Fraud and Innovation: Is There a Cheater's Discount?

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ABSTRACT

Fraudsters seem to possess many of the traits that are associated with innovators – they disrespect the established ways of doing things; they think outside the box to create their own ways of obtaining what they want; and in the process they embrace the risks of failure and of social sanctions. However, there are also good reasons to expect fraudulent firms to be less innovative than their nonfraudulent peers, as cheating buffers firms from external pressures and thus fosters managerial complacency. In this paper, we develop a theory that links resource acquisition with resource allocation. We argue that resources obtained through fraudulent means are less likely to be allocated to productive activities such as technological innovation. To test our theoretical predictions, we built a longitudinal dataset tracking the patenting behavior of 467 Chinese hi-tech firms applying for state grants promoting technological innovation. Because relying on the public-control agent for fraud identification would introduce selection bias, we use an unconventional approach – comparing two sets of financial books (which are assumed to report the same financial data) from the same firm – to identify fraudulent financial reporting among our sampled firms. We find that fraudster firms receiving state grants are less likely to create new knowledge.
Are fraudulent firms more innovative than their rule-abiding peers? While this question has rarely been examined directly, the management and organization theory literatures seem to suggest an answer of yes. By definition, innovators are individuals or organizations that are not constrained by the established ways of doing things (Schumpeter 1934; Kirzner 1973). When societal norms or the dominant design of technology prevents the achievement of their goals, innovators think outside the box and create their own ways of obtaining what they want (Merton 1938; Drucker 1985). When their new ways are socially accepted, innovators are labeled as entrepreneurs and are applauded for their heroic act of creative destruction (Schumpeter 1934). However, when the new ways are socially proscribed, the innovators who use them are labeled as deviants and run the risk of being punished as criminals (Merton 1938; Sutherland 1939; Podolny and Morton 2008). While the first group is generally perceived to be productive and the second group destructive (Baumol 1990), both bear the risks and uncertainties that face catalytic agents who seize new opportunities, shift the choice set, and increase “the probability that a new project will in fact be implemented” (Knight 1921; Harris 1973; Leff 1979: 47). As a journalist article summarizes, “Actually, creative fraudsters employ many of the same imperatives that any innovative organization should … They are innovative, realize the need for risk, create new products, take ownership of their ideas, seek to create value, and train those around them. It is an interesting – if frightening – parallel” (Brands and Zbar 2010).

There is good reason to hypothesize that fraud and innovation, more than being two sides of the same coin, could have a causal relationship. First, highly creative economic actors may be less rigid in interpreting rules and thus more likely to engage in rule-breaking behaviors (Gino and Ariely 2012). By creatively exploring the edges of institutions, rule-breaking organizations grant themselves a certain moral and regulatory “flexibility” in external dealings. This essentially builds up a cushion between these organizations’ internal operations and external pressures (Pfeffer and Salancik 1978; Oliver 1991), helping them avoid stakeholder-induced myopic behaviors such as R&D cuts (Stern 1989; Bushee 1998), technological switches from experimentation to exploration (Benner and Tushman 2002), or mimetic adoption of “standard” practices (Westphal, Gulati and Shortell 1997). Furthermore, fraud as such may help individuals and organizations gain external endorsements and thus help grease the wheels of their innovation (Leff 1964).
With more leeway in manipulating stakeholders’ perceptions, fraudsters may have better chances of gaining access to resources such as state grants, bank loans or industry credentials (Stuart and Wang 2013). To some extent, fraud is a special type of coping strategy, allowing firms to satisfy evaluation pressures in an institutionalized setting but without paying the cost of real actions (Oliver 1991). From this perspective, fraud – if undetected - is an inexpensive way for organizations to maintain resource exchanges with the environment (Pfeffer and Salancik1978: 113-142), facilitating their pursuit of technological innovation, organizational survival and business growth.

Given such benefits, it is not surprising that many firms have engaged in fraudulent behaviors. One survey of the CFOs of 169 U.S. public companies finds that about 20% of these firms misrepresent their economic performance through grey practices such as earnings management; and for such firms, 10% of earnings per share (EPS) is typically managed (Dichev et al. 2013). Using forensic accounting, Stuart and Wang (2013) find that more than 54.6% of sampled Chinese private technology firms engaged in large-scale book cooking. Similar behaviors are practices across a wide range of fields such as backdating executive stock options (Heron and Lie 2009), price-fixing among oligopolies (Darby and Karni 1973), curtailment of health benefits for retirees (Briscoe and Murphy 2012), and the use of performance enhancing drug among athletes (Palmer and Yenkey 2013), and across a wide range of geopolitical areas such as the U.S. (Staw and Szwajkowski 1995; Yue, Luo and Ingram 2013), Kenya (Yenkey 2013), India (Bertrand, Mehta and Mullainathan 2002), and Sweden (Jonsson, Greve and Greve 2009).

While some fraudsters are caught cheating and get punished, the common understanding is that those cases represent only the tip of the iceberg (Sutherland 1939; Mason and Calvin 1978), and that most transgressors walk away unpunished (Bryant and Eckard 1991).¹ The discrepancy between society’s weak sanction against fraudulent behaviors and its public condemnation of them has contributed to the existence, if not prevalence, of three kinds of cynicism: the private belief that fraudulent behavior is not only pervasive but also pays off (Darby and Karni 1973; Crittenden, Hanna and Peterson 2009); the secret admiration of fraud practitioners who have “mastered the art” and walked away from their doings scot-free (Sutherland 1939); and the widespread suspicion that

¹The authors estimate that the probability of a price-fixing conspiracy to be indicted by federal authorities is at most between 0.13 and 0.17 in a given year!
anyone successful must have their shares of fraudulent dealings (Lamont 1992; Gabor 1994; Kay and Jost 2003; Callahan 2007).

If most fraudsters walk away with their bounties unpunished, a natural question that scholars should ask is, why don’t all firms commit fraud? When cheating firms are better positioned to buffer external pressures, access resources, reduce production cost, and attract customers, non-cheating firms unavoidably put themselves in a disadvantaged position in the market place. As Bhide and Stevenson (1990) asked two decades ago, “Why be honest if honesty doesn’t pay?”

There are many possible explanations. For instance, one could look at firms’ risk orientation and argue that some of them are too risk averse to embrace practices that might invite regulatory scrutiny. One could also look at organizational culture and argue that some firms value ethics as such and are willing to pay a competitiveness cost to maintain their ethical standards.

This paper proposes an alternative explanation for why not all firms cheat. Beyond the inherent risk and the fact that being honest is the right thing to do, we argue there is at least one additional reason for straight dealing- fraudulent behaviors may constrain firms from exploring new investment and technological opportunities that are important for firms’ long-term competitiveness. Drawing on social psychology and organizational theory literatures that distinguish between resource acquisition and resource utilization (Penrose 1959; Pfeffer and Salancik 1978; Thaler 1985), we argue that while fraudulent firms have an advantage in acquiring external resources, the acts of misrepresenting information and image manipulation could have the unintended consequence of directing a firm’s resources and efforts away from productive activities such as technology innovation. As Penrose (1959:25) pointed out long ago, “resources consist of a bundle of potential service.” Firms may have different uses for the same resource because managers perceive different opportunities (or costs) for its investment (or consumption) (Mahoney 1995; Denrell, Fang and Winter 2003). On the cost side, when a firm receives external resources through fraudulent manipulation, these resources are likely to be perceived as “windfalls” rather than earned income; consequentially, consumption of these resources (instead of responsibly investing them in productive activities) is associated with less guilt or concern than would be otherwise (Thaler 1985). On the opportunity side, when fraud buffers firms
from external evaluation pressures, it contributes to the growth of managerial complacency and thus reduces incentives to take the actions that are required for the lengthy yet uncertain process of exploring new opportunities (Van de Ven 1986). While resource-grabbing through manipulative behaviors and capability-building through real efforts do not have to be mutually exclusive, as long as the above mechanisms operate, we should observe behavioral differences in technological efforts between fraudulent and nonfraudulent firms.

Using a dataset of 467 Chinese private technology firms where we can observe firms’ financial manipulation directly, we test how fraudulent firms and nonfraudulent firms behave differently in technological innovation, particularly when these firms receive grants from a public financing program. We find three robust statistical results in our analyses. First, fraudulent and nonfraudulent firms systematically differ from each other in their initial technological endowment, suggesting that they may be generally different in their orientation towards technological innovation; Second, controlling for firms’ initial technological capability, capital infusion from a public financing program increases post-grant patenting; Third, cheating and non-cheating firms diverge in their post-grant innovation trajectory, but only among the grantee firms, suggesting that cheating firms and non-cheating firms use their newly acquired external resources differently.

The rest of the paper proceeds as follows. Section II reviews the literature on fraud and innovation to develop our theoretical argument; Section III describes the empirical setting, data and research design; Section VI presents the empirical results and their robustness checks; and Section V discusses the paper’s limitations, contributions and potential for improvement.

**Theoretical Development**

To survive and grow, firms need at least two types of resources – a constant flow of commodity-like resources, such as capital and physical assets, from the environment (Pfeffer and Salancik 2003), and development of firm-specific resources that cannot be easily obtained from the strategic factor market (Wernerfelt 1984; Barney 1986). While an undisrupted flow of commodity resources is crucial for firm survival, especially for young firms (Levinthal 1991; Thornhill and Amit 2003), the sustainability of a firm’s competitive
advantage depends on its development and accumulation of internal, not easily replicated capabilities (Penrose 1959. Amit and Schoemaker (1993) have made an explicit distinction between resources and capabilities: resources are tradable and non-specific to the firm, while capabilities are firm-specific and are used to engage resources within the firm. Makadok (2001) further emphasizes that capabilities are “a specific type of resource, specifically an organizationally embedded non-transferable firm-specific resource whose purpose is to improve the productivity of the other resources possessed by the firm” (389).

While general resources such as financial capital are perceived to be both tradable across organizations and fungible within organizations, the way these resources are acquired may well influence how they are expended and the extent to which they will be transformed into complex and firm-specific capabilities such as innovation. This line of argument, although not explicitly elaborated at the organizational level, has a long tradition in the cognitive psychology literature. In their classic study of human decision-making, Kahneman and Tversky (1979) argued that the way economic agents subjectively frame an outcome or transaction in their mind affects the utility that they expect or receive. Rather than treating assets from different sources indifferently, there is a strong endowment effect in people’s behavior – they place a higher value on a good that they own than on an identical good that they do not own (Kahneman, Knetsch and Thaler 1990). In his study of individual and household consumption behavior, Thaler (1980, 1985) further shows that, in contrast to the standard consumption model where the consumption decision is conceptualized as one single optimization problem, people compartmentalize their income into different mental accounts and decide on their consumption within each of these accounts. This creates a direct link between spending behavior and the source of income. As the psychological pain associated with spending hard-earned money is much higher than spending “windfall” incomes (Kahneman and Tversky 1979), it is not surprising that empirical works find that individuals and households have a higher marginal propensity to consume unearned income and a higher marginal propensity to save/invest earned income, with the marginal propensity of consumption of the former three times larger than that of the latter (Christiaensen and Pan 2010: 3; Tonin and Vlassopoulos 2013).

The folk wisdom that income that is easily earned is also easily spent applies not only to individuals and households, but also to firms and other organizations (Fiegenbaum and
Thomas 1988). Since accessing resources through cheating requires a minimal amount of real action on the organization’s part, such ill-gotten gains can be considered a special type of unearned income, and thus more likely to be used for consumption rather than for investment. While there is no direct evidence, studies have documented links between corruption and extravagant consumption (Pacepa 1990; Di Tella and Weinschelbaum 2008; Gokcekus and Suzuki 2013), between windfall incomes and increased managerial compensation (Blanchard, Lopez-de-Silanes and Shleifer 1994), and between natural resource endowment and national level of corruption (Leite and Weidmann 1999). This suggests potential links between windfall incomes and unproductive activities at the firm, and even the national, level.

Along with the minimal mental pain associated with the disposal of a windfall, firms may also have little incentive to allocate income acquired by cheating for productive uses because cheating fosters managerial complacency and prolongs organizational inertia. Organizations that use cheating to improve their images are essentially trying to gain access to external resources without taking the real actions that are ordinarily required to receive the desired endorsement (Oliver 1991). While these manipulations help cheating organizations increase the likelihood of grabbing resources (Stuart and Wang 2013), they also deprive the organizations of the opportunity to act on external pressures to explore new opportunities through technological innovation and other experimentation (Miller and Chen 1994).

A theory of the growth of firms, according to Edith Penrose (1995:31-32), is “essentially an examination of the changing productive opportunity of firms; in order to find a limit to growth, or a restriction on the rate of growth, the productive opportunity of a firm must be shown to be limited in any period.” Managerial complacency is a contributing factor to this productive opportunity limitation. Although Penrose does not use the term, the applicability is unambiguous, “It is clear that this opportunity will be restricted to the extent to which a firm does not see opportunities for expansion, is unwilling to act upon them, or is unable to respond to them” (32).

Firms are often not eager or willing to find or act upon new opportunities (Hannan and Freeman 1984; Dobrev, Kim and Carroll 2003). Instead, they tend to stick to their old ways of doing things, avoiding the uncertainty and effort involved in change unless there are
strong external stimuli compelling them to change (Van de Ven 1986). It’s generally believed that crises, dissatisfaction, tension and significant external stress are the major preconditions for stimulating people to act (March and Simon 1958). By relaxing their moral standards, fraudster firms manipulate their images in the eyes of key stakeholders and thus build a buffer zone between themselves and the external pressure (Oliver 1991). To put it another way, when organizations cheat in order to build better images, they are delaying their own exposure to external stimuli, unconsciously building up managerial complacency and constraining themselves from exploring new business opportunities. Over time, these firms’ situation may become contemptible. As Van de Ven (1986: 595) argues, “Opportunities for innovative ideas are not recognized, problems swell into megaproblems, and at the extreme, catastrophes are sometimes necessary to reach the action threshold”.

Fraudulent behaviors may contribute most to managerial complacency when they are successful. While firms that fail to receive endorsements and resources despite cheating may re-examine themselves and raise doubts about cheating as a feasible strategy, successful cheaters may develop a belief that cheating is not only feasible but may serve as a cheaper alternative to real solutions (Sutherland 1983: 25). Even economic actors that simultaneously engage in cheating and real problem-solving (Pierce, Snow and McAfee 2013) may not be able to identify the real source of their success, and thus be tempted to use cheating as part of their “solutions” when new problems arise.

When they perceive manipulation as a substitute for real solutions, organizations unavoidably shy away from the hard work of diagnosing problems, researching solutions, implementing decisions, and adjusting action. This work is necessary in accumulating and managing the tacit knowledge required for innovation (Westphal, Gulati and Shortell 1997). Rather than embracing the uncertainty of technical innovation, organizations that cheat may choose to reverse engineer their rivals’ products, to use strategically hire outside R&D personnel, or even use bold, old-fashioned intellectual theft. Though it is not

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2 In contrast, when fraudulent firms are better positioned to access resources controlled by key stakeholders, firms that refuse to engage in cheating behaviors unavoidably put themselves in the position of facing a higher level of evaluation. Stripped of cheating and easy access to external resources, these firms have to make real efforts and deliver real outcomes to satisfy evaluation criteria. This pressure gives the non-fraudulent firms a higher level of alertness, forcing them to undertake initiatives through resource exploration and experimentation with new capabilities (Thompson 1967; George 2005).
directly about fraud, the logic underlying Luo’s (2004: 141-142) analysis of corruption could well apply here, “A firm relying on bribery generally perceives corrupt acts as a substitute for innovative technological and organizational skills. It may expect bribery to be a quicker, and perhaps more effective, strategic instrument by which it may accomplish its organizational goals, rather than focusing on building and upgrading its dynamic capability. When top managers attach high value to corrupt act, firms may experience greater organizational inertia and less commitment to the development of new organizational capabilities”.

Summarizing the arguments above gives us the following hypotheses:

H1: Fraudulent firms are associated with a lower level of innovation.

H2: The relationship between fraud and innovation is particularly salient among firms receiving infusions of external resources.

**Research Design and Empirical Setting**

Even though financial fraud and technological innovation have each drawn enormous attention from scholars, managers, and policy makers, these two issues have rarely been examined together. To a great extent, this omission is due to the dual challenges of fraud identification and the causal complications that fraud identification imposes on innovation. When fraudulent behaviors are normatively prohibited and legally publishable, firms committing them will try their best to conceal these actions; thus detected fraudsters may systematically differ from undetached fraudsters (Hagan and Parker 1985; Engel and Hines 1998), and studying only detected fraudsters would introduce selection bias. As Greve, Palmer and Pozner (2010: 94) have pointed out, “A frequent dilemma in research on misconduct is that data become available when a social-control agent detects misconduct and decides to act against it.” This makes it hard to interpret empirical findings that correlate honesty with innovation, because we do not know the extent to which they reflect the scenario that honest firms are more innovative or the alternative scenario that the innovative ones among fraudster firms are less likely to be investigated and/or caught by the social-control agent. To address these challenges, our field calls for new methodologies that can unbiasedly identify fraudulent behaviors.

Even if conventional methods could identify fraud without bias, they still would not allow us to test whether fraud facilitates or hinders innovation, since fraud investigation by
a public-control agent, once it becomes public, unavoidably disrupts the suspect firm’s resource exchanges and R&D activities. On one hand, key stakeholders fear the potential spillover of a scandalous affiliation and start to withhold, if not to withdraw, their resource endorsements (Jensen 2006; Kang 2008); on the other hand, the suspect firm must divert its managerial attentions and organizational resources from productive activities such as innovation towards preparing litigation and managing public relations. Under such circumstances, an observed divergence in innovation trajectories between fraudulent firms and their nonfraudulent peers could be caused by fraud, by the act of fraud identification, or by both.

In this paper, we use a hand-collected dataset of 467 Chinese hi-tech firms to examine how fraudulent and nonfraudulent firms may diverge in their innovation trajectories when they receive external financial resources that are meant to promote technological innovation. Several unique features in our research design allow us to directly address the empirical challenges listed above to test if a causal relationship exists between fraud and innovation. First, rather than relying on the public-control agent’s investigations, we observe fraudulent behaviors directly by comparing two sets of financial books filed by the same set of firms. Although these two sets of books are required by Chinese law to report the same financials, in our setting, firms have incentives to over-report their financial performances in one set but under-report their performances in the other. This allows us to use the discrepancies to identify beyond reasonable doubt whether a firm is cooking its financial data. As our method is independent of the often selective acts of the public-control agent, our empirical results are less subject to the selection bias suffered by most studies in the literature; furthermore, our method does not interrupt firms’ internal operations or external dealings and thus allows us to identify the relationship between fraud and innovation without the complication of the negative effects of fraud identification on innovation.

Second, all the firms in our sample applied for the Innovation Fund (Innofund), a Chinese state grant modeled after the U.S. Small Business Innovation Research (SBIR) program. Among firms in our dataset that won the Innofund grant, some cooked their financial books while the others reported financials honestly. Using the innovation trajectories of the non-grantee firms as a benchmark, the variation among the grantees
provides an opportunity to examine whether the way resources are acquired is linked with the way they are utilized. Furthermore, our sample data includes the evaluation scores used by Innofund in determining grant allocation. Combining this information with longitudinal data on firm-level patenting, we can use a quasi-experimental pre-test/post-test design to identify how cheating and non-cheating firms diverge in their post-test innovation trajectories. As each firm in our sample was evaluated by a panel of technical and financial experts rather than by Innofund officials, we can assume that firms lying closely on either side of the cutoff score are very similar to each other. This enables us to use regression discontinuity (RD) to identify how one intervention – a resource infusion from the state – may have different causal effects on innovation across cheating and non-cheating firms.

We choose to study Innofund because it is China's most important grant program for promoting technological innovation and commercialization in early-stage ventures. Modeled after the U.S. Small Business Innovation Research (SBIR) program, Innofund was created in 1999 by the Ministry of Science and Technology (MOST). While its initial budget was modest (about 0.5 billion yuan annually), Innofund has received increasing support from the central government. Its annual budget reached 4.8 billion yuan in 2012. Generally, grantees are awarded between 0.5 and 1 million yuan from MOST, with a guaranteed match of 50% to 100% from local government. For early-stage Chinese companies, a grant of this magnitude is substantial, especially since it does not dilute equity.

Further, a particular institutional feature makes Innofund applicants good candidates for the study of fraud and innovation. Innofund requires all firms to submit detailed financial statements in their grant applications; each firm is also independently required to submit a set of financial statements to its local State Administration of Industry and Commerce (SAIC). For each firm in the sample, we were able to obtain the financials submitted to each agency for the same time period. Chinese law unambiguously states that

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3 See http://www.innofund.gov.cn/english/02_fund_nature.htm
4 The SAIC is the primary state agency responsible for regulating domestic day-to-day commercial activities. According to China’s Corporate Law, all commercial entities in the country must register with the SAIC at the time of establishment and must submit annual inspection documents to maintain their legal status (Company Law 2006; SAIC 2006). These documents include detailed financial statements that must be approved by registered accounting firms. We purchased the SAIC data for the central province and one region of the coastal province through a credit rating firm with a national partnership network with law firms and local SAICs. We purchased the SAIC data for the rest of the coastal province from a local law firm. In spring 2012, the Chinese central government started to tighten up data control, asking local SAICs to reveal firm-level financials only with court orders. The implementation of this policy, however, has varied across regions.
these financial statements should be compiled according to the same accounting rules, leaving no legitimate reason for discrepancies. However, the firms in our sample have clear incentives to overreport income to MOST and underreport to SAIC, and so we can use the presence of discrepancies to measure fraud. We will discuss these points in more detail in the section on fraud identification.

All of the firms in our sample are from five Chinese regions, two major cities in a central province in 2005-2007 and another three major cities in a coastal province in 2007-2010. We exclude the following firms for practical reasons: 1) firms that are located in small cities, towns or villages, as the networks of our data providers were mainly concentrated in municipal cities rather than in counties or towns where the logistical cost of collecting the SAIC data tends to be prohibitively high; 2) firms that are younger than two years, as most of these firms have yet to report substantively meaningful financial data due to lack of revenue and to have established a patenting record that would allow us to control for their initial technological capability; and 3) firms that report directly to the province-level SAIC rather than municipal-level SAIC, as the barriers to purchasing data from the province-level SAIC is much higher.

Key Variables and Measurements

Innovation

We measure a firm’s innovation by counting its patent applications. While scholars have used patent to measure technological change (Jaffe et al. 1993), one concern is that the quality of individual patents varies widely: some inventions are extremely valuable, whereas others are of almost no commercial value. In the U.S. setting, using patent citation figures circumvents this problem; unfortunately, the Chinese patent system does not require firms to cite prior works that are related to their patents.

While we cannot use patent citation to measure a patent’s importance, one unique feature in the Chinese patenting system helps differentiate quality across patents. Patents are filed under three categories in China – invention, new utility and new design– in decreasing order of innovativeness and commercial value. The relative importance of an invention patent is reflected in the patent review system of China’s State Intellectual

5 According to China’s Patent Law, invention patents apply to new technological solutions relating to products, processes or their improvements, while design patents protect ornamental designs and utility patents protect any new technical solution relating to the shape, structure or both of a product which is fit for practical use. http://english.sipo.gov.cn/laws/lawsregulations/201101/t20110119_566244.html. Accessed on August 31st, 2013.
Property Office (SIPO), which imposes differential application fees, requirements for public notification, lengths of examination, and patent terms according to category. In evaluating applicants’ technological capability, Innofund’s rule of thumb is that one invention patent counts for six new utility patents. New design patents are generally dismissed. This clear hierarchy allows us to go beyond patent counts to differentiate between patents with potentially important commercial value and technological merit from those with marginal economic and technological merits.

As we study the different effects that a resource infusion from Innofund may have on fraudster and non-fraudster firms, our dependent variable is the number of invention patents that a firm applies for in each post-Innofund period. Given the time lag between grant application ($T_0$) and grant allocation -usually at the end of $T_0$ or in early $T_1$, and between R&D activities and patent filing, we further narrow the period investigated to $T_3$ (i.e. the third year since grant application) and later. We base this decision both on our knowledge that the Innofund grant is allocated either at the end of the grant application year ($T_0$) or in the early half of the first post-application year ($T_1$) and on the assumption that it takes at least two years for a firm to go from resource infusion through invention and project completion before filing for a patent. Even though the two-year assumption is a bit arbitrary, we feel that this period could be the upper bound between resource infusion and R&D project completion, as most of the firms in our sample are early-stage tech ventures that are racing to develop and commercialize technologies for survival. We winsorize our patent counts at 10 to reduce the skewedness of data dispersion.

We use patent applications rather than patents granted as the outcome variable for practical reasons. While it usually takes less than one year for the State Intellectual Property Office to decide whether to grant new utility and new design patents, it takes

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6 An invention patent must be publicized online for 18 months before an SIPO examination, while the other two patents are subject to no such requirement. Further, it may take up to three years before SIPO makes a final decision to grant or reject an invention patent (versus 18 months for a new utility). The final, but no less important, cost premium on an invention patent is that it is much more expensive to apply for (a 900 yuan application fee plus a 2,500 yuan examination fee versus the 900 yuan application fee only for the other kinds of patent). The institutional benefit for these costs is that an invention patent is in force twice as long as the other two kinds of patent - 20 years, rather than 10.

7 This is based on the second author’s interview conducted at the Innofund Fund on June 23rd, 2013.

8 As robustness check, we relax the assumption to include either all post-$T_1$ firm-years or all post-$T_3$ firm-years. Even though the estimated magnitude changes across models, the basic story of the relation between fraud and innovation does not change. Results are available upon request.

9 Even though all firms in our sample are applying for an Innofund grant to support high-tech innovation and commercialization, the sample has a high proportion of firms that do not file any invention patents. Instead, they file for new utility or new design patents that are of little technological/commercial merits but serve the purpose of help maintain their images of being hi-tech in eyes of key stakeholders.
much longer – usually up to three years – to decide the outcome of an invention patent application. As a result, a large proportion of the invention patents filed by our sample firms in their post-Innofund period were still under review as of June 2013. Using patents granted as the outcome variable would unavoidably discount the contribution of invention to our analyses.

Financial Fraud

Our key explanatory variable is whether a firm filed fraudulent financial statements. Rather than relying on the often selective actions of a public control agent in investigating and identifying fraud, we observe fraudulent practices directly by comparing the statements that our sampled firms submit to two different state agencies—the Ministry of Science and Technology (MOST) and the local State Administration of Industry and Commerce (SAIC).

Several unique features of the Chinese accounting system make the two sets of financials comparable. First, the fiscal year for all companies in China is the same, covering the solar year of January 1 to December 31. More importantly, China has adopted a “unified accounting system” statute with strict guidelines regarding how firms must prepare and file their financial statements; a 150-page handbook gives instructions for compliance (Accounting Law 2005). This unified accounting system is formulated and promulgated by a single central government agency, the Ministry of Finance of the State Council, and the country’s accounting and corporate laws mandate its implementation. Further, Chinese Accounting Law explicitly prohibits firms from creating different books for or changing accounting measures in reports prepared for different users. For instance, the following acts are explicitly singled out as violations of accounting law, “…(5) the measures for accounting arrangement are arbitrarily changed; and (6) the basis for preparing financial and accounting reports provided to different users of accounting documents is inconsistent” (Article 42). The Accounting Law further states that “Except for the statutory account books, a company shall not set up other account books” (Article 172).¹¹

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¹⁰ The Company Law requires each firm to “establish its own financial and accounting bylaws according to the laws, administrative regulations and provisions of the finance ministry of the State Council” (Article 164), and “after the end of each fiscal year, formulate a financial report and have it audited by a Certified Public Accounting (CPA) firm registered in China. The financial report shall be worked out according to the laws, administrative regulations and provisions of the finance ministry of the State Council” (Article 165).

¹¹ The following sections of the law are also relevant. Article 16 requires “All economic and business transactions that take place in a unit shall be recorded and calculated in the account books set up according to law, and no unit may, in
Even though Chinese accounting law requires that the books submitted to MOST and to SAIC by the same company for the same accounting period should report the same information, there are many instances of significant inconsistencies in the two sets of books (Stuart and Wang 2013). Most firms have clear incentives to underreport their financial performance to the local SAIC for the purpose of tax evasion. Although SAIC is not directly responsible for tax collection, its local offices collaborate with the State Administration of Taxation (SAT) to conduct joint inspections of and coordinate administrative actions against tax evaders (Lei 2010). Furthermore, some regions in China have recently built information technology systems to facilitate data-sharing among the local SAT, SAIC, and other departments (Wang 2011). Given the close relationship between these agencies, tax evaders have an incentive to underreport their profits to the local SAIC.

In contrast, MOST is likely to receive financial documents that overstate true profits. To support its primary goal of promoting technological innovation and the commercialization of new technologies, Innofund expressly considers financial performance in its evaluation of candidates, financial health and viability being seen as necessary to successful use of the grant funds for those purposes. Thus, each applicant is rated by a panel of financial and technical experts. Regardless of other merits, firms that receive a low financial rating are eliminated from further consideration. Therefore, in order to be considered for the meaningful amount of capital (without equity dilution) that Innofund offers, the typical firm in our sample has a strong incentive to exaggerate their financial performance in their MOST application.

Theoretically MOST and the local SAIC could coordinate with each other to share information and discourage firms from submitting inconsistent financial statements. This has yet to occur because of the fragmentation of authority and the “matrix muddle” of China’s state bureaucracies (Lieberthal 1995; Mertha 2009). MOST and SAIC are both violation of the provisions of this Law and the State's unified accounting system, set up privately any other account book for recording and calculating such transactions.” Article 20 also states that “financial accounting statements shall be prepared on the basis of the examined and verified records of the account books and related materials and information, and shall comply with the requirements set by this Law and the State's unified accounting system.” Article 25 further requires firms to “confirm, calculate and record assets, debts, owners’ equities, revenues, expenses, costs, and profits in accordance with the provisions of the uniform accounting system of the State on the basis of the economic transactions and operational matters which actually occur.”
ministry-level agencies, and neither has authority over the other. Geographic distance adds additional barriers to cross-agency coordination. While Innofund and MOST are located in Beijing, the local SAICs relevant to the firms in our sample are located more than 800 miles away. Lack of coordination between MOST and the local SAICs creates an opportunity for entrepreneurs to manipulate their data and submit different statements to each agency.

Among the financial statistics that firms report, we focus on total profit (i.e. earnings before interest and tax). As total profit measures a firm’s overall financial performance and has tax implications, it is likely to be manipulated by fraudulent firms. To measure fraud, we subtract the total profit filed with SAIC from the profit filed with MOST and use this discrepancy as a proxy for the magnitude of profit manipulation. However, the size of the firm matters: a one million dollar manipulation is a large amount for a small firm with a profit of half a million, but it could be a rounding error for a firm with a profit of one billion dollars. To take this into account, we use the absolute value of profit reported to MOST profit as a denominator to standardize the discrepancy. Thus, we use the following formula to calculate the weighted size of profit fraud:

\[
\text{Weighted Profit Fraud} = \frac{\text{Profit}_{MOST} - \text{Profit}_{SAIC}}{\text{Profit}_{MOST} + 1}
\]

We further created a dummy variable \textit{Fraud} to measure if a firm cooked its financial books. We code \textit{Fraudster} as 1 if a company’s weighted profit fraud is equal to or larger than .20. We feel that a 20% gap cannot be explained by accidental omissions of small earnings or cost items; thus companies with a discrepancy of this magnitude were beyond reasonable doubt cooking their books. According to this definition, 54.60% of firms in our sample manipulated their financial reports substantively across the two books.

\textit{External Resource Infusion} We also collected information on whether a firm received funding from Innofund. As early-stage ventures are often endowed with few resources, their potential for innovation may be constrained by financial bottlenecks, and they may need an infusion of external capital to fulfill their promises. \textit{Innofunded} is a dummy variable that equals one if a firm received an Innofund grant and 0 if it did not.

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12 We use the absolute value of the profit submitted to MOST as a denominator since some firms report losses.
13 As an additional check, we tried a higher percentage (30%) as the cut-off point, and this did not change our statistical results in any meaningful way.
14 For more detailed information, please see Stuart and Wang (2013).
About 54.0% of the firms in our sample received Innofund funding, higher than the Innofund average of 44.6% in the period of 2005-1010. The higher recipient rate reflects several factors in our sample construction: first, we excluded from our analysis the youngest firms – firms established for less than two years at the time of their Innofund application – as these firms often do not have complete financial records due to the lack of sales. This drives our rate upward because young firms lack a performance track record, making Innofund reluctant to fund them. Second, we excluded firms located in smaller cities because it is logistically challenging for our data suppliers to acquire these firms’ SAIC financials. It is likely that firms located in smaller cities are less competitive than their metropolitan peers in organizational capability, technological innovation, sales, and consequently grant applications.

**Interaction between Fraud and Grant**  As our main theoretical argument is that the way resources are acquired is linked to the way they are utilized, we expect firms receiving Innofund grants by fraudulent means to behave differently in post-grant innovation activities from their non-fraudulent grant-receiving peers. To test this hypothesis, we construct an interaction term between the dummy variables Fraudster and Innofunded. We expect the correlation between this interaction term and our outcome variable Innovation to be negative.

**Control Variables**  Many entrepreneur- and firm-level characteristics may be simultaneously associated with corporate fraud and innovation. From the detailed information that our sampled firms filed with their Innofund applications, we hand-coded the following demographic and educational information for each entrepreneur: Male is a dummy variable that equals 1 if the key founder is male; Founder’s Year of Birth is the year in which the firm’s key founder was born; Level of Education is four-category variable measuring the key founder’s highest educational achievement: 3 for doctoral degree, 2 for master’s degree, 1 for bachelor’s degree, and 0 for associate's degree or lower; Political Connection is a dummy variable that equals 1 if one or more company founders previously worked in the Chinese government or once held membership in the People’s Congress or the Chinese People’s Political Consultative Conference.

The following firm-level information is also controlled for in our analyses: Firm Age is
the number of years that a firm had been established at the time of application. Firm size is approximated by \textit{Employee}_{ln} and \textit{Registered Capital}_{ln}, which represent the natural logarithms of employee headcount and of registered capital, respectively. \textit{Shareholders} counts each firm’s number of shareholders; \textit{Venture Capital Investment} is dummy that equals 1 if a firm is backed by venture capital investors. \textit{Export} is a dummy variable measuring if a firm exported anything in the year \(T_{-1}\). \textit{Initial Invention} is a proxy for a firm’s initial technological capability, counting the weighted number of invention patents (i.e. total patent count divided by years) that the company had applied during the period \(T_{-2}, T_{0}\).  

Finally, we control for industrial sector and firms’ geographic location. 408 out of 467 firms in our sample operate in the seven industries that are targeted by Innofund. We group all the other firms together into one category and create eight dummy variables. We also add city dummies to control for firm location, as institutional and cultural factors affecting fraud and innovation may vary across regions.

**MODELS AND RESULTS**

We conduct empirical analyses in three steps. First, we examine whether fraudster firms are on average less innovative than non-fraudster firms, counting the number of patents filed each year in the post-Innofund period. Second, we examine if resource allocation for investment is different for grantees depending on whether they are fraudsters. Third, as a robustness check, we use both coarsened exact matching (CEM) and regression discontinuity (RD) to repeat our analyses.

**Descriptive Statistics**

Table 1 reports the correlation matrix among our key variables for the post-Innofund grant period (i.e. \(T >2\)). There is a negative association

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15 Most of the firms in our sample are relatively young (about five years old), with a small number (about six percent) being 10 years old or older.

16 We do not use more traditional measures such as R&D intensity, as firms have incentive to manipulate both their R&D spending and revenues in grant application. To be qualified for Innofund grants, a firm needs to dedicate at least five percent of sales to research activities, and there is no evidence of Innofund making deliberate efforts to verify a firm’s R&D intensity. In contrast, it is hard for a firm to fabricate patents, given that these forms of intellectual property are listed on the website of the State Intellectual Property Office. As a robustness check, we added the natural logarithm of R&D expenditure to the list of controls. This variable has a positive but statistically non-significant coefficient, and its inclusion does not change our main results in any meaningful way.

17 These are information technology (IT), optoelectronics, biotech and medicine, advanced materials, automation, new resources and environmental protection, conservation and renewable energy, and high-tech services.
between fraudster firms and post-grant invention patenting, providing tentative evidence that fraudulent firms are less innovative than their non-fraudulent peers. There is also a positive association between the receipt of an Innofund grant and invention patenting, suggesting that in the aggregate Innofund grants promote technological innovation.

[Table 1 Inserted Here]

Figure 1 illustrates patenting trends across different types of firms. Figure 1a shows that, in comparison with their unfunded peers, funded firms consistently filed a higher number of invention patents, both pre- and post-Innofund application. This suggests that Innofund generally selected innovative firms as grantees, although public funding of early-stage ventures generally suffers from problems such as information asymmetry and bureaucratic incompetence. This figure also shows that Innofund was more than merely picking up winners; the gap in patenting between funded and unfunded firms grew in the post-grant application period, suggesting that the infusion of an Innofund grant helps promote technological innovation. These results are consistent with the findings in Furman, Li and Wang (2013).

[Figure 1 Inserted Here]

Figures 1b and 1c show pair-wise comparisons between cheating and non-cheating firms based on whether they received an Innofund grant or not. Figure 1b examines patenting activities among grantee firms and shows diverging trajectories between cheating and non-cheating firms: While grantee firms that cooked their financials books showed an almost flat patenting trend in the post-grant period, non-cheating grantees had an innovation boost that lasted at least until T5. Figure 1c examines patenting activities among non-grantee firms. Within this group, even though cheating firms consistently filed a smaller number of invention patents than non-cheating firms both before and after the Innofund application, there is no clear evidence that the gap in patenting between the two groups grew in the post-application period. As these firms did not receive any external resource infusion, it is not surprising that we do not see diverging trajectories here.

**Regression Models** We run a series of regressions to test the relationship between fraud, external resource infusion and firm innovation. In Table 2, we first use random-effects regression to model post-grant patenting activities as a joint function of how a firm tried to acquire the external resources and whether there is an external resource infusion.
We control for the key entrepreneur’s demographic characteristics as well the firm’s initial endowments of capital, human resource and technology. We further add dummies for application year and province to control for time-period and location effects. Our basic model is:

\[ Innovation_{it} = a + b(Fraudster_i) + c(Innofunded_i) + d(EntrepreneurControls_i) + e(FirmControls_i) + f(Province_i) + g(ApplicationYear_i) + e_{it} \]  

(1)

Where Innovation\(_{it}\) is the number of invention patents that firm i applied during post-grant application year t; Fraudster\(_i\) measures whether a firm manipulated its financial data in its grant application; Innofunded\(_i\) measures whether firm i received grants from Innofund or not; EntrepreneurControl\(_i\) is a series of entrepreneur-level variables that include the key founder’s gender, age at the time of Innofund grant application, level of education, and political connection; FirmControl\(_i\) is a series of variables including firm i’s registered capital (in natural logarithm), number of employees, venture capital investment, and number of invention patents applied for in the year before the Innofund grant application.

To test our main argument that grantees allocate resources for investment differently depending on whether they are fraudsters, we add an interaction term to the basic model above:

\[ Innovation_{it} = a + b(Fraudster_i) + c(Innofunded_i) + d(EntrepreneurControls_i) + e(FirmControls_i) + f(Province_i) + g(ApplicationYear_i) + h(Fraudster_i \times Innofunded_i) + e_{it} \]  

(2)

In both models, our unit of analysis is firm-year and the dependent variable is the annual number of invention patent applications in the post-grant period (i.e. T >2).

Model 1 in Table 2 shows that, on average, an Innofund grantee filed .413 more invention patents than the non-grantees. In contrast, cheating firms on average filed .277 fewer invention patents than their non-cheating peers. Both results are statistically significant at the .10 level or lower. Once the interaction term between fraud and Innofund award is added as shown in Model 2, the coefficient of fraud loses its statistical significance. At the same time, we have a negative and statistically significant coefficient (B= -.534; S.E. = .269) for the interaction term between fraud and Innofund award. This shows that the main difference between cheating and non-cheating groups was among the grantee firms, suggesting that cheating and non-cheating firms use the newly infused external resources differently.
Robustness Check As Figure 1b suggests, cheating and non-cheating grantees were already on divergent patenting trajectories prior to the applying for Innofund support. One might argue that cheating grantees were inherently less innovative than their non-cheating peers and that the capability gap explains both the differences in cheating and in post-grant innovation across the two groups. To address this concern, we apply two methods–coarsened exact matching (CEM) and regression discontinuity (RD) – to reduce the possibility that cheating and non-cheating firms were drawn from different capability distributions.

Coarsened exact matching, or CEM, is a method of pruning sampled observations in order to reduce the imbalance in covariates between the treated and control groups (see Blackwell et al. 2010; Iacus, King, and Porro 2011). To put it another way, CEM identifies a subsample of observations that are comparable based on observable characteristics. In comparison to exact matching, CEM is “coarse” because it does not precisely match on covariate values. Instead, it coarsens the support of the joint distribution of the covariates into a finite number of strata, and then matches a “treated” observation if and only if a control observation can be found in the same stratum. An important advantage of CEM is that the researcher can guarantee the degree of covariate balance ex ante. In our study, we match non-cheating and cheating firms on the following dimensions that could simultaneously affect innovation and fraud: 1) year of Innofund application (within a range of +/-1 year); 2) firm location at the city level; 3) year of establishment (within a range of +/-2 years); 4) the weighted number of invention patents applied in the three-year era \( (T_2, T_0) \); 5) industrial sector; and 6) a five-category size classification of registered capital.

Figure 2 shows the patenting trends of our CEM matched subsample. In comparison to the full sample in Figure 1, cheating and non-cheating firms in this subsample are fairly well matched in their technological trajectory until the year of Innofund application. Figure 2a shows that among the matched grantees, non-cheating firms generally applied for a larger number of patents in the post-Innofund period. The divergence in patenting behavior is particularly salient from T3 – the third year after grant application (or two years after grant receipt). As there is an unavoidable lag between resource infusion, innovation, and patent application, we feel that Figure 2a is reassuring that the divergence observed in post-
grant patenting is due to a difference in resource utilization between the cheating and non-cheating firms, rather than solely due to differences in technological capability between the two groups. Figure 2b examines non-grantee firms. We do not see a clear pattern of divergence between cheating and non-cheating firms. Models 3 & 4 in Table 2 rerun the analyses of Models 1 & 2 with this CEM subsample and confirm the empirical patterns between fraud and innovation discovered in the prior models.

While the CEM procedure matches cheating and non-cheating firms based on their observable characteristics in the pre-Innofund application period, one may still be concerned about biases introduced by unobservable heterogeneities. To address this concern, we leverage the evaluation score assigned by a panel of outside technical and financial experts that Innofund used in deciding its grant awards. Given the expertise of the evaluators, we may assume that firms lying close to either side of the cut-off score are very similar to each other in quality. This enables us to use a regression discontinuity (RD) model to identify the differing causal effects one intervention—a resource infusion from a state agency—may have on innovation, depending how firms acquired the resources.

Figure 3 reports the raw table for our RD design. The x-axis indicates a firm’s Innofund score relative to the cut-off point for funding. Most firms filed only a small number of invention patents each year in the post-grant period, but there were also a few outliers that filed a large number of patents. As previously mentioned, these outlier observations are winsorized at 10. Figure 3 suggests that the Innofund grant helped non-cheating firms achieve a higher level of innovation than cheating firms when we use the post-grant patenting of their non-grantee peers as the benchmark. Models 5 & 6 in Table 2

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18 As with any matching method, causal inference using CEM cannot estimate the average treatment effect in the entire population, but rather the local average treatment effect for the matched observations remaining after data pruning. As Figures 2a and 2b suggest, our CEM-matched cases are mainly firms that had few patent applications in the pre-grant period.

19 One may be concerned that the evaluation score itself is manipulated in the sense that cheating firms cook their financial books to receive higher scores (and thus better chance of winning an award). While this could be a problem for an RD design for standard difference-in-difference (DID) estimation, the concern is reduced in our setting, as we are essentially doing a triple difference estimation: rather than comparing grantee and non-grantee firms before and after grant infusion (i.e. the “intervention”), we are comparing the DIDs for cheating and non-cheating firms. As long as cheating firms do not manipulate their evaluation scores in systematically ways across the cut-point score, our triple difference should give unbiased estimation.

20 It’s worthy of attention that some firms with many patent applications lay close to the cut-off. It’d be interesting to examine if this was a result of vagaries in the evaluation process, or does that mean that those firms were struggling financially and received lower scores because of that factor—and if so, were they more likely to cheat on their financial records? Further, did their financial woes affect their ability to leverage the grant infusion into further technological innovation? Although not questions for this paper, these issues are worthy of further investigations.
narrow the analyses to the subsample of firms lying close to the grant allocation cut-off point (+/- 5), and our theoretical prediction continues to receive statistically significant support.\textsuperscript{21}

\textbf{Discussion and Conclusion}

There is much research exploring how a focal organization may suffer reputational loss, stock market penalty, or legal liability when its fraudulent behavior is caught (Greve, Palmer and Pozner 2010: 85-89). However, we have very limited knowledge of how fraud may adversely affect an organization’s competitive edge even when it escapes the scrutiny of the social-control agent. To our knowledge, this paper is among the first to empirically examine how resources acquired through fraudulent tactics are deployed differently from resources acquired through honest means. While companies should always avoid fraudulent behavior for ethical reasons, we show that there is at least one additional reason for them to behave honestly.

Our paper uses an unconventional method of fraud identification. By comparing two sets of financial statements that are required by the law to report the same financials, we directly observe the existence or absence of data discrepancies and can identify beyond reasonable doubt whether a firm cooked its books. This method allows us to empirically examine how fraud is linked to innovation without the complications introduced by necessarily intrusive and often selective methods that public-control agents use to identify and combat fraud. Although our method is deeply rooted in the Chinese institutional context, similar approaches could be developed to study fraud in other contexts. For instance, scholars could design surveys to ask firms (or individuals) to report their performance on dimensions that can be objectively verified (such as the number of patent filed in the past year) and use the discrepancy between the self-reported number and the objective number as a proxy for dishonesty.

We assemble a panel dataset on our sample firms’ patenting behavior both before and after their Innofund grant applications. Using the discrepancy between financial data submitted to MOST and to SAIC in the year of Innofund application (T\textsubscript{0}) to measure fraud

\textsuperscript{21} We also analyzed the subsample of firms lying close to the grant allocation cut-off point (+/- 7.5) and found similar results.
while using patents filed in post-grant years (i.e. T₃, T₄ and etc.) to measure firms’ innovation capability gives us two advantages: first, it addresses the concern of reverse causality, as our outcome variable is firms’ patenting behavior in the post-grant period; second, it allows us to examine how fraudster and non-fraudster firms differ in their creation of new technological knowledge in the post-grant period, controlling for their original technological endowments.

There are at least four major shortcomings worthy of attention in this paper. First, we have no knowledge of the actual profit level of a firm (especially a cheating firm). Given that firms have incentive to overreport their performances to MOST but underreport to SAIC, a firm with the same figures in both sets of books was most likely to be honest in its reporting; however, we have no way to know whether the profit figure in either report was accurate in cases where the two did not match. Identified fraudsters could have cooked their MOST books, their SAIC books, or both sets. We can only rely on the assumption that firms cheating in one context (e.g., the report to SAIC) are most likely to cheat again in another context (e.g., the report to MOST), especially one that involves the large (0.5-1 million yuan) financial stakes represented by an Innofund grant. Using this assumption, however, ignores the possibility that some of the identified fraudster firms were honest in their MOST reporting, causing our empirical results overestimate the adverse effect of using fraudulent tactics to acquire resources.

Second, even if misidentification were not a problem in our study, one might still be concerned that some of the cases of fraud that we observe were just attempts by sinking ships to access the additional resources that would keep them afloat a bit longer. In this case, the health of the organization and thus the actual range of feasible actions that are available to it might be different for cheating and non-cheating firms – it is hard to look for new continents when one’s boat is sinking. We used several procedures to address this concern: first, we added a long list of variables in our regression to control for entrepreneur- and firm-level observables that could influence both firms’ motivation to

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22 Alternatively, one might argue that these firms were too lazy to cook their books twice and thus submitted the same fraudulent books to both stage agencies. There are three arguments why this should not be the case: 1) a typical Innofund application package has around 60 pages of information about the firm, including detailed descriptions of the firm’s technological features, business model, target market and potential business rivals. Interviews suggest that firms worked for weeks preparing these materials and understood that financial performance was a key evaluation factor; 2) the potential financial and non-financial rewards for winning an Innofund grant was too huge for these firms to be lazy; and 3) if these firms were lazy in working on their financial books, why would they be diligent in technological innovation, as observed in our study?
cheat and their capability to innovate; second, we used the coarsened exact matching (CEM) method to achieve parametric balance in key characteristics between the cheating and non-cheating firms. This method helped us identify a subgroup of cheating and non-cheating firms that exhibited high similarity in technological trajectory and financial health before the Innofund application. Third, taking advantage of the availability of the evaluation scores on which Innofund award decisions were based, we used regression discontinuity (RD) to analyze firms sitting close to either side of the cut-off score, assuming that observations with similar scores were essentially similar to each other.

Third, though the use of patent applications as a measure of technological innovation allowed us to circumvent the time lag that would have arisen from using approved patents, this choice of variable introduces problems of its own. While invention patents are of higher technological merit and commercial potential than utility and design patents in China, the quality among applications for invention patents can vary dramatically, especially among those that are filed but not yet approved or rejected. Further, there are clear limitations in using patents per se as a measure of new technology creation. According to Griliches (1979) and Pakes and Griliches (1980: 378), “patents are a flawed measure (of innovative output), particularly since not all new innovations are patented and since patents differ greatly in their economic impact.” That being said, patents can still serve as a second solution in measuring innovative activity. There is evidence that patents provide a fairly reliable measure of innovative activity at the industry level (Acs and Audretsch 1989), the state level (Acs, Audretsch and Feldman 1991) and the regional level (Acs, Anselin and Varga 2002). In the current version of this paper, we could not directly address these concerns about varied quality in patent applications and the aspects of technological not captured in patent records. However, there is at least one potential solution for use in future work: rather than examining patents—the outcome of innovation—we may examine the differences in how or whether cheating and non-cheating firms allocate the resources of an external capital infusion to R&D. The authors are in the process of linking their current data with China’s economic census dataset to collect information on firms’ R&D expenditures in the post-grant period.

Fourth, we do not have information on our sample firms’ underlying risk orientations. One might argue that risk-embracing firms are both more likely to cook their
financial books and to choose to work on inherently risky projects that have a higher likelihood of failure (and thus would not show up in patent application data). From this perspective, a firm’s risk preference might explain both its engagement in fraud and its “underperformance” in invention patenting. While we do not have information on firms’ risk orientation to address the issue directly, one observation helps reduce the concern. As noted above, firms apply for three types of patents in China: invention, new utility and new design (in order of decreasing technological merit and commercial value). If fraudulent firms are inherently more risk-embracing and thus prone to work on projects with a high likelihood of failure, we would expect these firms to file fewer invention patents, but also fewer utility and design patents. To test this, we ran the same analyses as in Table 2 but replaced post-grant invention patenting with post-grant non-invention patenting (i.e., the total number of new utility and new design patents applied for each year). We did not find a negative relationship between fraud and non-invention patenting.

There are several potential ways to extend this study. For instance, one might examine whether the relationship between fraud and innovation is moderated by such organizational characteristics as age and size. Organizational life cycle analysis states that, in the early stage of organizational development, power of top executives to influence organizational vision and values may be greatest, since no history exists to impede the introduction of an organizational design that will foster a particular kind (e.g., ethical, innovative) of organization (Dickson et al. 2001). Weberian theory further states that when growing in size, organizations unavoidably become bureaucratic in order to take advantage of expertise specialization, routinized division of labor, and increased delegation of authority. Such bureaucratic adjustments are not easily relinquished once the period of growth is done. As a result, the influence of top executives on the organization’s daily operations, resource allocation and even strategic orientation is much weaker in larger organizations. Thus we would expect that the relationship between an organization’s unethical practices and its innovativeness will be stronger for young and small organizations than for firms that are large and in the later stages of their organizational life cycles.
REFERENCES (Incomplete):


Bhattacharyya, Sambit and Roland Hodler, Natural resources, democracy and corruption, European Economic Review, Volume 54, Issue 4, May 2010, Pages 608-621


Miller and Chen 1994)


Table 1: Correlation Matrix (N = 1086)

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<td>Employee number, natural log</td>
<td>0.098</td>
<td>0.134</td>
<td>0.109</td>
<td>0.236</td>
<td>-0.071</td>
<td>0.103</td>
<td>0.117</td>
<td>-0.258</td>
<td>0.269</td>
<td>0.547</td>
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<td></td>
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<td>Number of shareholders</td>
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<td>-0.035</td>
<td>0.062</td>
<td>0.110</td>
<td>0.291</td>
<td>0.024</td>
<td>0.040</td>
<td>0.083</td>
<td>0.148</td>
<td>0.150</td>
<td>0.006</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Organizational shareholder: dummy</td>
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<td>-0.037</td>
<td>-0.033</td>
<td>0.021</td>
<td>0.465</td>
<td>0.084</td>
<td>0.039</td>
<td>0.206</td>
<td>-0.078</td>
<td>0.190</td>
<td>-0.011</td>
<td>0.234</td>
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<td></td>
</tr>
<tr>
<td>Number of prior patents**</td>
<td>0.470</td>
<td>-0.141</td>
<td>0.080</td>
<td>-0.066</td>
<td>0.216</td>
<td>0.023</td>
<td>0.042</td>
<td>0.150</td>
<td>-0.015</td>
<td>0.147</td>
<td>-0.007</td>
<td>0.038</td>
<td>0.114</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Export orientation: dummy</td>
<td>0.073</td>
<td>-0.019</td>
<td>-0.015</td>
<td>-0.072</td>
<td>-0.030</td>
<td>0.056</td>
<td>-0.070</td>
<td>0.069</td>
<td>0.174</td>
<td>0.186</td>
<td>0.159</td>
<td>0.098</td>
<td>0.041</td>
<td>0.015</td>
<td>1</td>
</tr>
</tbody>
</table>

Note: * Post-Innofund (T>2) invention patent applications, observations at the firm-year level
** Weighted number of invention patents applied during the year of grant application and previous two years.
Table 2: Financial Fraud and Technological Innovation, Random Effect Models

<table>
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<tr>
<th>DV: annual invention patent applications in the post-T2 period</th>
<th>Full Sample</th>
<th>CEM Subsample</th>
<th>Close neighborhood (+/-5) around the cutoff point</th>
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<td>1</td>
<td>2</td>
<td>3</td>
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<tr>
<td>Political connection</td>
<td>-0.421**</td>
<td>-0.416**</td>
<td>-0.393**</td>
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<td>Venture capital investment</td>
<td>-0.024</td>
<td>0.006</td>
<td>-0.174</td>
</tr>
<tr>
<td>Founder's age</td>
<td>-0.004</td>
<td>-0.003</td>
<td>-0.007</td>
</tr>
<tr>
<td>Founder's gender: male</td>
<td>0.177</td>
<td>0.146</td>
<td>0.319</td>
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<tr>
<td>Founder's education level</td>
<td>-0.067</td>
<td>-0.064</td>
<td>-0.117</td>
</tr>
<tr>
<td>Firm age</td>
<td>0.002</td>
<td>0.002</td>
<td>0.037</td>
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<tr>
<td>Registered capital, natural log</td>
<td>0.074</td>
<td>0.078</td>
<td>0.187**</td>
</tr>
<tr>
<td>Employee number, natural log</td>
<td>0.226+</td>
<td>0.232*</td>
<td>0.111</td>
</tr>
<tr>
<td>Shareholder number</td>
<td>0.017</td>
<td>0.019</td>
<td>0.082*</td>
</tr>
<tr>
<td>Number of prior patents</td>
<td>0.566***</td>
<td>0.565***</td>
<td>0.056</td>
</tr>
<tr>
<td>Export orientation</td>
<td>0.188</td>
<td>0.198</td>
<td>0.267</td>
</tr>
<tr>
<td>Fraudster</td>
<td>-0.277+</td>
<td>0.056</td>
<td>-0.324</td>
</tr>
<tr>
<td>Innofunded</td>
<td>0.413***</td>
<td>0.691***</td>
<td>0.329***</td>
</tr>
<tr>
<td>Fraudster x Innofunded</td>
<td>-0.534*</td>
<td>-0.687**</td>
<td>-0.938**</td>
</tr>
<tr>
<td>Constant</td>
<td>-1.127*</td>
<td>-1.307**</td>
<td>-1.473***</td>
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<tr>
<td>R-Squared</td>
<td>0.296</td>
<td>0.300</td>
<td>0.150</td>
</tr>
</tbody>
</table>

Note: Robust standard errors are presented below the coefficients. Asterisks denote significance levels of two-tailed test:
+ p<0.100, * p<0.05, ** p<0.01, *** p<0.001.
Figure 1: Patenting Trends across Different Types of Firms

1a: Funded vs. nonfunded firms

1b: Cheating vs. noncheating firms among the funded

1c: Cheating vs. noncheating firms among the unfunded
Figure 2: Patenting Trends among the CEM Firms

2a: Cheating vs. noncheating firms among the funded

2b: Cheating vs. noncheating firms among the unfunded
Figure 3: Invention Patent Applications in the Post-Grant (post-$T_2$) Period