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Firm performance and state innovation funding: Evidence from China's Innofund program☆

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A B S T R A C T

Can firms leverage public entrepreneurship investments to improve innovation and financial performance? Analysis of this question is frustrated by the difficulty of distinguishing treatment from selection effects. We take advantage of internal administrative data on applications to China's Innofund program in order (a) to identify which application features are associated with higher chances of obtaining grants and (b) to evaluate the causal impact of receiving a grant on firm performance using a regression discontinuity (RD) design. With regards to grant receipt, we find that firms possessing observable merits and political connections are more likely to receive Innofund grants. We also find evidence of bureaucratic intervention, as applicants' evaluation scores are non-randomly missing and that some firms whose scores did not meet funding standards nonetheless received grants. With regards to post-grant performance, we find that firms receiving high project evaluation scores and Innofund grants perform better than those that do not receive grants and have lower scores. These do not appear to be causal effects, however. Applying Fuzzy RD methods, we find no evidence that receiving an Innofund grant boosts survival, patenting, or venture funding. Our analysis demonstrates the value of administrative data for causal analysis and for uncovering evidence regarding the possibility that bureaucratic intervention affects firm and program outcomes.

1. Introduction

A central challenge faced by innovation-oriented, entrepreneurial ventures is the difficulty of obtaining financial resources to invest in their experimental technologies and business efforts (Hall and Lerner, 2010). This challenge is particularly severe in emerging economies (De Soto, 2000). While American and European entrepreneurs can often seek funding from angel investors or venture capital (VC) firms, capital markets for speculative, early-stage enterprises are often underdeveloped in the less developed world (White et al., 2005; Cumming and Johan, 2013; Taussig and Delios, 2015; Wang, 2016). Emulating innovation-oriented economies, an increasing number of countries have been adopting local or national policy interventions to overcome such market failures by providing direct financial support to entrepreneurial firms (Lerner, 2009; Hall and Lerner, 2010; OECD, 2013, 2014). While studies of subsidy programs have proliferated along with the programs themselves, there are still several important knowledge gaps in this literature. One is that we know relatively little about the functioning and effectiveness of R & D subsidies in developing economies, where the challenges to effective administration are often substantial (Özcelik and Taymaz, 2008; Czarnitzki and Lopes Bento, 2010). Second, less is known about the features of applicant firms that correlate to winning such grants and among winners, which firms benefit most (Klette et al., 2000). Third, our confidence that we understand the causal relationship between subsidy receipt and firm performance remains relatively low (Zhao and Ziedonis, 2014; Howell, 2014). This study addresses each of these areas by leveraging internal administrative data in the context of an innovation subsidy program in China, the Innofund.

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Historically, studies investigating the relationship between innovation subsidies and firm outcomes have focused on programs in the United States, Japan, and the leading innovator countries of Europe (Zúñiga-Vicente et al., 2014; Dimos and Pugh, 2016). To the extent that studies address non-leading economy programs, these have examined programs in specific regions facing particular economic challenges, such as Flanders (Aerts and Schmidt, 2008; et al., 2013), Eastern Germany (Almus and Czarnitzki, 2003), Hungary (Halpern and Muraközy, 2010), and Turkey (Özcelik and Taymaz, 2008). The increasing popularity of such programs in emerging economies suggests that these contexts deserve attention as well and we join Guo et al. (2016) in examining the Innofund in China. Existing research on subsidy programs in emerging economies emphasizes empirical analysis rather than a theoretical structure for predicting differences in program design, administration, or effects. A few clear differences exist between the emerging and leader innovator countries that may affect such programs. The most salient observation is that state capacity is weaker in an emerging economy context. This can have an impact in a number of ways. First, corruption in developing countries is typically widespread, which usually has an adverse effect on government programs of all kinds, including innovation subsidy programs (Ades and Di Tella, 1997; Hellman et al., 2003). Second, even if they are free of corruption, state agencies in such environments may face great pressures to "pick winners," i.e., to fund firms that would have been likely to succeed even in the absence of subsidies, thus 'wasting' government funding (Wallsten, 2000; Radicic et al., 2015). Third, the information asymmetry featured in venture financing is particularly salient when the investment is carried out by state bureaucrats. In contrast to professional investors, these bureaucrats possess limited technological and business expertise to judge venture quality (Lerner, 2009). Furthermore, market concerns may also play a role in the effectiveness of subsidy programs in emerging economies. Public financing, even if administered professionally, may be insufficient to promote firm innovation in countries where complementary institutional support for innovation, such as private venture funding or mentorship, is weak (Nelson, 1993; Martin and Scott, 2000; Gans et al., 2008).

In contrast to the limited work on subsidy programs in emerging economies, the literature on subsidy programs in the developed world is wide-ranging. The United States' Small Business Innovation Research and Advanced Technology Programs have received substantial attention (Lerner, 1999; Wallsten, 2000; Feldman and Kelley, 2003), as have the Framework and other programs of the European Union (Bayona-Sáez and García-Marco, 2010; Czarnitzki and Lopes Bento, 2013; Czarnitzki and Lopes Bento, 2014) and specific programs in Belgium (Meuleman and Maeseneire, 2012), Israel (Lach, 2002), Finland (Takalo et al., 2013), and other countries. The range of these studies is broad and the results they find are mixed. Some studies find that subsidy recipients invest more substantially in innovation, achieve higher innovative productivity, obtain future financing more easily, and are more likely to improve their financial performance than control sample firms (e.g., Lerner, 1999; Gonzales et al., 2005; Zhao and Ziedonis, 2014; Czarnitzki and Lopes Bento, 2014; Howell, 2014). Others, however, conclude that government innovation grants do not appreciably improve firm outcomes (e.g., Klette and Møen, 1999; Wallsten, 2000; Duguet, 2004; Gorg and Strobl, 2007; De Blasio et al., 2015). Antecedent results vary both because government programs differ in their details and regional contexts and because studies employ differing methodologies.

Research designs that involve assessing firm implications from policy interventions face substantial methodological challenges (David et al., 2000; Feldman and Kelley, 2003). Public funding programs naturally do not randomly assign awards to applicant firms, so it is difficult to disentangle whether observed outcomes arise because firms with higher quality projects win awards, i.e., selection effects, or because the awards have a positive impact on the firms that receive them, i.e., treatment effects (Klette et al., 2000). Running regressions predicting firm-level outcomes as a function of public funding can establish a correlation between grant receipt and firm performance. Such models, however, should not be interpreted as ascertaining whether grants *cause* the observed outcomes, as outcomes and awards are likely to be simultaneously determined or correlated with unobserved factors.

In this paper, we investigate (a) which firm features, if any, are correlated with the ability to win innovation subsidy grants, (b) whether administrative data can provide indicators of administrative malfeasance in the award of innovation subsidies, and (c) whether firms that receive innovation subsidies achieve greater performance as a result of winning these grants. We are able to do this, because we have obtained access to internal administrative data from China's Innovation Fund (Innofund) program. These data include original application documents and, most significantly, evaluation scores for each project application in the Zhongguancun (ZGC) region of Beijing. These scores enable us (a) to compare the features of applicants that won grants with those of applicants that did not, (b) to check whether administrators are following official procedures and evaluator recommendations in awarding grants, and (c) to apply a regression discontinuity (RD) design to identify the causal impact of grant receipt on firm outcomes. This RD analysis enables us to identify Local Area Treatment Effects (LATE) around the regression discontinuity threshold (Hahn et al., 2001; Imbens and Lemieux, 2008). As firm performance is multidimensional and a public funding program might affect some dimensions but not others, we examine a battery of performance outcomes, including firm survival, patenting, and receipt of equity investment. After having evaluated a number of detailed sources of firm-level data, we choose to focus on only these firm outcomes because each can be externally-verified and is therefore not likely to be subject to data manipulation.

In our analyses of selection, we find that firms with observable merits in innovation and financial capabilities are associated with higher scores and a higher likelihood to receive Innofund awards. This is consistent with expectations for one element of a well-functioning subsidy program, which is by no means guaranteed in emerging economies. That being said, we also find indicators of bureaucratic intervention that contradicts stated policy guidelines. First, we find that firms with political connections are more likely to receive state funding, though not higher scores. Second, we find a small group of firms (a) with scores below the funding threshold that received state funding and (b) with scores above the threshold whose funding application was rejected. In addition, we identified 111 observations with missing evaluation scores, despite other information indicating that their applications were reviewed by external experts and adjudicated by the Innofund. We do not know if the missing scores were the result of administrative negligence or deliberate actions, but we find that firms with missing scores are more likely to receive the Innofund grant and that among firms with missing scores, political connection is positively associated with funding. In combination, these patterns are consistent with the possibility that missing scores are not randomly generated.

Our analyses of the impact of grants on firm performance demonstrate the value of utilizing administrative data. In naïve regressions that do not leverage information on project scores, we find that, despite indicators of bureaucratic abuse of power, firms that received Innofund grants during 2005–2007, the years during which the program was overseen more carefully, are more likely to survive through our sample period, to file patents, and to receive equity investments from State- and Community-Owned enterprises than those that did not receive grants. If it were to obtain in the causal analyses, the lattermost finding would be consistent with prior evidence of a 'certification effect,' by which innovation subsidy receipt leads to follow-on funding (e.g., Toole and Turvey, 2009; Howell, 2014). In the absence of administrative data, we can only establish a correlation between firm outcomes and grant receipt. Employing a Fuzzy Regression Discontinuity design, we are able to ascertain the causal impact of grant receipt on firm outcomes. These analyses leverage information from the Innofund administrative data regarding application ratings (i.e., project scores) and grant receipts. Specifically, by instrumenting for grant receipt based on whether firm projects received rankings that were above the stated funding threshold and weighing observations based on their closeness to the funding threshold, we can draw conclusions about whether grant receipt induces a 'jump' (discontinuity) in firm outcomes around the funding threshold, i.e., whether winning the grant causes changes in firm outcomes or whether it is merely correlated with them.

These analyses lead us to draw more modest conclusions than would the raw data. Specifically, we find no evidence of a causal relationship between grant receipt and new equity investment from State- and Community-Owned Enterprises among "just funded" applicants, the 2005–2007 applicants included. Taken together, these analyses suggest that the Innofund is able to identify firms whose projects seem more promising but receiving the program grant has, at most, a limited causal impact on firm performance.[1]

A number of features enable this study to make novel contributions to our understanding of the relationship between firm performance and innovation policy. First, we are able to exploit rich, internal data from the Innofund, China's largest innovation subsidy program for early-stage technology-based firms. Second, these data enable us to provide initial evidence regarding the selection and treatment effects associated with innovation subsidy in an emerging market context. Third, we join Zhao and Ziedonis (2014), Howell (2014), and Bronzini and Piselli (2016) in making a methodological contribution by using regression discontinuity design to evaluate the impact of innovation policy intervention on firm performance. Further, while the prior authors employ Sharp RD analysis, we acknowledge imperfect compliance in the program (not all firms above the funding threshold get grants and some firms below the funding threshold do) and our study is the first innovation subsidy study of which we are aware that applies Fuzzy RD analysis to investigate the causal impact of funding on firm outcomes. Fourth, our study is the first within the innovation subsidy literature to open up the black box of grant allocation and shed lights on the potential role of bureaucratic intervention in the process. While past studies have looked at the role of information asymmetry and bureaucratic incompetence (e.g. Lerner, 2009), none has investigated how corruption, a prominent institutional feature in the developing world, distorts grant allocation.

2. Firm performance & innovation subsidies: background and antecedent evidence

2.1. Background – innovation subsidy programs in leading innovator and emerging economies

Two well-understood market failures are invoked in arguments supporting government intervention to support R & D for technology-oriented new ventures. The first is the public goods problem associated with R & D investment: Because knowledge spillovers to potential competitors prevent organizations that invest in R & D from reaping the full returns associated with their investments, private incentives for innovation fall short of socially optimal levels (Bush, 1945; Nelson, 1959; Arrow, 1962). The second is the information asymmetry between inventors and their potential financiers (Arrow, 1962). Investors cannot anticipate the value of early-stage technologies with confidence, particularly when the prospects for success are highly uncertain, time horizons are long, and multiple stages of investment are needed (Hall and Lerner, 2010). This problem is exacerbated by the fact that R & D cannot be used for collateral, with the exception of R & D effectively secured by IP rights (Hsu and Ziedonis, 2013). As a result, capital markets for venture funding are not likely to be optimally efficient.

A range of policy levers can be used to overcome these market failures, including intellectual property policies, government-conducted R & D, direct and indirect subsidies for R & D (e.g. Nishimura and Okamuro, 2011; Cappelen et al., 2012; Yang et al., 2012), public-private partnerships (e.g. Audretsch et al., 2002), public matching grants that build on private investment (e.g., Lanahan, 2016), local programs that supplement federal program (e.g., Lanahan and Feldman, 2015), translational research efforts to commercialize basic insights, and cluster policies (e.g. Klette et al., 2000; Hyytinen and Toivanen, 2005; Tödtling and Trippl, 2005; Dodgson et al., 2011; Nishimura and Okamuro, 2011). Most advanced industrial countries, particularly those in the OECD, have engaged in at least some of these policy interventions (OECD, 2013).

Direct subsidy programs are among the most widely used and extensively studied of these policy interventions. Economic models of subsidies suggest that it would be socially optimal for funding to flow to projects that offer high degrees of social returns, so that firms with more broad-based and basic technologies should be more likely to receive grants (Stiglitz and Wallsten, 1999). Stated differently, social planner should consider three issues when providing direct subsidies, including the subsidy's potential (a) to induce innovation that would otherwise not have been produced, (b) to generate knowledge spillovers (Stiglitz and Wallsten, 1999), and (c) to certify firm quality to attract additional outside investment (Lerner, 1999; Tool and Turvey, 2009). Some programs are set up with these aims in mind, while others, including the often-studied Small Business Innovation Research (SBIR) Program, contain a mix of goals (Lerner, 1999). Even among programs set up with the social planner's goals in mind, a number of factors could impede their realization. One pitfall could simply be that it is difficult to judge which applications are worthy of support. The evaluation of technological and business potential is, indeed, a difficult challenge. A second pitfall is that subsidies may end up being allocated to firms whose projects were highly likely to succeed anyway. Funding such projects may result in high-profile successes for the funding agency, but is not socially optimal, as it does not induce success that would not otherwise have been achieved and may crowd out other investment that could have taken place. This "picking winners" approach wastes public funding not by investing in firms that would fail, but by granting funds to firms that would have succeeded in any case (Wallsten, 2000).

There are a number of reasons to be particularly skeptical about the ability of subsidy programs to have a positive impact on innovation in emerging economies. First, state capacity is weaker in the emerging economy context and corruption is typically more widespread (Hellman et al., 2003). Politicians and state officials may use public funding programs to advance their private interests or those of their friends, families, or contacts (Johnson and Mitton, 2003Malesky and Taussig, 2009). In some cases, the diversion of public expenditure for private gain can be extreme; scholars have documented cases in which as much as 87 percent of intended public investment has been diverted by state officials for private gain (Reinikka and Svensson, 2004). Second, the information asymmetry that frustrates venture financing is particularly salient in countries where the investment is carried out by government bureaucrats with limited technological and business expertise (Lerner, 2009). Entrepreneurs could be highly motivated to misrepresent their information during grant application in countries featured with weak legal institutions (Stuart and Wang, 2016). Third, public financing, even if administered professionally, may be insufficient to promote firm innovation in countries with underdeveloped innovation ecosystem (Nelson, 1993; Martin and Scott, 2000; Gans et al., 2008). For example, capital infusion may not improve firm performance or innovative outcomes in the absence of institutions that protect intellectual property, promote information exchange, and facilitate cross-organizational collaboration (McDermott et al., 2009).

[1] These results differ from Guo et al. (2016), who find that Innofund recipients outperform a sample of carefully, matched control firms. We employ a slightly different sample of firms from Guo et al. (2016), i.e., firms in the ZGC area of Beijing vs. firms from around China, but the biggest difference in our studies is our ability to identify both funded and unfunded applicants and to measure heterogeneity in project quality, based on project application scores.

There are also reasons to be optimistic about the prospect of government subsidy policies being effective in emerging economies where innovation-oriented ventures are often financially constrained. In cases in which financial markets are less-than-perfect in allocating capital to the highest value investments, signals from informed, neutral arbiters may be of particularly high value (Zhao and Ziedonis, 2014). Further, government review can reduce the potentially high fixed costs of evaluating risky ventures, enabling private funders to allocate their resources more effectively across potential investment targets (Lerner 1999). This is particularly true if government funding resolves technical uncertainties, e.g., through the completion of risky prototypes, that can facilitate funding consideration by venture capitalists and other types of equity backers (Toole and Turvey 2009). Providing partial solutions to these information and financing difficulties may, thus, have a particularly strong effect in the context of emerging economies.

2.2. Evidence to date & opportunities going forward

A wide range of studies investigate whether innovation subsidies (a) crowd out or crowd in private investment (e.g. Wallsten, 2000; González et al., 2005), (b) serve as signals to induce additional funding (e.g., Lerner, 1999; Feldman and Kelley, 2006; Toole and Turvey, 2007), and (c) induce superior performance among recipient firms (e.g. Schneider and Veugelers, 2010; Zhao and Ziedonis, 2014). Despite the volume of these studies, they have found substantial variation in effects and it is reasonable to interpret the body of the evidence as mixed. Although notable exceptions exist, findings for U.S. programs are generally less optimistic regarding the impact of subsidies on investment and output than are the findings for European programs (see, e.g. Hall and Van Reenen, 2000; Zúñiga-Vicente et al., 2014; and Dimos and Pugh, 2016 for helpful reviews of the literature). The small number of studies of subsidy programs in emerging markets is optimistic about their effects, despite the concerns that we raise above. For example, Özcelik and Taymaz (2008) conclude that subsidy receipt has a positive impact on post-funding private R & D investment in Turkey and Guo et al. (2016) conclude that the Innofund, which we study here, induces innovation output in China.

Among the reasons for the lack of convergence across the set of empirical studies is that the design and implementation of subsidy programs are heterogeneous across countries, industries, and time and that researchers use different methods and units of analysis (see, Klette et al., 2000). A particularly important source of variation lies in the ability to estimate the counterfactual associated with subsidy receipt, i.e., what would have happened to recipient firms in the absence of funding (Jaffe, 2002, 2013). Since programs do not use random assignment to allocate grants, it is very difficult to isolate selection effects, i.e., which firms win subsidies, from treatment effects, i.e., the impact of the subsidy on firms that receive it. Research has used several approaches to overcome this problem, including identifying potential applicants via observable features (Lerner, 1999; Guo et al., 2016), estimating two-step selection models (Cappelen et al., 2012), comparing to a sample of applicants who did not receive grants (e.g., Meuleman and De Maeseneire, 2012), and using structural approaches (Takalo et al., 2013). One of the implications of the lack of cohesion among empirical findings is that limited theory exists to explain what types of effects we would anticipate as a result of institutional contexts or program features. Another implication is that it is particularly important to be cautious in attempting to generalize from innovation subsidy studies, including ours.

Greater convergence in research design and conclusions may help remedy this issue. Recently, a number of researchers have obtained administrative data that enable them to ascertain the ratings received by applicant firms and use these ratings in a regression discontinuity framework to isolate, at the firm level, the effects of selection into funding from the effects of funding. For instance, Zhao and Ziedonis (2014) use this approach to estimate the impact of subsidies programs in Michigan on recipient firms' survival, innovative productivity, and follow-on financing. Howell (2014) investigates the impact of the U.S. Department of Energy's SBIR Program on innovation and follow-on funding. We expand on these efforts by conducting the first RD analysis of which we are aware of to ascertain the causal impact of subsidy programs in a major developing economy, i.e., China, employing data from the Innofund program. Given that China has been perceived as a success story of "developmental state" where the visible hand of the government plays a key role in industrial development and firm competitiveness (e.g. Appelbaum et al., 2011), an empirical study of its main innovation subsidy program could shed insights on the program's operation and (lack of) success, thus helping nations learn whether and how to replicate such programs.

3. Institutional context: innovation funding in China and the innofund

3.1. Entrepreneurial finance in China

While the Chinese economy has grown substantially over the past three decades, the country's financial institutions are underdeveloped and dominated by large state-owned banks that are reluctant to make loans to private firms (Huang, 2002).[2] Early-stage technological ventures in China are further constrained because the country's venture capital (VC) industry is itself still in a formative stage (White et al., 2005). On paper, China has become the third largest VC market in the world after the U.S. and the EU, but most of the Chinese VC firms focus on late-stage mature ventures rather than on early-stage startups. Ernst & Young reports that "companies (receiving VC funding) in China are typically more developed, further along in their life cycle and positioned to exit within 18–24 months" (2014, p. 3). By contrast, the median time for a VC to exit a deal in the U.S. is 7.15 years.

As their needs are not met by the formal financial institutions, China's private firms have used alternative and informal channels to fund their growth and daily activities. While hard to measure precisely, China's informal financial sector has been estimated to comprise at least a quarter of all financial transactions (Tsai, 2002). Further estimates suggest that, by the end of 2003, 740–830 billion yuan RMB were managed by illegal entities such as underground money houses, informal banks, pawn brokers, and money lenders (Ayyagari et al., 2010).

The capital market difficulties faced by Chinese firms may have particular implications for innovation-oriented entrepreneurship. Prior research shows that firms operating in environments with underdeveloped financial institutions are less likely to engage in innovation because (a) financial constraints make other activities such as production and the purchase of new machines more expensive and (b) innovation requires long-term investment with uncertain returns that are hard to evaluate for less-qualified loan professionals. For example, based on a study of 14,400 firms in 27 transition economies, Gorodnichenko and Schnitzer (2013) find that firms operating in countries with more severe financial constraints are less likely engage in innovation and that the detrimental effect is greatest in countries with high costs of external finance and among small and young firms. The authors argue that transition and emerging market economies could benefit from emulating policies, like the U.S. SBIR program, that support innovation-oriented investment among firms most sensitive to financial frictions. In the context of China, Zhu et al., 2012 survey found that more than 60 percent of small and medium-sized private enter-

[2] For instance, by 2001, even though the private sector accounted for more than 50 percent of China's economy, it accounted for just 7 percent of state bank lending (Firth et al., 2009). Furthermore, private firms in China were estimated to pay twice what state-owned enterprises (SOEs) paid for external financing. Even though the total financial and interest expenses have declined on average for SOEs during the period of 1997–2006, they remained basically unchanged for private firms (Hale and Long, 2011).

prises cite financial constraints as one of the most severe barriers for their innovation activities. Using a panel of 120,753 manufacturing firms over the period 2000–2007, Guariglia and Liu (2014) find that Chinese firms' innovation activities are negatively affected by their financing constraints. In particular, private firms suffer the most, followed by foreign firms, while state-owned enterprises (SOEs) are the least financially constrained.

The Chinese government acknowledges these financial constraints and has implemented policies to alleviate them (OECD, 2008), for example, by establishing funding programs such as the Torch Program, the 863 Program, and the 973 Program.[3] Some international observers consider that China is "at an early stage in the most ambitious program of research investment since John F. Kennedy embarked on the moon race" (Wilson and Keeley, 2007). Taken together, these programs spent more than 27 billion yuan RMB ($4.34 billion) in 2012, about twice what was spent on the SBIR program that year.

3.2. The innofund

Initiated by China's State Council in 1999 as part of the Torch Program, the Innovation Fund for Technology-Based Small and Medium-Size Firms (the Innofund) is China's premier program targeting early-stage technological ventures. The Innofund is administrated by the Ministry of Science and Technology (MOST), though it is funded by the Ministry of Finance (MOF). The 863 and 973 Programs, which target large established (state-owned) enterprises and state research institutions, are older and larger than the Innofund. The Innofund, however, constitutes the largest source of state-supported R & D innovation financing for young, entrepreneurial ventures in China.

As a government program that aims to overcome market failures through public financing of early-stage innovation ideas that are promising but too risky for private investors, the Innofund has some features in common with the U.S. SBIR program, but it differs in important ways. The SBIR program is a federal program coordinated by the Small Business Administration but administered by separate federal agencies, some of which, such as the Department of Defense, use SBIR funds to achieve aspects of their missions. The Innofund, however, is administrated by a single government entity, the MOST Administration Center of the Innovation Fund, and is not committed to any particular mission championed by individual government agencies. It is committed to favor six broad industrial areas: electronics and information technology; biomedicine and pharmaceuticals; new materials; optics, machinery, and electric integration; environmental conservation; and new energy and energy efficiency.

Like the SBIR program, the Innofund defines "small and medium-sized firms" as for-profit businesses that have fewer than 500 employees and of which at least 50 percent of the equity shares are owned by one or more people who are current or former citizens (of the U.S. or of the People's Republic of China, respectively). Unlike the SBIR, however, the Innofund's grant application includes explicit guidelines on qualification, especially regarding R & D capabilities. An applicant's R & D expenditure must be at least 5 percent of its annual revenue and at least 30 percent of the firm's employees must have a college degree or higher.

An overview of the Innofund granting process appears in Fig. 1. Similar to the U.S. SBIR program, China's Innofund relies on external experts rather than internal staffs to evaluate grant applications. Although the Innofund has made substantial efforts to recruit expert evaluators from the private industry, it has had more success attracting them from public sector institutions, such as state universities and research centers. The Innofund requires that each application be reviewed by at least four technical experts and one financial expert. Each technical expert evaluates the project independently and assigns an initial score, after which all the technical experts discuss the project together and assign a single final technical score. The same procedure is followed by projects to which more than one financial expert has been assigned. The Innofund integrates the final financial and technical scores and generates the project's comprehensive or "total" score. The MOST Administration Center of the Innovation Fund coordinates the national version of this evaluation process. Before applications reach the MOST Administration Center, they are first subject to a parallel regional process, in which local ratings are computed and projects are screened for national review. The local scores are not used in the computation of the national financial and technical scores, but they are included, along with the national financial and technical scores, in the undisclosed formula by which national total scores are computed.

The Innofund ranks the applicants by total score and funds projects in rank order until its annual budget runs out. There are, however, two exceptions to this procedure. First, the Innofund reserves the right to veto its outside experts' decision to fund a firm if it learns that the firm has fabricated information in its application, that its technology is under IP dispute, or that its product or production process may cause serious environmental damage. Second, a firm with a financial score below 60 (out of 100) is automatically disqualified, regardless of its technical or total scores. A firm with a financial score between 60 and 65 is eligible only if its financial difficulty is judged to be temporary and caused by large R & D expenditures. This is consistent with the Innofund's effort to avoid financially-stressed firms. Because its budget is determined by the Ministry of Finance and is independent of project evaluation, the evaluators do not know the cutoff in advance. As a result, it should be hard for the evaluators or Innofund officials to game scores around the funding threshold, although the discretion enabled by the exceptions described above does provide the opportunity for officials to apply administrative discretion over grants and, potentially, to engage in manipulation of outcomes.

The Innofund has been the main innovation subsidy program for China's small and medium-sized technology firms since its founding in 1999. By 2012, it had financed 39,823 projects and invested 26.39 billion yuan RMB. Funds may be provided as equity-free grants, loan interest subsidies, or very occasionally as equity investments. Recipients typically receive 0.5–1.0 million yuan RMB (approximately $80,500–$161,000 in March 2015) from the MOST, plus a matched grant, equal to 50–100 percent of the Innofund award, from the local government. For early-stage technology ventures in China, this is a substantial grant, particularly when it comes without equity dilution.

Table 1 provides basic descriptive information on the Innofund's annual budget, yearly number of applications, awardee percentages, and the average funding size per winning proposal during the period of 1999–2012. One salient pattern in Table 1 is the dramatic increase in the Innofund's budget beginning in 2007, reflecting a switch in the Chinese government's mindset regarding the role of domestic innovation. In the 1990s, the Chinese government perceived foreign direct investment and international trade as the main sources of technological upgrading (Huang, 2002). In 2006, the government unveiled a national technological plan with the dual goals of decreasing reliance on foreign technology and developing indigenous technologies (Gao, 2013). This policy was officially adopted in late 2007.

Even though the Innofund has been the largest state-funding program to support early-stage technology ventures in China, efforts to quantify its effects are nascent (for an exception, see Guo et al., 2016). Casual observations often associate the Innofund with success. For example, of the first 28 firms listed on China's Growth Enterprise

[3] The Torch Program, established in 1988, was designed to develop high-tech firms in China by providing support for science and technology industry parks and technology business incubators and later the Innofund. The 863 Program (or State High Technology R & D Program) was established in March 1986 principally to provide R & D grants to domestic firms, although it also supports science and engineering education and training. The 973 Program, established in 1997 as a complement to the 863 and Torch Programs, provides funding to firms and universities engaging in basic research.

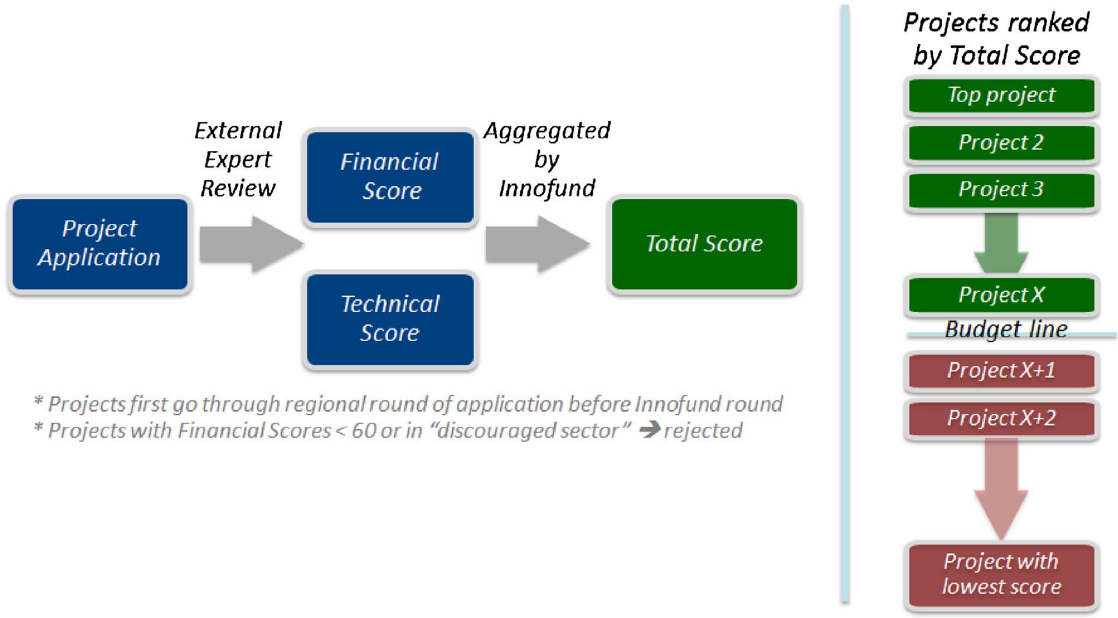

Fig. 1. Innofund project review and funding process.

Board in 2009, 24 had received Innofund grants.[4] Furthermore, around one-third of the firms listed on China's Small and Medium Board were Innofund awardees.[5] According to the Innofund's self-assessment, it had created more than 450,000 jobs during its first 10 years. However, one has to keep in mind that as the Innofund generally selects the most promising high-tech ventures, and thus the "success" described above may well conflate selection effect and treatment effect.

While the Innofund has funded some of the most promising technology ventures in China, there are also increasing doubts about its capability to filter out low-quality firms. One report shows that between 1999 and 2008, the Innofund terminated funding to more than 1295 firms it deemed incapable of completing their proposed projects (Shen et al., 2013). Even though early-stage technology ventures generally face high hazard rates, interviews suggest that many of the terminated projects are "zombie projects" set up by shell companies solely to snare state funding. Based on a rough estimation, these zombie projects reaped at least 2 billion yuan RMB in state funding between 1999 and 2012 (Shen et al., 2013).

Even among the non-shell companies, manipulation has been found to be prevalent. One study estimates that more than half of the Innofund applicants manipulated their financial data (Stuart and Wang, 2016). Arguably the most scandalous example of fraudulent behavior among Innofund recipients occurred at Hanxin Microprocessor. The firm's founder, Jin Chen, rose to national prominence in 2003 after he had reportedly invented one of the first digital signal processing (DCS) computer chips in China, which had been a stated priority of the Chinese government (Barboza, 2006). Although Chen's research laboratory at Shanghai Jiaotong University and his family of firms had received more than 110 million yuan RMB in state grants, including 3.21 million yuan RMB from the Innofund and local state agencies in Shanghai, Chen and his team never actually had microprocessor design capability (Zhang and Wo, 2006). In reality, the Hanxin chip that Chen claimed to have developed was a Motorola chip whose original identification had been sanded away by Chen's employees, and the follow-on chip innovations never actually worked, but it appeared as if they had, since Chen had faked the data. Once these frauds were uncovered, Chen was fired from his academic posts and was permanently embargoed from government-funded research, but he has never faced criminal or civilian investigation, perhaps due to his powerful political connections (Fuller and Douglas, 2016).

While these examples suggest that information asymmetry and

Table 1
Innofund program overview: Budget, applications, awards, and grant sizes, 1999–2012. Source: Innofund, various years.

Year	Initial budget (¥100m)	Number of applications	Number of awards	Percent awarded	Planned total grant (¥100m)	Average award size per grant (¥ 1000)
1999	10	3329	1089	32.71	8.16	749
2000	5	4974	872	17.53	6.59	756
2001	8	3682	1008	27.38	7.8	777
2002	5	4215	780	18.51	5.4	693
2003	5	4274	1197	28.01	6.64	555
2004	5	4925	1464	29.73	8.27	565
2005	6	5406	1552	28.71	9.88	637
2006	7.5	6399	1905	29.77	8.43	443
2007	11	(6582)	(2113)	(32.1)	(12.56)	(594)
2008	14	6765	2470	36.51	14.62	592
2009	28	10343	5855	56.61	34.84	595
2010	35	11517	5544	48.14	42.97	776
2011	37.7	9124	6545	71.73	46.4	709
2012	43.7	11968	7436	62.13	51.34	690
99–12	*220.9*	*(93503)*	*(39823)*	*(42.59)*	*(263.9)*	*(663)*
99–12 in $US (using 2012 exchange rates)	*$3.20b*				*$3.83b*	*$96.1k*

Notes: Data in parentheses are author estimates based on Innofund documents. Our sample includes data from the Zhongguancun (ZGC) Innofund Program from 2005 to 2009. These years are highlighted in grey. Data in parentheses involve estimates. We use 2012 exchange rates to convert renminbi to U.S. dollars. Exchange rates have varied somewhat over time, however. The yuan-to-dollar exchange rate rose from 0.12:1 in 2005–0.145:1 in mid-2008, after which it remained relatively stable until mid-2010, then rose relatively steadily to approximately 0.16:1 in mid-2012, around which it has remained relatively stable until January 2015. Variables computed across years (i.e., 1999-2012) are in italics.

[4] The Growth Enterprise Board is a Nasdaq-style stock exchange in China.

[5] The Small and Medium Board has a higher entry bar than the Growth Enterprise Board but a lower bar than the Main Board, which is the Chinese version of the New York Stock Exchange.

bureaucratic incompetence could lead the Innofund to choose firms unworthy of funding, there are also reasons to speculate that bureaucratic intervention could take place in the grant allocation process. Even though China has experienced substantial economic growth over the past three decades, one unfortunate companion of such development has been the prevalence of corruption (Wademan, 2012). Even though the Innofund has designed the program so that the evaluation process is conducted by external experts, final decision-making on grants are made by program officials, giving them substantial discretionary power in circumstances of limited transparency and external monitoring. The lack of external pressure could become particularly strong after China adopted “indigenous innovation” as “a core strategy for national development” in late 2007 at the 17th National Congress of the Chinese Communist Party (China News, 2007). Prior to this policy, the Ministry of Finance (MOF) and the Ministry of Science and Technology (MOST) wrestled regularly regarding the annual budget and the administrative leadership in grant allocation. The new policy provided the MOST with both administrative control over the program and security in its annual budget, consequentially reducing the incentives for the Innofund to work diligently in grant administration.

4. Data, sample, and context

The data we analyze derive from a number of sources. Most notably, we utilize information obtained directly from the Innofund program, including grant applications and project ratings. We supplement this with data on patent applications from China’s State Intellectual Property Office (SIPO) and data on firm survival and ownership structure from the Beijing Administration of Industry and Commerce (BAIC). We use patent applications rather than grants because the SIPO patent review delay is sufficiently large (about three years on average and up to seven years in our sample) that using patent grant would result in substantial censoring.

The use of internal Innofund data is one of the novel elements of this project. Historically, few studies on innovation subsidy have been able to take advantage of internal administrative documents to compare the evaluations of successful and unsuccessful applications (for exceptions, see Howell, 2014; Zhao and Ziedonis, 2014). We were able to obtain such information for the subset of Innofund applications in the ZGC region of Beijing for the years 2005–2010.

Sometimes referred to as China’s Silicon Valley, ZGC is one of China’s leading industrial clusters and is most noted for its computer, semiconductor, and telecommunications firms. Fig. 2 presents a map of the region of Beijing in which the ZGC Park was initially founded. The Chinese government identified ZGC as an official science and research area in the 1950s and has located an increasing number of science- and technology-oriented institutions there. In the 1980s, the government allowed a number of researchers to found new ventures not supported by state funds. In 1988, the State Council approved ZGC Science Park, or the “Z-Park,” as the country’s first science and technology park. Since that time, ZGC has expanded out of its original location and the name has come to refer to a broader geographic region in northwest Beijing, equivalent to a city district. By the end of 2009, the ZGC area included 10 official technology parks, the headquarters of a number of highly visible Chinese firms (including Baidu and Lenovo), the Chinese Academy of Sciences, China’s top two universities (Peking and Tsinghua), and three of its top 10 engineering schools. By the end of 2014, 254 ZGC-headquartered firms had gone public (156 listed in China and 98 listed overseas), with a total market capitalization of 3.1 trillion yuan RMB (Z-Park, 2015).

The fact that ZGC is a leading high-tech center in China raises questions about the extent to which data for this region generalizes to other parts of China. We consider this an open question. On the one hand, firms in this region benefit from a mobile talent market, relatively strong IP protection, and a deep pool of local venture funding. A positive correlation between Innofund support and firm performance may result not from state funding alone but from the interplay between public funding and complementary features of the local environment (McDermott et al., 2009). On the other hand, innovation subsidies may have a higher marginal impact in regions with a lower concentration of innovation-oriented firms. In the context of the U.S., Zhao and Ziedonis (2014) find that innovation subsidies in the state of Michigan particularly benefit firms that are distant from economic hubs. As we have only been able to obtain Innofund administrative data for the ZGC area, we cannot perform similar tests and must raise external validity as a concern for our study.

Our data include 1086 Innofund project applications from ZGC firms less than eight years old and fewer than 500 employees for the years 2005–2010. Of these, 540 applications were awarded Innofund grants, while 546 were not. Table 2 presents descriptive statistics for the sample. We obtain information on most firm-level characteristics from the Innofund application files. It is difficult, however, to verify the authenticity of these data as firms have incentives to put a positive spin on their application information (Stuart and Wang, 2016). The descriptive statistics shows substantial (and statistically significant) differences between the Funded and Unfunded firms, with the Funded firms achieving higher marks on all measures reported to the Innofund and on all firm outcome measures. Even though finding these differences in the sub-samples does not indicate the causal impact of the program on firm outcomes. It is an indicator, however, that Innofund grantees are associated with higher performance on dimensions that are observable to the evaluators before the funding decision and observable to analysts following grant receipt.

We attempt to avoid the pitfalls of reporting bias in evaluating the relationship between firm characteristics, grant receipt, and firm performance by considering only performance data that are not reported by the firm itself and that can be independently verified. We draw data on firm survival and changes in ownership from the Beijing Administration of Industry and Commerce (BAIC) and data on firm innovation from the Chinese State Intellectual Property Rights Office (SIPO)

The majority of our measures are relatively straightforward, but a few deserve further explanation. Because raw project scores are not comparable across application years, we center *Project Score* at the funding cut point for each year in our descriptive statistics and regression analysis throughout the paper. Specifically, $\textit{Project Score}_{it} = (\textit{Raw Project Score})_{it} - (\textit{Funding Threshold Score})_t$, where i indexes each project submitted for Innofund funding and t indexes each program year. Thus, positive *Project Scores* indicate that evaluators rated the project as above the threshold for funding, negative *Project Scores* indicate the opposite, and *Project Score* equals zero for any project whose score is exactly equivalent to that year’s funding threshold. Note that 111 projects do not have official Innofund scores, although their applications were reviewed and adjudicated by the Innofund. We explore these anomalies in greater detail below.

We have constructed two indicators of *Political Connections* based on resumes of the key firm leaders that were submitted with each firm’s Innofund application, one based on the connections of the founder/CEO and another based on the connections of other top management team members. Following Li and Zhang (2007) and Jia (2014), we code the first indicator variable (*CEO Political Connection*) as 1 if the firm’s key founder or chief executive officer (a) had previously worked in the Chinese government (including the army) or (b) had ever been a member of the People’s Congress or the Chinese People’s Political Consultative Conference. We code the second indicator variable (*Other Political Connection*) as 1 if any other top management team (TMT) members has similar career experiences as above. These are relatively conservative measures of a firm’s political ties, because it ignores connections among shareholders, families, and personal networks and because firms are less likely to report their key founders' prior political positions if they were fairly low-level. We code the *State Ownership* indicator variable as 1 if the application lists any SOE as a shareholder.

Fig. 2. Map of Beijing and the initial Zhongguancun Industrial District.
Source: Stanford Center at Peking University (2015).

Table 2
Descriptive statistics.

Variable	Full Sample					Funded			Unfunded			*T*-Test*
	N	Mean	Std dev	Min	Max	N	Mean	Std dev	N	Mean	Std dev	
Application characteristics (reported by the Innofund)												
Application Year	1086	2007.28	1.76	2005	2010	540	2007.70	1.79	546	2006.87	1.63	
Grant Awarded (0/1)	1086	0.50	0.50	0	1	540	1	0	546	0.00	0.00	***
Size of Grant (if awarded) (¥10k)	540	58.51	15.97	20	140	540	58.51	15.97	546	0.00	0.00	***
Project Score	975	0.52	10.62	−75	28.24	474	8.82	5.55	501	−7.34	7.96	***
Missing Scores	1086	0.10	0.30	0	1	540	0.12	0.33	546	0.08	0.28	**
Requested Project Duration (years)	1086	2.02	0.16	1	4	540	2.01	0.14	546	2.02	0.18	
Firm characteristics in application year t (as reported to the Innofund)												
Years Since Founding	1086	3.68	1.71	1	7	540	3.77	1.73	546	3.58	1.69	*
Employees (100 s)	1086	0.37	0.38	0.03	3.65	540	0.39	0.40	546	0.35	0.36	*
R & D Expenditures (¥10k)	1082	127.48	191.26	0	1757	540	147.46	208.07	546	106.78	170.41	***
Total Profits$_{t-1}$ (¥1m)	1086	0.60	2.09	−4.74	14.57	540	0.87	2.31	546	0.34	1.80	***
Political Connections, Founder & CEO (0/1)	1086	0.11	0.31	0	1	540	0.14	0.34	546	0.08	0.28	***
Political Connections, Other TMT (0/1)	1086	0.14	0.35	0	1	540	0.14	0.35	546	0.13	0.34	***
State Ownership (0/1)	1086	0.06	0.23	0	1	540	0.07	0.26	546	0.04	0.19	**
Team Has Prior Prize (0/1)	1086	0.21	0.41	0	1	540	0.28	0.45	546	0.15	0.35	***
# Firm Patents Claimed on Application	1086	1.94	3.08	0	20	540	2.46	3.55	546	1.42	2.42	***
CEO Indicates Prior Research Career	1086	0.32	0.47	0	1	540	0.37	0.48	546	0.27	0.45	***
Post-application year performance indicators												
Firm Failed Prior to 2015 (0/1)	1086	0.11	0.32	0	1	540	0.07	0.26	546	0.15	0.36	***
SIPO Innovation Patent Filed Post-application? (0/1)	1086	0.34	0.47	0	1	540	0.37	0.48	546	0.32	0.46	**
New State- or Community-owned Enterprise Owner? (0/1)	1086	0.08	0.28	0	1	540	0.13	0.33	546	0.04	0.21	***
New Venture Capital or Private Equity Owner? (0/1)	1086	0.11	0.31	0	1	540	0.12	0.33	546	0.09	0.29	*

^ *T*-Test indicates whether mean of Funded & Unfunded observations are statistically different at the following confidence levels, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Team Has Prior Prize is coded 1 if the key founder or any TMT member ever won a major prize at the national or provincial (ministerial) level. These prizes include, but are not limited to, the National Award for Progress in Science and Technology, National Model Worker, Project 863/973 grant recipient, and membership in the 1000 Talents Program.

Consistent with the Innofund's aim of supporting innovative and entrepreneurial firms, the average firm in the sample was founded between three and four years before its application, has 36 employees, and claims to have filed 1.94 SIPO patents. Slightly more than one-fifth of applicants report having won a national or provincial prize prior to the application. On average, firms report 1.27 million yuan RMB (approximately $192,000) in R & D expenditures and 0.6 million yuan RMB ($80,000) in prior-year profits.[6] ZGC Innofund grants average 585k yuan, which is equivalent to 45% of an average firm's average annual research budget.[7] Slightly less than one third of firms have CEOs with experience in scientific research and only six percent of firms have state owned enterprises as equity holders.

The industrial composition of firms appears in Table 3A. Approximately 61 percent of the applicants over the sample period were in information technology (classified by the Innofund as "electronic information"), while firms in the "optomechatronics," "biomedicine," and "resources and the environment" sectors make up 13.5 percent, 7.9 percent, and 6.1 percent, respectively.

Firms in the sample have a relatively high survival rate. Only 11 percent are identified as having failed as of 2015. We define a firm as having failed when its record at BAIC indicates its registration has been (a) terminated voluntarily or (b) terminated by the BAIC due to failure to file registration reports for two or more consecutive years. Post-grant patent information was collected from the State Intellectual Property Office (SIPO) and we include only data on "invention" patents, a category reserved by the SIPO for innovations of relatively high novelty and commercial value.[8] Only 34 percent of firms applied for invention patents in the post-grant period. This may reflect the fact that the majority of the firms operate in information technology, which employs patenting to a lesser degree than other industries (e.g., the chemical and pharmaceutical industries). Ownership change is also relatively infrequent; over the sample period, 8 percent of firms added significant public sector (SOE or COE) owners and slightly higher than 10 percent of firms received VC/PE investments.

Table 3B reports the number of ZGC Innofund applications and the fraction of awards granted between 2005 and 2010. The ZGC region experienced a funding boost in 2008, 2009 and 2010. Whereas fewer than 40% of applications were funded between 2005 and 2007, more than 60% won grants between 2008 and 2010. Since the bar for Innofund grant receipt was lower and the degree of government scrutiny to which the program was subjected was lessened during the 2008–2010 era, we anticipate that the program impact is likely to be lower during the later years of our data.

[6] The profit data were winsorized at 1% to reduce the influence of outliers.

[7] We must consider two factors when comparing the amount of Innofund grant support to the firm's R & D budget, each of which suggest that the actual fraction of Innofund grants to firm R & D may be higher than it initially appears. First, firms have incentives to over-report their R & D budgets in their applications to signal research activity. Second, the reported Innofund grant reflects the amount of funding that a winning firm received from the MOST without counting the local matched fund of 50% or higher. When all these factors are taken into consideration, state funding could be as large as a firm's annual R & D budget.

[8] There are three categories in the Chinese patent system, invention, new utility, and new design, which are listed in decreasing order of innovativeness and commercial value. The relative importance of a patent is reflected in SIPO's patent review system, which imposes differential application fees, requirements for public notification, lengths of examination, and patent terms according to category. In evaluating an applicant's technological capability, Innofund's rule of thumb is that one "invention" patent counts for six "new utility" patents. "New design" patents are not viewed a substantial innovations. As a result of this clear hierarchy, we focus solely on invention patents.

Table 3A
ZGC Innofund applications by industry, 2005–2010.

Industry	Obs	%
Biomedicine	86	7.9
Electronic information	660	60.8
High-tech services	26	2.4
New energy & energy-efficiency	45	4.1
New material	56	5.2
Opto-Mechatronics	147	13.5
Resources & environment	66	6.1
Total	1086	100%

Table 3B
ZGC Innofund applications and award percentage by year, 2005–2010.

Year	Applications	Awarded
2005	240	38.8%
2006	185	40.5%
2007	193	37.8%
2008	135	53.3%
2009	163	69.3%
2010	170	67.1%

5. What explains innofund grant receipt?

We investigate two key questions in our analysis: First, we examine which features of project applications enable firms to win Innofund grants, i.e., what drives selection into grant funding. Second, we investigate whether grant receipt has an impact on firm outcomes, i.e., whether Innofund grants induce a treatment effect. Our ability to answer both sets of questions derives from our use of Innofund administrative data.

In many cases, researchers studying firm subsidies know the identities of firms that receive funding but not the identities of firms that applied and were turned down (Lerner, 1999; Guo et al., 2016). In such cases scholars interested in assessing selection and treatment effects often create control groups, using propensity score matching or other techniques, that enable them to identify a set of firms whose features may match with applicant firms on some observable dimensions but that may or may not have applied for innovation subsidies (Czarnitzki and Lopes Bento, 2014; Guo et al., 2014). While making it possible to compare firms that receive funding with a set of similar firms, this does not identify the features that drive the specific decision to fund some applicants rather than others and thus leaves open the possibility that unobserved factors play a key role in the funding decision. Our ability to compare across all applicant firms – and to leverage the information about project application scores – alleviates many of these concerns.

We begin our analysis by employing three types of analyses to understand the Innofund's grant allocation process. First, we use OLS regressions to test which firm- and entrepreneur-level features are associated with higher evaluation scores. Second, we conduct logit regressions to investigate the antecedents of grant winning, both with and without controlling for evaluation scores. Third, we look at the descriptive statistics of firms with missing scores and firms with scores below the cutoff point but having received funding. The last set of analyses is rudimentary but helps open up the black box of the Innofund's grant allocation to shed lights on the role of bureaucratic intervention in state funding.

Table 4 presents the results of regressions on project evaluation and grant allocation. Each model in the table includes dummy variables for each application-year, industry sector, and application type, as well as variables reflecting project characteristics, an indicator of whether the firm had previously applied for Innofund support, and information on the firm founder's professional experiences and education. Each model also includes data on firm characteristics, including age, size, innovation investment, political connection, state ownership, and whether anyone in the founding

Table 4
Selection models – correlates of Project Score and Grant Funding.

Model	(4 − 1)	(4 − 2)	(4 − 3)	(4 − 4)	(4–5)	(4–6)
Method	OLS	OLS	OLS	Logit	Logit	Logit
Dependent Variable	Project Score	Project Score	Project Score	Funded	Funded	Funded
Sample Years	2005–2007	2008–2010	All Years	2005–2007	2008–2010	All Years
Variables reported on Innofund Application						
Profit (t-1) (mil. RMB)	0.649	0.426	**0.578***	0.091	0.055	0.091
	(0.398)	(0.213)	**(0.230)**	(0.116)	(0.080)	(0.063)
Reported patents	**0.610****	**0.204***	**0.335****	− 0.066	0.067	0.041
	(0.124)	**(0.066)**	**(0.115)**	(0.080)	(0.043)	(0.036)
Employee Count (hundreds)	− 1.122	− 2.600	− 1.047	− 0.205	− 0.413	− 0.325
	(1.017)	(1.633)	(0.777)	(0.608)	(0.852)	(0.517)
R & D Expenditure (t-1)	0.394	0.166	0.291	0.046	0.016	0.022
	(0.230)	(0.294)	(0.164)	(0.166)	(0.086)	(0.069)
Variables computed by or verified by authors based on information reported on Innofund Application						
Political Connection via COE or Founder	1.198	0.302	0.741	0.608	**1.852*****	**1.021*****
	(1.139)	(2.162)	(1.014)	(0.519)	**(0.558)**	**(0.367)**
Political Connection via Other TMT Member	0.892	0.579	0.920	− 0.266	0.121	− 0.253
	(0.316)	(1.778)	(0.522)	(0.391)	(0.468)	(0.293)
State ownership stake	− 0.049	0.826	0.276	− 1.525*	0.282	− 0.298
	(2.213)	(0.954)	(1.003)	(0.865)	(0.751)	(0.600)
Team has prior prize	**3.526***	1.474	**2.751*****	**1.349*****	0.464	**0.839*****
	(1.198)	(0.909)	**(0.664)**	**(0.508)**	(0.465)	**(0.294)**
Variables made available to authors by Innofund						
Project Score				**0.638*****	**0.479*****	**0.529*****
				(0.076)	**(0.062)**	**(0.046)**
Project Score is Missing				**1.107***	**1.402*****	**1.321*****
				(0.652)	**(0.391)**	**(0.292)**
Observations	568	407	975	615	467	1086
R^2	0.148	0.180	0.306			
Adjusted R^2	0.110	0.129	0.286			
Log lik.	− 2067.506	− 1419.015	− 3508.574	− 117.066	− 127.980	− 256.019
Chi-squared				102.298	93.974	195.103

Robust Standard errors in parentheses; * p < 0.10, ** p < 0.05, *** p < 0.01. Bold values indicate statistically significant results.

Notes: Variables included in all models but not reported above (due to space considerations include Project Duration, Dummy if Firm had Applied for Grant in Prior Year, Founder Experience as a Researcher, Founder Experienced in State-Owned Enterprise, Founder Education = MA, Founder Education = PhD, Firm Age in Application Year, Application Year, Industry Sector, Application Type, and a Constant term. Project Scores are centralized around the funding threshold in their year of application. For some projects, the Innofund did not record or report a Project Score. For these observations, the variable Project Score is set to zero and the Project Score is Missing dummy is set to 1. Bold values indicate statistically significant results.

team had previously won a government-sponsored innovation or research prize. All models employ robust Huber-White standard errors, clustered by application year to address the possibility that errors are independent across years but correlated within year.

Models 4-1 to 4-3 show that three factors stand out as correlates of the centralized project score: reported profit, reported patent count, and whether the firm's founder or top management team had received any major prize at the national or provincial (ministerial) level. Each of these variables has a positive relationship with the score that underlies the grant selection process, although their levels of statistical significance vary, particularly across sample time periods. The relatively low R^2 in Columns 1–3 is consistent with prior estimations of subsidy grant receipt, which have found that grant scores have a substantial idiosyncratic component (Czarnitzki and Lopes Bento, 2014). The statistical significance and economic magnitude implied by models (4-1) and (4-3) suggest that firm features that we expect to be associated with higher scores are, indeed, positively correlated with Innofund scores during the stricter funding regime of the 2005–2007 time period. This is especially noticeable in the coefficients of variables that achieve statistical significance at the 95% level in some of the models, including *Profits (t-1), Reported Patents,* and *Team Has Prior Prize.*[9] *For example, the coefficient on Team Has Prior Prize suggests that, among the 2005–2007 Innofund applicants, those whose founders or top management team had previously won prestigious prizes prior to applying for Innofund grants were evaluated 3.5 points higher on the centralized project score than those without such prizes. This result suggests that the Innofund considered the past track record of firm leaders as a cue in inferring the firm's quality and grant worthiness.*

For the 2008–2010 applicants, even though we continue to see positive associations between observable merits and evaluation score, the results for the 2008–2010 suggest that the Innofund relaxed its requirements during this time period, as the relationship between *Project Scores,* observable merits, such as patents and prior prizes, is weaker in this period than in 2005–2007. For instance, those 2008–2010 applicants with prior prizes were only evaluated 1.47 points higher than their peers without such prizes, a level that is statistically indistinguishable from zero, considering the precision with which the coefficient is measured. Reporting higher profits is also associated with higher grant scores, although here, too, the magnitude of the relationship is slight and the noise in measurement is considerable. According to (4-3), each additional standard deviation in reported profits (2 million yuan RMB) is associated with a single additional point for the full sample. While this is a statistically significant result, it does not constitute a result of particular economic magnitude, as the standard deviation in *Project Score* (10.6) is substantially larger than 1.

While (4-1) to (4-3) suggest that *Project Scores* are highly idiosyncratic to the project, the models in the remaining columns of Table 4 document that these scores play a substantial role in explaining *Grant Funding*. Models (4-4) to (4-6) report the results of logit models

[9] In a robustness check that we do not present in the tables, we find that the count of actual SIPO patents filed prior to grant application are also a statistically significant predictor of *Project Score*, though not *Funding* conditional on the score. This suggests that, while there is certainly reason to doubt the veracity of information reported to the Innofund, there is also reason to believe that self-reported information may be correlated with underlying features of the firm.

Table 5
Political connection and Innofund grant among firms with missing scores.

		(1) Funded		(2) Grant size	
	Obs.	Mean	Std. Dev.	Mean	Std. Dev.
A. Political connection via CEO or cofounder					
Firms with no political connection	102	0.559	0.049	30.922	3.256
Firms with political connection	9	1.000	0.000	60.556	13.423
Difference between two groups		**−0.441*****	0.167	**−29.634****	11.644
B.					
C. Political connection via CEO, cofounder, or Top Management Team					
Firms with no political connection	90	0.556	0.053	31.656	3.515
Firms with political connection	21	0.762	0.095	40.476	8.337
Difference between two groups		**−0.206***	0.118	−8.821	8.310

Asterisks denote significance levels of two-tailed test: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Bold values indicate statistically significant results.

explaining *Grant Funding* as a function of the centralized *Project Score*, the variables previously used to explain *Project Scores*, and a dummy variable indicating whether the an applicant's project score was missing in the final Innofund data. Both time periods (2005–2007 and 2008–2010) experience a statistically significant and economically important relationship between *Project Score* and the probability of *Grant Funding,* suggesting that evaluators' scores are an important predictor of grant receipt in the ZGC district. The coefficient on *Project Score* in the full sample regression (4-6) implies that each additional score point around the mean corresponds to an increase of 70 percent in the odds of receiving a grant.

Although these findings provide evidence that the Innofund rewards applications that excel on the observable innovation-focused dimensions of merit the program seeks, other results in Tables 4 and 5 raise the possibility of bureaucratic intervention that may not be consistent with the program's aims. Although it is insignificant in predicting evaluation scores (4-1 to 4-3), CEO/Founder *Political Connection* is a significant predictor of grant receipt, particularly for the subgroup of firms that applied during the period of 2008–2010 (4-5 and 4-8). Controlling for *Project Score,* firms with CEO/Founder political connections have odds of grant funding six times as high in 2008–2010 and 2.7 times greater than firms without such connections. In unreported analyses, which are available upon request, we find that connected firms receive approximately 50,000 yuan RMB more than similar firms without such connections, an amount equivalent to one-sixth of the mean funding amount. Since the positive correlation between political connection and funding outcomes is observed while controlling for project score, this leads us to consider that the funding decision may not be based on score alone, as prescribed in the policy guideline of the Innofund.

Two other features of the funding decision are consistent with the concerns above and raise questions about Innofund grant administration. First, our sample contains fifty-one applications that earned *Project Scores* greater than the funding threshold but that were, nonetheless, not offered Innofund support. The Innofund's policy guidelines state that program officials may reject external experts' funding recommendations if applicants are discovered to have fabricated data or have product or production process that could lead to serious environmental damages. It is possible, therefore, that many of these firms were denied funding for legitimate reasons. However, our sample also contains seven applicants with *Project Scores* judged to be below the funding threshold that, nonetheless, received Innofund grants. These grant decisions contradict strict Innofund guidelines against funding firms with scores below the threshold. Although we have interviewed Innofund officials, we were unable to identify the specific mechanisms underlying these irregular cases. Their existence is consistent with and, indeed, strongly suggests bureaucratic intervention in grant allocation. Second, there are 111 observations in our sample with missing evaluation scores. Even though we do not know if the missing scores were the result of administrative negligence or deliberate actions, there is evidence consistent with bureaucratic intervention as missing scores are positively associated with grant receipt in each sample period, in (4-4) through (4–6). The coefficient on *Missing Score* in (4–6) suggests that, across all years of the sample, the odds of a firm with missing scores receiving Innofund funding are 3.7 greater than those of firms without missing scores. This relationship is measured to have an even greater magnitude in (4–5), during the years, 2008–2010, when the Innofund operated with relatively relaxed funding requirements.

Although the association between missing score and grant receipt could reflect random, benign administrative negligence, we cannot rule out the possibility that these findings arise from off-the-books activity that results in Innofund officials giving preferential treatment to particular applications. Table 5 reports additional evidence consistent with this explanation. Panel A of the table shows that among observations with missing scores, all nine firms with politically connected founders/CEOs received Innofund grants and that these firms receive larger grants. When we use a broader definition of political connection – a firm being coded as connected if any of its top management team member or cofounders have experiences working in the government (in Panel B), we continue to observe a significant and positive correlation between political connection and winning Innofund grants, although this correlation is not statistically significant in regressions.

Overall, the selection analyses provide a mixed view of the Innofund's application evaluation and grant allocation processes. On the one hand, we find that the Innofund uses observable firm- and entrepreneur-level features to assign evaluation scores and that the score is a key predictor of grant receipt. These outcomes are consistent with the view that this program has been professionally managed. On the other hand, the results also suggest that (a) the program relaxed its requirements during the 2008–2010 period when the MOST secured grant funding and administrative leadership over the Innofund under China's new innovation policy and (b) the existence of nonrandom missing scores, of firms receiving grants with scores lower than the funding threshold suggest bureaucratic interventions that are incompliant with the Innofund's official guidelines and are unlikely to be associated with the effective functioning of the program.

6. Impact of grant funding on firm outcomes

We conduct two sets of analyses relating ZGC Innofund grant receipt to firm outcomes. In our initial analysis, we estimate linear probability models predicting firm outcomes as a function of information on the observable quality of the grant application, the features of the applicant firm, and the Innofund's decision to fund the firm. In our subsequent analysis, we leverage *Project Scores* and the stated threshold for Innofund grant receipt. Specifically, we apply a regression discontinuity

(RD) design, which relies on the assumption that applications whose scores fall closely below or above the funding cutoff differ appreciably in the probability of funding though not in project quality and, therefore, can serve as a sampling frame within which we can identify the causal impact of funding on firm outcomes (Imbens and Lemieux, 2008; Lee and Lemieux, 2010). In recognition of the fact that the treatment rule is imperfectly applied, i.e., that some firms above the threshold do not get funding and that some firms below the threshold do, we employ a fuzzy rather than sharp regression discontinuity design. The results show the importance of accessing internal program data in estimating a causal relationship between state subsidies and post-funding firm performance, as data access often constrains the method that researchers could utilize and that different estimation strategies could lead to very different empirical conclusions.

6.1. OLS analysis

In Table 6, we report the results of models predicting firm performances using all the observations in our data and using information on applicant features, funding awards, and firm performance outcomes. Specifically, we estimate:

$$Y_{it+1} = \beta\ Funded_{it} + \gamma\ X_{it} + \varepsilon_{it+1}, \tag{1}$$

where Y_{it+1} reflects firm outcome measures that may be affected by Innofund grant receipt, *Funded* indicates whether the Innofund approves the firm's grant application, X_{it} indicates a vector of firm- and application-specific characteristics and control variables, and ε_{it+1} reflects the mean zero error term. The subscript t denotes the time period of the application and $t + 1$ indicates the post-application period.

Ideally, we would like to investigate the impact of Innofund grant receipt on a battery of firm performance measures, including multiple accounting measures and in a panel data context. Although we obtained access to multiple data sources that reported a number of such measures, we found few that we considered accurate and reliable. We focus, therefore on three types of post-grant outcomes that provide important indicators of firm performance: firm survival, patenting, and receipt of equity investments. We explain these in greater details below. We conduct separate analyses on the subgroup of firms that applied during the period of 2005–2007, the subgroup of firms that applied during the period of 2008–2010, and the full sample of applicants. We distinguish these time periods to acknowledge that the latter represents an episode with substantially relaxed funding requirements (and thus potential post-grant performance implications).

We report the results of linear probability models predicting firm post-grant outcomes in Table 6. Panel A predicts the relationship between observable attributes of the firm's application and the probability that the firm is registered by the Beijing Administration of Industry and Commerce (BAIC) as no longer existing as of 2015. While we are confident that BAIC's data on firm survival are not biased by Innofund receipt, we are less confident about the accuracy of the dates of firm failure. We therefore conduct cross-sectional analyses of firm survival to the end of the data period rather than a hazard analysis of the probability of survival in any one year between the application year and 2015. To control for cohort differences in probability of death by 2015, these models include a series of dummy variables for application years. To account for variation in application type and industry membership, we include dummy variables for these factors as well as for a vector of other firm characteristics. In the interest of space, we do not report coefficients for these variables. Each of our models, in this table and in subsequent tables, uses robust Huber-White −standard errors. To be consistent with the RD regressions, we exclude all observations for which *Project Score* is missing.

The principal finding in these models is that grant receipt is negatively associated with the likelihood of firm death by 2015 in the overall sample and among the subsample of firms applying between

Table 6
Linear probability models predicting post-application firm outcomes.

	2005–2007			2008–2010			All Years		
	(6−1)	(6−2)	(6−3)	(6−4)	(6−5)	(6−6)	(6–7)	(6–8)	(6–9)
Panel A: DV = Firm Death by 2015									
Funded	**−0.105*****	**−0.117*****	**−0.109*****	0.028	**0.031***	**0.031***	**−0.084*****	**−0.057*****	**−0.053****
	(0.030)	**(0.031)**	**(0.033)**	(0.018)	**(0.018)**	**(0.019)**	**(0.020)**	**(0.020)**	**(0.021)**
Year & Industry FEs		Yes	Yes		Yes	Yes		Yes	Yes
Other Controls			Yes			Yes			Yes
R^2	0.018	0.051	0.068	0.005	0.042	0.079	0.017	0.073	0.086
Panel B: DV = SIPO Patent Application by 2015									
Funded	**0.088****	**0.110*****	0.039	0.053	0.054	0.022	0.046	**0.088*****	0.030
	(0.043)	**(0.042)**	(0.043)	(0.047)	(0.048)	(0.046)	(0.030)	**(0.032)**	(0.031)
Year & Industry FEs		Yes	Yes		Yes	Yes		Yes	Yes
Other Controls			Yes			Yes			Yes
R^2	0.008	0.061	0.149	0.003	0.057	0.180	0.002	0.060	0.146
Panel C: DV = Equity Investment from State- or Community-Owned Enterprise (SOE/COE) by 2015									
Funded	**0.112*****	**0.114*****	**0.098*****	**0.044***	**0.050***	0.039	**0.076*****	**0.086*****	**0.072*****
	(0.027)	**(0.027)**	**(0.027)**	**(0.026)**	**(0.026)**	(0.028)	**(0.018)**	**(0.019)**	**(0.020)**
Year & Industry FEs		Yes	Yes		Yes	Yes		Yes	Yes
Other Controls			Yes			Yes			Yes
R^2	0.038	0.051	0.120	0.006	0.017	0.067	0.019	0.031	0.074
Panel D: DV = Equity Investment from VC or Private Equity Firm by 2015									
Funded	0.036	0.042	0.027	−0.016	−0.017	−0.019	0.022	0.018	0.007
	(0.026)	(0.026)	(0.026)	(0.034)	(0.035)	(0.035)	(0.019)	(0.021)	(0.021)
Year & Industry FEs		Yes	Yes		Yes	Yes		Yes	Yes
Other Controls			Yes			Yes			Yes
R^2	0.004	0.020	0.066	0.001	0.041	0.125	0.001	0.023	0.071
Observations	568	568	568	406	406	406	974	974	974

Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Bold values indicate statistically significant results.
Notes: "Other Controls" include the following variables: Employee count (hundreds), CEO Political Connection, Other Top Management Team Political Connection, Reported Patents, Team Has Prior Prize, Founder Experienced as a Researcher, Founder Experienced in a State-Owned Enterprise, Founder Education = Master's Degree, Founder Education = PhD, Indicator of whether Firm had Previously Applied for Innofund Grant. All models exclude observations with missing Project Scores.

2005 and 2007, a period when the Innofund held relatively stringent criteria in award allocation. By contrast, we find a positive and statistically significant association between Innofund grant and firm death by 2015 for the subgroup of firms applying between 2008 and 2010, when the Innofund relaxed its selection requirements. The coefficients in Panel A (6-1) to (6-3) imply that funded firms experience a 10–12 percentage point lower likelihood of failure by 2015 than do unfunded firms, controlling for year and industry dummies, and a battery of other firm and project controls. The results in Panel A (6-4) to (6-6) come as a surprise to us, as they suggest that receiving funding during the looser funding regime, controlling for *Project Score*, is associated with a slight (3–4% point) increase in the probability of *Firm Death by 2015*. This is, indeed, a relatively small effect, less than one third as great as the reduction in the probability of Firm Death induced by funding during the 2005–2007 time period. We lack an explanation for this finding and it bears further scrutiny in our RD analyses.

Panel B reports the results of models in which the dependent variable indicates whether the firm applied for a SIPO invention patent by 2015.[10] Our results imply the possibility of a meaningful relationship between post-grant patenting and Innofund grant receipt. During the period in which grant funding was somewhat difficult to receive (2005–2007), funded applicants are between 4 and 11% points more likely to apply for SIPO patents than unfunded firms, although this result is only statistically significant in the absence of controls or with just year and industry fixed effects and not additional application-level covariates. No statistically significant results are evident for the looser funding regime of 2008–2010, during which the relationship is estimated to be approximately zero with the same precision as the 2005–2007 coefficients that were estimated to be positive. We examine whether this pattern holds around the funding threshold in the RD analyses that follow.

The next two panels report the results of regressions in which the dependent variables reflect new equity investments in the post-grant period. Panel C focuses on investment from State- or Community-Owned Enterprises (SOE/COE), while Panel D focuses on investment from Venture Capital (VC) and Private Equity (PE) Firms. The results suggest that SOE and COE investors are more likely to invest in funded firms in both the strict and loose funding regime periods, although no such statistically significant relationship exists for VC/PE investment. Specifically, the results in Panel C suggest that funded firms were 10–12 percentage points more likely to receive post-application funding boosts from SOE or COE firms for the 2005–2007 applicants and between 7 and 9 percentage points more likely to receive such boosts over the entire sample period. To the extent that prior studies suggest that public innovation funding can serve a signaling function that certifies recipient firms as worthy of private support, this relationship does not appear to exist among the more sophisticated of the potential investor sets in this case.

We interpret the results in Table 6 as suggesting that funded firms are (a) less likely to have failed than unfunded firms, (b) more likely to have received equity infusions from State-Owned and Community-Owned Enterprises across the sample period, and (c) potentially more likely to have applied for patents for the 2005–2007 application subgroup. Analyses like these that do not exploit the funding discontinuity might reach the conclusion that funding drove these outcomes. Before making any pronouncements about the causal impact of the Innofund on affected firms, however, we proceed to our RD approaches to the analysis.

[10] We should exercise caution when using patents as an outcome variable measuring firm performance in the post-grant period. Although the Innofund does not engage in post-grant reviews to see if grantees have patented their technology, grantees may nonetheless feel encouraged to engage in this behavior. Thus, if we find that patenting increases following grant receipt, this could be the result of institutional pressure rather than true innovation.

6.2. RD design – assumptions and conditions for analysis

The linear probability analyses above leverage two important features of the ZGC Innofund data – the identities of all applicant firms and the decision on whether each applicant did or did not receive Innofund grants. In the remaining analyses, we exploit information available from two other important features of these data − the annual threshold score for project funding and the scores that each project received. While firms with particularly high project scores may differ systematically from those with low scores, it is reasonable to assume that projects with scores extremely close to the funding threshold differ substantially in the probability of their receiving Innofund grans, but not substantially in the quality of their projects. If funding is, indeed, assigned randomly around the threshold, we could exploit this threshold in a regression discontinuity framework to ascertain the impact of Innofund grants on firm outcomes.

A number of assumptions need to be satisfied in order to have confidence that an RD analysis can identify the causal impact of Innofund receipt on firm outcomes (Imbens and Lemieux, 2008; Lee and Lemieux, 2010): First, a breakpoint must exist between the probability of funding and firm application scores. That is, the probability of funding cannot be a continuous linear function of application score. Second, firm features in the region of the threshold must be similar. Otherwise, firm outcomes may be the product of these features rather than of the funding received. Third, the outcome of the assignment (being funded or not) must not be subject to manipulation by the firms in the sample. We examine each of these assumptions below.

We examine whether the first requirement is satisfied in Fig. 3, which plots the likelihood of a project receiving funding as a function of its total score. The figure suggests a clear discontinuity around the cutoff point (i.e. centralized *Project Score* of zero), providing evidence that the first assumption is upheld. However, it is important to note that some observations below the funding threshold receive funding, while some above do not. While not casting doubt on whether RD is an appropriate design, this suggests that fuzzy RD is more appropriate for assessing causality than sharp RD.

We examine the second assumption by comparing the observable features of projects in the regression discontinuity region. In Table 7, we compare the mean values of key variables for those projects whose scores are close to the funding threshold, using two different-sized windows. The first window corresponds 3.05 points above and below the funding threshold, a figure which corresponds to the bandwidth suggested by the method of Imbens and Kalyarnaraman (Imbens and Kalyanaraman, 2012) and the other window corresponds to a bandwidth of approximately 5.23 points above and below the funding threshold, a figure which corresponds to the bandwidth suggested by Calonico et al., 2014 (CCT, 2014). Projects just below the threshold differ from those just above it on two key dimensions: centralized *Project Score* and *Funded*. The fact that application scores are higher in the above group is true by construction. For the IK (CCT) window, the fact that 71(79)% of firms just above the threshold received grants, whereas only six (three) percent of those just below it did, is consistent with the discontinuity point above. Firms just above and just below the funding threshold are statistically comparable on measures of age, size, political connectedness, prior innovation, employee count and founder characteristics. The one exception to this is that the average level of profits for firms above the funding threshold but inside the CCT window is statistically greater than the average level of profits for firms in the window but below the funding threshold. Despite this one departure, we believe that the firms in the neighborhood of the funding discontinuity are sufficiently similar that the RD assumptions are likely to hold.

The third assumption, the non-manipulation condition, requires that firms are unable to affect their assignment to the treated or non-treated group. We investigate this by comparing the distribution of observations around the funding threshold with the McCrary density test. McCrary (2008) posits that a discontinuity in density at the cutoff value

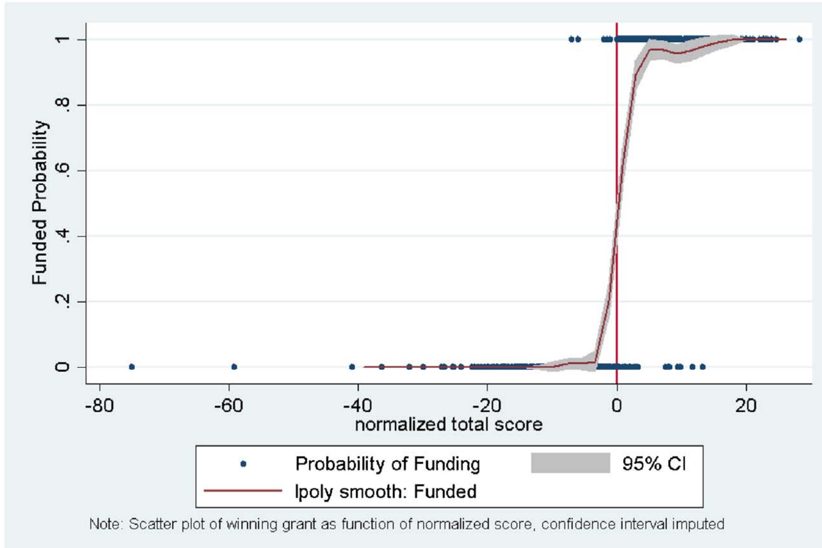

Fig. 3. Probability of funding as a function of Innofund project total score.

Table 7
Means for observations in the regression discontinuity region.

Variable	Imbens- Kalyanaraman (IK) bandwidth (+/−3.05)			Calonico Cattaneo Titiunik (CCT) bandwidth (+/−5.23)		
	Mean below	Mean above	p-value of 2-tailed *t*-test	Mean below	Mean above	p-value of 2-tailed *t*-test
Project Score	−1.50	−1.50	**0.00*****	−2.85	2.65	**0.00*****
Grant awarded (0/1)	0.06	0.71	**0.00*****	0.03	0.79	**0.00*****
Application Year	2007.57	2007.32	0.37	2007.35	2007.03	0.12
Year since founding	3.84	4.14	0.23	3.73	3.82	0.63
Employee Count	33.19	37.91	0.35	35.93	39.80	0.33
Founder/CEO Pol connection (0/1)	0.13	0.11	0.71	0.14	0.13	0.76
TMT Pol Connection (0/1)	0.15	0.19	0.53	0.13	0.17	0.34
Total profit	0.37	0.76	0.17	0.30	0.78	**0.02*****
State-ownership (0/1)	0.03	0.02	0.61	0.04	0.03	0.36
Team has Prior Prize (0/1)	0.20	0.25	0.38	0.20	0.24	0.41
Self-reported Pre-application Patents	0.65	0.89	0.53	0.49	1.02	0.20
Observations	86	91		161	160	

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Bold values indicate statistically significant results.
Compares means for observable variables whose project scores fall within RD bandwidth, using alternative measures of theRD bandwidth.

could suggest that parties affect their own treatment status. We implement this test in Fig. 4 and find no statistical difference between densities of *Project Score* on either side of the funding threshold. The density of *Project Scores* is lower at the threshold than it is on either side of it. These differences fall within the 95-percent-confidence interval, but do arouse a concern that Innofund may manage the scores so that fewer of them fall at the funding threshold.

One important caveat to note is that, even if all assumptions are upheld, regression discontinuity analyses are informative about treatment impact in the local area of the funding cut-point for "compliers" whose treatment is induced by the instrument (Angrist et al., 1996). These Local Area Treatment Effects (LATE) may generalize across the sample, but the experiments provided by the discontinuity cannot speak to other ranges of the forcing (*Project Score*) variable (Hahn et al., 2001; Imbens and Lemieux, 2008). Thus, while RD designs enable casual inference, they achieve this at the cost of generality, and we will not be able to draw conclusions about the average treatment effect (ATE) for the population of Innofund applicants as a whole (Heckman, 1997).

6.3. Firm performance and grant receipt − fuzzy RD analysis

To ascertain the impact of Innofund grant receipt on firm performance, we employ a fuzzy regression discontinuity design. This choice reflects the fact that cutoffs are not strictly implemented in Innofund's grant allocation process: Our sample contains several (seven) grant-winning firms with scores below the threshold and a considerable number of firms (51) with scores above the threshold whose applications were rejected. The existence of such observations violates the complete compliance assumption under Sharp RD.

Starting with Trochim (1984), scholars have adopted a fuzzy RD design to deal with this setting. The fuzzy RD design allows for a smaller jump in the probability of assignment to the treatment at the threshold and only requires the probability of assignment is different across the threshold (Lee and Lemieux, 2009). Following Jacob and Lefgren (2011), we employ a fuzzy RD design that involves estimating an instrumental variables regression in which the second stage is given by Eq. (1) above and the first stage is represented by:

$$Funded_{it} = \beta_1\ Above\ Threshold_{it} + \gamma\ X_{it} + \varepsilon_{it+1}, \quad (2)$$

in which *Above Threshold* is an indicator variable equal to 1 when the centralized *Project Score* is equal to or greater than 0 (i.e. the raw score is on or above the funding threshold).

Table 8 reports the results of regressions with Fuzzy RD design. For each sample time period and for each firm outcome measure, we run two-stage least squares, instrumenting for grant receipt, as described in (2) above. We report results for local linear model and both local

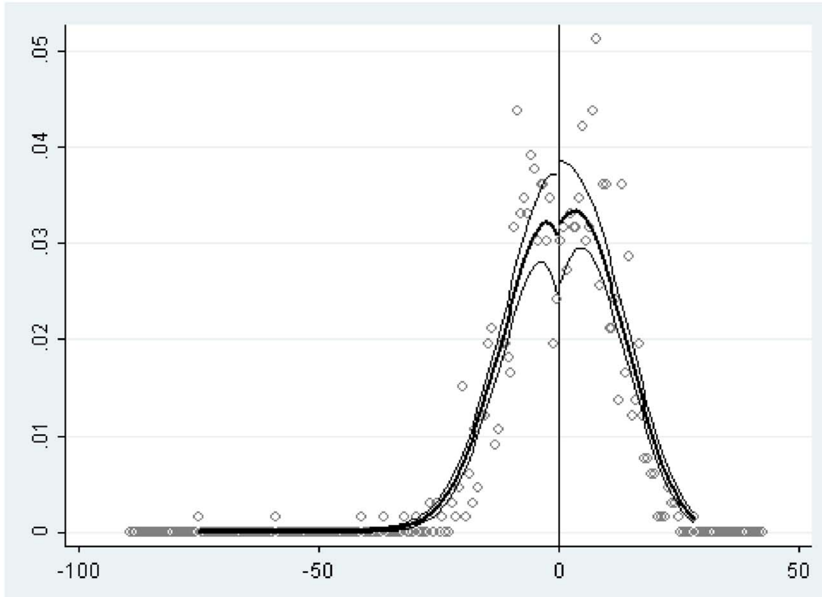

Fig. 4. McCrary test for density discontinuity at the funding threshold.

quadratic and local cubic polynomial models. In each reported regression, we employ the Calonico et al., 2014 bandwidth and weight the observations in the RD window based on a triangular kernel. The results suggest that the true casual estimates of the impact of funding on firm outcomes are starkly different from what one might conclude by simply comparing those firms that received funding with those that did not, i.e., from the results in Table 6. For each of our firm outcome measures, for each time period, we find no evidence that grant receipt had a causal impact on performance. We consider the models that employ local linear regression as our preferred specification, but since debate exists in the RD literature about ideal bandwidths and estimation techniques, we conduct numerous robustness checks using different kernel weighting approaches and bandwidths (Gelman and Imbens, 2014; and Card et al., 2014).

Each variation yields results consistent with the local linear specification, with the exception of the global polynomial regressions using a uniform kernel weighting. For example, we continue to find no statistically significant relationship between funding and post-grant changes in firm performance if we employ narrower bandwidths (e.g., the Imbens-Kalyanaraman bandwidth) or wider bandwidths (+/7) and if we use alternative weights (e.g., rectangular or Epanechnikov kernel) for observations within the bandwidth. We do, however, find a statistically significant relationship between new equity investments by State- and Community-Owned enterprises in global (infinite bandwidth) polynomial versions of our fuzzy RD specifications. These regressions, however, accord greater weight to the observations that are distant from the funding threshold and, thus, achieve greater statistical power at the cost of greater confidence in a causal relationship.[11]

It is possible that the null results arise not because there is no causal impact of grant funding on firm outcomes, but because the measures are highly noisy. The standard errors in the local RD analyses (in Table 8) are, as a matter of course, substantially larger than in the full sample LPM models (Table 6). We interpret the coefficients in Table 8 as implying no causal impact exists between grant receipt and firm outcomes. That is, we interpret this a funding of no impact rather than an inability to determine whether there was an impact. Were they statistically significant, the Fuzzy RD coefficients for *Firm Death* (in 8-1) would imply an effect one fifth the size of that in the full-sample LPM analysis (i.e., a 2.0 percentage point decline in the probability of firm failure). Were the *Patenting* results statistically significant, they would imply a different direction of impact from expectations and different from that found in the full sample results (i.e., a negative impact of grant receipt on patenting). Further, the coefficients on both types of follow-on *Equity Investment* vary in magnitude and direction of effect across the local linear and polynomial regressions.

We should reiterate that the FRD results are informative about the "compliers," those firms that received Innofund grants when their scores were sufficiently high and those that did not when their scores did not meet the funding threshold. The data also include a group of "always-takers," that are funded even though they did not meet the criteria for funding. In the event that such firms (a) obtain funding for projects with no potential to be productive and (b) also received *Project Scores* above the funding threshold, this may bias our results toward finding no positive impact of grant receipt on firm performance outcomes. Table 5 suggests that some politically connected firms may fall into this category.

The intuition behind the differences in the results in Tables 6 and 8 and our relative confidence in the null results is demonstrated by the graphics in Fig. 5. These figures report binned scatter plots for each of our firm outcomes for observations above and below the funding threshold. It is important to note that these reflect the raw data, rather than our Fuzzy RD results. They are, nonetheless, illustrative in thinking about the underlying patterns in the data. We report one panel for each outcome variable and divide the x-axis into 20 equally-sized bins based on Project Score. The left-most figure in each panel reports the zero-ordered plot up to 20 *Project Score* points above and below the funding threshold. The middle figure and right-most figures report local linear plots and local quadratic plots, respectively. Fig. 5A-1, the zero-ordered RD plot of *Firm Death by 2015* demonstrates that for scores within 20 points of the cutpoint, the average probability of firm death is lower for firms with scores above the funding threshold. This is consistent with the result in Table 6 suggesting that firms that received grants are more likely to survive than those that did not. Figs. 5A-2 and

[11] In versions of our analysis that employ a Sharp RD design, we also find a statistically significant relationship between firm survival to 2015 and grant funding. We do not report these models, however, as the fact that assignment to treatment is stochastic rather than deterministic suggests that a Fuzzy RD design is more appropriate. In earlier versions of this paper, we had reported the sharp RD results in order to make the methodological point that analyses of innovation subsidies that employ sharp RD techniques may obtain misleading results when fuzzy RD are more appropriate. We omit them here to prevent confusion about the results in which we have the greatest confidence.

Table 8
Fuzzy Regression Discontinuity analysis, using 2SLS/IV to estimate the relationship between grant receipt and firm outcomes.

RD type	2005–2007			2008–2010			All Years		
	local linear (9–1)	local polynomial (9–2)	global polynomial (9–3)	local linear (9–4)	local polynomial (9–5)	global polynomial (9–6)	local linear (9–7)	local polynomial (9–8)	global polynomial (9–9)
Panel A: DV = Firm Death by 2015									
Funded	−0.022	−0.079	0.037	0.019	0.005	−0.012	0.043	−0.024	−0.023
	(0.358)	(0.602)	(0.589)	(0.169)	(0.198)	(0.132)	(0.216)	(0.383)	(0.464)
Panel B: DV = SIPO Patent Application by 2015									
Funded	−0.190	−0.179	−0.144	0.238	−0.016	−0.208	−0.005	−0.112	−0.368
	(0.426)	(0.725)	(0.710)	(0.371)	(0.549)	(0.545)	(0.278)	(0.503)	(0.698)
Panel C: DV = Equity Investment from State- or Community-Owned Enterprise (SOE/COE) by 2015									
Funded	0.248	0.200	−0.073	0.102	0.123	0.280	0.182	0.152	0.049
	(0.164)	(0.221)	(0.181)	(0.207)	(0.221)	(0.299)	(0.130)	(0.155)	(0.140)
Panel D: DV = Equity Investment from VC or Private Equity Firm by 2015									
Funded	0.074	−0.068	−0.209	0.249	0.097	−0.483	0.154	−0.007	−0.371
	(0.235)	(0.476)	(0.549)	(0.274)	(0.398)	(0.541)	(0.168)	(0.311)	(0.519)
Observations	180	180	180	141	141	141	321	321	321

Robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Notes: First stage regression conducted as indicated in Equ. (2). First stage F-statistics for included instruments (and associated *p*-values) = 679.76 (0.000), 281.64 (0.000), and 1136.55 (0.000), for 2005–2007, 2080–2010, and All Years, respectively. All regressions omit observations with missing Project Scores.

5A-3 accounting for *Project Scores*, however, and help explain why the Fuzzy RD results do not reach the same conclusion: While the probability of firm failure by 2015 is lower for firms with higher scores, there is no discontinuous drop in the probability of firm death when we fit either local linear or local quadratic lines within the ± 5 range of the funding threshold. This same pattern holds across the other firm outcome measures in Fig. 5 and, in the case of post-application patenting, is even clearer. The only exception to this pattern occurs in the case of *Equity Investments by State- and Community-Owned Enterprises*, whose local linear and local polynomial plots could be interpreted as consistent with a jump at the funding threshold. This suggests that we should remain open to the possibility that there is a causal effect here, although the Fuzzy RD results do not provide strong evidence of such an interpretation.

To investigate the impact of firm features on outcomes associated with Innofund awards, we estimated models that interact *Funding* with firm features. None of the self-reported firm features that are correlated with selection into Innofund grant receipt show robust, significant effects. Because it is positively correlated with winning grants, though not with *Project Scores*, Political connections through the CEO and/or Founder is particularly interesting. In Table 9, we present local linear fuzzy RD estimates of the relationship between our firm outcome variables and grant receipt, separating those firms without and with *Founder/CEO Political Connections*. The magnitudes of the coefficients in these regressions differ for firms with politically connection. These estimates are, however, quite noisy, as a result of the relatively small sample sizes, particularly for politically connected firms. Were they to be significant, they would imply slightly superior performance for politically connected firms with regards to survival and receipt of VC funding across both sample periods and in patenting and public funding in the 2008–2010 period. These results invite future study, but are not dispositive.

Overall, we interpret the results of our fuzzy RD regressions as providing evidence that, while the Innofund may be able to select firms that have positive performance features, ZGC Innofund grants have not induced superior chances of survival, patenting, or financing in the region near the funding threshold.

7. Discussion

In this paper, we investigate (a) the factors that affect the receipt of innovation subsidies and (b) the impact of those subsidies on firm performance in the context of the Innofund program in the Zhongguancun (ZGC) region of Beijing. The novelty of this effort derives from its context, analytic approach, associated insights, and is based on our ability to leverage internal administrative data. Although a number of projects have examined correlations between firm performance and innovation subsidies in the U.S., the EU, and Japan, our effort is one of the first to examine firm behavior and outcomes associated with a major innovation subsidy program in an emerging market. Our access to Innofund administrative data on application scores allows us to estimate with some confidence both the firm characteristics that correlate with winning Innofund grants and, using regression discontinuity design, the causal impact of those grants on measures of firm performance. While such designs have been applied widely in research in economics, particularly in program evaluation studies, few projects in strategic management and innovation studies have used it. Along with Zhao and Ziedonis (2014), Howell (2014), and Bronzini and Piselli (2016), we are among the first to apply RD analysis to innovation subsidies and the first to employ fuzzy RD to a program that does not assign grants deterministically based on project scores.

Our analysis of the correlates of selection yields specific insights into the nature and effectiveness of the ZGC Innofund program. First, our analysis finds that Innofund grant receipt correlates with a number of the features that the program has been designed to reward. Specifically, firms that *report* greater innovation (patents and science or innovation prizes) and better financial performance (profits) are more likely to receive higher evaluation scores and consequentially more likely to win grants than firms with otherwise similar characteristics. The fact that reported profits, patent filings, and prizes are correlated with higher evaluation scores is consistent with an interpretation in which the Innofund's experts and administrators are faithfully ranking applications and granting awards according to their own stated criteria and the final selection process is acknowledging reviewers' opinions. Considering the difficulties of administering an innovation subsidy program in an emerging market with few institutional supports and no demonstrated history of prior successful subsidy programs, this strikes us as evidence that elements of the Innofund program are functioning as intended.

Further, three elements of the selection regressions are, however, not consistent with stated program goals. First, firms whose founders are likely to have acquired political connections through their professional experience are more likely to win grants, even though their connections are not associated with higher project scores. Second, firms with missing scores are more likely to win grants. Third, there are firms with scores above the cut point that failed to receive grants and firms

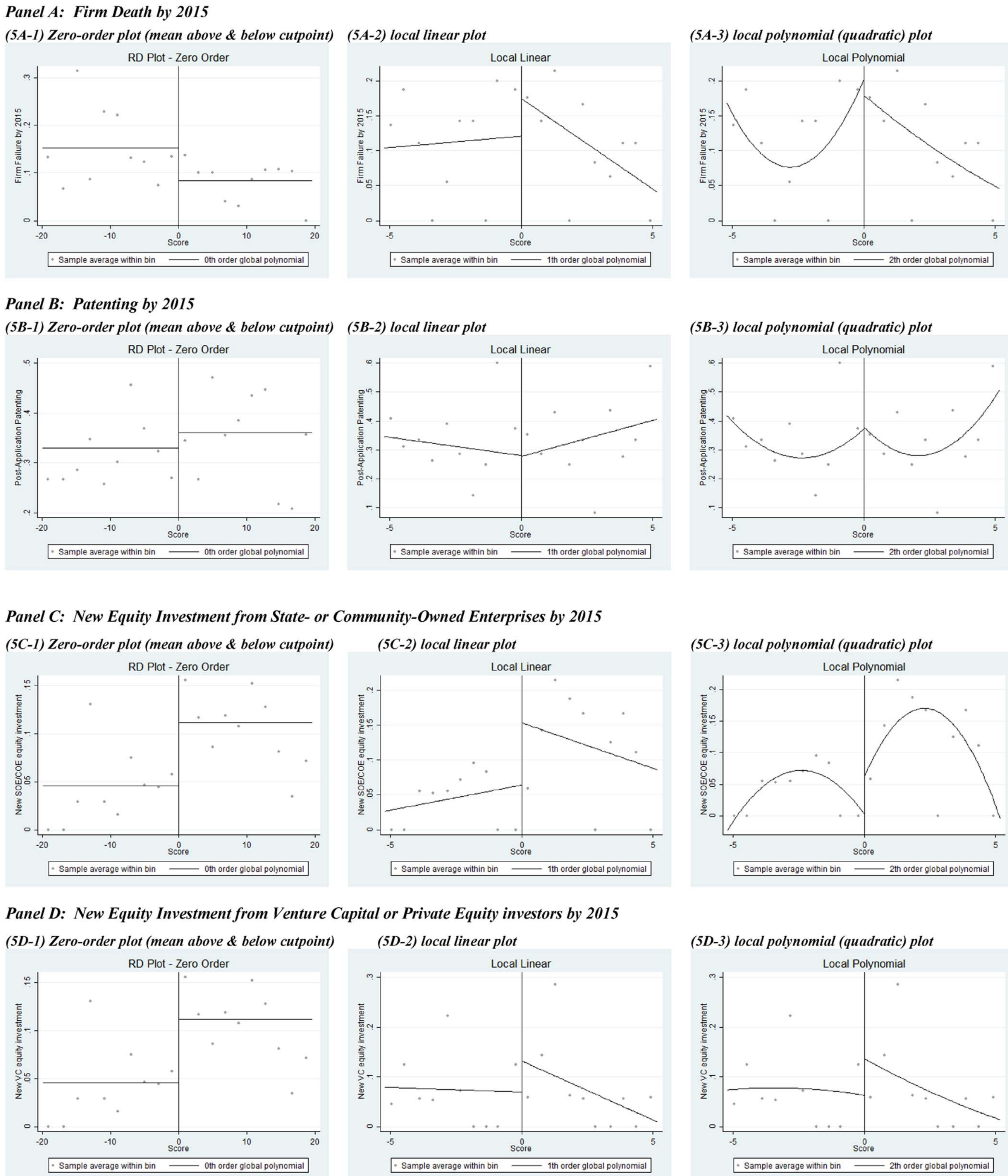

Fig. 5. Firm Outcomes as a function of Project Score.
Each graph presents binned scatter plots and fitted lines displaying firm outcomes for observations above and below the funding threshold. We divide the x-axis into 20 equally-sized bins based on the centralized Project Score.
Panel A: Firm Death by 2015
(5A-1) Zero-order plot (mean above & below cutpoint) (5A-2) local linear plot (5A-3) local polynomial (quadratic) plot
Panel B: Patenting by 2015
(5B-1) Zero-order plot (mean above & below cutpoint) (5B-2) local linear plot (5B-3) local polynomial (quadratic) plot.
Panel C: New Equity Investment from State- or Community-Owned Enterprises by 2015
(5C-1) Zero-order plot (mean above & below cutpoint) (5C-2) local linear plot (5C-3) local polynomial (quadratic) plot
Panel D: New Equity Investment from Venture Capital or Private Equity investors by 2015
(5D-1) Zero-order plot (mean above & below cutpoint) (5D-2) local linear plot (5D-3) local polynomial (quadratic) plot.

Table 9
Fuzzy Regression Discontinuity analysis, using 2SLS/IV, comparing firms by Political Connection.

	2005–2007		2008–2010		All Years	
	Founder/CEO Political Connection =		*Founder/CEO Political Connection =*		*Founder/CEO Political Connection =*	
	0 (not connected) (9–1)	*1 (connected)* (9–2)	*0 (not connected)* (9–4)	*1 (connected)* (9–5)	*0 (not connected)* (9–7)	*1 (connected)* (9–8)
Panel A: DV = Firm Death by 2015						
Funded	0.144	−0.499	0.130	−0.903	0.186	−0.624
	(0.462)	(0.507)	(0.125)	(1.401)	(0.236)	(0.544)
Panel B: DV = SIPO Patent Application by 2015						
Funded	−0.158	−0.282	0.131	1.305	−0.013	0.056
	(0.521)	(0.708)	(0.354)	(1.341)	(0.300)	(0.627)
Panel C: DV = Equity Investment from State- or Community-Owned Enterprise (SOE/COE) by 2015						
Funded	0.348	−0.051	0.013	0.982	0.176	0.157
	(0.235)	(0.057)	(0.192)	(1.210)	(0.146)	(0.224)
Panel D: DV = Equity Investment from VC or Private Equity Firm by 2015						
Funded	−0.086	0.564	0.158	0.982	0.040	0.719
	(0.310)	(0.395)	(0.255)	(1.210)	(0.179)	(0.474)
Observations	152	28	127	14	279	42

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Notes: First stage regression results as described at the bottom of Table 8.

with scores below the cut point but having received grants. The former may be a benign finding, as political connections may be an indicator of firm quality, but it becomes more troubling in light of the latter two findings.

These results raise but do not answer some questions about the administration of the fund over the sample period. To our surprise, a number of final project scores are missing from the data, despite having intermediate financial and technical merit scores and final funding decisions. Projects whose scores are missing have a greater chance of being funded than those that do not have missing scores. Moreover, projects with missing scores are disproportionately associated with firms with politically connected founders or top management teams. These facts raise the possibility of administrative negligence or interference on behalf of particular firms.

Our analysis of treatment effects sheds additional light on these issues. First, we compare performance outcomes for firms that received grants with outcomes for those that did not, using a linear probability regression framework to control for observable differences between each set of firms. These analyses suggest that recipient firms survive longer and patent more than non-recipients. By considering the entire sample of firms in the data, such analyses cannot be interpreted as providing evidence of the causal impact of grant receipt on firm outcomes, but they do suggest that grants are going to firms that ultimately live longer and innovate more. These outcomes are consistent with an interpretation in which the Innofund is able to *pick* winners, though it should not be interpreted as suggesting that grants *create* winners.

To assess the causal impact of grant receipt on performance, we apply regression discontinuity techniques. Our preferred analyses involve a fuzzy RD approach, which use *Above Threshold* and *(Above Threshold)*(Project Score)* as instruments for *Funded* in a 2SLS analysis of the impact of funding on firm outcomes. In all models that employ windows near the funding threshold, these models fail to find evidence of a treatment effect on firm outcomes. Unreported regressions using infinite bandwidths find statistically significant correlations with firm survival and equity funding from state- and community-owned enterprises, but these analyses rely on observations quite distant from the funding threshold and are, therefore, less clearly able to identify causal effects. As a result, we cannot express confidence that the Innofund program exerts a causal impact on firm outcomes.

We should be careful to note that our analysis exploits detailed data on a particular geographic location and a particular innovation subsidy program and its results may not generalize, either to other regions of China or to programs in other emerging economies. Indeed, our results may arise exactly because of the particular features of the Innofund and its administration. Nonetheless, our analyses demonstrate the value of internal administrative data in innovation program evaluation. Our conclusions may differ from the recent findings that Innofund recipients outperform a set of carefully-matched control firms that did not receive Innofund grants (Guo et al., 2016) because we are able to leverage information on project scores as well as grant receipt. As our analyses in Table 6 suggest, we would likely reach the conclusion that grant receipt is associated with positive outcomes if we were unable to take advantage of funding data and instrument for grant receipt.

Our overall assessment of the Innofund depends, to a substantial extent, on our expectations for the program. Relative to expectations framed by reports of fraud and zombie Innofund recipients, the results provide reasons for optimism. Relative to expectations framed by reports about the high fraction of Innofund-supported firms on Chinese exchanges, the results are not as encouraging. Our conclusion is therefore mixed: The Innofund program appears to be ranking applications in a thoughtful way. However, we do not find evidence that the program is driving positive innovation or firm outcomes. Moreover, we do not find that the loosening of funding following 2007 had a positive impact on program outcomes. This suggests that increasing resources to programs that appear successful may not be an optimal policy response. In the case of the Innofund, it may be that the additional funding results in a decline in the marginal value of each newly-funded project.

Our findings raise a number of questions that could also be usefully incorporated into future empirical and theoretical analyses of subsidy programs, particularly in emerging economies. The fact that we find evidence consistent with manipulation raises questions about the potential for administrative interference to affect program functioning, including firm selection and firm and program outcomes, in other subsidy settings. In addition, by highlighting how particular features of the Innofund Program predict selection (e.g., the emphasis on government prizes for project scores), our analyses complement other work in highlighting the importance of program features and program administration on innovation subsidy project selection and outcomes. To date, little formal theory guides hypotheses or empirical work on these issues (Dimos and Pugh, 2016). Our analysis also points to a number of reasons that subsidy programs in emerging markets may have greater or lesser impact on affected firms than similar programs in leading innovator countries. Indeed, some ideas, such as the impact of weak financial markets, could cut in either direction. Going forward, it would be valuable to generate more precise predictions for emerging markets and to compare the relationship between program features and program outcomes across institutional contexts.

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