimating our baseline RDD equation by means of OLS with pre-determined observables as dependent variables: $Y_{ic}^{Post} = \alpha + \beta Grant_{ic} + f\left(Rank_{ic}\right) + \delta_c + \varepsilon_{ic}$. Estimates are obtained using different bandwidths around the threshold (i.e. an infinite one, ±10 or ±5 centered ranks). The sample includes only applicants that have filed a patent before the competition. All regressions include linear polynomials of the running variable on both sides of the threshold, competition fixed effects, and pre-competition number of patents. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

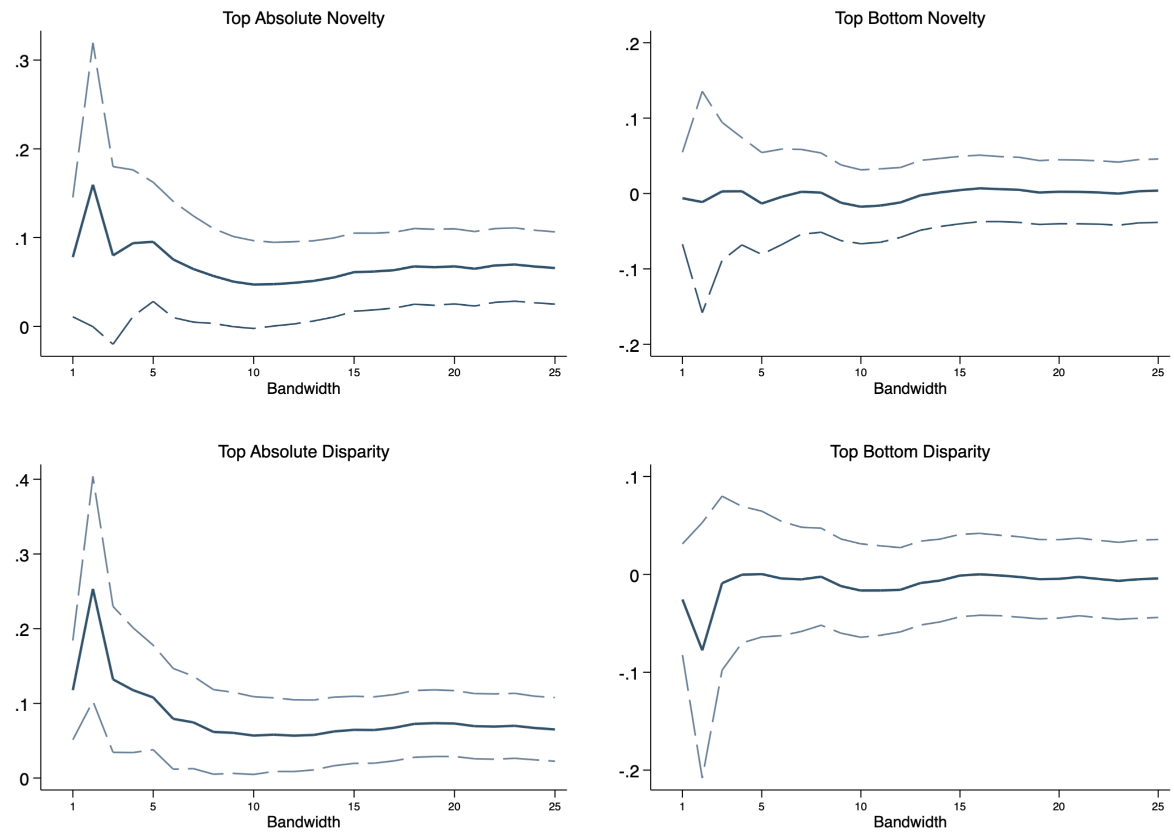
Table A8: Effects on absolute novelty

	(1) All	(2) ± 10	(3) ± 5
LHS: Top Absolute Disparity$_{ic}^{Post}$			
Grant	0.067***	0.057**	0.108***
	(0.020)	(0.026)	(0.037)
N	14296	2338	1378
R^2	0.11	0.20	0.24
AIC	196.23	469.51	324.68
LHS: Top Absolute Novelty$_{ic}^{Post}$			
Grant	0.069***	0.047*	0.095***
	(0.020)	(0.026)	(0.036)
N	14296	2338	1378
R^2	0.11	0.18	0.24
AIC	-555.09	459.30	309.79
LHS: Bottom Absolute Disparity$_{ic}^{Post}$			
Grant	0.016	-0.017	0.000
	(0.018)	(0.025)	(0.036)
N	14296	2338	1378
R^2	0.04	0.10	0.15
AIC	-94.59	553.69	302.95
LHS: Bottom Absolute Novelty$_{ic}^{Post}$			
Grant	0.030	-0.018	-0.013
	(0.019)	(0.026)	(0.038)
N	14296	2338	1378
R^2	0.04	0.10	0.14
AIC	614.07	758.60	467.87

Notes: results obtained estimating our baseline RDD equation by means of OLS with post-competition outcomes as dependent variables: $Y_{ic}^{Post} = \alpha + \beta Grant_{ic} + f\,(Rank_{ic}) + \theta Y_{ic}^{Pre} + \delta_c + \varepsilon_{ic}$. Estimates are obtained using different bandwidths around the threshold (i.e. an infinite one, ± 10 or ± 5 centered ranks). All regressions include linear polynomials of the running variable on both sides of the threshold, competition fixed effects, and pre-competition number of patents. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Estimates by bandwidth

Figure A2: Point estimates with varying bandwidths



Falsification tests

Table A9: Placebo tests

	(1) [0;10]	(2) [-10;0]	(3) [0;5]	(4) [-5;0]
LHS: Top Relative Disparity$_{ic}^{Post}$				
Placebo Grant [2]	-0.056		-0.042	
	(0.041)		(0.059)	
Placebo Grant [-2]		-0.066		-0.044
		(0.056)		(0.079)
N	648	1650	507	831
R^2	0.29	0.23	0.32	0.31
LHS: Top Relative Novelty$_{ic}^{Post}$				
Placebo Grant [2]	-0.055		-0.014	
	(0.044)		(0.060)	
Placebo Grant [-2]		-0.029		0.007
		(0.059)		(0.079)
N	648	1650	507	831
R^2	0.29	0.20	0.35	0.31
LHS: Bottom Relative Disparity$_{ic}^{Post}$				
Placebo Grant [2]	0.024		0.048	
	(0.040)		(0.054)	
Placebo Grant [-2]		0.042		0.124
		(0.060)		(0.079)
N	648	1650	507	831
R^2	0.23	0.13	0.27	0.20
LHS: Bottom Relative Novelty$_{ic}^{Post}$				
Placebo Grant [2]	0.004		-0.016	
	(0.042)		(0.059)	
Placebo Grant [-2]		-0.022		0.047
		(0.060)		(0.083)
N	648	1650	507	831
R^2	0.23	0.13	0.27	0.22

Notes: results obtained using a placebo threshold between ranks -3 and -2 or, alternatively, between rank 2 and 3. For the placebo threshold above the actual one, estimates are obtained using bandwidths from centered ranks 0 to 10 (or 0 to 5). For the placebo threshold below the actual one, estimates are obtained using bandwidths from centered ranks -10 to 0 (or -5 to 0). All regressions include linear ranks on both sides of the threshold, the pre-grant dependent variable and competition fixed effects. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Local Randomization estimates

Table A10: Local Randomization Estimates

	Top Abs. Disparity$_{ic}^{Pre}$	*Top Abs. Novelty*$_{ic}^{Pre}$
Diff-in-Means	0.018	0.006
p-value	[0.656]	[0.928]
Window	1	1
N_{left}	163	163
N_{right}	173	173
N	336	336
	Bottom Abs. Disparity$_{ic}^{Pre}$	*Bottom Abs. Novelty*$_{ic}^{Pre}$
Diff-in-Means	0.006	-0.012
p-value	[0.906]	[0.698]
Window	1	1
N_{left}	163	163
N_{right}	173	173
N	336	336
	Top Abs. Disparity$_{ic}^{Post}$	*Top Abs. Novelty*$_{ic}^{Post}$
Diff-in-Means	0.119	0.077
p-value	[0.000]	[0.004]
Window	1	1
N_{left}	163	163
N_{right}	173	173
N	336	336
	Bottom Abs. Disparity$_{ic}^{Post}$	*Bottom Abs. Novelty*$_{ic}^{Post}$
Diff-in-Means	-0.024	-0.006
p-value	[0.272]	[0.878]
Window	1	1
N_{left}	163	163
N_{right}	173	173
N	336	336

Notes: results obtained employing the regression-discontinuity local randomization approach (Cattaneo et al., 2015) restricting the window around the threshold to [-1,1]. Models are estimated with `rdrandinf` (Cattaneo et al., 2016). Fisherian *p-values* are obtained using 1,000 permutations. Dependent variables are demeaned to account for competition fixed effects. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Non-parametric RDD estimates

Table A11: Non-parametric RDD estimates - relative novelty

	$\mathbb{1}\vert new\ classes_{ic}^{Post}$	$\mathbb{1}\vert new\ classes_{ic}^{Post}$
RD Estimate	0.140	0.136
	[0.044]	[0.046]
BW	16.8	12.6
BW type	mserd	cerrd
Eff. Number of obs (left)	920	694
Eff. Number of obs (right)	300	297
Robust *p-value*	0.047	0.047
	$log(new\ classes{+}1)_{ic}^{Post}$	$log(new\ classes{+}1)_{ic}^{Post}$
RD Estimate	0.205	0.181
	[0.063]	[0.069]
BW	15.5	11.7
BW type	mserd	cerrd
Eff. Number of obs (left)	864	638
Eff. Number of obs (right)	300	295
Robust *p-value*	0.056	0.081
	$(new\ classes/families)_{ic}^{Post}$	$(new\ classes/families)_{ic}^{Post}$
RD Estimate	0.222	0.178
	[0.076]	[0.084]
BW	14.9	11.2
BW type	mserd	cerrd
Eff. Number of obs (left)	806	638
Eff. Number of obs (right)	299	295
Robust *p-value*	0.076	0.152

Notes: results obtained employing local polynomial RD estimators with automated bandwidth selection developed by Calonico et al. (2014). Specifications employ either a mean-squared error (MSE) or a Coverage Error Rate (CER) optimal bandwidth that vary for each outcome. All models include a linear adjustment of the running variable on both sides of the threshold, competition fixed effects and use a triangular kernel. Standard errors are clustered at the competition level.

Table A12: Non-parametric RDD estimates - relative novelty

	$Top\ Relative\ Novelty^{Post}_{ic}$	$Top\ Relative\ Novelty^{Post}_{ic}$
RD Estimate	0.130	0.119
	[0.041]	[0.044]
BW	15.8	11.9
BW type	mserd	cerrd
Eff. Number of obs (left)	864	638
Eff. Number of obs (right)	300	295
Robust *p-value*	0.026	0.045
	$Top\ Relative\ Disparity^{Post}_{ic}$	$Top\ Relative\ Disparity^{Post}_{ic}$
RD Estimate	0.123	0.110
	[0.039]	[0.042]
BW	14.9	11.2
BW type	mserd	cerrd
Eff. Number of obs (left)	806	638
Eff. Number of obs (right)	299	295
Robust *p-value*	0.029	0.048
	$Bottom\ Relative\ Novelty^{Post}_{ic}$	$Bottom\ Relative\ Novelty^{Post}_{ic}$
RD Estimate	-0.066	-0.069
	[0.039]	[0.043]
BW	13.6	10.2
BW type	mserd	cerrd
Eff. Number of obs (left)	750	587
Eff. Number of obs (right)	299	292
Robust *p-value*	0.087	0.135
	$Bottom\ Relative\ Disparity^{Post}_{ic}$	$Bottom\ Relative\ Disparity^{Post}_{ic}$
RD Estimate	-0.090	-0.090
	[0.041]	[0.046]
BW	12.7	9.6
BW type	mserd	cerrd
Eff. Number of obs (left)	694	539
Eff. Number of obs (right)	297	291
Robust *p-value*	0.031	0.065

Notes: results obtained employing local polynomial RD estimators with automated bandwidth selection developed by Calonico et al. (2014). Specifications employ either a mean-squared error (MSE) or a Coverage Error Rate (CER) optimal bandwidth that vary for each outcome. All models include a linear adjustment of the running variable on both sides of the threshold, competition fixed effects and use a triangular kernel. Standard errors are clustered at the competition level.

Table A13: Non-parametric RDD estimates - balancing tests

	$Top\ Absolute\ Novelty_{ic}^{Post}$	$Top\ Absolute\ Novelty_{ic}^{Post}$
RD Estimate	0.017	0.004
	[0.025]	[0.028]
BW	18.8	14.0
BW type	mserd	cerrd
Eff. Number of obs (left)	2830	2261
Eff. Number of obs (right)	703	701
Robust *p-value*	0.877	0.926
	$Top\ Absolute\ Disparity_{ic}^{Post}$	$Top\ Absolute\ Disparity_{ic}^{Post}$
RD Estimate	0.038	0.024
	[0.025]	[0.028]
BW	17.7	13.2
BW type	mserd	cerrd
Eff. Number of obs (left)	2692	2111
Eff. Number of obs (right)	703	699
Robust *p-value*	0.545	0.733
	$Bottom\ Absolute\ Novelty_{ic}^{Post}$	$Bottom\ Absolute\ Novelty_{ic}^{Post}$
RD Estimate	-0.029	-0.030
	[0.022]	[0.023]
BW	19.2	14.3
BW type	mserd	cerrd
Eff. Number of obs (left)	2971	2261
Eff. Number of obs (right)	703	701
Robust *p-value*	0.472	0.444
	$Bottom\ Absolute\ Disparity_{ic}^{Post}$	$Bottom\ Absolute\ Disparity_{ic}^{Post}$
RD Estimate	-0.018	-0.023
	[0.021]	[0.023]
BW	17.5	13.0
BW type	mserd	cerrd
Eff. Number of obs (left)	2692	2111
Eff. Number of obs (right)	703	699
Robust *p-value*	0.492	0.432

Notes: results obtained employing local polynomial RD estimators with automated bandwidth selection developed by Calonico et al. (2014). Specifications employ either a mean-squared error (MSE) or a Coverage Error Rate (CER) optimal bandwidth that vary for each outcome. All models include a linear adjustment of the running variable on both sides of the threshold, competition fixed effects and use a triangular kernel. Standard errors are clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A14: Non-parametric RDD estimates - absolute novelty

	$Top\ Absolute\ Novelty_{ic}^{Post}$	$Top\ Absolute\ Novelty_{ic}^{Post}$
RD Estimate	0.059	0.057
	[0.020]	[0.022]
BW	17.7	13.2
BW type	mserd	cerrd
Eff. Number of obs (left)	2692	2111
Eff. Number of obs (right)	703	699
Robust *p-value*	0.054	0.054
	$Top\ Absolute\ Disparity_{ic}^{Post}$	$Top\ Absolute\ Disparity_{ic}^{Post}$
RD Estimate	0.066	0.066
	[0.021]	[0.022]
BW	18.4	13.7
BW type	mserd	cerrd
Eff. Number of obs (left)	2830	2111
Eff. Number of obs (right)	703	699
Robust *p-value*	0.021	0.023
	$Bottom\ Absolute\ Novelty_{ic}^{Post}$	$Bottom\ Absolute\ Novelty_{ic}^{Post}$
RD Estimate	-0.002	-0.010
	[0.020]	[0.022]
BW	18.5	13.8
BW type	mserd	cerrd
Eff. Number of obs (left)	2830	2111
Eff. Number of obs (right)	703	699
Robust *p-value*	0.690	0.522
	$Bottom\ Absolute\ Disparity_{ic}^{Post}$	$Bottom\ Absolute\ Disparity_{ic}^{Post}$
RD Estimate	-0.006	-0.011
	[0.019]	[0.020]
BW	18.7	13.9
BW type	mserd	cerrd
Eff. Number of obs (left)	2830	2111
Eff. Number of obs (right)	703	699
Robust *p-value*	0.634	0.507

Notes: results obtained employing local polynomial RD estimators with automated bandwidth selection developed by Calonico et al. (2014). Specifications employ either a mean-squared error (MSE) or a Coverage Error Rate (CER) optimal bandwidth that vary for each outcome. All models include a linear adjustment of the running variable on both sides of the threshold, competition fixed effects and use a triangular kernel. Standard errors are clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Rao-Stirling

We use here the Rao-Stirling index as an alternative indicator of innovation novelty. Rao-Stirling diversity was introduced by Stirling (2007) to measure diversity in article references. More recently, it has been used by Yang et al. (2022) to measure novelty as an alternative to the atypical combination index proposed by Uzzi et al. (2013).

Computed at the patent level, Rao-Stirling diversity is a generalization of disparity since it includes in its definition the relative frequency of the different technology codes assigned to the patent and not only their distance. For each patent family f, we can define:

$$\text{Patent Rao-Stirling}_f = \sum_{j,k \in T_f; j \neq k} s_{jf} s_{kf} \left(1 - p_{jk}\right), \tag{10}$$

where T_f is the set of technology classes in the patent family f, s_{jf} and s_{kf} are the relative frequencies of classes j and k in the patent family and p_{jk} is the proximity between these technology classes.

By replicating the procedure followed to obtain the relative and absolute disparity at the firm-competition level, we can define for each firm i and competition c:

$$\text{Relative Rao-Stirling}_{ic} = \sum_{j \in T_i^{old},\, k \in T_i^{new}} s_{ji} s_{ki} \left(1 - p_{jk}\right), \tag{11}$$

where T_i^{old} is the set of technology classes in the firm's patent families before the competition, T_i^{new} is the set of newly introduced classes, s_{ji} is the frequency of class j among the technological classes assigned to the firm before the competition, s_{ki} is the frequency of class k in the newly introduced technological classes, and p_{jk} is their distance. From this continuous variable, we obtain dummy variables that identify firms in the top (bottom) tercile of the relative Rao-Stirling distribution (*Top (Bottom) Relative Rao-Stirling*$_{ic}$).

We then define the absolute Rao-Stirling dummies as:

$$\text{Top Absolute Rao-Stirling}_{ic}^{Pre(Post)} = \mathbb{1} \left| \left[\exists f \text{ for } f \in \left(PP_i^{Pre(Post)} \cap P_{top33}^{RS} \right) \right] \right., \tag{12}$$

where $PP_i^{Pre(Post)}$ is the patent portfolio of firm i in the pre (post) competition period and P_{top33}^{RS}

is the top tercile of the patent Rao-Stirling distribution. This distribution is determined for each year and technology class. The percentile of a patent in this distribution is equal to the weighted average of its percentile in the distributions of its technology classes.

The dummy variable *Bottom Absolute Rao-Stirling*$_{ic}^{Pre(Post)}$, instead, refers to firms whose best patent in terms of novelty is in the bottom tercile of the distribution.

Table A15: Bias against novelty?

	(1) Grant	(2) Grant	(3) log(Ranks)	(4) log(Ranks)
Top Absolute Rao-Stirling$_{ic}^{Pre}$	0.025***	0.000	-0.236***	-0.018
	(0.006)	(0.008)	(0.029)	(0.034)
Controls	No	Yes	No	Yes
N	14296	13757	14296	13757
R^2	0.03	0.06	0.37	0.43
AIC	-3629.65	-3668.74	38294.82	35632.12
Bottom Absolute Rao-Stirling$_{ic}^{Pre}$	0.014**	-0.009	-0.163***	0.017
	(0.006)	(0.008)	(0.027)	(0.031)
Controls	No	Yes	No	Yes
N	14296	13757	14296	13757
R^2	0.03	0.06	0.37	0.43
AIC	-3613.94	-3670.17	38359.61	35632.20

Notes: results obtained by means of OLS estimating variants of the following equation: $Y_{ic} = \alpha + \beta Y_{ic}^{Pre} + \gamma X + \delta_c + \varepsilon_{ic}$. Dependent variable in columns 1 and 2 is a dummy variable indicating whether a firm has received a grant. In columns 3 and 4 the dependent variable is the log of uncentered rankings. All regressions include competition fixed effects. Even columns add the following controls: a dummy for patents, number of citations, amount of funding requested, proposal duration, 2-digit sector fixed effects, country fixed effects, age fixed effects, consortium fixed effects and first applicant fixed effects. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A16: Effects on relative novelty

	(1) All	(2) ±15	(3) ±10
LHS: Top Relative Rao-Stirling$^{Post}_{ic}$			
Grant	0.094**	0.089*	0.081
	(0.040)	(0.047)	(0.056)
N	4364	1151	861
R^2	0.06	0.15	0.20
AIC	3033.14	761.65	540.29
LHS: Bottom Relative Rao-Stirling$^{Post}_{ic}$			
Grant	-0.006	-0.040	-0.091*
	(0.036)	(0.046)	(0.055)
N	4364	1151	861
R^2	0.05	0.12	0.18
AIC	2998.97	787.64	524.79

Notes: results obtained estimating our baseline RDD equation by means of OLS with pre-determined observables as dependent variables: $Y^{Post}_{ic} = \alpha + \beta Grant_{ic} + f\,(Rank_{ic}) + \delta_c + \varepsilon_{ic}$. Estimates are obtained using different bandwidths around the threshold (i.e. an infinite one, ±10 or ±5 centered ranks). The sample includes only applicants that have filed a patent before the competition. All regressions include linear polynomials of the running variable on both sides of the threshold, competition fixed effects and the pre-competition number of patents. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A17: Effects on absolute novelty

	(1) All	(2) ±10	(3) ±5
LHS: Top Absolute Rao-Stirling$^{Post}_{ic}$			
Grant	0.062***	0.047*	0.078**
	(0.020)	(0.026)	(0.036)
N	14296	2338	1378
R^2	0.12	0.20	0.23
AIC	195.58	540.22	342.66
LHS: Bottom Absolute Rao-Stirling$^{Post}_{ic}$			
Grant	0.011	-0.025	-0.016
	(0.018)	(0.024)	(0.033)
N	14296	2338	1378
R^2	0.04	0.11	0.14
AIC	85.66	558.32	290.21

Notes: results obtained estimating our baseline RDD equation by means of OLS with post-competition outcomes as dependent variables: $Y^{Post}_{ic} = \alpha + \beta Grant_{ic} + f\,(Rank_{ic}) + \theta Y^{Pre}_{ic} + \delta_c + \varepsilon_{ic}$. Estimates are obtained using different bandwidths around the threshold (i.e. an infinite one, ±10 or ±5 centered ranks). All regressions include linear polynomials of the running variable on both sides of the threshold, the pre-grant dependent variable and competition fixed effects. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Top 50 vs Bottom 50

Table A18: Bias against novelty?

	(1) Grant	(2) Grant	(3) log(Ranks)	(4) log(Ranks)
Top Absolute Disparity$_{ic}^{Pre}$	0.031***	0.012	-0.247***	-0.029
	(0.006)	(0.008)	(0.023)	(0.030)
Controls	No	Yes	No	Yes
N	14296	13757	14296	13757
R^2	0.03	0.06	0.37	0.43
AIC	-3651.27	-3671.76	38250.72	35631.45
Top Absolute Novelty$_{ic}^{Pre}$	0.031***	0.010	-0.240***	-0.009
	(0.006)	(0.008)	(0.023)	(0.030)
Controls	No	Yes	No	Yes
N	14296	13757	14296	13757
R^2	0.03	0.06	0.37	0.43
AIC	-3650.14	-3670.91	38262.60	35632.41
Bottom Absolute Disparity$_{ic}^{Pre}$	0.015***	-0.012	-0.173***	0.029
	(0.005)	(0.008)	(0.024)	(0.030)
Controls	No	Yes	No	Yes
N	14296	13757	14296	13757
R^2	0.03	0.06	0.37	0.43
AIC	-3616.28	-3671.76	38341.54	35631.45
Bottom Absolute Novelty$_{ic}^{Pre}$	0.015***	-0.010	-0.184***	0.009
	(0.005)	(0.008)	(0.024)	(0.030)
Controls	No	Yes	No	Yes
N	14296	13757	14296	13757
R^2	0.03	0.06	0.37	0.43
AIC	-3617.06	-3670.91	38332.45	35632.41

Notes: results obtained by means of OLS estimating variants of the following equation: $Y_{ic} = \alpha + \beta Y_{ic}^{Pre} + \gamma X + \delta_c + \varepsilon_{ic}$. Dependent variable in columns 1 and 2 is a dummy variable indicating whether a firm has received a grant. In columns 3 and 4 the dependent variable is the log of uncentered rankings. All regressions include competition fixed effects. Even columns add the following controls: a dummy for patents, number of citations, amount of funding requested, proposal duration, 2-digit sector fixed effects, country fixed effects, age fixed effects, consortium fixed effects and first applicant fixed effects. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A19: Effects on relative novelty

	(1) All	(2) ±15	(3) ±10
LHS: Top Relative Disparity$_{ic}^{Post}$			
Grant	0.091**	0.139***	0.111**
	(0.043)	(0.048)	(0.055)
N	4364	1151	861
R^2	0.14	0.21	0.26
AIC	2657.71	747.20	507.42
LHS: Top Relative Novelty$_{ic}^{Post}$			
Grant	0.080*	0.145***	0.112*
	(0.045)	(0.054)	(0.059)
N	4364	1151	861
R^2	0.12	0.20	0.24
AIC	2759.05	743.52	493.92
LHS: Bottom Relative Disparity$_{ic}^{Post}$			
Grant	-0.002	-0.045	-0.094*
	(0.038)	(0.047)	(0.056)
N	4364	1151	861
R^2	0.05	0.12	0.19
AIC	3027.48	797.76	533.79
LHS: Bottom Relative Novelty$_{ic}^{Post}$			
Grant	-0.003	-0.035	-0.080
	(0.036)	(0.046)	(0.054)
N	4364	1151	861
R^2	0.05	0.12	0.18
AIC	2962.71	772.29	512.23

Notes: results obtained estimating our baseline RDD equation by means of OLS with pre-determined observables as dependent variables: $Y_{ic}^{Post} = \alpha + \beta Grant_{ic} + f\left(Rank_{ic}\right) + \delta_c + \varepsilon_{ic}$. Estimates are obtained using different bandwidths around the threshold (i.e. an infinite one, ±10 or ±5 centered ranks). The sample includes only applicants that have filed a patent before the competition. All regressions include linear polynomials of the running variable on both sides of the threshold, competition fixed effects and the pre-competition number of patents. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A20: Effects on absolute novelty

	(1) All	(2) ±10	(3) ±5
LHS: Top Absolute $Disparity_{ic}^{Post}$			
Grant	0.079***	0.062**	0.088**
	(0.023)	(0.030)	(0.042)
N	14296	2338	1378
R^2	0.14	0.22	0.27
AIC	4089.28	1124.63	637.76
LHS: Top Absolute $Novelty_{ic}^{Post}$			
Grant	0.076***	0.059**	0.080**
	(0.023)	(0.029)	(0.039)
N	14296	2338	1378
R^2	0.14	0.23	0.29
AIC	3833.67	1083.41	595.11
LHS: Bottom Absolute $Disparity_{ic}^{Post}$			
Grant	0.041*	-0.009	-0.015
	(0.023)	(0.030)	(0.043)
N	14296	2338	1378
R^2	0.05	0.11	0.16
AIC	4585.41	1325.92	762.23
LHS: Bottom Absolute $Novelty_{ic}^{Post}$			
Grant	0.043*	-0.006	-0.009
	(0.023)	(0.030)	(0.042)
N	14296	2338	1378
R^2	0.05	0.12	0.16
AIC	4700.29	1335.76	778.23

Notes: results obtained estimating our baseline RDD equation by means of OLS with post-competition outcomes as dependent variables: $Y_{ic}^{Post} = \alpha + \beta Grant_{ic} + f\left(Rank_{ic}\right) + \theta Y_{ic}^{Pre} + \delta_c + \varepsilon_{ic}$. Estimates are obtained using different bandwidths around the threshold (i.e. an infinite one, ±10 or ±5 centered ranks). All regressions include linear polynomials of the running variable on both sides of the threshold, the pre-grant dependent variable and competition fixed effects. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Quadratic adjustment

Table A21: Effects on new technology classes

	(1) All	(2) ±15	(3) ±10
LHS: $\mathbb{1}\lvert new\ classes_{ic}^{Post}$			
Grant	0.088	0.094	0.159
	(0.070)	(0.080)	(0.112)
N	4364	1151	861
R^2	0.13	0.25	0.30
AIC	4938.48	1230.84	876.84
LHS: $log(new\ classes{+}1)_{ic}^{Post}$			
Grant	0.132	0.134	0.191
	(0.103)	(0.113)	(0.158)
N	4364	1151	861
R^2	0.14	0.25	0.30
AIC	7482.26	1924.68	1412.83
LHS: $(new\ classes/families)_{ic}^{Post}$			
Grant	0.169	0.162	0.111
	(0.119)	(0.143)	(0.191)
N	4364	1151	861
R^2	0.06	0.17	0.21
AIC	9784.91	2403.45	1722.15

Notes: results obtained estimating our baseline RDD equation by means of OLS with pre-determined observables as dependent variables: $Y_{ic}^{Post} = \alpha + \beta Grant_{ic} + f\left(Rank_{ic}\right) + \delta_c + \varepsilon_{ic}$. Estimates are obtained using different bandwidths around the threshold (i.e. an infinite one, ±10 or ±5 centered ranks). The sample includes only applicants that have filed a patent before the competition. All regressions include quadratic polynomials of the running variable on both sides of the threshold, competition fixed effects, and pre-competition number of patents. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A22: Effects on relative novelty

	(1) All	(2) ±15	(3) ±10
LHS: Top Relative Disparity$_{ic}^{Post}$			
Grant	0.068	0.098	0.148
	(0.061)	(0.075)	(0.098)
N	4364	1151	861
R^2	0.14	0.21	0.27
AIC	2661.07	750.21	504.11
LHS: Top Relative Novelty$_{ic}^{Post}$			
Grant	0.072	0.113	0.148
	(0.069)	(0.084)	(0.101)
N	4364	1151	861
R^2	0.12	0.20	0.25
AIC	2763.01	746.69	486.93
LHS: Bottom Relative Disparity$_{ic}^{Post}$			
Grant	-0.021	-0.107	-0.105
	(0.053)	(0.073)	(0.098)
N	4364	1151	861
R^2	0.05	0.12	0.19
AIC	3030.60	799.43	535.84
LHS: Bottom Relative Novelty$_{ic}^{Post}$			
Grant	-0.020	-0.088	-0.066
	(0.051)	(0.069)	(0.095)
N	4364	1151	861
R^2	0.05	0.12	0.19
AIC	2966.10	774.54	513.36

Notes: results obtained estimating our baseline RDD equation by means of OLS with pre-determined observables as dependent variables: $Y_{ic}^{Post} = \alpha + \beta Grant_{ic} + f\left(Rank_{ic}\right) + \delta_c + \varepsilon_{ic}$. Estimates are obtained using different bandwidths around the threshold (i.e. an infinite one, ±10 or ±5 centered ranks). The sample includes only applicants that have filed a patent before the competition. All regressions include quadratic polynomials of the running variable on both sides of the threshold, competition fixed effects, and pre-competition number of patents. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A23: Effects on absolute novelty

	(1) All	(2) ±10	(3) ±5
LHS: Top Absolute Disparity$_{ic}^{Post}$			
Grant	0.080**	0.109**	0.166**
	(0.031)	(0.044)	(0.075)
N	14296	2338	1378
R^2	0.11	0.20	0.24
AIC	197.70	468.70	325.44
LHS: Top Absolute Novelty$_{ic}^{Post}$			
Grant	0.074**	0.094**	0.084
	(0.029)	(0.042)	(0.078)
N	14296	2338	1378
R^2	0.11	0.19	0.24
AIC	-553.84	458.93	311.44
LHS: Bottom Absolute Disparity$_{ic}^{Post}$			
Grant	-0.007	0.006	-0.027
	(0.025)	(0.036)	(0.068)
N	14296	2338	1378
R^2	0.04	0.10	0.15
AIC	-101.77	554.57	303.01
LHS: Bottom Absolute Novelty$_{ic}^{Post}$			
Grant	0.005	0.014	0.030
	(0.028)	(0.039)	(0.070)
N	14296	2338	1378
R^2	0.05	0.10	0.14
AIC	602.39	758.04	466.75

Notes: results obtained estimating our baseline RDD equation by means of OLS with post-competition outcomes as dependent variables: $Y_{ic}^{Post} = \alpha + \beta Grant_{ic} + f\left(Rank_{ic}\right) + \theta Y_{ic}^{Pre} + \delta_c + \varepsilon_{ic}$. Estimates are obtained using different bandwidths around the threshold (i.e. an infinite one, ±10 or ±5 centered ranks). All regressions include quadratic polynomials of the running variable on both sides of the threshold, competition fixed effects, and pre-competition number of patents. Standard errors are robust and clustered at the competition level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.