# Who Captures the State in China? Evidence from Irregular Awards in a Public Innovation Grant Program*

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**Abstract** Access to state-controlled resources can be a major source of firm-level competitive advantage. However, we know little regarding which firms are most likely positioned to capture the state and access resources beyond what their rule-complying merits command. This is partially due to the challenge in identifying irregular state funding that violates official resource-allocation rules. We study a leading innovation grant program in China, and we leverage unique access to the focal grant agency's administrative data to trace its grant allocation process. We observe occurrences of rule-violating funding and show that firms vary in capability to influence the agency's funding decision, depending on geographic proximity, as well as other institutional variables. The observed irregular awards are most likely associated with crony capitalism rather than bureaucratic heroism.

* The author names are listed in reverse alphabetical order. This project is partly supported by the National University of Singapore Start Up Grant (R-313-000-130-133) and Humanities and Social Sciences (HSS) Faculty Research Fellowship to Yanbo Wang and the China National Natural Science Foundation (No.71772103) to Jizhen Li. We thank Danyang Chen, Yun Hou, Ao Shen, Tao Wu, and Chengcheng Liu for capable research assistance and the Carnegie Mellon University SETChange Seminar, the ESSEC-INSEAD-NUS-SMU First Cut Seminar, Taiwan Symposium on Innovation Economics and Entrepreneurship, the NUS EAI and Strategy and Policy Seminars, the sixth AIEA-NBER Conference, and the Hong Kong University of Science and Technology (Guangzhou) IPE Seminar for insightful feedback. We also thank Joao Santos Silva, Josh Errickson and Yanhui Wu for their methodological help. All errors are our own. Please send correspondences to Yanbo Wang (yanbo.wang@hku.hk).

## INTRODUCTION

We study how and why some firms are well positioned to "capture the state," defined as the exercise of influence upon government officials to access state-controlled resources beyond what their rule-complying merits command. It is well known that state-controlled resources can be key for firm survival and growth (e.g., McDermott, Corredoira, and Kruse, 2009; Armanios et al. 2017; Hiatt, Carlos, and Sine, 2018). It is also well known that firms make deliberate efforts to influence the state's resource allocation (e.g., Choi, Jia, and Lu, 2014; Birhanu, Gambardella, and Valentini, 2016; Jeong and Siegel, 2018). While a large literature has investigated firms' formal and legal lobbying activities that influence policymaking and state-resource allocation (e.g., Hornstein and Zhao, 2018; Kim, 2019; Shi, Gao, and Aguilera, 2021), we know relatively little about firms' illicit efforts that result in rule-violating state-resource allocation (Greve, Palmer, and Pozner, 2010). The fact that there have been so few studies on firms' illicit efforts and state-resource misallocation is all the more striking given the academic community's demonstrated interest in the topic of illegal strategic behavior by firms, and also given the applicability of a wide range of theoretical perspectives in studying these activities (e.g., Dorobantu, Kaul, and Zelner, 2017; Castro, Phillips, and Ansari, 2020; Jia, Markus, and Werner, 2021).

The foremost obstacle to studying state capture has been misconduct identification. Due to their legal and ethical implications, dealings such as state resource misallocation are usually concealed by the involved actors for self-protection. Thus, data on such activities usually "become available when a social-control agent detects misconduct and decides to act against it" (Greve et al., 2010:94). However, social-control agents rarely act randomly (Delios et al., 2021; Bergemann and Aven, forthcoming); caught misconduct may systematically differ from uncaught misconduct. For example, when illicit-action takers are politically powerful, media and law enforcement are likely to look away from their transgressions deliberately or under influences (Graffin et al., 2013; Ang and Jia, 2014). Studying only cases of caught misconduct is likely to introduce significant biases.

Scholars have also used surveys to elicit information on illicit behaviors such as bribery, corruption and other forms of state capture (e.g. Wu, 2009; Birhanu et al., 2016). While insight-generating, this approach has limitations. Due to social desirability and legal concerns (Aven, 2015), corruption-entangled

individuals have minimal motivations to honestly report their illicit activity to researchers. Also, given the secretive nature of illicit deeds, individuals not directly involved can only report speculated rather than actual occurrences (Delios et al., 2021). Survey-based studies are likely to conflate perception- and experience-based measures.

The empirical challenges above can be yet more daunting in studying private firms' capture of government bureaucrats. In contrast to legislators and politicians that are in the spotlight of public scrutiny, bureaucrats are much less visible as they usually operate behind the iron curtain of government bureaucracy (Wilson, 1989). Furthermore, given politicians' power and visibility, researchers can often infer their exercise of influence (and abuse of power) in channelling state resources to family and friends (e.g. Fisman, 2001). Bureaucrats, however, are usually at lower levels of power and their offenses tend to be "petty" and less likely to attract the attention of social-control agents such as the mass media.

We study firms' capture of state bureaucrats to access public innovation grants in China. Rather than regular awards that are allocated according to firm merits and well-specified funding rules, we investigate "irregular awards" that are allocated to firms whose rule-complying merits would not have earned them such access. We conceptualize irregular awards as the outcome of public-private collusion in which grant officials deliberately misallocate state fund to illicitly advance certain private firms' interests. We look at the cost of information acquisition and collusion coordination and examine how three sets of factors—the geographic proximity between grant officials and resource-seeking firms, the bureaucratic structure and process within which grant allocation decisions are made, and the focal firm's state affiliation through equity ownership— jointly shape the two parties' likelihood to collude.

The focal grant program setting provides advantages in studying illicit state capture. First, we use the funding agency's internal, administrative record to directly observe the incidence of public resource misallocation. By observing state officials' deliberate violation of well-specified policy rules regardless of whether they were caught by the media or law-enforcement agencies, our approach helps reduce the concern of selection biases in illicit behavior identification.

Second, this setting allows us to examine how firms interact with an important yet understudied actor—government bureaucrats—in nonmarket strategy research. While studies have examined firms'

efforts to access state resources (for reviews, see Henisz and Zelner, 2012), the nonmarket strategy literature has mainly focused on how firms design strategies and utilize connections to influence (usually top) policymakers. Prior literature has found that top-level politicians are motivated above all else by extending their time in office (for a review, see Besley, 2005). Politicians have also been shown to value the advancement of their policy goals and their post-political-career employment possibilities (e.g. i Vidal, Draca, and Fons-Rosen, 2012).

To understand the differential motivations of bureaucrats, the most influential theory is from Wilson (1989), who argues that bureaucrats often place high priority on securing professional standing within their governmental agency. As Wilson (1989) explains, this often involves a combination of embracing the larger agenda, goals, and mission of their agency, of staying consistent with the norms of their technical field that may well be highly represented in the government agency, and of following orders as directed from above at their agency. From this perspective, it is also important to look at the organizational structure and process within which bureaucrats implement policies to understand entrepreneur-bureaucrat collusion in state resource misallocation.

In part due to the prior focus on high-level politicians, the nonmarket strategy literature has paid minimal attention to bureaucrats. These individuals, hiding behind the iron curtain of bureaucracy, hold some of the least visible yet most decisive positions in the nexus of business-government relations. While in relative obscurity, they are often directly in charge of policy program implementation and state resource distribution. Indeed, ever since Weber (1924) and Lasswell (1936), scholars have noted that seemingly unremarkable bureaucratic decisions play a critical role in the politics of "who gets what, when and how."

Our research is also related to the literature on the effectiveness of public grant programs in promoting firm-level innovation. The prior literature usually had information on grant allocation but rarely distinguished between legally-acquired and illicit, misallocated resources. While these studies may generate important insights when finding evidence of such programs promoting innovation (e.g. Howell, 2017; Lanahan and Feldman, 2018), the picture becomes murky when supportive evidence is missing. This is because a program's lack of success could be due to inherent deficiency in program design, corruption in program implementation, or their combination. Only by opening the black box of grant proposal evaluation

and funding allocation can we examine the prevalence, antecedents and consequences of state resource misallocation. Knowledge about who captures the state and when and how may generate critical insights to help guide the (re)design of these funding programs. As we study the causes of how firms get state bureaucrats to violate policy rules that are strict and quantitative in nature, ours is part of an anti-corruption literature that seeks to analyse firms' illegal strategic behaviors so that we as strategy scholars can begin to recommend solutions to aid in reducing illegal strategic behaviours on the part of firms.

## THEORETICAL ARGUMENTATION

We conceptualize state capture as a collusion game between resource-seeking firms and resource-allocating officials that takes place in the shadow of public enforcement of law. While varying in power, both players face the challenge of information asymmetry and moral hazards as they contemplate illicit behaviors. On one hand, resource seekers may not know whom among the funding agents to bribe, how much to pay, and whether the "service" will be delivered after a payment is made; on the other hand, public officials may not know who will (truly) bribe, how much will be paid, and whether the "deal" may be leaked or used by the other party for blackmail. On top of information, collusion-seekers need also to consider the cost of coordination. Operating in the shadow of law and moral code of conduct, public officials and private firms have incentives to conceal their illicit interactions from external scrutiny. Arguably, the two parties seek forms of collusion that leave behind no proof of what really took place. With such information and coordination challenges in mind, this paper investigates the effect of geographic proximity between resource-seeking firms and resource-allocating officials as well as the bureaucratic structure and process through which resource allocation decisions are made. We study this phenomenon in the specific context of irregular awards, which are a form of public-private collusion in state resource misallocation.

**Geographic distance and public-private collusion.** There are good reasons to believe that physical proximity enables collaborations, illicit or not. First, geographic proximity reduces the cost of both information acquisition and opportunity appraisal, which are key for the success of collaboration (Alcácer and Chung, 2007; Chakrabarti and Mitchell, 2013; Chen, Kale and Hoskisson, 2018). When two parties are spatially collocated, they become more likely to have chance encounters and to interact repeatedly face to face for deliberate tie initiation and action coordination. Even in the age of "free" social media,

videoconferencing, and texting, modern technologies are still relatively counterproductive for detecting facial cues and other nonverbal forms of communication (Flaherty, Pearce, and Rubin, 1998; Jiang et al. 2012), and therefore, face-to-face communication remains vitally important for successful interpersonal interactions (Mortensen and Neeley, 2012). As a result, only with face-to-face communication can tacit information be shared and strong mutual confidence be achieved. Such deeper communication also enables the parties to exchange tacit information at an earlier stage of collaboration preparation. With more advanced notice of mutual expectations, the firm is better prepared to provide what the bureaucratic decision-maker is ultimately valuing (Hiatt and Kim, 2019).

Second, geographic proximity is known from prior research to enable two parties to collude without leaving a trace of discoverable culpability (Mohliver, 2018). Being secretive is critical for implementing illicit deeds and avoiding scrutiny and punishment (Aven, 2015; Yenkey, 2018). As Price (2008: 400) states in the context of collusion over prices bid for government contracts,

> Individuals that reside in close geographic proximity are more likely to interact in the proverbial "smoke-filled room" without drawing the suspicion of antitrust authorities. Second, such bidders likely interact in multiple contexts. This expands the set and severity of punishments for deviating from a collusive arrangement. Finally, empirical evidence suggests localized market agglomeration generates increased information sharing.

The idea here is that irregular awards of bureaucratic discretion require nontrivial departure from formal rules guiding state resource allocation. If two parties wish to collude in violating these rules, they will often do so by making agreements that cannot be documented on paper or even through electronic communication. When communicating entirely based on face-to-face meetings, they are more likely to coordinate without confusion or misunderstanding.

The negative association between geographic distance and state capture may be particularly strong when the targets are government bureaucrats rather than politicians. On one hand, politicians are usually high-profile and thus well visible. Firms intending to influence politicians often have an idea about "who are in charge of what, when and how." In contrast, bureaucrats are hidden behind the iron curtain of state bureaucracy, and thus their actions, positions, and specific roles are less visible to the outside community. Members of the public (and even well-informed voters in countries of high transparency) know little about

the administrative procedures and organizational arrangements within governmental agencies, let alone their policy implications (West, 1997; Egeberg, 2012).

On the other hand, politicians, at least in countries holding democratic elections, are usually open to formal channels of influence. For example, firms may hire law firms for lobbying or make political donations to get an audience with politicians and thus potential opportunities to sway their opinions on policy issues. In contrast, there are few direct and formal channels for private parties to influence state bureaucrats as these policy implementors are often hidden in the maze of bureaucratic organizations and their behaviors are more guided by policy rules and standard operating procedures (SOPs) (Wilson, 1989). When bureaucrats' actions are hard to observe and the formal channel for influence is absent, geographic collocation can be a key determinant of a firm's likelihood of still figuring out a way to establish relationships (directly or indirectly), develop trust, and coordinate on illicit actions with grant officials. Therefore, we have the following hypothesis:

**Hypothesis (H1).** *Geographic distance between a resource-seeking firm's headquarters and the resource-allocating bureaucrats' office is associated with a lower probability of irregular awards.*

**Bureaucratic process and public-private collusion.** There are reasons to expect that the geographic distance-irregular award association is moderated by the bureaucratic process within which grant decisions are made. Government bureaucrats are not merely belts of transmission for external forces to convert their "inputs" into policy implementation "outputs;" instead, their decisions are strongly influenced by the administrative structures and processes that define oversight and accountability, opportunities for outside participation, and other legal and administrative arrangements (McCubbins, Noll and Weingast, 1989; West, 1997). These features specify more or less who is expected to do what and how (Wilson, 1989) and thus define the relationship between an agency and its policymaking environment (Egeberg, 2012).

One basic dimension of bureaucratic process concerns the degree to which agency decisions are constrained by elements of due process such as "adversary hearings, decision making on the record, and rigorous judicial review" (West, 1997:606). Organizations are in part defined by their incentive systems and, naturally, the more stringent are the procedures and the burden of proof, the more difficult it is for an agency to exercise discretion, especially when discretion would enter in the realm of rule breaking.

Institutional arrangements such as judicial review, the launch of an independent commission, and shared leadership (i.e. two or more ministries being tasked with handling a common program) bring forth the kind of oversight that may induce government bureaucrats to adhere to role expectations and codes of conduct (McCubbins et al., 1989; Macey, 1992; O'Toole, 2012).

Such constraints can be particularly strong and binding when bureaucrats in one state agency must themselves secure the approval for overall budget funding from a distinct, external state agency. The literature on government policy change shows that discretion does not typically occur when there are heterogeneous institutional actors with each holding a veto point on any kind of policy change (Henisz, 2000; Treisman, 2000). Freestanding agencies have been shown to be capable of being highly effective, and even more effective than ideologically fragmented legislative bodies, in blocking sudden new regulatory changes (Crepaz, 1998, 2002). Irregular awards are a type of policy change because each of them represents its own divergence from the regular status-quo policy. Whether the irregular award is based on a consistent and objective assessment of merit or something less consistent and objective, the central fact is that under the scenario of an irregular award, policy and policy implementation are being taken in a new direction each time as the standardized criteria for an award are being changed through exceptions.

Inter-organizational constraints do not have to rely on the presence of veto power per se to be effective. As long as there are external agencies that simultaneously hold the power and incentive to engage in oversight (McCubbins et al., 1989; Macey, 1992), they would render it more difficult for the focal agency's bureaucrats to transact with rent seekers for resource misallocation. When the political opponent has strong incentives to wrestle away an agency's administrative power over a policy program, then it simply needs a mechanism to act on those incentives. Such mechanism can be found in the rival agency's insertion as part of the program's due process for actions such as budget approval, financial auditing, or committee review hearings. By having a role in the due process, the rival agency would be conferred with the ability to review the program's implementation and serve as a "watch dog" to hold the focal agency accountable for its actions. Even without diving into full reviews, catching incidents of resource misallocation could still help the rival agency to pull the "fire alarms" to challenge the focal agency's authority and legitimacy. Indeed, such external constraints often create incentives for the focal agency to establish detailed internal SOPs and

bookkeeping practices to demonstrate its transparency and compliance (Pfeffer and Salancik, 1978; West, 1997). Such practices not only help enhance the agency's legitimacy but also further discourage its bureaucrats from violating policy rules governing resource allocation. State officials can be particularly reluctant to collude with firms located afar when the funding program faces sharp scrutiny from powerful political opponents that have incentives to sabotage its authority and funding. With their own authority and careers in jeopardy, state bureaucrats are unlikely to bend the resource-allocation rules unless they are sure about the colluding entrepreneur's "quality" and intention. However, such a level of confidence can be rarely achieved other than through direct and repeated interaction, which can be prohibitively expensive when two parties are not situated in the same geographic location. This leads us to state the following hypothesis:

**Hypothesis (H2).** *When the focal bureaucratic agency faces monitoring, budget screening, and an approval role from an external and competing bureaucratic agency, then the negative effect of geographic distance on irregular awards is magnified.*

Another important dimension of bureaucratic process concerns the locus of interaction between state agencies and the target of the policy under their administration. While street-level bureaucrats interact directly with the public in policy implementation (Lipsky, 1980), central agencies often rely on intermediary (and usually subordinate) agencies to interact with policy targets for program promotion and implementation (e.g. McDermott et al., 2009). Like economic exchanges, policy implementations take place not only in geographic spaces but also in social spaces (e.g. Hupe and Hill, 2007); by linking two parties that are otherwise unconnected, intermediary agencies help construct a social space to bring about meetings that could not readily happen otherwise (Dutt *et al.*, 2016; Armanios et al, 2017).[1]

Intermediaries connecting firms and the central grant agency have the potential to moderate the liability of geographic distance in irregular awards. While an out-of-town entrepreneur is unlikely to engage in direct relationship building with grant officials, she may nevertheless benefit from the brokerage

[1] There is an emerging literature on the "darker side" of institutional intermediaries. For instance, Eberhart and Eesley (2018) shows that the establishment of junior stock exchange – an institutional intermediary aimed to foster the creation of new firms – has undermined venture growth in Japan as it channels investment into new technology firms and thus reduces investment in other sectors. While their work investigates the unintended consequence of institutional changes that lead to (totally legal) resource misallocation in the marketplace, ours looks at deliberate public-private collusion that leads to illicit state-resource misallocation.

provided by a third party of routinized interactions with the central agency. Such a third party has been shown to bring the shadows of both the past and the future into the dyad members' interactions for fine-grained information collection and opportunism deterrence (e.g. Granovetter, 1985). Central officials may place much more value on trust-related judgements obtained from a trustworthy third party than from other third parties. A trustworthy intermediary's role can be particularly strong when the dyads are located far away and thus unlikely to use repeated, face-to-face meetings for informational verification and relationship building. In contrast, when they are collocated, even a weak tie can be of help, as its initial referral can be complemented with in-person meetings for info collection and tie strengthening. These follow-up actions required for collaboration would be too expensive to be feasible when grant officials and entrepreneurs are located far away from each other. This leads us to state the following hypothesis:

**Hypothesis (H3).** *The negative effect of geographic distance on irregular awards is reduced when the two parties are connected with an intermediary state agency with direct and routinized interactions with the central grant agency.*

**Firm ownership and public-private collusion.** We may also expect a firm's state-capture capability varies across ownership types and that those with state-affiliated equity owners are especially well positioned to collude with grant officials. First, these firms are likely to possess tacit knowledge about the structure and process of public bureaucracies and therefore know whom to bribe, when and what amount to pay, and how to communicate and implement the deeds "appropriately." Second, these firms are likely to receive preferential treatment by public agents solely because of their shared state affiliations. A large literature has documented how actors can have implicit and even explicit bias in evaluation, holding preferences towards individuals with similar traits and experiences (McPherson et al., 2011). Similar demographics, career and life experiences, and even wealth levels can induce empathetic emotions as shared background and experiences make it more likely for the parties to identify with each other, perceive each other positively and form ties. Relative to other firms, government agents may find those with state ownership more appealing given their shared identity of being affiliated with the state. Such affiliations make them "insiders of the regime," thus distinguishing them as members of the ruling class vs the rest of the society (Dickson, 2003), making grant officials feel more at ease to receive these entrepreneurs for meetings and socialization. Prior studies have documented that firms with state ownership tend to have

privileged access to government-controlled resources (e.g. Huang, 2003; Zhou et al. 2017), and we further argue that such firms may have easier access to state agencies to exercise influence for illicit resource access.

We expect such shared identity to particularly help entrepreneurs located in Beijing. While facilitating two parties to understand each other's concerns, expectations and behavioural patterns for the development of social rapport and even trust, shared identity conveys aggregate, group-level information rather than individual-specific traits or behavioural patterns. From this perspective, shared identity may help open the doors for tie initiation but cannot substitute for face-to-face communication and relationship building in tie formation, especially when the tie is for illicit collusion.

**Hypothesis (H4).** *The positive effect of geographic proximity on irregular funding awards is enhanced if the resource-seeking firm is itself owned wholly or in part by the state.*

## RESEARCH DESIGN AND EMPIRICAL SETTING

The foremost obstacle to research on irregular awards is identification. Since irregular awards are administratively rule-inconsistent, grant officials who have approved them naturally strive to conceal the occurrences for self-protection. Therefore, detected irregular awardees are likely to differ from the undetected ones in skill, behavior, and network ties systematically (e.g. Greve et al., 2010).

We follow the recent literature using administrative data for misconduct identification to reduce the concern of selection bias (e.g. Graffin et al., 2013; Aven, 2015; Pierce et al., 2015; Jeong and Siegel, 2018; Yenkey, 2018). We examine a unique dataset on 6,903 applications to a flagship public innovation grant program in China. Instead of relying on court actions or media coverage, we identify grant misallocation by gaining access to the program's internal, administrative data. To keep the program anonymous, we will call it the X-program and its administrative agency the X-centre in the paper. We gained access to the program's administrative data through Tsinghua University's Research Center for Technological Innovation (RCTI).

The X-program is among China's most prominent state innovation grant programs. Modelled after the U.S. Small Business Innovation Research (SBIR) program, the X-program was established in the late 1990s by China's State Council to "facilitate and encourage the innovation activities of small and medium technology-based enterprises." Like its U.S. counterpart, the program relies on external experts rather than

internal staff to evaluate grant proposals. To minimize the impact of individual biases, each proposal is evaluated by a panel of (usually five) experts, each assigning sub-scores to gauge a variety of firm-level merits such as tech capabilities, founding team strengths, business model innovativeness, and financial track records (for "innovation track" firms only).[2] These sub-scores are recorded through a proprietary data management system and once submitted, cannot be changed unless with the backend IT's help. The system would aggregate the sub-scores and combine them with other factors to generate the final score. X-program grant winners usually receive a sum of 0.5–1 million yuan from the central government and a 50–100 percent match from the local governments. For startup firms operating in an under-developed financing environment, a grant of this size without equity dilution is substantial.

This dataset uniquely enables us to trace the process of grant proposal evaluation to directly observe the occurrence of rule-incongruent irregular awards of funding. In comparison to public records of *prosecuted* corruption, we can also identify *uncaptured* state resource misallocations; in comparison to survey-based studies of *speculated* deeds of state capture, we study events of public-private collusion that have *happened*. While not capturing all types of illicit dealings, our study does provide a unique approach to overcome some well-documented empirical challenges and offers a rare opportunity to investigate the antecedents and impact of irregular awards, one type of state resource misallocation in which public officials distribute innovation grants to certain firms beyond what their rule-complying merits would have commanded.

To be concrete, we use winning X-program grants without evaluation scores on record for irregular award identification. Two features of the X-program make this a reasonable choice. First, as a merit-based grant scheme, the X-program is required to distribute funding according to firms' ranking by evaluation score. Both a reading of the agency's internal documents and interviews with grant officials confirm that the program awards first the highest-scoring firm and then goes down the list until its annual budget runs out. As firms without scores cannot be ranked, their funding is a clear sign of grant rules violation. Second,

[2] The X-program has two tracks of application: While most firms apply through the "innovation track", a small number of firms apply through the "startup track." Firms in the first category tend to be more mature and usually have performance track records such as revenue and profit; firms in the second category are younger, i.e. usually less than two years old at grant application, and do not have much of a performance track record. As a result, innovation-track projects are evaluated by both technical and financial experts but startup-track projects are evaluated only by technical experts.

the X-program's proprietary data management system documents every step of a firm's movement in proposal submission, evaluation and grant allocation/rejection. Since this system records when and through whom a proposal has reached a given review procedure, it allows us to identify whether a firm has received a grant without being reviewed or having undergone the review but without the score on record for ranking. Both cases violate the well-specified official rules of grant allocation.

We have also obtained granular measures of each firm's pre-proposal performance metrics, resource endowment, equity ownerships and accreditations that the evaluators have used in assessment. As this written material is the sole basis of evaluation, we observe and measure the same information that evaluators use in firm appraisal and score assignment. This, along with the sub-scores, allows us to estimate the potential score that an irregular winner could have received from the evaluators. Comparing irregular winners and their estimated scores with firms of similar yet factual scores allows us to test if the irregular winners would have received the grants based on their own merits, a counterfactual helping us understand whether these firms' scores were accidentally or deliberately erased.

We have further collected each firm's post-grant performance information. By looking at both the "bottom line" (i.e. firm death) and the "top line" (i.e. initial public offering), we examine if grant officials have deliberately violated policy rules to fund low-score yet high-promise firms that are well positioned to fulfil the program's policy goals. Such tests allow us to investigate whether irregular awards are the result of grant officials' heroic initiation for more meaningful policy program implementation.

## INSTITUTIONAL FEATURES OF THE X-PROGRAM

Along with the research design advantages above, the X-program has two institutional features that are relevant to our study. First, the X-program was under the dual leadership of two ministries whose rivalry initially generated informal checks and balances but this system came to an end due to a new national-level policy initiation, thus providing a unique opportunity to investigate how, even in an authoritarian system, inter-agency checks and balances may generate public accountability. Second, grant proposals are submitted to the X-program through intermediary agencies. Differentially located within China's bureaucracy system, these intermediaries vary in the opportunity to interact with and influence the X-

program's funding decisions, providing an opportunity to study the boundary conditions for the geography effect of resource misallocation.

**Inter-ministry rivalry and the X-program.** The X-program was under the joint leadership of the Ministry of Science and Technology (MOST) and the Ministry of Finance (MOF). While the MOST administered the program through its subsidiary, the X-center, in proposal solicitation, evaluation and grant allocation, the MOF was institutionalized to take charge of the program's annual budget approval, review and operation monitoring and auditing. While such formal institutions as transparent elections, open media, and *trias politica* for public accountability are underdeveloped in China, the X-program's administrative vs. financing power partition did create a delicate dynamic of checks and balances through inter-agency politics to induce a certain level of accountability (Lieberthal, 2003; Yang, 2006).

By "financing power," we refer to the monitoring power provided by China's budget making system to the MOF over the MOST and the X-center. For Chinese central agencies, the budget making starts item by item with the grass-roots units and moves up level by level to final compilation by a ministry. The ministry then submits its draft budget to the corresponding bureau of the MOF for review and approval. Afterward, the MOF compiles the budget by department and submits it to the National People's Congress for deliberation and amendments before the ratified budgets go into implementation (Yang 2004: 235-237). The MOF during those years was able to engage in the X-program's budget making and monitoring. China's State Council (1999) granted the MOF the authority to "review and provide guidelines," to "approve the annual budget," and to "supervise and inspect the allocation of the grant as well as the operation of the funding program." The MOF and the MOST also jointly "hold the authority to review and investigate the outcome of proposal evaluation" of the X-program.

The MOST-MOF tension over the X-program was significant in terms of inter-ministry checks and balances. In theory, the MOST was China's flagship agency in science, technology and innovation policy making and implementation; in practice, the MOST's power was much weaker than its name had suggested as multiple other agencies also claimed some degree of power over these domains. The MOF has in particular led many efforts to promote China's industrial upgrading and tech innovation through policy tools such as state procurement, tax subsidies, and the establishment of industry-growth funds. One of the

MOF's self-claimed core missions is to "administer the central government expenditures for economic development, the appropriation for central government financed projects, and funds for technological innovation" (MOF, 2008).

As project evaluation and grant administration are key components of its expertise, the MOF perceived running the X-program as a natural extension of its authority and thus the MOST's involvement an infringement of its administrative terrain. The resentment towards the X-center was particularly strong from the Bureau of Enterprise, an MOF subsidiary implementing a similar function as the X-center but with a broader scope. In an era of bureaucratic reshuffling and downsizing, letting others infringe upon one's organizational mandates runs the risk of being seen as weak or even irrelevant, a deadly label in Chinese politics (Yang, 2004; Mertha, 2009). Unwilling to be a passive coffer, the MOF had proposed alternative ways to administer the X-program such as through its own subsidiaries, through MOF-MOST subsidiaries jointly, and through local rather than central agencies, all of which would have diluted and even bypassed the X-center's administrative authority.

Given the MOF's scrutiny and pressures, the X-center made deliberate efforts to improve its operation and performance to justify its administrative authority and relevance. For instance, the center was among the first state offices to adopt e-governance and used an online system for public feedback regarding candidate winners' qualification; it also invested heavily to recruit external experts for proposal evaluation and built sophisticated software to document the processes of proposal submission, evaluation, and grant allocation. To enhance its legitimacy, the center also sponsored many projects and conferences to disseminate positive information on innovation subsidies and its own contribution to China's high-tech sector growth. Despite these efforts, the X-program's budget rarely increased before 2007, fluctuating around 500-800 million yuan annually (Appendix Figure A2).

While the X-center was seriously concerned about the MOF's competition and sabotage, the pressure greatly diminished after 2006 due to a new national initiative on innovation. Since 1992, China had embraced a foreign direct investment-focused development strategy, hoping that the knowledge spillover from foreign investors would facilitate the growth of local innovation. China started to re-evaluate this policy in the new century due to widespread criticism of its lack of success. A new direction was heralded

in 2006 at the National Science and Technology Conference when China's top leaders unequivocally announced that the key for the country's long-term growth was "indigenous innovation." Once the top leaders had laid down the direction, ministry-level agencies started working together to define the policy parameters for implementation. Throughout 2006, 16 cross-agency "leadership taskforces" formed for this purpose and at the ruling party's 2007 National Congress, "indigenous innovation" was enshrined as "a core strategy for national development."

Although not intended to break down inter-agency checks and balances, "indigenous innovation" nevertheless relieved the X-center of budget concerns and led to its greater de facto administrative control of the program. First, the new policy greatly enhanced the MOST's position among the ministries since the State Council assigned it as the leading agency to design the concrete policies and their implementations (State Council, 2006a). The newly gained power and influence of the MOST helped increased both the political status and administrative security of the X-center. Second, the policy was clear that, "in order to increase our nation's indigenous innovation capability and core competence, R&D expense must be dramatically increased" (State Council, 2006b). Third, the policy designated innovation subsidies as a key tool to promote technological innovation and commercialization (SDRC, 2006). As a result, "indigenous innovation" elevated the X-program to a new level of prominence and its annual budget grew fivefold between 2006 and 2010, increasing from 0.7 to 3.5 billion-yuan RMB. Overall, the new policy provided the X-center with both administrative control and budget security and reduced the inter-agency pressure that had incentivized it to work meticulously in grant administration. As a former X-program director put, "It's up to the MOF to decide whether to support us or not. Supporting innovation has become a core national strategy and the MOF's action would tell whether it was with or against the top leaders … The game was not about the MOST-MOF rivalry any longer." [3]

**Intermediary agencies and the X-program.** One feature distinguishing the X-program from the U.S. SBIR program is that the X-program requires firms to submit their proposals through local state agencies rather than independently. Such intermediary agencies include MOST subsidiaries (i.e., the Commission of Science and Technology, or COST), major science parks (e.g. Zhongguancun Science Park

[3] Private interview on Jan 28, 2018.

in Beijing and Zhangjiang Science Park in Shanghai), and specially administered political units (e.g. Xinjiang Production and Construction Corp.). As the program attracts tens of thousands of applications each year, the X-center has strong incentives to get the local agencies involved in program promotion and even preliminary screening. Differentially positioned within China's bureaucratic system, these intermediary agencies vary in their opportunities to interact with X-center officials and thus in their ability to influence the program's funding decisions.

[Insert Figure 1 Here]

Figure 1 depicts the bureaucratic matrix related to the X-program. Among all the intermediaries, only the provincial COSTs interact with the X-center on a routine basis as both of them are parts of the MOST system and located immediately next to each other in the ministry's reporting-line hierarchy. In contrast, other intermediaries such as municipal COSTs, local science parks, and special political units are either one more degree separated from the X-center within the MOST or outside the MOST system. It is well documented that in China's bureaucratic system, government officials rarely jump past their immediate supervisors to interact with higher authorities; it is even rarer for them to reach out to higher-rank officials across ministerial lines (Liberthal 2003; Mertha 2009). As a result, other intermediary officials have much fewer opportunities to interact and build personal relationships with the X-program than do provincial COST officials. This will turn out to be an empirical example of Tirole's (1986) theoretical conception of how cooperative ties developed through routinized and bureaucratic tasks can lead bureaucrats to learn over time who can be trusted to cooperate (and collude).

## KEY VARIABLES AND SUMMARY STATISTICS

Our data include 6,903 X-program applications between 2005 and 2010 from three province-level regions: Beijing - China's capital city where the X-center is located- and two Yangtze River regions that are about 1000 kilometres away from Beijing. Our data include both the original grant proposals and the X-center's internal administrative archive that records the funding decisions, evaluation scores, and the administrative procedures that a given proposal has gone through in the review process.

**Grant misallocation**. The dummy variable *irregular award* measures if a firm received an X-program grant without the final score on record. The X-program is a merit-based grant where a firm's

funding eligibility is determined by its evaluation score ranking. As firms without scores cannot be ranked, the financing of such firms clearly violates the official policy protocol guiding grant allocation. Most of the X-program winners received awards due to their high scores; however, about 3.0% of the firms received grants but had no merit-ranking scores on record.

While missing scores could have been caused by administrative negligence, this scenario is less likely than are events of bureaucratic discretion. First, under the scenario of clerical errors, irregular winners would have been randomly distributed; however, statistical analyses suggest otherwise, i.e. their pattern of occurrence being consistent with deliberate grant misallocation. Second, although the X-program allows the presence of no-score firms, they should have been automatically disqualified rather than receiving funding. Overall, in the context of a merit-based program where a firm's eligibility to funding is determined by its evaluation score ranking, we should not have expected the existence of grant winners without scores. Please see Appendix III for more information on other scenarios.

**Geographic distance**. The dummy variable *Beijing* measures whether a grant applicant and the X-center are co-located in Beijing to proxy their physical proximity. Table 1 shows that the majority (68.1%, 141 out of 207 cases) of irregular awards occurred in Beijing, a region accounting for 38.4% of the grant applications. The mere fact of Beijing being three times (5.3% vs. 1.6%) more likely to have no-score winners than the provinces suggests that geographic proximity facilitates entrepreneur-bureaucrat coordination for irregular grant allocation.

[Insert Tables 1-2 and Figure 2 Here]

**Institutional context**. The dummy variable *indigenous innovation* measures the X-program's institutional context. We assign a value of one to the years of 2007-2010 and zero to the years of 2005-2006 to measure whether a grant allocation took place in the *indigenous innovation* era. While facing intense MOF pressures before 2007, the X-center greatly secured its budget and administrative authority once the new national policy was in place. Figure 2 shows three patterns in irregular award across years. First, prior to *indigenous innovation*, there were only 10 cases of irregular awards in the data; however, the number soared to 63 in 2007, stayed around 30 in 2008 and 2009, and then jumped up again to 73 in 2010. Second, strikingly *all* ten irregular winners in the more scrutinizing era were from Beijing. Third, about one third of

the irregular winners during *indigenous innovation* were from outside Beijing. These patterns suggest that when external scrutiny was stringent, irregular awards were less likely to happen, especially for firms distantly located from the grant agency. Table 2 reports t-tests, showing that *indigenous innovation* was associated with higher probability of irregular awards for both Beijing and non-Beijing firms. The confidence interval comparison for the pre- and post-*indigenous innovation* difference between Panels B and C further shows two important patterns: on one hand, the increase in the likelihood of irregular award was larger for Beijing-based firms; on the other hand, it became possible for non-Beijing based firms to have irregular awards in the *indigenous innovation era*.

**Intermediary agency.** The dummy variable *direct intermediary* measures if a firm submits its application through a provincial COST that interacts with the X-center on a routine basis. About 39.3 percent of applicants submitted their proposals through provincial COSTs and Table 3's first panel shows that these firms are twice (4.4% vs. 2.1%) likely to have irregular awards. The second panel further shows that direct intermediaries particularly help firms outside Beijing: No matter their venue of application, Beijing firms have an irregular award rate of around 5%; in contrast, among non-Beijing firms, the rate would be four times higher (3.4% vs. 0.7%) when the intermediary is well connected with the funding agency than otherwise. Given their physical proximity to the X-center, Beijing firms can make their own initiatives; however, firms located afar have to rely on intermediaries in order to develop ties and collude with the funding agency.

[Insert Tables 3 & 4 Here]

**Shared political identity.** We have also hand-collected firm ownership information through the grant proposals to examine if an applicant and the funding agency have shared identity, i.e. both being affiliated with the state. We create a dummy s*tate ownership* to measure if a firm has state-affiliated equity owners such as the State-Owned Assets Supervision and Administration Commission, public university, state research institute, and government bureau and public organization. About 10 percent of the applicants have state-affiliated equity owners and Table 4 shows that such firms are three times (9.26% vs. 2.28%) more likely to have irregular awards than are completely private firms. This pattern varies across regions: Among Beijing firms, state-affiliated ones are five times (18.82% vs. 3.68%) as likely to have irregular awards as

the non-state-affiliated ones; the ratio is much lower (2.82% vs. 1.41%) among provincial firms. These statistics shows that state ownership particularly helps Beijing firms to receive irregular awards in innovation subsidy, suggesting that shared identity, while helping draw two parties together for initial contacts, does not convey information that is fine-grained enough for state officials to infer entrepreneur-specific behavioral patterns.

**Controls.** We control for a long list of firm and entrepreneur characteristics in analyses. *Founder education* indexes the key founder's highest level of education being: associate or below, bachelor degree, master degree, or PhD. Most founders in our data are well-educated and 38% of them have received master degrees or above. We further collect information on firm attributes such as firm age, size, and ownership structure. Our firms are generally young (i.e. 4.38 years old at grant application); on average they have 3.52 equity owners and about 34% of them have organizational equity owners such as corporations, state agencies or public organizations. In addition, 5.5% of them have foreign equity owners. We use registered capital and employee number as proxies for firm size. The average registered capital for our firms was 6.34 million-yuan RMB and the head count 64 employees. Appendix Table A1 reports descriptive statistics and the correlation matrix.

We also control for a set of other firm traits that are potentially associated with firm quality. We expect that firms of high and visible quality are more likely to receive grants through legitimate means and thus have lower incentives to collude illicitly with grant officials. *Registered returnee firm* measures if a firm is established by individuals who returned from overseas. Returnee firms are entitled to receive certain special regulatory treatment from the state such as tax reduction and rental subsidies and their founders might have brought socially responsible norms and practices back to China (Luo et al. 2021). About 10.7% of our firms fall into this category. To index the type of tech standard that a firm has adopted, we create a five-category variable *tech standard* to indicate standards set up by (i) an International Standard Organization (10.33%), (ii) the Standardization Administration of China (24.51%), (iii) an industry association (15.73%), or (iv) a firm itself (45.24%). Another 4.19% of firms claim that none of these categories applies to them.

Furthermore, we control for each firm's proposed *grant size*. Since firms capture the state for funding, those applying for larger grants may have stronger incentives to lobby the funding agency. On average, our firms have applied for 823.36 thousand-yuan RMB but the number is larger for irregular winners than for other firms (1.05 vs. 0.82 million yuan). The variable *applications* records a firm's frequency of grant application between 2005 and 2010. About 79 percent of observations come from single-application firms, while irregular winners have applied more frequently (1.38 vs. 1.23) than the other firms. We also collect program level information on the annual budget to account for the X-center's potential relaxation of policy implementation rigor when the budget is abundant.

Last but not least, we use two sets of dummy variables to control for each firm's market niche and tech sector. Most applicants offer final consumer products, industrial (intermediate) products, or services; however, about 14% of applicants specify no market niche at all. We follow the X-program's practice to group proposals into seven technological sectors: 1) electronics and information technology, 2) biomedicine and pharmaceuticals, 3) new materials, 4) optics, machinery, and electric integration (opto-mechatronics), 5) environmental conservation, 6) new energy and energy efficiency, and 7) high-tech services.[4]

**MULTIVARIATE RESULTS**

We conduct two sets of regression analyses. We first examine the antecedents of irregular awards to test our theoretical predictions; we then examine the differences in both *ex ante* trait and *ex post* performance between irregular and regular winners and between irregular winners and regular firms that would have been similarly appraised. This second set of analyses helps answer questions regarding the nature of irregular awards, namely are they X-center officials' illicit grant misallocation or heroic efforts to promote high-promise yet low-score applicants?

We run logit models in Table 5 for antecedent analyses as the outcome is dichotomous. We consulted senior statisticians on the issue that non-Beijing firms had a zero probability of success in the pre-indigenous innovation era. They pointed out that including that zero-probability non-Beijing pre-indigenous

[4] Please note that firms in a given tech sector may operate across multiple industrial sectors. For example, an information technology firm may operate in the sectors of real estate (SIC Code 65), legal services (SIC Code 81), or durable goods wholesale trade (SIC Code 50). In a similar fashion, a new material firm may operate in manufacturing sub-sectors such as paper and allied products (SIC Code 26), industrial machinery and equipment (SIC Code 35), or transportation equipment (SIC Code 37). As grant applicants are required to report their tech but not industrial sectors, we control tech sectors in our analyses.

innovation group would render it impossible for maximum likelihood models to estimate the odds ratio for the interaction term *Beijing* x *indigenous innovation.* In fact, they pointed out that while STATA software may report a coefficient with the zero-probability group included, the resulting coefficient should not in any way be relied upon. They advised us to run logit models with the OR option on the sample temporarily excluding zero-probability non-Beijing pre-indigenous innovation group. Those results are presented in Table 5. They also advised us to utilize the known fact of zero probability of irregular awards for the non-Beijing, pre-*indigenous innovation* group to make cross-group comparisons in estimating the extent to which indigenous innovation moderated the geographic effect in irregular awards. We also report full-sample results in Appendix Table A2 for readers' reference.

Model 1 of Table 5 examines the control variables and shows the occurrence of irregular awards to be negatively associated (i.e. odds ratio < 1) with firms that have a large number of employees and are (co)founded by returnees. In contrast, firms that are older, have organizational equity owners, request larger grants, and have applied repeatedly are more likely to have irregular awards. All models include dummies for each firm's product niches, founder's highest level of education, and technological sectors and standards.

[Insert Table 5 & Figure 3 Here]

Models 2-5 add each focal variable incrementally and show that irregular awards have positive (i.e. odds ratio > 1) and statistically significant associations with firm location in Beijing, the era of "indigenous innovation", and the channel of direct MOST subsidiaries for application. The odds ratio for the coefficient *Beijing* is 2.196, suggesting that Beijing-based firms have a 120% higher odds of receiving irregular awards than non-Beijing firms. Point estimations for model 2 show when holding the continuous variables at their means and the category variables at the most frequent categories, e.g. "electronics and info tech" for industrial sector and bachelor degree for founder education, a Beijing firm is 1.365% more likely (2.536% vs. 1.171%) to have an irregular award than an otherwise similar but non-Beijing firm. While the absolute amount is small, the change in relative magnitude is large (i.e. an increase of 117%). Point estimations in model 3 show that the *indigenous innovation* era is associated with a 6.5-fold increase (0.272% vs. 2.040%) in the likelihood of irregular awards, corresponding well to the sharp rise of events around 2007 documented in Table 2. Models 4 and 5 look at the venue of proposal submission and state equity ownership; point

estimations suggest an increase of irregular award likelihood by 0.807% (1.390% vs. 2.197%) and 2.402% (1.708% vs. 4.110%) respectively. Model fit tests show that the inclusion of each focal variable helps improve the model fit vs. the original specification with only control variables.

Models 7-9 sequentially add the interaction terms between firm location and the other key variables. Model 7's interaction term shows that application channels matter most for provincial firms—who are more likely to receive irregular awards if they have applied through direct MOST subsidiaries than other channels; however, for Beijing firms, application channels do not make much difference. Model 9 shows that only Beijing firms benefit from their state ownership in government resource misallocation. Figure 3 shows the point estimations for each interaction term. For the controls, we once again hold every continuous variable at the mean and every category variable at the mode (i.e. the most frequent category).

We manually calculate the heterogeneous impact of *indigenous innovation* across locations on firms' likelihood of receiving irregular awards. Point estimations for Model 6 show when holding the continuous variables at their means and the categorical variables at the most frequent categories, Beijing firms' likelihood of irregular awards increases from 0.39% to 3.86% across the two periods. In contrast, non-Beijing firms' likelihood increases from zero to 1.32%. These numbers reveal two simultaneous dynamics: On one hand, Beijing firms were associated with a higher increase (3.47% vs. 1.32%) in the probability of irregular awards from the pre-*indigenous innovation* era to the *indigenous innovation* era, suggesting that the relaxation of external scrutiny and checks and balances created more frequent collisions between the X-program officials and the Beijing-based firms. At the same time, *indigenous innovation* also made it at least possible for non-Beijing firms to access irregular awards as the relaxation of external pressures reduced the grant officials' requirement towards information quality and coordination secrecy in resource misallocation. Thus, the non-Beijing firms' probability of getting an irregular award rose from zero to a substantively meaningful positive probability.

We further run multiple sets of robustness checks. First, we examine the *indigenous innovation* era only since the 2005-2006 period had merely ten cases of irregular awards. Appendix Table A3 shows similar empirical patterns as in Table 5 regarding geographic distance, intermediary agency, and Tables state ownership. Second, we investigate the geographic proximity effect focusing solely on Beijing firms.

Being a metropolis of 21.5 million people, Beijing's traffic is commensurate with the largest cities around the world. Appendix Table A4 show that, being located closer in miles and in travel time to the X-center is positively associated with irregular awards among the Beijing firms. Third, we add the evaluation scores—actual ones for regular firms and estimated ones for irregular winners — to re-run the analyses in Table 5. Appendix Table A5 shows that the empirical patterns on the antecedents of irregular awards continue to hold. Our next section discusses missing score estimation in details.

**Irregular awards: Bureaucratic heroism or resource misallocation?**

Careful readers may ask what irregular awards truly measure in our context and to what extent they can be classified as corruption. One may even argue that discretion shall be an inherent part of bureaucrats' decision making as without it, state agencies would become too rigid to implement policies meaningfully.[5] As policymakers cannot specify all contingencies in grant proposal evaluation and grant award allocation, can the irregular awards be an outcome of state bureaucrats' initiatives for more meaningful policy implementation?

We examine the nature of irregular awards in our context from three perspectives: a) a grant policy perspective regarding whether irregular awards fall into legitimate bureaucratic discretion, b) a legal perspective regarding how the deeds of irregular awards, if caught and put on trial, would have been judged in the court of Chinese laws, and c) an empirical perspective to gauge irregular winners' likelihood of receiving grants based on rule-complying merits by estimating the scores that they could have received. These steps help reveal the nature of irregular awards in our context: are they the outcome of clerical negligence (i.e. accidental deletion of grant-worthy scores), bureaucratic heroism (i.e. deliberate violations of formal rules to support low-score yet high-promise ventures), or public-private collusion of resource misallocation (i.e. to firms without grant-worthy merits)?

[5] Clearly, not all bureaucratic discretion is illegal and there is an extensive literature on bureaucrats' exercise of discretion. Michael Lipsky's (1980) has particularly pointed out that the exercise of discretion can be widespread among street-level bureaucrats in policy implementation, especially when these bureaucrats are under time pressure, supported by limited resources, and guided by vaguely specified rules. James Q Wilson (1987) further suggests that bureaucratic exercise of discretion varies across types of public organization, depending on whether an organization is featured with explicit SOPs and whether bureaucratic actions can be visible/verifiable.

**Irregular awards and bureaucratic discretion.** The X-program has a well-designed process for grant allocation. It uses the final score as a measure of firm merit, and allocates grants accordingly, i.e. awarding its first grant to the highest-score proposal, and going down the list until its annual budget runs out. The X-program also provides grant officials with a certain level of "decision discretion" but the discretion is confined to screening out disqualified firms rather than financing low-score or un-scored firms. There are two exceptions to the score-based rule: First, the X-center reserves the right to exclude high-score firms from receiving grants if it learns that these firms have fabricated grant proposal information, are under serious IP or ownership disputes, have ongoing X-program grants, or operate in "strategically discouraged" sectors with pollution or overcapacity concerns. Second, among "innovation track" firms whose financial numbers are evaluated, the X-program does not fund those with dubious financial prospects (i.e. financial scores below 60 in a scale of 0 to 100) regardless of their final score ranking. Firms with financial scores between 60 and 65 are eligible for grants only if their financial challenges are deemed temporary and caused by large R&D expenditures. Overall, these exceptions are to exclude unqualified high-score firms from receiving grants rather than to enable the funding of un-evaluated or evaluated-yet-no-score firms. Clearly, no-score awardees fall outside the X-program's policy protocol and thus are signs of grant rule violation.

**Irregular awards and corruption.** In our context, irregular awards violate not only the focal program's policy rules but also Chinese laws and thus are subject to legal sanctions. China's Criminal Law covers crimes of abuse of power and negligence of duties and its Article 397 is particularly relevant to our study—"Any functionary of a State organ who abuses his power or neglects his duty, thus causing heavy losses to public money or property or the interests of the State and the people, shall be sentenced to fixed-term imprisonment of not more than three years or criminal detention; if the circumstances are especially serious, he shall be sentenced to fixed-term imprisonment of not less than three years but not more than seven years, except as otherwise specifically provided in this Law." The same article further specifies that if the malpractice is committed by the State organ functionary "for personal gain," the punishment shall be more severe and each sentence term could be increased by another two to three years (Criminal Law, 1997).

The Chinese Supreme People's Procuratorate (2006) further specifies the case criteria and defines "the crime of abuses of powers" as "the act whereby state functionaries cause great losses to public property,

state interests or public interests as a result of going beyond their powers, illegally deciding or handling any matter which they have no power to decide or handle, or handing public affairs in violation of rules." The law and accompanying interpretations further define the threshold for "great losses" and severity of sentences. As the X-program's minimum grant is 200,000-yuan RMB, a direct economic loss of this magnitude would qualify the offending bureaucrat for a fixed-term imprisonment of "not more than three years;" this sentence could be increased by another two to three years if bribery is involved. Although China's court system and ruling party tended to look away from these "petty crimes," such chosen ignorance does not change these practices' illegality and the country's recent anti-corruption campaigns have targeted both "big tigers" and "tiny flies" (Wedeman, 2017).

**Irregular awards and heroism.** We take three steps to empirically examine whether irregular awards indicate illicit grant misallocation or state officials' heroic initiation to promote low-score-yet-high-promise ventures. We first estimate the possible final scores for irregular winners, leveraging the availability of subscores and their association with the final scores. This procedure allows us to identify a matched group of regular firms with actual final scores. As the irregular winners and their matches would have been appraised similarly by the X-program's external experts, using the latter as a benchmark enables us to estimate the likelihood of irregular winners to receive grants based on their policy-complying merits.

We use a regression approach to estimate irregular winners' missing scores. We first run OLS analysis on regular firms, regressing their final scores on subscores and firm-level observables such as grant application year, firm location, and technological sector. We then combine the OLS coefficients with the value of relevant observables to estimate irregular winners' final scores (please see Appendix VII for more information). For innovation-track firms that are evaluated for both financials and tech merits, our model achieves an $R^2$ of 0.9171; for earlier-stage, startup-track firms that are only evaluated by technological experts, the $R^2$ is 0.9243. The actual-estimated score correlations are 0.9577 and 0.9603 respectively for firms with actual scores in each track, providing high levels of confidence that the estimated scores are proximate to the actual scores.

We identify a group of regular firms that are similar to the irregular winners using the method of coarsened exact matching (CEM) (Iacus, King and Porro, 2012). The two groups are matched along the

following dimensions: (i) final evaluation scores - factual ones for regular firms and estimated ones for irregular winners, (ii) technological sectors, (iii) firm location, (iv) firm age, (v) registered capital, (vi) grant application year, (vii) grant application track, and (viii) size of proposed grant. The CEM procedure identifies 73 pairs of firms that are extremely like each other across these dimensions (Figure 4). The average actual score for the matched regular firms is 65.20, slightly but not statistically significantly higher than the average estimated score of 64.81 for the irregular winners, both being much lower than the average cut-off score (70.98) in our observed period. To put things in perspective, the standard deviation for evaluation scores in our data is 9.57. Except for three (4.11% of 73), none of the CEM-matched regular firms have received X-program funding, providing strong evidence that irregular winners are unlikely to have received grants based on policy-complying merits independently.

[Insert Figure 4 and Table 6 here]

We next examine whether irregular winners possess *ex-ante* technological traits distinguishing them from similarly-scored firms or regular winners. The presence of such traits could have led grant officials to believe that these firms are better positioned to fulfill the X-program's policy mission. We also examine the differential grant sizes between irregular and regular winners. When grants without scores measure state capture, we expect irregular winners to receive larger funding than do regular winners: When grant officials collude with an entrepreneur through rule-violation means, they may as well have incentives to help him receive a larger rather than a typical grant.

Table 6 reports the multivariate results. We proxy each firm's technological capability by its R&D expenditure and patenting as reported in the grant proposal. While firms may apply for three types of patents - invention, new utility, and new design- in China, only invention patents represent meaningful technological advancement and commercial potential (e.g. Wang et al. 2017; Jia, Huang, and Zhang, 2019). Models 1-6 focus on the CEM subgroup, finding no evidence of irregular winners being more active in R&D or patenting than the matched regular firms. Instead, Model 4 suggests the opposite, showing irregular winners to have lower R&D expenditures per employee than their matches.

Models 7-14 look at grant winners and find strong evidence that irregular winners are associated with lower R&D and patenting activities. For example, model 10 shows that irregular winners on average spent

8,130 yuan less in R&D per employee than did regular winners at the time of grant application. This is a large amount as grant winners on average spent about 30.73 thousand yuan in R&D per employee. Despite their lower merits in technology, irregular winners nevertheless receive an extra 87.14 thousand yuan in X-program grants in comparison to regular winners (Model 14). To put the number in context, the average grant size for regular winners is 609.7 thousand yuan.[6]

In the third step, we examine whether irregular winners are associated with a higher level of *ex post* performance than are regular winners as well as the CEM-matched regular firms. Such an empirical pattern, if established, would be consistent with the view that irregular awards reflect grant officials' heroic initiations to promote low-score yet high-promise ventures. However, if the opposite pattern is established, we may interpret irregular awards as occurrences of corrupt deeds, especially since these irregular winners do not possess *ex ante* traits to justify their rule-incompatible grant access.

We examine firms' post-grant performance across two dimensions, i.e. the "bottom line" of survival (into 2018) and the "top line" of having an initial public offering (IPO) event (also, before 2018). We collect the survival and IPO information from China's National Enterprise Credit Information Publicity System managed by the State Administration for Market Regulation (SAMR). To operate legally, Chinese firms are required by the law to renew their business licenses annually and to report major events such as IPO to the SAMR.

[Insert Tables 7 & 8 here]

Table 7 reports t-tests. Panel A shows that irregular winners and similarly appraised regular firms with actual scores are not significantly different in post-grant performances, despite that almost none of the latter group have received X-program resource infusion. Panel B looks at grant winners, showing the irregular ones to be more likely (16.4% vs. 12%) to fail before 2018 than the regular ones. Irregular winners are also less likely to have IPO events before 2018 (1.4% vs. 2.2%) but this difference has no statistical significance.

[6] We have also carried out additional analyses to investigate whether firms with irregular awards were more likely to be associated with other capability-related characteristics/activities such as international patenting, export, and having bank credit lines. For more information, see Appendix Table A8.

While t-tests compare group means, Table 8 further uses multivariate analyses to control for firm-level observables. Once again, irregular winners and similarly appraised regular firms are not significantly different from each other in post-grant survival (Model 2). As only one IPO event occurred among these CEM-matched firms, we do not run IPO analyses for them. Models 4 and 6 further show that relative to regular winners, irregular winners are both more likely to fail and less likely to have an IPO event before 2018 – an empirical pattern inconsistent with the speculation that irregular awards reflect grant officials' heroic initiations to promote high-risk-and-high-promise ventures. For point estimation, we temporarily set the value for the control variables at the median, the location as Beijing, the venue of application as direct MOST subsidiary, the tech sector as "electronics and info technology", and the application year as 2008. At such values, the likelihood for an irregular winner to go defunct before 2018 is 20.63%, twice that of a regular winner (9.60%). In contrast, the likelihood for a regular winner to have an IPO event is 1.01%, three times higher than that of an irregular winner (0.33%).

Overall, we observe three empirical patterns. First, among firms that would have been similarly appraised, irregular winners are associated with neither higher levels of *ex ante* technological traits nor better *ex post* financial performances, although the CEM-matched regular firms barely received any X-program grants. Second, among firms receiving X-program grants, the irregular winners are associated with both lower levels of *ex ante* technological traits and lower levels of *ex post* financial performances than are the regular winners. Third, despite their lower likelihood of having gained grant accesses based on policy-complying merits, irregular winners nevertheless received larger grants than did the regular winners. Collectively, these empirics provide layers of evidence that the documented irregular awards are more likely to be cases of grant misallocation rather than the product of bureaucrats' heroism in promoting low-score yet high-promise ventures.

## DISCUSSSION AND CONCLUSION

This study examines entrepreneurs' irregular access to state-controlled resources in a major innovation grant program in China. We use unique archival data to identify illicit entrepreneur-bureaucrat collusions in grant misallocation. While prior studies have documented that state resource access can be a key advantage for firms in the marketplace, ours takes one step further in opening up the black box of a

state agency's decision-making process to examine the mechanisms through which such access comes to exist at the violation of law and policy rules.

Our study documents four empirical patterns that help advance our collective understanding of private firms' capture of public agencies. First, firms are more likely to receive irregular awards when they are geographically collocated with the funding agency than otherwise, suggesting that physical distance could be an important encumbrance against public-private collusion. Second, a dramatic jump occurred in grant misallocation after China introduced "indigenous innovation". Our interpretation is that the new policy unintendedly reduced the inter-bureau rivalry that used to impose checks and balances upon the funding agency; consequently, the incentives for the X-center officials to select grants entirely based on merit then diminished, opening opportunities for private firms to capture the state for irregular awards. Third, an intermediary agency's capability to facilitate public-private collusion in irregular awards is greatly shaped by its formal position within the state bureaucratic system. While prior studies have generally assumed that firms lobby the state directly, direct interactions rarely take place between central government agencies and startup firms, especially when they are located afar geographically. To exercise influence, firms often have to rely on intermediary brokers. In contexts where the law prohibits lobbying through professional advocates, sponsorship from government insiders such as local state agencies that interact routinely with the central agency becomes a key channel to exercise influence. Last but not least, firms with state equity owners are more likely to have irregular awards, particularly when they are located within the same city as the grant agency. Our results build on the prior literature's insights on the privileged access to government resources in China by the state-owned enterprises but takes them one step further to show that such privilege can be due to resource-allocation rule violation rather than deliberate resource-allocation rule design.

Back of the envelope calculation suggests irregular awards documented here are of substantive significance. The 207 irregular winners received a total of 171.41 million-yuan RMB of subsidies from the X-program, representing 7.8 percent of the total amount issued by the program to all the grant winners in our data. We shall also keep in mind that the amount documented above was from the X-program only, not considering the local governments' matched funding. While we cannot declare that irregular awards were all used on unproductive activities, post-grant analyses nevertheless suggest that irregular grants were less

likely to have been used for productive purposes associated with either the improvement of the "bottom line" (i.e. survival) or the achievement of the "top line" (i.e. IPO) than were regular grants that had been allocated according to merit-ranking evaluation scores.

Our empirical results have implications for understanding public accountability and corporate citizenship, especially in emerging economies where the usual institutions for transparency, law and order are underdeveloped. While governmental agencies with overlapping administrative terrain are commonly perceived as bureaucratic redundancy to be streamlined, our study suggests that having a competing ministry with oversight over a focal agency helps create certain levels of accountability because of informal checks and balances associated with inter-bureau rivalry. Our study also suggests that a certain level of bureaucratic distance may be introduced to the grant submission-administration process to reduce intermediary agencies' likelihood of brokering illicit deals. For instance, mid- and lower-level agencies can still participate in grant program promotion but firms should be able to submit applications directly to the central agency rather than through intermediaries. Third, given the outsized effect of state ownership, grant programs may consider creating two tracks – one for firms with state ownership and another for those without. While likely to run into political opposition, anything of such a dual-track nature may help isolate the impact of ownership-based political preference that would have disproportionately reduced private firms' funding opportunities.

There are potential boundary conditions for our hypotheses. Bureaucratic organizations are not alike. In his classic study of bureaucracy and compliance, Wilson (1989: 154-175) broadly categorizes public organizations into four types—production, procedural, craft and coping organizations—based on their levels of observability in compliance across the dimensions of policy *output* (i.e. the efforts and behaviours in policy implementation) and policy *outcome* (i.e. the impact or effectiveness of the policy program). The X-program falls more into the procedural type than the others. This is because the program is featured with clear SOPs and policy guidelines regarding proposal evaluation and grant allocation but its impact on firm performance is hard to observe or verify (e.g., Hall and Lerner, 2010; Wang et al. 2017). These features have important implications about firms' opportunities to capture the state. On the one hand, when a policy program's *outcome* is hard to verify, there is room for entrepreneurs and bureaucrats to collude for state-

resource misallocation; on the other hand, such collusions have to take place with caution because when the program's *output* is traceable, social control agents may leverage the verifiable dimension for policy violation identification.

Although without data on the other three types of bureaucracy, we can still hypothesize about the occurrence of state resource misallocation based on the observability of policy implementation and outcomes. For instance, one can expect that when grant programs are administrated by production organizations that are featured with high levels of verifiability in both policy output and policy outcome, the room for public-private collusion in state resource misallocation would be lower (Marquis and Qian, 2014) than in procedural organizations that are featured with compliance verifiability in only one dimension. Furthermore, as the demand for information quality and coordination secrecy becomes higher, the negative association between physical distance and collusion would be magnified and the need for trustworthy brokers in long-distance deals would be more acute in production organizations than in procedural organizations. In contrast, for coping organizations where neither the effort nor the impact of policy programs can be tracked, state capture behaviors would be prevalent and the negative role of geographic distance on irregular award would be reduced (in comparison to the situation in production and procedural organizations). When policy violations are hard to observe or verify, state bureaucrats would also lower their demand regarding information quality and coordination secrecy in collusion and thus the moderating role of both external rivalries and institutional intermediaries become weaker. As craft organizations are also featured with observability in one dimension in compliance, we expect them to be associated with a similar level of corruption as procedural organizations.

Our study certainly has limitations. For example, we focus on one type of bureaucratic discretion—allocating state grants to firms without merit-gauging evaluation scores—while ignoring other types that may also advance private firms' interests at the violation of policy rules. For instance, we do not account for cases in which the public agents coordinated with external experts to "pre-fix" evaluation scores so that certain firms would have guaranteed yet seemingly legitimate access to grants regardless of their lack of merits. From this perspective, our study estimates the lower bound of state capture behaviours in the focal funding program.

Furthermore, our study examines only one state funding program. Although many innovation subsidy programs in the world share certain institutional features with ours (for example, the reliance on external experts for proposal appraisals and the use of evaluation score rankings as a proxy for firm merit in grant allocation), some other features of the X-program are unique (e.g. the dual leadership form two ministries and the local state agency endorsement requirement). As a result, additional study of other programs around the world is warranted before extrapolating the empirical results here to other state funding programs.

In summary, our study utilizes a unique research design to circumvent the challenges in the identification of irregular state funding behaviours. By examining the administrative data of a Chinese grant agency, we trace the proposal evaluation and grant allocation process to identify rule-incompatible awards. We find systematic evidence that firms vary in their capability to influence the focal agency's funding decisions, depending on the two parties' geographic proximity, the firm's equity ownership as well as the bureaucratic structure and process within which the grant officials operate. Furthermore, the observed irregular awards are more likely to be associated with corruption and cronyism rather than clerical negligence or bureaucratic heroism. By studying irregular awards that firms would not have received based on their independent merits, our study sheds lights on the social as well as political mechanisms through which private firms exercise influence upon public agents to access state-controlled resources.

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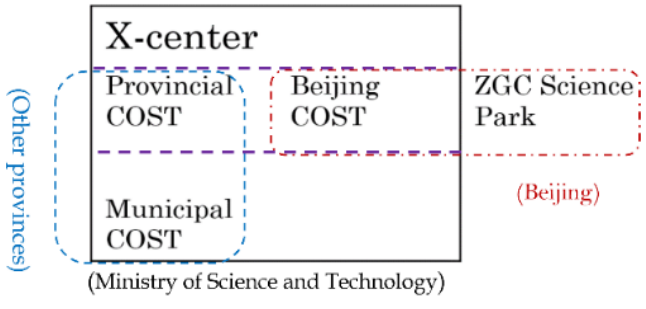
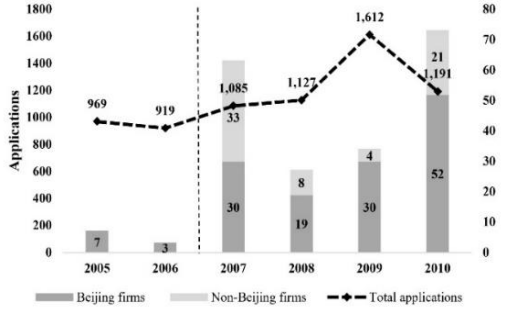
**Figure 1. Bureaucratic matrix for the X-program related state agencies**



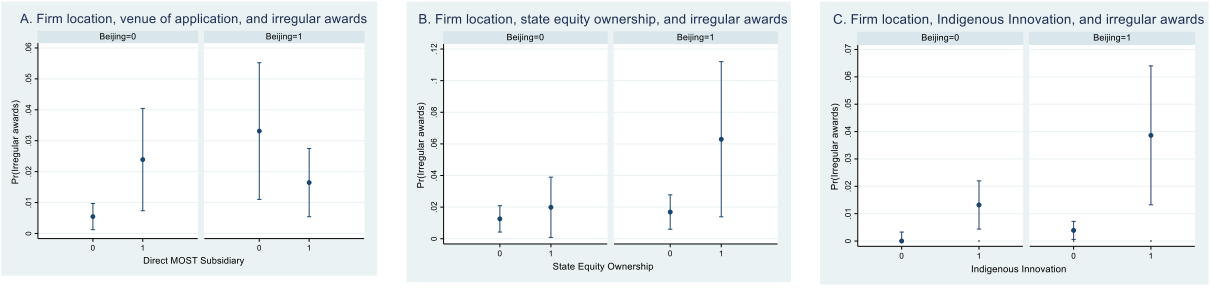

Note: Organizations within the solid square are under the administration of the Ministry of Science and Technology (MOST); organizations within the dash-line square are under the administration of provincial government; and organizations within the dash-line rectangle are under the administration of Beijing municipal government. Please note that major metropolises like Beijing and Shanghai are provincial-level administrative units in China and thus Beijing COST is a direct and provincial-level subsidiary of the MOST.

**Figure 2. Distribution of irregular awards across years (2005-2010)**



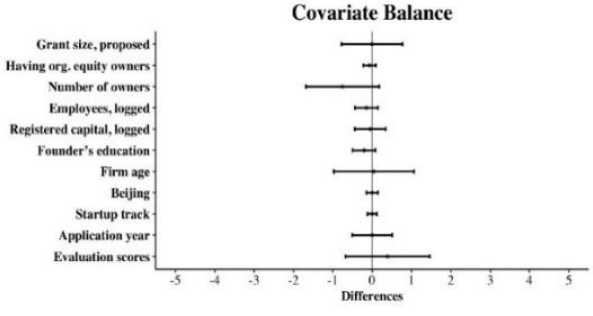
## Figure 3. Point estimations for the antecedents of irregular awards

These graphs illustrate the point estimations for the interaction terms of Table 6 Models 7-8. For all continuous variables, their values are temporarily held for this visualization at the mean; for all non-focal dummy variables, their values are temporarily held for this visualization at the mode (i.e. the category of higher frequency).




Please note that in Figure 3C for non-Beijing firms in the pre-Indigenous Innovation era, the confidence bounds are 0 and .003 (~ 3/916), not overlapping with the confidence bounds (.004, .022) of the Indigenous Innovation era. We have calculated the confidence bound for the pre-Indigenous Innovation era based on the "Rule of Three" in statistical analysis, which states that if a certain event did not occur in a sample with n subjects, the interval from 0 to 3/n is a 95% confidence interval for the rate of occurrences in the population. For more information, see Hanley, James A. and Abby Lippman-Hand. "If nothing goes wrong, is everything all right? Interpreting zero numerators." *JAMA* 249 13 (1983): 1743-5.

## Figure 4. Covariate balance for the coarsened exact matching (CEM) subsample (73 pairs)




## Table 1. Distribution of irregular awards across geographic areas

| | Observations | Mean | Std. Err. |
|---|---|---|---|
| Firms located in Beijing | 2,650 | .0532 | .0044 |
| Firms located in other regions | 4,253 | .0155 | .0019 |
| All firms | 6,903 | .0300 | .0021 |
| Difference between two groups | | .0377*** | .0042 |

Note: +$p$<0.10, *$p$<0.05, **$p$<0.01, ***$p$<0.001

## Table 2. Distribution of irregular awards across Indigenous Innovation

| | A. Full sample | | | B. Beijing firms only | | | C. Non-Beijing firms only | | |
|---|---|---|---|---|---|---|---|---|---|
| | Obs. | Mean | S.E. | Obs. | Mean | S.E. | Obs. | Mean | S.E. |
| Pre-Indigenous Innovation | 1,888 | .0053 | .0017 | 972 | .0103 | .0032 | 916 | 0 | 0 |
| Indigenous Innovation | 5,015 | .0393 | .0027 | 1,678 | .0781 | .0066 | 3,33 | .0198 | .0024 |
| Difference | | -.0340*** | .0046 | | -.0678*** | .0090 | | -.0198*** | .0046 |
| 95% confidence intervals | | (-.0430 , -.0250) | | | (-.0854, -.0502) | | | (-.0288, -.0108) | |

Note: +$p$<0.10, *$p$<0.05, **$p$<0.01, ***$p$<0.001.

## Table 3. Distribution of irregular awards across types of intermediary institutions

| | A. Full sample | | | B. Beijing firms only | | | C. Non-Beijing firms only | | |
|---|---|---|---|---|---|---|---|---|---|
| | Obs. | Mean | Std. Err. | Obs. | Mean | Std. Err. | Obs. | Mean | Std. Err. |
| Direct MOST subsidiaries | 2,711 | .0443 | .0040 | 1,334 | .0547 | .0062 | 1,377 | .0341 | .0049 |
| Others | 4,192 | .0208 | .0022 | 1,316 | .0517 | .0061 | 2,876 | .0066 | .0015 |
| Difference | | .0235*** | .0042 | | .0031 | .0087 | | .0275*** | .0040 |

Note: +$p$<0.10, *$p$<0.05, **$p$<0.01, ***$p$<0.001

## Table 4. Distribution of irregular awards across ownership types

| | A. Full sample | | | B. Beijing firms only | | | C. Non-Beijing firms only | | |
|---|---|---|---|---|---|---|---|---|---|
| | Obs. | Mean | Std. Err. | Obs. | Mean | Std. Err. | Obs. | Mean | Std. Err. |
| State affiliated | 713 | .0926 | .0109 | 287 | .1882 | .0231 | 426 | .0282 | .0080 |
| State unaffiliated | 6,190 | .0228 | .0019 | 2,363 | .0368 | .0039 | 3,827 | .0141 | .0019 |
| Difference | | .0698*** | .0067 | | .1513*** | .0137 | | .0141* | .0063 |

Note: +$p$<0.10, *$p$<0.05, **$p$<0.01, ***$p$<0.001

## Table 5 The antecedents of irregular awards (n = 5987)

All analyses are logit models with odds ratio and *p*-values based on robust standard errors reported. All analyses have tech sector dummies, tech standard dummies, product category dummies, and a founder's highest education level dummies in controls. We exclude non-Beijing, prior-*indigenous innovation* firms from the analyses here as no irregular awards were observed within this group, rendering it impossible for maximum likelihood models to estimate the odds ratio for the interaction term *Beijing* x *indigenous innovation.* As we know this group's likelihood of event was zero, we manually calculate the change of likelihood for non-Beijing firms across the *indigenous innovation* era. We further report the full sample analysis in Appendix V.

| | 1<br>Controls only | 2<br>Adding Beijing (BJ) | 3<br>Adding indigenous innovation | 4<br>Adding venue of application | 5<br>Adding state ownership | 6<br>Controls + key singletons | 7<br>Adding BJ x venue of application | 8<br>Adding BJ x state ownership | 9<br>Adding all inter-actions |
|---|---|---|---|---|---|---|---|---|---|
| Firm age | 1.033 | 1.029 | 1.027 | 1.031 | 1.023 | 1.011 | 1.010 | 1.009 | 1.008 |
| | (0.081) | (0.140) | (0.162) | (0.101) | (0.226) | (0.614) | (0.647) | (0.693) | (0.733) |
| Owner size | 0.985 | 0.985 | 0.982 | 0.988 | 0.981 | 0.975 | 0.965 | 0.975 | 0.965 |
| | (0.506) | (0.484) | (0.453) | (0.577) | (0.399) | (0.321) | (0.177) | (0.326) | (0.181) |
| With organization as equity owner | 1.967 | 1.859 | 2.003 | 1.944 | 1.399 | 1.314 | 1.343 | 1.348 | 1.378 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.096) | (0.181) | (0.146) | (0.146) | (0.117) |
| With foreign equity owner | 1.028 | 1.130 | 0.992 | 1.063 | 1.177 | 1.300 | 1.278 | 1.300 | 1.286 |
| | (0.932) | (0.701) | (0.981) | (0.848) | (0.616) | (0.453) | (0.480) | (0.464) | (0.476) |
| Register capital, logged | 1.073 | 1.066 | 1.086 | 1.081 | 1.044 | 1.052 | 1.068 | 1.044 | 1.059 |
| | (0.348) | (0.380) | (0.284) | (0.292) | (0.572) | (0.495) | (0.388) | (0.564) | (0.454) |
| Employees, logged | 0.813 | 0.880 | 0.791 | 0.830 | 0.843 | 0.932 | 0.923 | 0.928 | 0.922 |
| | (0.088) | (0.301) | (0.054) | (0.122) | (0.167) | (0.584) | (0.536) | (0.567) | (0.532) |
| Registered returnee enterprise | 0.569 | 0.691 | 0.484 | 0.622 | 0.536 | 0.597 | 0.623 | 0.618 | 0.653 |
| | (0.075) | (0.249) | (0.025) | (0.132) | (0.049) | (0.110) | (0.138) | (0.144) | (0.187) |
| Ind. park or incubator location | 1.374 | 1.034 | 1.584 | 1.798 | 1.472 | 1.257 | 0.621 | 1.296 | 0.630 |
| | (0.119) | (0.875) | (0.028) | (0.019) | (0.059) | (0.443) | (0.088) | (0.388) | (0.102) |
| Innovation track | 0.872 | 0.828 | 0.897 | 0.903 | 0.933 | 0.904 | 0.883 | 0.927 | 0.912 |
| | (0.638) | (0.518) | (0.715) | (0.724) | (0.812) | (0.736) | (0.672) | (0.801) | (0.756) |
| Total applications, firm level | 1.449 | 1.444 | 1.430 | 1.413 | 1.447 | 1.407 | 1.464 | 1.407 | 1.462 |
| | (0.007) | (0.008) | (0.010) | (0.011) | (0.009) | (0.019) | (0.009) | (0.021) | (0.010) |
| Proposed grant size, firm level | 1.024 | 1.023 | 1.025 | 1.021 | 1.023 | 1.022 | 1.020 | 1.022 | 1.020 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Total budget, fund level | 0.998 | 0.999 | 0.998 | 0.998 | 0.998 | 0.997 | 0.998 | 0.997 | 0.998 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Total applications, fund level | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Beijing | | 2.196 | | | | 2.923 | 10.816 | 2.307 | 8.578 |
| | | (0.000) | | | | (0.000) | (0.000) | (0.001) | (0.000) |
| Indigenous innovation era | | | 7.646 | | | 10.214 | 9.770 | 10.474 | 9.979 |
| | | | (0.000) | | | (0.000) | (0.000) | (0.000) | (0.000) |
| Direct MOST subsidiary | | | | 1.594 | | 1.233 | 3.597 | 1.240 | 3.557 |
| | | | | (0.013) | | (0.342) | (0.000) | (0.330) | (0.000) |
| With state ownership | | | | | 2.466 | 2.544 | 2.611 | 1.329 | 1.312 |
| | | | | | (0.000) | (0.000) | (0.000) | (0.444) | (0.491) |
| Beijing x direct MOST subsidiary | | | | | | | 0.129 | | 0.128 |
| | | | | | | | (0.000) | | (0.000) |
| Beijing x state ownership | | | | | | | | 2.600 | 2.673 |
| | | | | | | | | (0.022) | (0.023) |
| Tech sector | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Tech standard | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Product category | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Founder education | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Constant | 0.001 | 0.001 | 0.001 | 0.001 | 0.002 | 0.001 | 0.000 | 0.001 | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Log likelihood (ll) | -726.715 | -719.275 | -705.521 | -723.758 | -718.376 | -681.794 | -667.973 | -679.048 | -665.186 |
| Model comparison | n/a | 1 vs. 2 | 1 vs. 3 | 1 vs. 4 | 1 vs. 5 | 1 vs. 6 | 6 vs. 7 | 6 vs. 8 | 6 vs. 9 |
| Change in ll | n/a | -7.440 | -21.229 | -2.957 | -8.339 | -44.921 | -13.831 | -2.746 | -16.608 |
| LR chi2 (d.f.) | n/a | 14.88 (1) | 42.388 (1) | 5.914(1) | 16.678(1) | 89.842(4) | 27.642(1) | 5.492(1) | 33.216(2) |
| Prob > chi2 | n/a | 0.0001 | 0.0000 | 0.0150 | 0.0000 | 0.0000 | 0.0000 | 0.0191 | 0.0000 |

## Table 6. Irregular award, R&D expenditure, patenting, and X-fund grant

All analyses are generalized linear models (GLM) and have technology sector, application year, founder's highest education level, and product category dummies as controls. The first six models look at CEM-matched firms only and the next eight models look at grant winners, no matter whether they have evaluation scores on record or not. *P*-values based on robust standard errors are reported in parentheses. Due to the presence of missing value for R&D expenditure, the number of observations could vary across models.

| | Panel A. CEM-Matched firms only | | | | | | Panel B. Grant winners only | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) |
| | ln(R&D expenditure) | | R&D per employee | | Invention patents | | ln(R&D expenditure) | | R&D per employee | | Invention patents | | Size of received grant | |
| Irregular awards | | -0.115 | | -1.018 | | -0.227 | | -0.172 | | -0.813 | | -1.096 | | 8.714 |
| | | (0.464) | | (0.025) | | (0.524) | | (0.004) | | (0.000) | | (0.036) | | (0.000) |
| Beijing | 0.628 | 0.634 | 1.567 | 1.623 | 0.966 | 0.981 | 0.252 | 0.261 | 0.570 | 0.615 | 0.147 | 0.207 | -0.466 | -0.942 |
| | (0.018) | (0.016) | (0.024) | (0.017) | (0.058) | (0.058) | (0.000) | (0.000) | (0.002) | (0.001) | (0.267) | (0.150) | (0.397) | (0.084) |
| Direct MOST subsidiary | -0.220 | -0.241 | -0.219 | -0.404 | -0.572 | -0.609 | -0.292 | -0.289 | -0.824 | -0.810 | -0.279 | -0.261 | 1.374 | 1.229 |
| | (0.260) | (0.221) | (0.725) | (0.524) | (0.086) | (0.081) | (0.000) | (0.000) | (0.000) | (0.000) | (0.005) | (0.010) | (0.001) | (0.003) |
| State ownership | 0.091 | 0.117 | 0.634 | 0.867 | 1.051 | 1.111 | 0.025 | 0.041 | 0.235 | 0.307 | 0.388 | 0.486 | 0.938 | 0.160 |
| | (0.754) | (0.694) | (0.583) | (0.455) | (0.117) | (0.121) | (0.637) | (0.445) | (0.392) | (0.267) | (0.163) | (0.116) | (0.229) | (0.836) |
| Firm age | 0.077 | 0.075 | 0.192 | 0.181 | 0.040 | 0.038 | 0.016 | 0.016 | 0.032 | 0.033 | -0.004 | -0.003 | 0.106 | 0.095 |
| | (0.001) | (0.001) | (0.014) | (0.021) | (0.277) | (0.305) | (0.000) | (0.000) | (0.008) | (0.008) | (0.811) | (0.867) | (0.089) | (0.124) |
| Owner size | 0.005 | 0.008 | -0.027 | -0.003 | -0.011 | -0.006 | 0.010 | 0.010 | 0.036 | 0.035 | 0.005 | 0.004 | 0.121 | 0.130 |
| | (0.761) | (0.667) | (0.699) | (0.969) | (0.804) | (0.907) | (0.052) | (0.057) | (0.042) | (0.048) | (0.715) | (0.771) | (0.048) | (0.032) |
| With org. equity owner | 0.098 | 0.092 | 0.490 | 0.432 | -0.089 | -0.096 | -0.014 | -0.012 | 0.109 | 0.118 | 0.141 | 0.153 | -0.090 | -0.183 |
| | (0.606) | (0.627) | (0.516) | (0.550) | (0.853) | (0.845) | (0.687) | (0.729) | (0.486) | (0.449) | (0.405) | (0.354) | (0.849) | (0.696) |
| With foreign owner | 0.537 | 0.579 | 1.670 | 2.045 | 0.406 | 0.492 | 0.135 | 0.138 | 0.454 | 0.471 | 0.444 | 0.463 | 2.082 | 1.930 |
| | (0.110) | (0.083) | (0.252) | (0.140) | (0.651) | (0.618) | (0.036) | (0.031) | (0.154) | (0.140) | (0.414) | (0.397) | (0.035) | (0.043) |
| Registered capital, logged | -0.023 | -0.031 | 0.030 | -0.040 | 0.131 | 0.114 | 0.188 | 0.188 | 0.646 | 0.647 | 0.203 | 0.203 | 0.084 | 0.081 |
| | (0.760) | (0.667) | (0.906) | (0.874) | (0.390) | (0.487) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.665) | (0.674) |
| Employees, logged | 0.800 | 0.814 | -0.920 | -0.798 | 0.062 | 0.095 | 0.525 | 0.524 | -1.617 | -1.623 | 0.056 | 0.047 | 0.016 | 0.083 |
| | (0.000) | (0.000) | (0.003) | (0.007) | (0.769) | (0.660) | (0.000) | (0.000) | (0.000) | (0.000) | (0.504) | (0.558) | (0.959) | (0.788) |
| Returnee enterprise | 0.447 | 0.425 | 1.201 | 1.009 | 0.205 | 0.169 | 0.041 | 0.036 | 0.356 | 0.337 | 0.113 | 0.090 | -0.876 | -0.689 |
| | (0.063) | (0.091) | (0.076) | (0.158) | (0.603) | (0.690) | (0.477) | (0.522) | (0.255) | (0.283) | (0.583) | (0.673) | (0.140) | (0.253) |
| Ind. parks/incubators | 0.044 | 0.036 | -0.075 | -0.146 | -0.331 | -0.340 | -0.092 | -0.092 | -0.257 | -0.255 | -0.098 | -0.098 | 1.245 | 1.248 |
| | (0.783) | (0.825) | (0.906) | (0.818) | (0.485) | (0.479) | (0.061) | (0.062) | (0.243) | (0.245) | (0.609) | (0.609) | (0.049) | (0.046) |
| Innovation track | -0.385 | -0.380 | -1.646 | -1.605 | -0.159 | -0.149 | 0.086 | 0.067 | 0.085 | -0.003 | -0.525 | -0.639 | 11.547 | 12.455 |
| | (0.153) | (0.151) | (0.222) | (0.214) | (0.762) | (0.774) | (0.135) | (0.245) | (0.749) | (0.991) | (0.216) | (0.172) | (0.000) | (0.000) |
| Total apps, firm level | 0.326 | 0.327 | 0.987 | 0.991 | 1.170 | 1.174 | 0.060 | 0.068 | -0.005 | 0.033 | 0.009 | 0.063 | 1.046 | 0.613 |
| | (0.002) | (0.002) | (0.027) | (0.018) | (0.003) | (0.003) | (0.037) | (0.018) | (0.961) | (0.761) | (0.938) | (0.534) | (0.022) | (0.185) |
| Proposed grant size | 0.011 | 0.011 | 0.041 | 0.040 | -0.001 | -0.001 | 0.004 | 0.004 | 0.012 | 0.014 | 0.011 | 0.013 | 0.449 | 0.426 |
| | (0.013) | (0.014) | (0.099) | (0.096) | (0.919) | (0.899) | (0.000) | (0.000) | (0.000) | (0.000) | (0.189) | (0.143) | (0.000) | (0.000) |
| Budget, fund-level | 0.000 | 0.000 | 0.000 | 0.000 | -0.001 | -0.001 | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 | -0.005 | -0.004 |
| | (0.642) | (0.597) | (0.989) | (0.882) | (0.118) | (0.146) | (0.302) | (0.236) | (0.362) | (0.292) | (0.776) | (0.580) | (0.000) | (0.001) |
| Total apps, fund level | 0.000 | 0.000 | -0.000 | -0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.003 | 0.002 |
| | (0.740) | (0.771) | (0.992) | (0.939) | (0.048) | (0.050) | (0.031) | (0.013) | (0.284) | (0.168) | (0.005) | (0.000) | (0.000) | (0.000) |
| Tech sector dummies | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Tech standard dummies | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Product categories | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Founder education levels | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Application year dummies | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Constant | -0.637 | -0.616 | 0.885 | 1.072 | -2.016 | -2.047 | 0.745 | 0.698 | 4.002 | 3.784 | -1.656 | -1.958 | -3.939 | -1.540 |
| | (0.463) | (0.482) | (0.807) | (0.770) | (0.183) | (0.176) | (0.000) | (0.000) | (0.000) | (0.000) | (0.022) | (0.018) | (0.100) | (0.518) |
| Number of observations | 142 | 142 | 142 | 142 | 146 | 146 | 3174 | 3174 | 3174 | 3174 | 3520 | 3520 | 3520 | 3520 |
| Log likelihood (ll) | -156.821 | -156.477 | -332.968 | -330.694 | -276.574 | -276.289 | -3468.207 | -3463.909 | -8276.357 | -8271.704 | -8504.439 | -8491.664 | -13350.64 | -13298.625 |
| Comparison across models | n/a | 1 vs. 2 | n/a | 3 vs. 4 | n/a | 5 vs. 6 | n/a | 7 vs. 8 | n/a | 9 vs. 10 | n/a | 11 vs. 12 | n/a | 13 vs. 14 |
| Change in ll | n/a | -0.344 | n/a | -2.274 | n/a | -0.285 | n/a | -4.298 | n/a | -4.653 | n/a | -12.775 | n/a | -52.011 |
| LR chi2 (d.f. for LR test) | n/a | 0.688 (1) | n/a | 4.548(1) | n/a | 0.57(1) | n/a | 8.596(1) | n/a | 9.306(1) | n/a | 25.550(1) | n/a | 104.021(1) |
| Prob > chi2 | n/a | 0.4064 | n/a | 0.0330 | n/a | 0.4507 | n/a | .0034 | n/a | .0023 | n/a | .0000 | n/a | .0000 |

## Table 7. Post-grant performances in mortality and IPO across firm types

| | Obs | Failure before 2018 Mean | Std. error | IPO before 2018 Mean | Std. error |
|---|---|---|---|---|---|
| Panel A: CEM matched firms only | | | | | |
| Regular firms | 73 | .151 | .042 | .014 | .014 |
| Irregular winners | 73 | .137 | .041 | .000 | .000 |
| Difference | | .014 | .058 | .014 | .014 |
| Panel B: Grant winners only | | | | | |
| Regular winners | 3,313 | .120 | .006 | .022 | .003 |
| Irregular winners | 207 | .164 | .026 | .014 | .008 |
| Difference | | -.044* | .024 | .007 | .010 |

Note: * p<0.10; ** p< 0.05; *** p<0.01

## Table 8. Irregular winners and post-grant performance

All analyses are logit models and have technology sector, application year, founder's highest education level, and product category dummies as controls. The first two models look at CEM-matched firms only and the next four models look at grant winners, no matter whether they have evaluation scores on record or not. Sixteen observations drop out of models 1 and 2 as all firms from the sectors of "new energy" and "high-technology service" survived into 2018. For IPO, we focus on firms listed on (a) the main and second boards of China's Shenzhen and Shanghai Stock Exchanges, (b) the NYSE or Nasdaq in the US, (c) the Hong Kong Stock Exchanges, and (d) Singapore Stock Exchange. We exclude China's third or fourth boards due to their minimal listing barrier. *P* values based on robust standard errors are reported in parentheses.

| | Panel A. CEM firms | | Panel B. Grant Winners | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | Failure before 2018 | | Failure before 2018 | | IPO before 2018 | |
| Irregular awards | | 0.005 | | 0.895 | | -1.129 |
| | | (0.993) | | (0.000) | | (0.082) |
| Beijing | 2.587 | 2.586 | -0.573 | -0.624 | 0.669 | 0.718 |
| | (0.036) | (0.036) | (0.000) | (0.000) | (0.115) | (0.094) |
| Direct MOST subsidiary | 1.765 | 1.766 | 0.466 | 0.441 | -0.109 | -0.113 |
| | (0.062) | (0.058) | (0.000) | (0.001) | (0.749) | (0.743) |
| State ownership | -0.666 | -0.668 | 0.142 | 0.068 | -0.202 | -0.108 |
| | (0.548) | (0.548) | (0.487) | (0.742) | (0.593) | (0.774) |
| Firm age | -0.217 | -0.217 | -0.101 | -0.105 | 0.003 | 0.003 |
| | (0.109) | (0.106) | (0.000) | (0.000) | (0.935) | (0.932) |
| Owner size | 0.121 | 0.121 | -0.048 | -0.049 | 0.048 | 0.047 |
| | (0.322) | (0.314) | (0.036) | (0.030) | (0.066) | (0.081) |
| With org. owner | -1.058 | -1.057 | 0.243 | 0.225 | 0.902 | 0.900 |
| | (0.197) | (0.194) | (0.098) | (0.127) | (0.004) | (0.004) |
| With foreign owner | 2.900 | 2.898 | 0.124 | 0.118 | -0.178 | -0.150 |
| | (0.080) | (0.073) | (0.630) | (0.645) | (0.704) | (0.752) |
| Registered capital, logged | 0.414 | 0.414 | -0.146 | -0.146 | 0.029 | 0.039 |
| | (0.412) | (0.412) | (0.018) | (0.018) | (0.829) | (0.772) |
| Employees, logged | -0.702 | -0.702 | -0.269 | -0.256 | 1.107 | 1.104 |
| | (0.404) | (0.404) | (0.003) | (0.004) | (0.000) | (0.000) |
| Returnee enterprise | -1.683 | -1.681 | 0.061 | 0.101 | 0.041 | 0.064 |
| | (0.281) | (0.271) | (0.747) | (0.595) | (0.937) | (0.900) |
| Ind. parks/incubators | -1.032 | -1.031 | 0.226 | 0.219 | 0.591 | 0.595 |
| | (0.396) | (0.385) | (0.319) | (0.334) | (0.204) | (0.208) |
| Innovation track | 4.207 | 4.208 | -0.234 | -0.147 | -1.301 | -1.408 |
| | (0.006) | (0.007) | (0.304) | (0.516) | (0.013) | (0.008) |
| Total apps, firm level | 0.001 | 0.001 | -0.266 | -0.328 | 0.119 | 0.145 |
| | (0.999) | (0.999) | (0.092) | (0.041) | (0.678) | (0.615) |
| Proposed grant size | -0.030 | -0.030 | 0.001 | -0.001 | 0.007 | 0.010 |
| | (0.252) | (0.260) | (0.787) | (0.724) | (0.170) | (0.085) |
| Budget | -0.006 | -0.006 | -0.000 | -0.000 | 0.001 | 0.001 |
| | (0.070) | (0.071) | (0.457) | (0.469) | (0.222) | (0.348) |
| #applications | 0.000 | 0.000 | -0.000 | -0.000 | -0.000 | -0.000 |
| | (0.795) | (0.794) | (0.009) | (0.003) | (0.011) | (0.026) |
| Tech sector dummies | YES | YES | YES | YES | YES | YES |
| Tech standard dummies | YES | YES | YES | YES | YES | YES |
| Product categories | YES | YES | YES | YES | YES | YES |
| Founder's highest education | YES | YES | YES | YES | YES | YES |
| Application year dummies | YES | YES | YES | YES | YES | YES |
| Constant | 1.926 | 1.931 | 1.853 | 2.136 | -8.721 | -8.965 |
| | (0.621) | (0.629) | (0.002) | (0.000) | (0.000) | (0.000) |
| Number of observations | 146 | 146 | 3520 | 3520 | 3520 | 3520 |
| Log likelihood (ll) | -38.628 | -38.628 | -1185.3165 | -1178.6999 | -281.410 | -279.709 |
| Comparisons | n/a | 1 vs. 2 | n/a | 3 vs. 4 | n/a | 5 vs. 6 |
| Change in ll | n/a | -0.000 | n/a | -6.617 | n/a | -1.701 |
| LR chi2 (d.f. for LR test) | n/a | .000 (1) | n/a | 13.233(1) | n/a | 3.402(1) |
| Prob > chi2 | n/a | 0.9941 | n/a | .0003 | n/a | .0651 |

# Appendix

## Who Captures the State in China? Evidence from Irregular Awards in a Public Innovation Grant Program

## ONLINE APPENDIX

## Appendix I

## Figure A1. Sample grant winners.

Three types of grant winner are illustrated. Firm-A is a typical winner with complete info on the final and aggregate score and the subscores on technology and finance that are used to calculate the aggregate score. Firm-B is a typical irregular winner–although the firm has gone through the evaluation process, it has neither the final score nor the funding recommendation on record. The system most likely recommended not to fund the company due to its original but now-missing low score; nevertheless, the applicant received 650k yuan RMB, exactly 100% of its requested grant size. Figure-C illustrates a case of relative rarity where the X-program received the firm's proposal and funded it but did not go through the review process, an unequivocal violation of program rules. This third case corresponds well with our private conversations (January 28, 2018) with a former program director who acknowledged that scores could be missing for certain grant winners because higher-up people had made "special requests" on behalf of these firms.

(A)


(B)


(C)

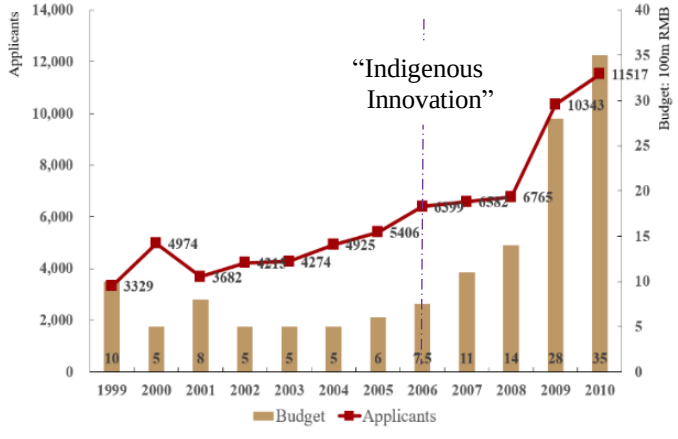
## Appendix II. Inter-ministry rivalry and the X-program

The X-program was under the dual leadership of the Ministry of Science and Technology (MOST) and the Ministry of Finance (MOF). While the MOST administrated the program through its subsidiary, the X-center, in proposal solicitation, evaluation and grant allocation, the MOF was institutionalized to take charge of the program's annual budget approval, review as well as operation monitoring and auditing. When setting up the X-fund, the State Council was explicit on the following issues in its official policy letter (State Council, 1999, Letter No.47):

1. The MOF "holds the regulatory authority over the X-fund". It "reviews and provides guideline upon the work of the funding program". It is also tasked to "supervise and inspect the operation of the funding program as well as the allocation of the grant".
2. "When needed, the MOF as well as the MOST hold the authority to review and investigate the outcome of proposal evaluation".
3. "The annual budget of the X-fund program is determined/defined by the MOF. The MOST reports to the MOF about fund usage following the relevant MOF policy guidelines and the fund usage is subject to the MOF's review and supervision".

Even though the MOF was unlikely to micromanage how the X-center administered any particular project, grant officials did worry that the MOF would catch individual fraudulent cases (in the process of random auditing and/or investigation of tipped-off cases) and then went onto in-depth review and auditing. This concern was particularly strong when the MOF had incentives to find excuses to reduce the X-program budget and to even dismantle it as an organization. Under such pressures, X-program officials had lower incentives to carry out misdeeds in the proposal evaluation and grant allocation process, particularly before 2007 when the X-center were liable to bureaucratic restructure and when the MOST was weak in China's innovation and technology policy making and implementation.

**Figure A2. Annual budget and applications for the X-program (1999-2010)**



## Appendix III
**Alternative scenario of missing Scores.**

Firms may legitimately drop out of the review process before the expert evaluation stage for the following reasons: (1) their application material was incomplete; (2) their proposed projects were incompatible with the fund's sectoral priority, e.g. falling into industries "not encouraged" by the central government; and (3) they were ineligible for the grant due to serious IP disputes, information fabrications, and/or incompletion of a pervious grant-winning project. In very rare cases, firms may also have scores missing due to external experts' failure to complete the evaluation in the specified time window for proposal review. One may wonder why X-program officials would not raise a firm's final score to make it look legitimately fundable. A former program director informed us this was due to the program's impressive, although imperfect, efforts in designing a software system to show off its technological capability and to curtail rule transgressions in award allocation. Although multiple senior officials have access to the system, it is more challenging for them to change rather than delete the scores as these scores are generated through an algorithm based on the sub-scores embedded in the back-end data system. For proposals that have gone through the review process, the system records not only the sub-scores assigned by each expert but also the timing of each expert's review activities, i.e. system log-in and log-out as well as score submission at the expert-proposal level. Once the scores are submitted and the expert signs out of the review, theses scores would be saved in the system and cannot be changed unless with the help of the back-end IT personnel. Since these personnel are contract workers provided by an outside company, such requests would raise "unnecessary" suspicions and create hazards of information leakage, especially when they take place days after the completion of evaluation.

## Appendix IV

### Table A1. Correlation matrix and descriptive statistics (n = 6903)

| Variables | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1. Irregular awards | 1.000 | | | | | | | | | | | | | | | | | |
| 2. Beijing | 0.107 | 1.000 | | | | | | | | | | | | | | | | |
| 3. Indigenous innovation era | 0.089 | -0.165 | 1.000 | | | | | | | | | | | | | | | |
| 4. Direct MOST subsidiary | 0.067 | 0.179 | -0.043 | 1.000 | | | | | | | | | | | | | | |
| 5. State ownership | 0.125 | 0.013 | -0.052 | 0.010 | 1.000 | | | | | | | | | | | | | |
| 6. Firm age | 0.064 | -0.072 | 0.068 | 0.010 | 0.058 | 1.000 | | | | | | | | | | | | |
| 7. Owner size | 0.006 | 0.053 | -0.048 | -0.017 | 0.075 | 0.091 | 1.000 | | | | | | | | | | | |
| 8. With org. equity owner | 0.086 | 0.068 | -0.073 | -0.004 | 0.469 | 0.008 | 0.085 | 1.000 | | | | | | | | | | |
| 9. With foreign owner | 0.013 | -0.040 | -0.020 | -0.046 | 0.037 | 0.020 | -0.042 | 0.265 | 1.000 | | | | | | | | | |
| 10. Registered capital, logged | 0.068 | -0.072 | -0.002 | -0.045 | 0.167 | 0.246 | 0.114 | 0.272 | 0.112 | 1.000 | | | | | | | | |
| 11. Employees, logged | 0.028 | -0.236 | -0.045 | -0.033 | 0.035 | 0.485 | 0.108 | 0.088 | 0.065 | 0.543 | 1.000 | | | | | | | |
| 12. Returnee enterprise | -0.025 | -0.009 | 0.138 | -0.104 | 0.037 | -0.208 | -0.046 | 0.030 | 0.132 | -0.093 | -0.301 | 1.000 | | | | | | |
| 13. Ind. parks/incubators | 0.029 | 0.478 | -0.040 | -0.303 | -0.037 | -0.064 | 0.036 | 0.003 | 0.005 | -0.050 | -0.140 | 0.079 | 1.000 | | | | | |
| 14. Innovation track | 0.026 | 0.098 | -0.178 | 0.050 | -0.018 | 0.354 | 0.066 | 0.013 | 0.021 | 0.248 | 0.413 | -0.265 | 0.017 | 1.000 | | | | |
| 15. Total apps, firm level | 0.051 | -0.059 | -0.040 | 0.029 | 0.027 | 0.067 | 0.016 | 0.012 | 0.003 | 0.045 | 0.107 | -0.027 | -0.079 | 0.130 | 1.000 | | | |
| 16. Proposed grant size | 0.147 | 0.051 | -0.118 | 0.111 | 0.061 | 0.349 | 0.084 | 0.091 | 0.043 | 0.371 | 0.468 | -0.212 | -0.035 | 0.676 | 0.124 | 1.000 | | |
| 17. Budget, fund-level | 0.010 | -0.169 | 0.620 | -0.107 | -0.044 | 0.050 | -0.050 | -0.063 | -0.022 | 0.004 | -0.034 | 0.093 | -0.048 | -0.164 | -0.059 | -0.123 | 1.000 | |
| 18. Total apps, fund level | 0.059 | -0.149 | 0.606 | -0.135 | -0.054 | 0.082 | -0.040 | -0.060 | -0.034 | 0.053 | -0.023 | 0.104 | -0.008 | -0.319 | -0.083 | -0.139 | 0.724 | 1.000 |
| Mean | 0.030 | 0.384 | 0.726 | 0.393 | 0.103 | 4.376 | 3.523 | 0.342 | 0.055 | 5.714 | 3.760 | 0.107 | 0.125 | 0.816 | 1.239 | 82.336 | 1190.781 | 8152.163 |
| Mean for irregular awards | 1.000 | 0.681 | 0.952 | 0.580 | 0.319 | 5.908 | 3.628 | 0.575 | 0.072 | 6.184 | 3.902 | 0.063 | 0.179 | 0.874 | 1.382 | 104.502 | 1204.928 | 8921.560 |
| Means for others | 0 | 0.375 | 0.720 | 0.387 | 0.097 | 4.328 | 3.519 | 0.335 | 0.055 | 5.699 | 3.755 | 0.109 | 0.123 | 0.815 | 1.235 | 81.651 | 1190.344 | 8128.378 |
| Difference | 1.000 | .306*** | .232*** | .193*** | .222*** | 1.580*** | .109 | .240*** | .018 | .485*** | .147** | -.046** | .056** | .060** | .147*** | -22.85*** | 14.584 | 793.182*** |

Asterisks denote significance levels for t-tests of differences: *$p$<0.10, **$p$<0.05, ***$p$<0.01.

## Appendix V
### Antecedent analyses of irregular awards with full observations

As Figure 2 shows, there are no cases of irregular awards for non-Beijing firms in the pre-indigenous innovation era. Because of the c group, running a logit model on the full sample is substantively way in estimating the maximum likelihood for the interaction term *Beijing* x *indigenous innovation*. That being said, logit models are perfectly in estimating other variables of interests and we report the full-sample analyses here. Just in case readers would like to see how the statistical results look like for the *Beijing* x *indigenous innovation* interaction term, we also report it here in Models 7 and 10.

### Table A2. The antecedents of irregular awards, logit specification (n = 6903)

All analyses are logit models and *p*-values based on robust standard errors are reported in parentheses. The outcome variable is a dummy indicating whether a grant applicant received X-fund grant without evaluation scores on record.

| | 1<br>Controls only | 2<br>Adding Beijing (BJ) | 3<br>Adding indigenous innovation | 4<br>Adding venue of application | 5<br>Adding state Ownership | 6<br>Controls + key singletons | 7<br>Adding BJ x indigenous innovation | 8<br>Adding BJ x venue of application | 9<br>Adding BJ x state ownership | 10<br>Adding all inter-actions |
|---|---|---|---|---|---|---|---|---|---|---|
| Firm age | 0.037 | 0.030 | 0.027 | 0.035 | 0.028 | 0.011 | 0.011 | 0.010 | 0.009 | 0.008 |
| | (0.041) | (0.113) | (0.153) | (0.059) | (0.137) | (0.614) | (0.614) | (0.649) | (0.693) | (0.733) |
| Owner size | -0.015 | -0.015 | -0.018 | -0.012 | -0.020 | -0.026 | -0.025 | -0.036 | -0.026 | -0.036 |
| | (0.516) | (0.487) | (0.451) | (0.605) | (0.410) | (0.318) | (0.321) | (0.175) | (0.322) | (0.181) |
| With organization as equity | 0.666 | 0.600 | 0.694 | 0.659 | 0.326 | 0.269 | 0.273 | 0.293 | 0.295 | 0.321 |
| owner | (0.000) | (0.000) | (0.000) | (0.000) | (0.104) | (0.187) | (0.181) | (0.149) | (0.151) | (0.117) |
| With foreign equity owner | -0.004 | 0.124 | -0.018 | 0.046 | 0.138 | 0.263 | 0.262 | 0.248 | 0.262 | 0.252 |
| | (0.989) | (0.693) | (0.957) | (0.883) | (0.666) | (0.453) | (0.453) | (0.476) | (0.466) | (0.476) |
| Register capital, logged | 0.084 | 0.073 | 0.086 | 0.091 | 0.057 | 0.053 | 0.051 | 0.067 | 0.045 | 0.057 |
| | (0.257) | (0.310) | (0.262) | (0.217) | (0.445) | (0.476) | (0.495) | (0.376) | (0.545) | (0.454) |
| Employees, logged | -0.272 | -0.158 | -0.249 | -0.242 | -0.239 | -0.075 | -0.070 | -0.086 | -0.079 | -0.082 |
| | (0.024) | (0.204) | (0.041) | (0.044) | (0.051) | (0.560) | (0.584) | (0.508) | (0.546) | (0.532) |
| Registered returnee | -0.534 | -0.306 | -0.731 | -0.424 | -0.592 | -0.510 | -0.516 | -0.469 | -0.476 | -0.426 |
| enterprise | (0.090) | (0.333) | (0.024) | (0.173) | (0.061) | (0.114) | (0.110) | (0.140) | (0.148) | (0.187) |
| Ind. park or incubator | 0.428 | 0.018 | 0.502 | 0.765 | 0.501 | 0.234 | 0.229 | -0.483 | 0.265 | -0.462 |
| location | (0.036) | (0.934) | (0.017) | (0.002) | (0.015) | (0.435) | (0.443) | (0.085) | (0.380) | (0.102) |
| Innovation track | -0.146 | -0.210 | -0.108 | -0.090 | -0.079 | -0.103 | -0.101 | -0.125 | -0.079 | -0.092 |
| | (0.614) | (0.473) | (0.716) | (0.755) | (0.785) | (0.732) | (0.736) | (0.672) | (0.795) | (0.756) |
| Total applications, firm level | 0.347 | 0.348 | 0.351 | 0.322 | 0.347 | 0.338 | 0.342 | 0.379 | 0.337 | 0.380 |
| | (0.010) | (0.011) | (0.011) | (0.018) | (0.012) | (0.021) | (0.019) | (0.010) | (0.023) | (0.010) |
| Proposed grant size, firm | 0.025 | 0.023 | 0.025 | 0.022 | 0.024 | 0.022 | 0.021 | 0.020 | 0.022 | 0.020 |
| level | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Total budget, fund level | -0.001 | -0.001 | -0.002 | -0.001 | -0.001 | -0.003 | -0.003 | -0.002 | -0.003 | -0.002 |
| | (0.000) | (0.001) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Total applications, fund level | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Beijing | | 1.033 | | | | 1.126 | 14.045 | 2.445 | 0.886 | 15.351 |
| | | (0.000) | | | | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Indigenous innovation era | | | 2.492 | | | 2.586 | 15.296 | 2.515 | 2.606 | 15.502 |
| | | | (0.000) | | | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Direct MOST subsidiary | | | | 0.611 | | 0.219 | 0.210 | 1.291 | 0.225 | 1.269 |
| | | | | (0.001) | | (0.322) | (0.342) | (0.000) | (0.310) | (0.000) |
| With state ownership | | | | | 0.880 | 0.933 | 0.934 | 0.959 | 0.283 | 0.271 |
| | | | | | (0.000) | (0.000) | (0.000) | (0.000) | (0.443) | (0.491) |
| Beijing x indigenous | | | | | | | -12.972 | | | -13.202 |
| innovation | | | | | | | (0.000) | | | (0.000) |
| Beijing x direct subsidiary | | | | | | | | -2.064 | | -2.054 |
| | | | | | | | | (0.000) | | (0.000) |
| Beijing x state ownership | | | | | | | | | 0.965 | 0.983 |
| | | | | | | | | | (0.020) | (0.023) |
| Tech sector dummies | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Tech standard dummies | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Product category dummies | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Founder edu dummies | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Constant | -7.406 | -7.977 | -7.274 | -7.621 | -7.301 | -7.825 | -20.497 | -8.394 | -7.641 | -21.149 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Log likelihood (ll) | -745.437 | -731.989 | -709.839 | -740.176 | -737.388 | -684.181 | -681.794 | -670.108 | -681.374 | -665.186 |
| Comparison across models | n/a | 1 vs. 2 | 1 vs. 3 | 1 vs. 4 | 1 vs. 5 | 1 vs. 6 | 6 vs. 7 | 6 vs. 8 | 6 vs. 9 | 6 vs. 10 |
| Change in ll | n/a | -13.448 | -35.598 | -5.261 | -8.049 | -61.256 | -2.387 | -14.073 | -2.807 | -18.995 |
| LR chi2 (d.f. for LR test) | n/a | 26.896(1) | 71.196(1) | 10.522(1) | 16.098(1) | 122.512(4) | 4.774(1) | 28.146(1) | 5.614(1) | 37.990(3) |
| Prob > chi2 | n/a | .0000 | .00000 | .0012 | .0001 | .0000 | 0.0289 | .0000 | .0178 | .0000 |

# Appendix VI
## Table A3. The antecedents of irregular awards, Indigenous Innovation era only

All analyses are logit models and focus on the era of 2007-2010. The outcome variable is a dummy indicating whether a grant applicant received X-fund grant without evaluation scores on record. A set of dummy variables on tech sector, tech standard, product category, and a founder's highest education level are included as controls. *P*-values based on robust standard errors are reported in parentheses.

| | 1<br>Controls only | 2<br>Adding Beijing | 3<br>Adding venue of application | 4<br>Adding state Ownership | 5<br>Controls + key singleton variables | 6<br>Adding Beijing x venue of application | 7<br>Adding Beijing x state ownership | 8<br>Adding all inter-actions |
|---|---|---|---|---|---|---|---|---|
| Firm age | 0.023 | 0.015 | 0.021 | 0.015 | 0.006 | 0.005 | 0.004 | 0.002 |
| | (0.238) | (0.463) | (0.291) | (0.464) | (0.772) | (0.816) | (0.867) | (0.919) |
| Owner size | -0.016 | -0.020 | -0.013 | -0.023 | -0.025 | -0.036 | -0.025 | -0.037 |
| | (0.523) | (0.435) | (0.594) | (0.394) | (0.350) | (0.185) | (0.355) | (0.188) |
| With org. owner | 0.657 | 0.571 | 0.648 | 0.296 | 0.188 | 0.212 | 0.218 | 0.241 |
| | (0.000) | (0.001) | (0.000) | (0.168) | (0.381) | (0.320) | (0.314) | (0.264) |
| With foreign owner | -0.168 | -0.029 | -0.137 | -0.038 | 0.115 | 0.093 | 0.117 | 0.103 |
| | (0.643) | (0.935) | (0.705) | (0.918) | (0.759) | (0.802) | (0.762) | (0.784) |
| Registered capital, logged | 0.077 | 0.072 | 0.085 | 0.048 | 0.041 | 0.059 | 0.032 | 0.049 |
| | (0.337) | (0.355) | (0.283) | (0.559) | (0.601) | (0.465) | (0.685) | (0.544) |
| Employees, logged | -0.216 | -0.096 | -0.192 | -0.176 | -0.041 | -0.053 | -0.045 | -0.054 |
| | (0.076) | (0.447) | (0.115) | (0.158) | (0.748) | (0.682) | (0.730) | (0.682) |
| Returnee enterprise | -0.652 | -0.396 | -0.565 | -0.718 | -0.445 | -0.409 | -0.406 | -0.360 |
| | (0.045) | (0.223) | (0.081) | (0.030) | (0.175) | (0.206) | (0.226) | (0.275) |
| Ind. parks/incubators | 0.519 | 0.047 | 0.784 | 0.607 | 0.216 | -0.548 | 0.256 | -0.530 |
| | (0.019) | (0.840) | (0.003) | (0.007) | (0.494) | (0.064) | (0.422) | (0.079) |
| Innovation track | 0.026 | -0.038 | 0.063 | 0.079 | 0.028 | -0.003 | 0.054 | 0.032 |
| | (0.934) | (0.902) | (0.837) | (0.799) | (0.929) | (0.992) | (0.866) | (0.919) |
| Total apps, firm level | 0.324 | 0.323 | 0.299 | 0.319 | 0.310 | 0.354 | 0.308 | 0.353 |
| | (0.016) | (0.017) | (0.026) | (0.021) | (0.027) | (0.012) | (0.030) | (0.013) |
| Proposed grant size | 0.025 | 0.024 | 0.023 | 0.024 | 0.022 | 0.020 | 0.023 | 0.021 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Budget, fund level | -0.002 | -0.003 | -0.002 | -0.003 | -0.003 | -0.002 | -0.003 | -0.003 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| #applications, fund level | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Beijing | | 1.108 | | | 1.100 | 2.480 | 0.832 | 2.221 |
| | | (0.000) | | | (0.000) | (0.000) | (0.001) | (0.000) |
| Direct MOST subsidiary | | | 0.493 | | 0.161 | 1.246 | 0.171 | 1.236 |
| | | | (0.009) | | (0.481) | (0.000) | (0.456) | (0.000) |
| With state ownership | | | | 0.948 | 1.026 | 1.053 | 0.335 | 0.317 |
| | | | | (0.000) | (0.000) | (0.000) | (0.377) | (0.431) |
| Beijing x direct subsidiary | | | | | | -2.170 | | -2.184 |
| | | | | | | (0.000) | | (0.000) |
| Beijing x state ownership | | | | | | | 1.056 | 1.089 |
| | | | | | | | (0.013) | (0.014) |
| Tech sector dummies | YES | YES | YES | YES | YES | YES | YES | YES |
| Tech standards | YES | YES | YES | YES | YES | YES | YES | YES |
| Product categories | YES | YES | YES | YES | YES | YES | YES | YES |
| Highest education levels | YES | YES | YES | YES | YES | YES | YES | YES |
| Constant | -5.039 | -5.512 | -5.247 | -4.909 | -5.442 | -6.094 | -5.219 | -5.881 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Number of observations | 5015 | 5015 | 5015 | 5015 | 5015 | 5015 | 5015 | 5015 |
| Log likelihood (ll) | -645.751 | -631.428 | -642.592 | -637.651 | -621.940 | -607.247 | -618.735 | -603.978 |
| Comparisons | n/a | 1 vs. 2 | 1 vs. 3 | 1 vs. 4 | 1 vs. 5 | 5 vs. 6 | 5 vs. 7 | 5 vs. 8 |
| Change in ll | n/a | -14.323 | -3.159 | -8.1 | -23.811 | -14.693 | -3.205 | -17.962 |
| LR chi2 (d.f. for LR test) | n/a | 28.646(1) | 6.318(1) | 16.2(1) | 47.622(3) | 29.386(1) | 6.41(1) | 35.924(2) |
| Prob > chi2 | n/a | .0000 | .0120 | .0001 | .0000 | .0000 | .0113 | .0000 |

## Appendix VII
## Table A4. Geographic distance and irregular awards, Beijing firms only

This table looks at Beijing firms only to investigate how geographic distance between a firm and the state funding agency may affect the occurrence of irregular awards. The key explanatory variable in Models 2-6 is the absolute value of geographic distance between a firm and the funding agency, as measured in 10 kilometres. The key explanatory variable in Models 7-11 is the estimated one-way travel time in hour by car from a focal firm to the funding agency based on data from AutoNavi Maps, i.e. Gaode Maps – the leading Chinese web mapping, navigation and location-based service provider headquartered in Beijing. *P*-values based on robust standard errors are reported in parentheses. One thing to keep in mind is that the correlation between the two distance measures is extremely high (i.e. 0.94).

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Controls only | Key variable measurement: Distance in 10 kilometers | | | | | Key variable measurement: Distance in travel time (unit: hour) | | | | |
| Firm age | 0.043 | 0.038 | 0.026 | 0.040 | 0.022 | 0.012 | 0.039 | 0.026 | 0.040 | 0.022 | 0.012 |
| | (0.090) | (0.148) | (0.245) | (0.130) | (0.438) | (0.667) | (0.152) | (0.256) | (0.132) | (0.440) | (0.660) |
| Owner size | -0.010 | -0.007 | -0.011 | -0.014 | -0.014 | -0.027 | -0.007 | -0.011 | -0.014 | -0.013 | -0.026 |
| | (0.585) | (0.667) | (0.495) | (0.315) | (0.425) | (0.108) | (0.692) | (0.535) | (0.342) | (0.454) | (0.139) |
| With org. | 0.966 | 0.949 | 0.967 | 0.956 | 0.564 | 0.589 | 0.934 | 0.950 | 0.943 | 0.550 | 0.576 |
| owner | (0.004) | (0.006) | (0.006) | (0.005) | (0.101) | (0.101) | (0.007) | (0.007) | (0.006) | (0.124) | (0.119) |
| With foreign | 0.369 | 0.444 | 0.491 | 0.392 | 0.556 | 0.572 | 0.446 | 0.499 | 0.391 | 0.557 | 0.571 |
| owner | (0.446) | (0.357) | (0.327) | (0.400) | (0.297) | (0.302) | (0.360) | (0.326) | (0.402) | (0.301) | (0.307) |
| Registered | 0.164 | 0.180 | 0.187 | 0.173 | 0.146 | 0.148 | 0.180 | 0.187 | 0.173 | 0.145 | 0.148 |
| capital, logged | (0.069) | (0.049) | (0.037) | (0.057) | (0.127) | (0.104) | (0.042) | (0.031) | (0.052) | (0.109) | (0.090) |
| Employees, | -0.241 | -0.222 | -0.189 | -0.236 | -0.173 | -0.143 | -0.226 | -0.193 | -0.241 | -0.180 | -0.149 |
| logged | (0.203) | (0.280) | (0.357) | (0.251) | (0.396) | (0.480) | (0.255) | (0.332) | (0.225) | (0.359) | (0.444) |
| Returnee | -0.221 | -0.222 | -0.335 | -0.235 | -0.234 | -0.391 | -0.189 | -0.298 | -0.205 | -0.200 | -0.357 |
| enterprise | (0.610) | (0.590) | (0.430) | (0.549) | (0.547) | (0.293) | (0.645) | (0.481) | (0.598) | (0.605) | (0.336) |
| Ind. parks/ | -0.141 | -0.159 | -0.119 | -0.594 | -0.116 | -0.535 | -0.163 | -0.124 | -0.590 | -0.119 | -0.526 |
| incubators | (0.751) | (0.732) | (0.788) | (0.001) | (0.808) | (0.004) | (0.722) | (0.775) | (0.001) | (0.800) | (0.003) |
| Innovation | 0.032 | 0.036 | 0.084 | -0.027 | 0.151 | 0.139 | 0.021 | 0.068 | -0.039 | 0.134 | 0.124 |
| track | (0.956) | (0.951) | (0.877) | (0.965) | (0.798) | (0.813) | (0.972) | (0.900) | (0.949) | (0.820) | (0.832) |
| Total apps, | 0.240 | 0.214 | 0.223 | 0.280 | 0.216 | 0.288 | 0.215 | 0.222 | 0.281 | 0.219 | 0.290 |
| firm level | (0.325) | (0.406) | (0.376) | (0.333) | (0.444) | (0.351) | (0.399) | (0.373) | (0.326) | (0.431) | (0.342) |
| Proposed grant | 0.010 | 0.009 | 0.010 | 0.011 | 0.008 | 0.009 | 0.010 | 0.010 | 0.011 | 0.008 | 0.009 |
| size | (0.215) | (0.252) | (0.221) | (0.235) | (0.362) | (0.331) | (0.232) | (0.199) | (0.219) | (0.331) | (0.303) |
| Budget, fund | -0.001 | -0.001 | -0.002 | -0.001 | -0.001 | -0.002 | -0.001 | -0.002 | -0.001 | -0.001 | -0.002 |
| level | (0.288) | (0.285) | (0.000) | (0.368) | (0.193) | (0.000) | (0.287) | (0.000) | (0.369) | (0.195) | (0.000) |
| #applications, | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| fund level | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Distance to X- | | -0.296 | -0.326 | -0.282 | -0.315 | -0.335 | -0.894 | -1.022 | -0.817 | -0.928 | -0.984 |
| center | | (0.059) | (0.047) | (0.103) | (0.050) | (0.066) | (0.029) | (0.015) | (0.073) | (0.026) | (0.038) |
| Indigenous | | | 1.932 | | | 1.914 | | 1.945 | | | 1.926 |
| innovation era | | | (0.000) | | | (0.000) | | (0.000) | | | (0.000) |
| Direct MOST | | | | -0.688 | | -0.734 | | | -0.677 | | -0.714 |
| subsidiary | | | | (0.181) | | (0.162) | | | (0.185) | | (0.170) |
| With state | | | | | 1.157 | 1.144 | | | | 1.152 | 1.141 |
| ownership | | | | | (0.000) | (0.000) | | | | (0.001) | (0.001) |
| Tech sectors | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Tech standards | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Prod | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| categories | | | | | | | | | | | |
| Highest edu. | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Constant | -7.971 | -7.558 | -7.229 | -7.222 | -7.413 | -6.646 | -7.447 | -7.084 | -7.144 | -7.312 | -6.546 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| N | 2650 | 2650 | 2650 | 2650 | 2650 | 2650 | 2650 | 2650 | 2650 | 2650 | 2650 |
| Log likelihood(ll) | -423.137 | -420.084 | -405.528 | -416.737 | -410.629 | -393.271 | -420.354 | -405.582 | -417.133 | -411.004 | -393.584 |
| Comparisons | n/a | 1 vs. 2 | 2 vs. 3 | 2 vs. 4 | 2 vs. 5 | 1 vs. 6 | 1 vs. 7 | 7 vs. 8 | 7 vs. 9 | 7 vs. 10 | 1 vs. 11 |
| Change in ll | n/a | -3.053 | -14.556 | -3.347 | -9.455 | -29.866 | -2.783 | -14.772 | -3.221 | -9.35 | -29.553 |
| LR chi2 (d.f.) | n/a | 6.106 (1) | 29.112(1) | 6.694(1) | 18.91(1) | 59.732(4) | 5.566(1) | 29.544(1) | 6.442(1) | 18.7(1) | 59.106(4) |
| Prob > chi2 | n/a | .0135 | .0000 | .0097 | .0000 | .0000 | .0183 | .0000 | .0111 | .0000 | .0000 |

# Appendix VIII
## Table A5. Evaluation scores and antecedents of irregular awards

All analyses are logit models and the outcome variable is a dummy indicating whether a grant applicant received X-fund grant without evaluation scores on record. All analyses have tech sector dummies, tech standard dummies, product category dummies, and a founder's highest education level dummies in controls. Evaluation scores are the factual ones for regular firms and estimated ones for the irregular winners. We use subscores and other firm-level observables such as location, applied grant size and tech sectors to estimate the possible value for the missing evaluation scores. *P*-values based on robust standard errors are reported in parentheses.

| | 1<br>Controls only | 2<br>Adding Beijing | 3<br>Adding indigenous innovation | 4<br>Adding venue of application | 5<br>Adding state ownership | 6<br>Controls + key singleton variables | 7<br>Adding Beijing x indigenous innovation | 8<br>Adding Beijing x venue of application | 9<br>Adding Beijing x state ownership | 10<br>Adding all three interactions |
|---|---|---|---|---|---|---|---|---|---|---|
| Evaluation score | -0.059 | -0.061 | -0.063 | -0.059 | -0.058 | -0.065 | -0.065 | -0.065 | -0.066 | -0.066 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Firm age | 0.037 | 0.032 | 0.026 | 0.035 | 0.029 | 0.010 | 0.009 | 0.009 | 0.007 | 0.007 |
| | (0.036) | (0.093) | (0.183) | (0.055) | (0.117) | (0.648) | (0.663) | (0.685) | (0.734) | (0.773) |
| Owner size | -0.000 | -0.001 | -0.004 | 0.003 | -0.004 | -0.012 | -0.012 | -0.022 | -0.013 | -0.022 |
| | (0.990) | (0.954) | (0.856) | (0.901) | (0.843) | (0.625) | (0.631) | (0.400) | (0.617) | (0.399) |
| With org. owner | 0.685 | 0.613 | 0.703 | 0.681 | 0.348 | 0.271 | 0.274 | 0.295 | 0.302 | 0.328 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.086) | (0.188) | (0.184) | (0.148) | (0.145) | (0.112) |
| With foreign owner | 0.056 | 0.196 | 0.061 | 0.099 | 0.181 | 0.345 | 0.354 | 0.311 | 0.355 | 0.333 |
| | (0.855) | (0.521) | (0.851) | (0.747) | (0.568) | (0.329) | (0.316) | (0.380) | (0.334) | (0.362) |
| Registered capital, | 0.103 | 0.087 | 0.111 | 0.110 | 0.078 | 0.076 | 0.071 | 0.087 | 0.067 | 0.074 |
| logged | (0.173) | (0.229) | (0.160) | (0.139) | (0.311) | (0.322) | (0.353) | (0.264) | (0.387) | (0.343) |
| Employees, logged | -0.212 | -0.090 | -0.192 | -0.181 | -0.178 | 0.002 | 0.009 | -0.012 | -0.006 | -0.013 |
| | (0.083) | (0.476) | (0.125) | (0.137) | (0.150) | (0.986) | (0.944) | (0.929) | (0.964) | (0.925) |
| Returnee | -0.601 | -0.338 | -0.855 | -0.494 | -0.665 | -0.588 | -0.593 | -0.570 | -0.572 | -0.548 |
| enterprise | (0.061) | (0.297) | (0.011) | (0.121) | (0.041) | (0.092) | (0.090) | (0.100) | (0.110) | (0.124) |
| Ind. | 0.537 | 0.082 | 0.578 | 0.883 | 0.603 | 0.233 | 0.230 | -0.467 | 0.260 | -0.450 |
| parks/incubators | (0.009) | (0.700) | (0.006) | (0.000) | (0.004) | (0.442) | (0.447) | (0.100) | (0.396) | (0.118) |
| Innovation track | -0.067 | -0.146 | 0.000 | -0.016 | -0.016 | -0.028 | -0.023 | -0.072 | -0.007 | -0.042 |
| | (0.829) | (0.643) | (0.999) | (0.958) | (0.957) | (0.932) | (0.943) | (0.822) | (0.983) | (0.896) |
| Total apps, firm | 0.311 | 0.315 | 0.287 | 0.279 | 0.307 | 0.266 | 0.270 | 0.306 | 0.261 | 0.303 |
| level | (0.026) | (0.026) | (0.051) | (0.049) | (0.032) | (0.087) | (0.085) | (0.050) | (0.099) | (0.055) |
| Proposed grant size | 0.023 | 0.022 | 0.024 | 0.021 | 0.023 | 0.021 | 0.021 | 0.019 | 0.021 | 0.019 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Budget, fund level | -0.001 | -0.001 | -0.002 | -0.001 | -0.001 | -0.002 | -0.002 | -0.002 | -0.003 | -0.002 |
| | (0.001) | (0.001) | (0.000) | (0.001) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| #applications, fund | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| level | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Beijing | | 1.129 | | | | 1.268 | 13.739 | 2.574 | 1.023 | 15.793 |
| | | (0.000) | | | | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Indigenous | | | 2.613 | | | 2.746 | 15.016 | 2.636 | 2.753 | 15.934 |
| innovation era | | | (0.000) | | | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Direct MOST | | | | 0.641 | | 0.212 | 0.199 | 1.278 | 0.215 | 1.247 |
| subsidiary | | | | (0.001) | | (0.354) | (0.384) | (0.000) | (0.348) | (0.000) |
| With state | | | | | 0.850 | 0.891 | 0.905 | 0.926 | 0.213 | 0.242 |
| ownership | | | | | (0.000) | (0.000) | (0.000) | (0.000) | (0.578) | (0.551) |
| Beijingx indigenous | | | | | | | -12.516 | | | -13.513 |
| innovation | | | | | | | (0.000) | | | (0.000) |
| Beijing x direct | | | | | | | | -2.054 | | -2.042 |
| subsidiary | | | | | | | | (0.000) | | (0.000) |
| Beijing x state | | | | | | | | | 0.996 | 0.987 |
| ownership | | | | | | | | | (0.021) | (0.026) |
| Tech sectors | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Tech standards | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Product categories | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Highest education | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Tech sectors | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Constant | -4.110 | -4.662 | -3.736 | -4.358 | -4.054 | -4.346 | -16.561 | -4.895 | -4.079 | -17.875 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| N | 6903 | 6903 | 6903 | 6903 | 6903 | 6903 | 6903 | 6903 | 6903 | 6903 |
| ll | -714.143 | -698.633 | -676.584 | -708.457 | -706.704 | -648.689 | -646.493 | -635.426 | -645.820 | -630.691 |
| Comparisons | n/a | 1 vs. 2 | 1 vs. 3 | 1 vs. 4 | 1 vs. 5 | 1 vs. 6 | 6 vs. 7 | 6 vs. 8 | 6 vs. 9 | 6 vs. 10 |
| Change in ll | n/a | -15.51 | -37.559 | -5.686 | -7.439 | -65.454 | -2.196 | -13.263 | -2.869 | -17.998 |
| LR Chi2 (d.f.) | n/a | 31.02(1) | 75.118(1) | 11.372(1) | 14.878(1) | 130.91(4) | 4.392(1) | 26.526(1) | 5.738(1) | 35.996(3) |
| Prob > chi2 | n/a | .0000 | .0000 | .0007 | .0001 | .0000 | .0361 | .0000 | .0166 | .0000 |

## Appendix IX
### Missing evaluation score estimation and CEM matching

We use a regression approach to estimate irregular winners' missing scores. We first run OLS analysis on regular firms, regressing their final scores on subscores and firm-level observables such as grant application year, geographic location, and technological sector.

According to interviews with X-center officials, the program used an algorithm to weigh the subscores and other factors for final score calculation. We tried multiple times throughout the years requesting the formula but never gained access. As a second-best option, we use a regression approach to make the estimation. Our linear model uses the factual score of the regular firms as the left-hand side variable and includes the following items as the right-hand side variables: (i) tech score, (ii) tech score squared, (iii) financial score (for innovation-track firms), (iv) financial score squared (for innovation-track firms), (v) applied grant size, (vi) region dummies, (vii) application year dummies, and (viii) tech sector dummies.[7] Our model has a very high level of explanatory power. For innovation-track firms that are evaluated for both financials and tech merits, our model achieves an $R^2$ of 0.9171; for earlier-stage, startup-track firms that are only evaluated by technological experts, the $R^2$ is 0.9243. We then combine the OLS coefficients with the value of relevant observables to estimate irregular winners' final scores. The actual-estimated score correlations are 0.9577 and 0.9603 respectively for firms with actual scores in each track, providing high levels of confidence that the estimated scores are proximate to the actual scores.[8]

We then identify a group of regular firms that are similar to the irregular winners using the method of coarsened exact matching (CEM) (Iacus, King and Porro, 2012). The two groups are matched along the following dimensions: (i) final evaluation scores - factual ones for regular firms and estimated ones for irregular winners, (ii) technological sectors, (iii) firm location, (iv) firm age, (v) registered capital, (vi) year of grant application, (vii) track of grant application (innovation vs. startup), and (viii) size of proposed grant. The CEM procedure identifies 73 pairs of firms that are extremely similar to each other across these dimensions (see Figure 3).

**Table A6. Covariate balance for the coarsened exact matching (CEM) subsample**

| Variable | Regular firms (n=73) | Irregular winners (n=73) | Diff. (s.e.) | Pr(\|T\| > \|t\|) | 95% CI, LB | 95% CI, HB |
|---|---|---|---|---|---|---|
| Evaluation scores | 65.200 | 64.807 | 0.393 (0.541) | 0.469 | -.6761633 | 1.461535 |
| Application year | 2008.11 | 2008.11 | 0 (0.257) | 1.000 | -.5073158 | .5073158 |
| Startup track | 0.151 | 0.151 | 0 (0.060) | 1.000 | -.1178505 | .1178505 |
| Beijing | 0.740 | 0.740 | 0 (0.073) | 1.000 | -.1445483 | .1445483 |
| Firm age | 4.315 | 4.274 | 0.041 (0.516) | 0.937 | -.9783913 | 1.060583 |
| Founder's education | 3.219 | 3.425 | -0.205(0.146) | 0.1620 | -.4944351 | .0834762 |
| Registered capital, logged | 5.820 | 5.870 | -0.050 (0.199) | 0.803 | -.442709 | .3433795 |
| Employees, logged | 3.572 | 3.719 | -0.147(0.148) | 0.3247 | -.4397568 | .1465915 |
| Number of owners | 3.342 | 4.096 | -0.753(0.472) | 0.113 | -1.687091 | .1802413 |
| Having org. equity owners | 0.342 | 0.411 | -0.068 (0.081) | 0.3966 | -.2277228 | .0907365 |
| Grant size, proposed | 83.507 | 83.562 | -0.055(3.940) | 0.989 | -7.842032 | 7.732442 |

Asterisks denote significance levels of two tailed test: *$p$<0.10, **$p$<0.05, ***$p$<0.01

[7] Adding additional firm- and entrepreneur-level observables barely improves the actual-estimated score correlation. For instance, adding the number of employees, registered capital, and owner size would only raise the correlation from 0.9577 to 0.9581 for innovation-track firms.

[8] We also estimated the possible final scores for the 48 irregular winners without subscores. We first run OLS analysis regressing the final scores of firms with actual final scores on a long list of firm-level variables and then use the coefficients and firm-level values to estimate the possible final scores. This procedure generates a very low level of actual-estimated score associations for firms with actual final scores (0.3283 for "startup track" firms and 0.2678 for "innovation track" firms). Due to the low accuracy, we exclude these 48 irregular winners from the main analyses.

## Appendix X
## Table A7. Alternative time regime for studying the antecedents of irregular awards

We re-run the analysis on the antecedents of irregular awards with more balanced window as Indigenous Innovation took place in 2007 and our data covered the period of 2005-2010. The panels compare the era of 2005-2006 with the eras of 2007-2008 (Panel A), 2008-2009 (Panel B), and 2009-2010 (Panel C) respectively. While the size of coefficients and the level of statistical significance vary from those in Table 5, the main empirical patterns as predicated by our hypotheses continue to hold. *P*-values based on robust standard errors are reported in parentheses.

| | 1<br>Controls only | 2<br>Adding Beijing | 3<br>Adding indigenous innovation | 4<br>Adding venue of application | 5<br>Adding state ownership | 6<br>Controls + key singleton variables | 7<br>Adding Beijing x indigenous innovation | 8<br>Adding Beijing x venue of application | 9<br>Adding Beijing x state ownership | 10<br>Adding all three interactions |
|---|---|---|---|---|---|---|---|---|---|---|
| All controls | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Panel A: 2005-2006 vs. 2007-2008 (n = 4100) | | | | | | | | | | |
| Beijing | | 0.461 | | | | 0.346 | 14.195 | 1.205 | 0.176 | 14.461 |
| | | (0.071) | | | | (0.227) | (0.000) | (0.002) | (0.565) | (0.000) |
| Indigenous | | | 7.091 | | | 7.307 | 20.850 | 7.505 | 7.353 | 20.706 |
| innovation era | | | (0.000) | | | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Direct MOST | | | | 0.394 | | 0.402 | 0.378 | 0.992 | 0.400 | 0.952 |
| subsidiary | | | | (0.099) | | (0.142) | (0.165) | (0.002) | (0.143) | (0.003) |
| With state | | | | | 0.657 | 0.717 | 0.721 | 0.751 | 0.357 | 0.391 |
| ownership | | | | | (0.038) | (0.027) | (0.026) | (0.023) | (0.425) | (0.403) |
| Beijing x indigenous | | | | | | | -13.986 | | | -13.579 |
| innovation | | | | | | | (0.000) | | | (0.000) |
| Beijing x direct | | | | | | | | -1.339 | | -1.306 |
| subsidiary | | | | | | | | (0.005) | | (0.006) |
| Beijing x state | | | | | | | | | 0.608 | 0.592 |
| ownership | | | | | | | | | (0.252) | (0.271) |
| Constant | -17.206 | -17.811 | 25.080 | -17.396 | -17.088 | 25.794 | 12.285 | 27.109 | 26.225 | 14.384 |
| | (0.000) | (0.000) | (0.001) | (0.000) | (0.000) | (0.001) | (0.115) | (0.001) | (0.001) | (0.072) |
| Log likelihood(ll) | -396.244 | -394.707 | -378.571 | -394.855 | -393.903 | -373.159 | -369.598 | -369.523 | -372.466 | -365.493 |
| Comparisons | n/a | 1 vs. 2 | 1 vs. 3 | 1 vs. 4 | 1 vs. 5 | 1 vs. 6 | 6 vs. 7 | 6 vs. 8 | 6 vs. 9 | 6 vs. 10 |
| Change in ll | n/a | -1.537 | -17.673 | -1.389 | -2.341 | -23.085 | -3.561 | -3.636 | -0.693 | -7.666 |
| LR Chi2 | n/a | 3.074(1) | 35.346(1) | 2.778(1) | 4.682(1) | 46.17(4) | 7.122(1) | 7.272(1) | 1.386(1) | 15.332(3) |
| Prob > chi2 | n/a | .0795 | .0000 | .0955 | 0.0304 | .0000 | .0076 | 0.0070 | .2391 | .0016 |
| Panel B: 2005-2006 vs. 2008-2009 (n = 4627) | | | | | | | | | | |
| Beijing | | 1.662 | | | | 1.734 | 14.909 | 2.453 | 1.610 | 14.589 |
| | | (0.000) | | | | (0.000) | (0.000) | (0.000) | (0.001) | (0.000) |
| Indigenous | | | 1.229 | | | 1.540 | 14.694 | 1.482 | 1.547 | 13.791 |
| innovation era | | | (0.012) | | | (0.002) | (0.000) | (0.003) | (0.002) | (0.000) |
| Direct MOST | | | | 1.191 | | 0.526 | 0.498 | 1.210 | 0.543 | 1.198 |
| subsidiary | | | | (0.001) | | (0.207) | (0.229) | (0.058) | (0.187) | (0.063) |
| With state | | | | | 0.966 | 0.993 | 0.991 | 0.986 | 0.767 | 0.666 |
| ownership | | | | | (0.015) | (0.021) | (0.021) | (0.023) | (0.263) | (0.365) |
| Beijing x indigenous | | | | | | | -13.291 | | | -12.426 |
| innovation | | | | | | | (0.000) | | | (0.000) |
| Beijing x direct | | | | | | | | -1.085 | | -1.066 |
| subsidiary | | | | | | | | (0.166) | | (0.182) |
| Beijing x state | | | | | | | | | 0.295 | 0.404 |
| ownership | | | | | | | | | (0.660) | (0.567) |
| Constant | -10.492 | -11.019 | -9.832 | -10.923 | -10.423 | -10.388 | -23.350 | -10.850 | -10.301 | -22.847 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Log likelihood(ll) | -232.990 | -222.418 | -229.554 | -227.334 | -229.092 | -211.686 | -210.637 | -210.774 | -211.606 | -209.688 |
| Comparisons | n/a | 1 vs. 2 | 1 vs. 3 | 1 vs. 4 | 1 vs. 5 | 1 vs. 6 | 6 vs. 7 | 6 vs. 8 | 6 vs. 9 | 6 vs. 10 |
| Change in ll | n/a | -10.572 | -3.436 | -5.656 | -3.898 | -21.304 | -1.049 | -0.912 | -0.08 | -1.998 |
| LR Chi2 (d.f.) | n/a | 21.144 (1) | 6.872(1) | 11.312(1) | 7.796(1) | 42.608(4) | 2.098(1) | 1.824(1) | 0.16(1) | 3.996(3) |
| Prob > chi2 | n/a | .0000 | .0088 | .0008 | .0052 | .0000 | .1475 | .1769 | .6896 | .2618 |
| Panel C: 2005-2006 vs. 2009-2010 (n = 4691) | | | | | | | | | | |
| Beijing | | 1.987 | | | | 2.110 | 15.018 | 4.230 | 1.740 | 15.916 |
| | | (0.000) | | | | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Indigenous | | | 10.442 | | | 8.731 | 20.879 | 9.411 | 8.777 | 21.181 |
| innovation era | | | (0.055) | | | (0.121) | (0.000) | (0.101) | (0.126) | (0.000) |
| Direct MOST | | | | 0.674 | | -0.175 | -0.184 | 2.185 | -0.181 | 2.114 |
| subsidiary | | | | (0.032) | | (0.636) | (0.616) | (0.002) | (0.621) | (0.002) |
| With state | | | | | 1.132 | 1.264 | 1.260 | 1.290 | -0.219 | -0.274 |
| ownership | | | | | (0.001) | (0.000) | (0.000) | (0.000) | (0.719) | (0.671) |
| Beijing x indigenous | | | | | | | -12.968 | | | -12.120 |
| innovation | | | | | | | (0.000) | | | (0.000) |
| Beijing x direct | | | | | | | | -3.378 | | -3.307 |
| subsidiary | | | | | | | | (0.000) | | (0.000) |
| Beijing x state | | | | | | | | | 1.900 | 1.898 |
| ownership | | | | | | | | | (0.004) | (0.006) |
| Constant | -11.857 | -13.189 | 2.085 | -11.956 | -11.718 | -1.572 | -15.288 | -1.944 | -1.300 | -14.078 |
| | (0.000) | (0.000) | (0.766) | (0.000) | (0.000) | (0.828) | (0.041) | (0.791) | (0.860) | (0.062) |
| Log likelihood(ll) | -348.636 | -328.609 | -346.517 | -346.288 | -342.448 | -319.763 | -318.904 | -307.831 | -316.180 | -304.113 |
| Comparisons | n/a | 1 vs. 2 | 1 vs. 3 | 1 vs. 4 | 1 vs. 5 | 1 vs. 6 | 6 vs. 7 | 6 vs. 8 | 6 vs. 9 | 6 vs. 10 |
| Change in ll | n/a | -20.027 | -2.119 | -2.348 | -6.188 | -28.873 | -0.859 | -11.932 | -3.583 | -15.65 |
| LR Chi2 (d.f.) | n/a | 40.054(1) | 4.238(1) | 4.696(1) | 12.376(1) | 57.746(4) | 1.718(1) | 23.864(1) | 7.166(1) | 31.3(3) |
| Prob > chi2 | n/a | .0000 | .0395 | .0302 | .0004 | .0000 | .1900 | .0000 | .0074 | .0000 |

# Appendix XI.

## Table A8. Additional tests to rule out irregular award winners being high-promise ventures

OLS regressions for models 1-2, 7-8 and logit regressions for models 3-6, 9-12. The first six models look at CEM-matched firms and the next six models look at grant winners. P-values are reported in parentheses. Across both samples, we find no evidence that grant officials were violating policy rules to promote high-promise firms. Instead, model 8 shows that in comparison to regular grant winners, irregular winners were associated with a lower level of international patenting activities. *P* values based on robust standard errors are reported in parentheses.

| | CEM-matched sample | | | | | | Grant winners | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | International patenting | | Exporting | | Having bank credit line | | International patenting | | Exporting | | Having bank credit line | |
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| Irregular awards | | -0.021 | | 1.125 | | -0.260 | | -0.161 | | 0.340 | | 0.039 |
| | | (0.716) | | (0.174) | | (0.724) | | (0.007) | | (0.242) | | (0.862) |
| Beijing | 0.136 | 0.137 | -2.469 | -2.330 | 1.087 | 1.037 | -0.067 | -0.059 | -0.198 | -0.207 | -1.066 | -1.068 |
| | (0.312) | (0.317) | (0.042) | (0.074) | (0.363) | (0.383) | (0.035) | (0.064) | (0.346) | (0.326) | (0.000) | (0.000) |
| Direct MOST | 0.076 | 0.073 | -0.767 | -0.974 | -0.164 | -0.177 | -0.013 | -0.010 | -0.395 | -0.400 | -0.711 | -0.711 |
| | (0.316) | (0.310) | (0.576) | (0.461) | (0.817) | (0.804) | (0.541) | (0.633) | (0.007) | (0.006) | (0.000) | (0.000) |
| State ownership | 0.067 | 0.073 | -3.063 | -3.966 | -1.627 | -1.589 | 0.080 | 0.095 | -0.285 | -0.306 | 0.266 | 0.263 |
| | (0.495) | (0.490) | (0.053) | (0.022) | (0.125) | (0.133) | (0.138) | (0.096) | (0.224) | (0.195) | (0.136) | (0.143) |
| Firm age | -0.005 | -0.005 | 0.013 | -0.001 | 0.249 | 0.248 | -0.002 | -0.002 | 0.060 | 0.060 | 0.091 | 0.091 |
| | (0.498) | (0.490) | (0.919) | (0.993) | (0.033) | (0.037) | (0.302) | (0.346) | (0.000) | (0.000) | (0.000) | (0.000) |
| Owner size | 0.006 | 0.007 | -0.221 | -0.243 | -0.108 | -0.102 | -0.001 | -0.001 | -0.001 | -0.000 | 0.005 | 0.005 |
| | (0.396) | (0.400) | (0.187) | (0.066) | (0.148) | (0.190) | (0.555) | (0.500) | (0.965) | (0.997) | (0.743) | (0.740) |
| With org. owner | -0.054 | -0.055 | 1.084 | 1.708 | -0.779 | -0.746 | -0.009 | -0.007 | -0.078 | -0.076 | -0.441 | -0.441 |
| | (0.441) | (0.442) | (0.184) | (0.118) | (0.283) | (0.280) | (0.708) | (0.759) | (0.619) | (0.629) | (0.000) | (0.000) |
| With foreign | -0.003 | 0.005 | -2.162 | -3.491 | 1.849 | 1.917 | 0.138 | 0.140 | 1.060 | 1.049 | 0.428 | 0.426 |
| | (0.975) | (0.963) | (0.180) | (0.099) | (0.096) | (0.086) | (0.125) | (0.117) | (0.000) | (0.000) | (0.067) | (0.069) |
| Registered | -0.029 | -0.031 | 0.505 | 0.669 | -0.176 | -0.236 | 0.015 | 0.015 | 0.006 | 0.007 | 0.082 | 0.082 |
| | (0.348) | (0.337) | (0.326) | (0.248) | (0.629) | (0.541) | (0.209) | (0.207) | (0.923) | (0.916) | (0.093) | (0.093) |
| Employees, | 0.005 | 0.009 | 0.376 | 0.311 | 0.996 | 1.043 | -0.042 | -0.043 | 0.886 | 0.885 | 1.061 | 1.061 |
| | (0.903) | (0.857) | (0.415) | (0.475) | (0.029) | (0.015) | (0.018) | (0.014) | (0.000) | (0.000) | (0.000) | (0.000) |
| Returnee | 0.135 | 0.131 | -0.057 | 0.195 | 0.793 | 0.757 | 0.284 | 0.280 | 0.529 | 0.526 | 0.268 | 0.268 |
| | (0.203) | (0.238) | (0.973) | (0.888) | (0.370) | (0.400) | (0.000) | (0.000) | (0.058) | (0.060) | (0.203) | (0.203) |
| Ind. | 0.084 | 0.085 | 0.308 | 0.014 | 1.115 | 1.167 | -0.003 | -0.003 | 0.219 | 0.209 | -0.108 | -0.108 |
| | (0.152) | (0.154) | (0.850) | (0.993) | (0.265) | (0.221) | (0.937) | (0.936) | (0.406) | (0.428) | (0.603) | (0.602) |
| Innovation track | -0.151 | -0.149 | -3.179 | -3.402 | -2.523 | -2.561 | -0.067 | -0.084 | 0.484 | 0.530 | 0.346 | 0.350 |
| | (0.162) | (0.160) | (0.163) | (0.090) | (0.093) | (0.088) | (0.213) | (0.137) | (0.114) | (0.083) | (0.085) | (0.086) |
| Total apps, firm | 0.221 | 0.221 | 0.408 | 0.384 | 1.505 | 1.494 | -0.030 | -0.022 | 0.163 | 0.149 | 0.259 | 0.258 |
| | (0.037) | (0.039) | (0.510) | (0.552) | (0.023) | (0.026) | (0.133) | (0.247) | (0.271) | (0.312) | (0.034) | (0.036) |
| Proposed grant | 0.004 | 0.004 | 0.065 | 0.069 | 0.046 | 0.047 | 0.002 | 0.003 | 0.004 | 0.003 | 0.002 | 0.002 |
| | (0.056) | (0.056) | (0.187) | (0.103) | (0.107) | (0.099) | (0.013) | (0.008) | (0.107) | (0.289) | (0.458) | (0.505) |
| Budget | 0.001 | 0.001 | 0.000 | 0.000 | 0.001 | 0.001 | 0.000 | 0.000 | 0.000 | 0.000 | -0.000 | -0.000 |
| | (0.023) | (0.026) | (0.937) | (0.858) | (0.639) | (0.668) | (0.268) | (0.344) | (0.673) | (0.578) | (0.176) | (0.179) |
| #applications | 0.000 | 0.000 | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 | -0.00 | -0.00 | -0.00 | -0.00 |
| | (0.342) | (0.343) | (0.673) | (0.375) | (0.410) | (0.407) | (0.305) | (0.639) | (0.002) | (0.001) | (0.009) | (0.009) |
| Tech sectors | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Tech standards | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Prod categories | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Highest edu. | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Application year | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Constant | -1.047 | -1.049 | -7.433 | -7.233 | -6.381 | -6.027 | -0.029 | -0.073 | -5.95 | -5.86 | -4.50 | -4.49 |
| | (0.029) | (0.030) | (0.323) | (0.280) | (0.203) | (0.252) | (0.748) | (0.458) | (0.000) | (0.000) | (0.000) | (0.000) |
| (R^2)chi2 | (0.375) | (0.376) | 44.525 | 55.891 | 64.130 | 63.389 | (0.077) | (0.080) | 398.695 | 401.491 | 793.274 | 793.213 |
| ll | 0.633 | 0.742 | -31.679 | -30.949 | -43.404 | -43.334 | -2894.64 | -2887.97 | -1006.56 | -1005.85 | -1513.97 | -1513.97 |
| N | 146 | 146 | 129 | 129 | 140 | 140 | 3520 | 3520 | 3520 | 3520 | 3520 | 3520 |