# TWO ESSAYS ON CORPORATE INNOVATION

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# Two Essays on Corporate Innovation

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# CERTIFICATE OF ORIGINALITY

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# ABSTRACT

This dissertation consists of two essays on corporate innovation. In the first essay, I exploit an exogenous policy shock to investigate whether and how the policy push affects firm innovation. The Chinese 12$^{th}$ Five-Year Plan sets a target to double the invention patents per 10,000 people over 2011-2015, which I show stimulates less innovative provinces to catch up with their peers, thus provoking more government actions. Using a difference-in-differences approach, I find that firms in less innovative provinces file more patent applications, but the increased patents receive few citations and have little economic value. This effect is more pronounced among SOEs and for firms with large employee size. Additional tests reveal that the policy push has no impact on R&D expenditures. In contrast, it is positively related to the labor inputs in innovation activities. Finally, I find that the government reciprocates treated firms, especially SOEs, with more subsidies.

The second essay investigates the impact of local inventors on corporate innovation. Using a sample of publicly listed firms in China, a country featured with concentrated corporate R&D activity and a household registration system restraining inventor mobility, I document that firms surrounded by more inventors produce high-quality patents and breakthrough innovations. Skilled labor supply and the escape of competition are two possible channels through which local inventors stimulate firm innovation. Further analyses show that inventor quality strengthens local inventors' impact, and the human capital accumulation is positively related to local inventors. Surprisingly, remote inventors significantly decrease patent quality.

These two studies shed new light on the role government and local inventors played in corporate innovation. The findings show that firms adopt a strategy to trade quality for quantity under government pressure. Given no technological breakthroughs in the policy-induced patents, the potential gain in economic development and firm growth could be less than desired. Besides, government officials allocate subsidies on the condition that firms respond to their appeal to boost patent counts, which may lead to the misallocation of innovation resource. On the other hand, firms could enhance their innovation performance by establishing research and development facilities in regions with rich talents. Alternatively, the government can loosen inventor mobility restriction, thus reducing the adverse effect of firm headquarter location on innovation activities.

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## 1.1 Introduction

Technological innovation is the primary source of new knowledge and long-term economic growth (Solow, 1957; Arrow, 1962). In a competitive market, it is difficult for innovators to gain from innovative success due to knowledge spillovers. As a result, society underinvests in research and development (R&D), resulting a market failure that necessitates government intervention (e.g., subsidies, R&D tax credit, and IPR protection). Furthermore, one of the macroeconomic policy objectives is to promote long-term economic growth. The government, without a doubt, sees innovation as a critical step in achieving this aim. This logic indicates that government action promotes corporate innovation.

However, government interventions in technological innovation do not always work and may even lead to unintended consequences for many reasons. The literature on politicians and firms claims that politicians frequently pursue private interests at the expense of shareholders (see Shleifer and Vishny, 1994; Shleifer and Vishny, 1998; Djankov et al., 2003). Moreover, government officials are often information-constrained, lack the intention or ability to implement appropriate policy analysis, suffer from conflict of different interest groups, and are undoubtedly subject to bureaucracies (e.g., Nelson and Winter, 1982). According to these views, government intervention could impede innovation and even drive businesses to respond strategically.

In this study, I use a new and specific policy, Chinese 12$^{th}$ Five-Year Plan that sets a target on the number of invention patents per 10,000 people over 2011-2015, as a quasi-natural experiment to study whether and how the policy push affects firm innovation[1]. In 2011, the 12th Five-Year Plan, for the first time, sets a target on the number of invention patents per 10,000 people[2], an indicator that reflects country and province-level innovation performance. The national plan's goal is to *double* this measure from 1.7 (the national average in 2010) to 3.3 by 2015, and many provincial governments adopt the same or similar goal in their plans. Such a "per capita" policy target was particularly challenging for lagging provinces (i.e., provinces that lagged behind the national average of that indicator), given their low innovative capacity and lack of infrastructure for science and technology. Nonetheless, some provinces that were lagging the national average still set ambitious targets. For example, Anhui had 0.66 invention patents per 10,000 people in 2010 and planned to raise that indicator to 3.4 in 2015, while Guangxi planned to increase that indicator from 0.29 to 3.0 in five years. At the end of 2015, central and many provincial governments overshoot the planned targets. The national average reaches 6.3 in 2015, which almost quadruples the figure in 2010. A similar surge can also be found at the provincial level, with Anhui's and Guangxi's numbers increasing to 4.3 and 2 in 2015, respectively.

This exogenous policy shock of Chinese 12th Five-Year Plan offers a quasi-natural experiment to investigate government intervention on innovation. This policy shock allows us to conquer some common identification challenges including omitted variables

[1] Originating from the Soviet Union, the planning system acts as a mechanism to govern resource allocations. It was introduced to China in the early 1950s. Except for the central planner, the Chinese government decentralized the planning system to create planning commissions at provincial and lower-government levels (see Perkins, 1973). This top-down and multilayer structure has existed ever since. Since the reform and opening-up in 1978, the Chinese government has embraced the market economy and abandoned short-term plans. The Five-Year Plan for the National Economic and Social Development (hereafter, Five-Year Plan or FYP) is still alive, although its role has transited from economic planning to public affairs governance planning (Hu, 2013).

[2] This measure is known in Chinese as "每万人口发明专利拥有量", and it is defined as total amount of invention patents (in force) divided by population.

and reverse causality. The first one is how to capture government intervention on firm innovation. Prior studies have used state ownership and political connections to proxy for government intervention, assuming that politicians significantly influence state-owned enterprises (SOEs) and connected managers (see, e.g., Fan et al., 2007; Chen et al., 2011). Although these measures reflect government involvement to some degree, they tell us little about the direct interference on innovation activities. Considering the state ownership, it could provide SOEs protection against expiration in the absence of legal protection on intellectual property (Fang et al., 2017). Second, Regions with weaker property rights institutions could have fewer innovation activities and more government intervention simultaneously. Third, even if we observe a positive correlation between government intervention and corporate innovation, it could be subject to reverse causality concern. For example, less innovative firms may turn to the government for support because they are more likely to lose the technology competition and go bankrupt (Eisdorfer and Hsu, 2011).

To examine this policy shock, I compare the growth rate in the number of patents in lagging provinces in the 11$^{th}$ FYP and 12$^{th}$ FYP periods. I find that during the 11$^{th}$ FYP period (2006-2010), the province-level growth rates in the number of patents filed by industrial enterprises are unrelated to the difference between a province's invention patents per 10,000 people and the national average. In contrast, I find that during the 12$^{th}$ FYP period (2011-2015) the provincial-level growth rates in patents filed by industrial enterprises are significantly and positively correlated with the increasing differences between a province's per-capita rate and the national average. This suggests that provinces that lag the national averaged in the 11$^{th}$ FYP period exert greater efforts during the 12th FYP period to catch up with the national average. I find a similar trend if we compare a provinces' patent growth to adjacent provinces rather than the national average. On the other hand, I also examine province-level R&D investment. Compared to the provinces leading in innovation, less innovative provinces in fact report lower R&D investment after 2011. It is thus plausible for us to assume that firms located in less innovative provinces face more policy push following the 12th Five-Year Plan.

I construct a sample using firms listed in the Chinese A-share market between 2007 and 2016. To gain a complete picture of firm innovation, I require audited R&D expenditures, and so the sample period started in 2007, as listed firms are required to disclose this item since then. Following existing literature (e.g., Fang et al., 2017; Tan et al., 2020), I use invention patents and utility model patents to measure innovation outputs. In the spirit of Balsmeier et al. (2017) and Bhattacharya et al. (2017), I distinguish incremental innovations from breakthrough ones by the distribution of forward citations and economic value of patents, respectively.

Using a panel of 14,613 firm-year observations from 2,140 unique firms for the 2007-2016 period, I first implement univariate difference-in-differences (DiD) analyses to examine the impact of the per-capita policy target on firm innovation. The univariate DiD tests show that after the enactment of the 12th Five-Year Plan, firms in the lagging provinces exhibit a 31.72% increase in the number of patents than that of firms in leading provinces. When I look at the change in incremental versus breakthrough innovations, the DiD estimates are only significantly positive for less-cited patents and low value patents. In other words, the increased patents by treated firms are mainly from incremental innovations, as they receive very few citations and trigger weak stock market reactions. According to the results, 95.41% of the increased patents are low-value ones that fall into the bottom 30th percentile of the value distribution within their type-technology class-year.

We also estimate full DiD regressions that include firm fixed effects, year fixed effects, and an extensive list of control variables that may affect firm innovation. Consistent with the univariate results, I find that government intervention strongly affects patent counts and low-quality patents, but has no effect on the number of high-quality patents. The implementation of the 12th Five-Year Plan results in a 28.68% larger increase in the number of patents among firms in less innovative provinces when compared to those in more innovative provinces. Moreover, the application of less cited patents (low-value) patents is more active by 23.38% (30.09%) among firms exposed to the policy push. For highly cited and high-value patents, I find no significant difference between the treated and control firms. In the robustness check, I obtain similar results after controlling for local business conditions and using different definitions of incremental and breakthrough innovations.

The validity of DiD analysis depends on the outcome variables' parallel trends prior to the exogenous shock, as Imbens and Wooldridge (2009) explained. To verify this assumption, I follow Bertrand and Mullainathan (2003) and Atanassov (2013) to test the dynamics of innovation around the 12th Five-Year Plan passage in 2011. The results confirm the pre-treatment trends assumption, as there is no increasing innovation in the treatment group before 2011. I only find the positive and persistent impact of policy push on patent counts and incremental innovations in the post-policy period. Moreover, the dynamic regression shows an immediate and long-lasting effect of the 12th Five-Year

Plan. This pattern is at odds with prior studies[3]. Usually, any changes in inputs or incentives would take time to affect corporate innovation because technological change is a long-term process (Holmstrom, 1989; Manso, 2011).

The DiD approach assumes the before-after changes in control firms' innovation to be the counterfactual outcome of treated firms. To address the concern that these two groups may not be comparable, I employ the Propensity Score Matching method to construct a matched sample. Following Fang et al. (2017) and Tan et al. (2020), I require the treated firm and its matched firm to have a similar patent growth rate before the policy shock. After addressing the sample selection issue, the treatment effects are still considerable in this alternative sample. Specifically, firms from less innovative provinces have 33.91% more patent applications following the 12$^{th}$ Five-Year Plan. By comparison, it is only 28.68% in the baseline study. Besides, I find a positive relationship between policy push and incremental innovations but not impactful ones.

My identification strategy relies on a single shock to government intervention, which may raise the concern that potential omitted variables coinciding with other policy shocks or economic conditions directly affect firm innovation. I try to alleviate this concern from two aspects: (1) implementing a falsification test using the 11$^{th}$ Five-Year Plan that did not specify patent output targets; (2) performing a placebo test by randomly assign treated firms. I find no significant results in these tests, suggesting that my baseline findings are specific to the 12$^{th}$ Five-Year Plan and cannot be simply attributed to luck.

[3] If the risk-taking incentive were behind the patent surge, the impact of policies, such as privatization, antitakeover laws, and smoke-free laws, mostly occur two years after the implementation. (see Fang et al., 2017; Atanassov, 2013; Gao et al., 2019).

I also examine sample firms' innovative activities in other dimensions: R&D expenditures and labor inputs. I find that treated firms did not increase R&D spending relative to that of control firms following the 12th Five-Year Plan. This result is robust to different measures of R&D inputs, namely the natural logarithm of 1 plus R&D expenditure, R&D expenditure scaled by total assets, R&D expenditures per employee, and R&D expenditures per inventor. Conversely, treated firms indeed have more employees as inventors than control firms do in the post-policy period, and their employees are more capable of patenting. The economic magnitude is sizable. Compared to control firms, treated firms have 23% higher percentage of inventors in 1,000 employees and 15% larger increase in the number of patents per 1,000 employees relative to the control firms, all other things being equal. Given the findings that more employees in treated firms become inventors to file for patents, the increase in (low-quality) patents should be positively correlated with employee size[4]. To test this implication, I partition the whole sample into two groups by the median of employees each year and then re-estimate the baseline DiD regression. I find that the increase in patent counts and low-quality patents only appear in treated firms with more employees. We have two possible explanations for these findings: first, Chinese firms may prefer keeping their innovation as business secrets before the 12th Five-Year Plan, and become more aggressive in patenting their innovation after. Second, treated firms are reluctant to increase R&D spending; instead they trade quality for quantity to help bureaucrats meet patent target quickly[5].

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[4] Note that I already control log total assets, so the difference is not due to firm size.

[5] As Manso (2011) points out, the commitment of resource and early failure tolerance is essential for exploration. In my setting, government officials count on patents that are viewed as successful discovery outcome, and firms exploit

The baseline results and further tests suggest that government officials intervene in firm innovation to achieve the planned patent targets, which points to the “grabbing hand” story. To provide more evidence on this argument, I conduct a subsample analysis based on ownership. Theoretical and empirical studies suggest that government intervention is more common among state-owned enterprises (see, e.g., Shleifer and Vishny, 1994; Chen et al., 2011; Gu et al., 2020). Besides, SOEs dominate the Chinese stock market in terms of market capitalization. The effect of policy push on innovation is expected to be stronger for SOEs than non-SOEs. Indeed, when the dependent variables are patent counts and less cited patents, the treatment effect is only statistically significant in the SOEs group. For low-value patents, the treatment effect is larger and more influential among SOEs than that of non-SOEs.

Finally, I examine firms’ incentives to comply with government intervention, especially whether they receive any political favors, as politicians who obtain private benefits from firms would reward them by tax deductions, bank loan preference, or subsidy (see, e.g., Chen et al., 2020; Gu et al., 2020). In this study, I focus on government subsidies for two reasons. First, firms need to disclose the details of government subsidies received. Second, the subsidy has been an important policy tool used by the Chinese government to advance technological innovation[6]. Using subsidies data from CSMAR, I find a significant positive relationship between the patents owned by treated firms and government subsidies ($t$-*statistics* = 3.88). Our result thus reveals that the reciprocal

their workers’ tacit knowledge. Consequently, the increase in patents mainly reflects incremental progress instead of groundbreaking innovations.

[6] Fang et al. (2018) show that R&D subsidies make up around 1% of Chinese GDP over 2005-2015.

relationship between local governments and corporate managers may be a potential source of resource misallocation.

My study contributes to the literature in four ways. First, I present novel findings on the effect of government initiatives on innovation. In this line of research, most studies document that government regulations and laws, such as IPR protection, privatization of state-owned enterprises, and anti-corruption campaigns, have a real effect on corporate innovation (see Ang, Cheng, and Wu, 2014; Fang, Lerner, and Wu, 2017; Xu and Yano, 2017). I use a DiD approach to draw causal inferences on the effect of a new per-capita policy target imposed in China's 12$^{th}$ Five-Year Plan on innovation activities.

Second, my findings add novel evidence to the emerging literature on the real effects of China's Five-Year Plans. Prior studies have documented the positive effects of these plans on emissions (Shi and Xu, 2018), corporate social responsibilities (Li and Lu, 2020), and industry expansion (Cen et al., 2020)[7]. While I find that the plan has stimulated the firm patenting intensity, I also question its real impact by documenting the deterioration of the quality of new patents and highlight the potential resource distortion or indicator manipulation triggered by the rigid policy targets.

Third, my work complements the nascent literature on the adverse effects of policy uncertainties on firm-level innovation, which requires long-term investment

[7] Using the target of reducing $SO_2$ emission by 10% in the 11$^{th}$ Five-Year Plan as a shock, Shi and Xu (2018) find that environmental regulation significantly reduces firm export in pollution-intensive industries. Li and Lu (2020) use more social indicators in the 12$^{th}$ Five-Year Plan as an exogenous shock to the government CSR initiative. They document that the plan has a positive influence on firm CSR performance. However, the effect varies with the incentives of government officials and corporate CEOs. Cen et al. (2020) find an adverse effect of China's industry growth on the number of establishments and employees of the same industry in the United States. They identify a causal relation using China's Five-Year Plans as a shock to industry expansion.

(Bhattacharya et al., 2018; Liu and Ma, 2020; Cong and Howell, 2021)[8]. I present empirical evidence on how a sudden change in policy targets can distort firms' innovation activities and choices, and encourage their rent-seeking behaviors.

Lastly, my work offers new, broad perspectives on the unintended consequences of government intervention. The literature on politicians and firms propose two countervailing effects of government intervention. The grabbing hand hypothesis states that government officials expropriate shareholder wealth from public firms (Shleifer and Vishny, 1994; Shleifer and Vishny, 1998). The helping hand hypothesis argues that shareholders gain from a close connection with politicians (Faccio, 2001). My findings provide novel evidence for the "grabbing hand" hypothesis: that is, the implementation of 12th Five-Year Plan does not increase levels of corporate R&D; instead, it encourages firms to trade quality for quantity in their innovation activities, which may adversely affect China's long-term development.

The remainder of this paper is structured as follows. The next section provides the background information on the Five-Year Plans and patent target. Sections 1.3 describes the variables, data sources, and summary statistics. In section 1.4, I present the main empirical results and validation tests for DiD analysis. Section 1.5 provides additional tests and Section 1.6 includes several extensions and robustness checks. I conclude the paper in Section 1.7.

[8] Bhattacharya et al. (2017) find that innovation activities are not affected by policies that are in place but decrease significantly in the presence of high policy uncertainty. Cong and Howell (2021) exploit occasional initial public offering interventions in China to study how policy uncertainty affects firm innovation. They show that temporary listing delays reduce innovation, as measured by patenting activity. Liu and Ma (2020) find that China's accession to the World Trade Organization alleviated trade policy uncertainty and promoted firm innovation.

## 1.2 **Institutional Background**

### 1.2.1 Government goal on technological innovation

Although China's innovation strategy centers on acquiring and absorbing foreign technologies in the early days, the focus gradually moves to advance indigenous science and technology[9]. In the 16th National Congress of the Communist Party of China held in November 2002, the then-president Jiang Zeming stated, "We must encourage scientific and technological innovation and acquire key technology and independent intellectual property rights in key areas." [10] Following this appeal, the State Council expends more than three years to compile the National Median- and Long-Term Science and Technology Development Plan (2006-2020). One primary goal of this plan is to expedite the inputs and outcomes of technological innovation. By 2020, the R&D expenditures to GDP are expected to be 2.5% or above, and China would be among the top five countries in the world regarding the invention patents granted to residents. For comparison, World Bank statistics show that R&D expenditure made up 1.31% of Chinese GDP in 2005.

The central government initiated a series of policies subsequently, including linking government procurements to innovation developed in China and various government-guided funds. Aside from these new policies, the central government has an established way to achieve its objectives: the Five-Year Plan for National Economic and Social Development (hereafter, Five-Year Plan or FYP).

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[9] Several studies analyze the evolvement of China's innovation policies since 1978. In particular, Liu et al. (2011) conduct a quantitative analysis of 336 innovation policies issued by the central government agencies over 1980-2008, which covers a portfolio of S&T, industrial, financial, tax, and fiscal measures. Fu et al. (2016) discuss the innovative strategy in China after 1978, especially on the change from imported technologies to the domestic innovation.

[10] Details of the report by Mr. Jiang Zeming can be accessed through http://www.china.org.cn/english/features/49007.htm (accessed December 20, 2020)

### 1.2.2 Five-Year Plan and target setting

The Soviet Union first developed the Five-Year Plan in 1928, which served as a strategic blueprint to guide and coordinate economic activities in the planned economy. After establishing the People's Republic of China, the Chinese government also built up a similar planning apparatus with the help of Soviet experts. In the earlier days, the Five-Year Plan's role mainly concentrates on setting overall goals for the economy and translating them into specific targets for all sectors and key industries (Perkins, 1973). For example, in the First Five-Year Plan covering 1953-1957, the tasks include constructing 694 large- and medium-sized industrial projects. Since the reform and opening-up, China has embraced the market economy and gradually transformed the Five-Year Plan from economic planning to public affairs governance planning (Hu, 2013).

As a top-down system, the State Council is responsible for formulating the national plan, which the National People's Congress then approves. Accordingly, the local plan (usually at the provincial and municipal level) is developed by the local government and approved by the local people's congress. Even though local governments can set goals and targets in accommodating local conditions, it has mostly followed the national plan. Hu (2013) finds that 74.9% of the Twelfth Five-Year Plan indicators are consistent between the provincial and central government. Wu et al. (2019) show that the central government's preference is crucial for the local Five-Year Plans.

Perkins (1973) argues that a long-term plan looking for five years ahead would quickly be ignored by private enterprises in the market economy, even by government agencies themselves. To avoid this dilemma, the central government has strengthened the monitoring. Specifically, in 2006, the Law of the People's Republic of China on

Supervision by the Standing Committee of the People's Congress at All Levels was promulgated[11], under which the government at various levels shall submit a mid-term assessment report on the implementation of the plan to the standing committee of the People's Congress for deliberation. The law also stipulates that any mid-term adjustments have to receive approval from the People's Congress. In addition, the central government controls over personnel, and the subnational government runs the bulk of the economy in the Chinese regionally decentralized authoritarian system (Xu, 2011). In this scheme, target is one of the incentive mechanisms for local officials to compete in the promotion tournament (Li et al., 2019).

### 1.2.3 Target on invention patents per 10,000 people

We list the policy targets for science and technology in the 11th and 12th Five-Year Plans in Table 1.1[12]. The 11th Five-Year Plan has only one target: a R&D-to-GDP ratio of 2%. The realized R&D-to-GDP ratio was 1.75% in 2006-2010. There are two policy targets in the 12th Five-Year Plan: a R&D-to-GDP ratio of 2.2% and 3.3 invention patents per 10,000 people. Specifically, in the 12th Five-Year Plan, the Chinese central government for the first time sets a target of doubling this measure from 1.7 (the national average in 2010) to 3.3[13].

To verify whether provincial plans also adopt the same target, I manually check 31 provincial 12th Five-Year Plans for their respective targets and presents them in Table 1.2.

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[11] For details, please see the document at the official website of Nation People's Congress: http://www.npc.gov.cn/zgrdw/englishnpc/Law/2008-01/02/content_1388018.htm

[12] Data source: http://www.gov.cn/2011lh/content_1825838_2.htm

[13] This policy is reported to exert a remarkable effect on domestic patent applications. For example, see "China's patent targets mask weak innovation: Study" Reuters, August 21, 2012, and "Patent fiction: Are ambitious bureaucrats fomenting or feigning innovation?" The Economist, December 13, 2014. We acknowledge that CNIPA also sets its own target for patent numbers in the FYP for National Patent Work, but this plan applies only to the intellectual property administration at various levels.

The FYPs of 13 provinces state the intention to double the number of invention patents per 10,000 people: Anhui, Guangxi, Hainan, Hebei, Heilongjiang, Henan, Hubei, Hunan, Liaoning, Shandong, Sichuan, Tianjin, and Xinjiang. 11 other provinces use a different measure of innovation: Beijing, Chongqing, Fujian, Guangdong, Inner Mongolia, Jiangsu, Ningxia, Shanghai, Shaanxi, Shanxi, Yunan. Finally, 7 provinces do not report a target: Gansu, Guizhou, Jiangxi, Jilin, Qinghai, Tibet, and Zhejiang.

In Table 1.3, I tabulate the regional distribution of invention patent per 10,000 people in 2010, as a benchmark for the 12th FYP data. Several interesting patterns emerge. First, this statistics vary greatly by locations, ranging from 19.89 in Beijing to 0.2 in Tibet. Second, the economically developed regions have more patents, such as Beijing, Shanghai, and Guangdong. Third, most provinces lag behind the national average, and the invention patents per ten thousand people in 18 provinces is less than 1, especially in those provinces with a large population (e.g., Henan and Sichuan).

To examine how firms in different provinces react to the 12th FYP, in Figure 1.1, I plot the average province-level growth rates in the number of patents by industrial firms in the lagging provinces (i.e., provinces that lagged behind the national average of innovation activities). Panel A demonstrates the average growth rate during the 11th FYP (2006-2010) of provinces that lagged behind the national average of 4.9 invention patents per 10,000 people at the end of 2006 (the earlies data for which this statistic is available). The fitted line shows that there are no differences between the patent growth rates of different provinces, and thus patent growth rates during this period is unrelated to whether a province's patents lag behind the national average. In contrast, Panel B demonstrates the average growth rate during the 12th FYP (2011-2015) of provinces lagging behind the national average at the end of 2010 of 1.7 invention patents per 10,000 people. Its trend line has a negative slope, showing a significant difference between the patent growth rates of different provinces in the 12th FYP period. In particular, firms in provinces that lag further behind the national average have higher patent growth rates during this period, and these rates are consistent with the per-capita target of the 12th FYP.

[Insert Figure 1.1 here]

Chen et al. (2020) argue that adjacent provinces share the same economic conditions and the provincial officials compete for promotion. Hence, the incentive to facilitate innovation activities may be correlated among a province and its nearby regions. In Figure 1.2, I examine each province's "excess" patent growth, which is its patent growth rate minus the average patent growth of its neighboring provinces. In this way, we remove the effects of co-movement in economic development and of differences in support from the central government. Again, I find a flat trend line during the 11th FYP period, but a strongly negative sloped trend line during the 12th FYP period. All of these patterns presented in Figure 1.2 suggest that firms in lagging province become more innovative in the 12th FYP period cannot be attributed to common economic trends. By the end of 2015, not only the national target but also all provincial targets are exceeded. The invention patents per ten thousand in China was 6.3 in 2015, almost doubling the original national target.

[Insert Figure 1.2 here]

## 1.3 **Data and Summary Statistics**

### 1.3.1 Measuring policy push

I define the policy push by a dummy variable equal to one for firms located in the lagging province after 2010 and zero otherwise[14]. The lagging region here refers to provinces that had fewer invention patents per 10,000 people in 2010 than the national average. As discussed above, governments in these lagging provinces would have a stronger incentive to stimulate innovation activities. Prior studies also observe a similar pattern. Hu et al. (2017) suggest that the urge to boost patent counts is likely to be stronger in regions that had lagged in innovation and patenting. Fei (2018) finds a stronger response to the National InnoFund VC Program in less developed areas.

To check the validity of this measure, I compare innovation inputs and outcomes between the innovatively leading and lagging provinces around the 12$^{th}$ Five-Year Plan. Table 1.4 presents the results of difference-in-difference regression at the provincial level. After implementing the 12$^{th}$ Five-Year Plan, I find that the lagging provinces have lower R&D expenditures but faster growth in the number of patents (utility model and design patents) than the leading regions, and there is no difference in the growth rate of invention patents. Such a finding is in line with the notion that policy push is behind the innovation activities.

[14] Following existing literature (i.e., Chen et al., 2018; Gu et al., 2020), we use the registration address rather than the headquarter address to locate the firm. Chen et al. (2018) find that a firm's factories are located near its registration city. It is reasonable to expect that provincial government has more influence on the factories than the headquarter. We verify in untabulated results that the baseline results are robust to the choice of location.

### 1.3.2 Measuring firm innovation

I construct five patent measures to capture firm innovation. The China National Intellectual Property Administration (CNIPA) issues three types of patents: invention patents, utility model patents, and design patents. The invention patent is equivalent to the utility patent in the U.S., which requires substantial examination and provides 20 years of protection from the date of application. Utility model and design patent share the same protection period with ten years, with the exception that the former has more technical components than the latter. Following existing studies (see Fang et al., 2017; Tan et al., 2020), I only use invention and utility model patents. I construct the first measure by the patent counts-$LnPatent_{i,t}$, which equals the natural logarithm of one plus the number of invention and utility model patents filed by (and eventually granted to) firm $i$ in year $t$.

Patents vary significantly in technological and economic value (Trajtenberg, 1990; Kogan et al., 2017). Meanwhile, simple patent counts cannot distinguish breakthrough discoveries from incremental innovations (Trajtenberg, 1990). To capture the variation in patent quality, I follow Balsmeier et al. (2017) and Bhattacharya et al. (2017) to construct four measures using the patent's distribution of citations and economic value. In particular, I generate the $LnPatLowCited_{i,t}$ as the logarithm of one plus the number of patents that were not cited or fall into the bottom 30$^{th}$ percentile of the citation distribution among all patents in the same patent type, three-digit IPC class, and application year. I create the $LnPatLowValue_{i,t}$ by changing the sorting variable to the economic value of patents. Since impactful patents tend to receive more citations and trigger stronger market reaction, I calculate them by the number of patents that fall into the top tenth percentile of the citation (value) distribution among all patents in the same patent type, three-digit

IPC class, and application year. $LnPatTopCited_{i,t}$ ($LnPatTopValue_{i,t}$) is then defined as the logarithm of one plus the impactful patents in citation counts (economic value).

I collect all of the patent information from the data project assembled by Lin and Yu (2020). They match all patents in CNIPA to publicly traded companies and their subsidiaries by a name-matching algorithm. This data set has two unique advantages. First, Lin and Yu (2020) have managed to retrieve patent citations from the State Intellectual Property Operating Platform, an organization affiliated with CNIPA. Second, they adapt Kogan et al. (2017)'s paradigm for estimating patent value to accommodate the three patent categories in China, providing an ex-ante assessment of patent quality.

As shown in Hall et al. (2001), patent data suffers two truncation biases: one is with the patent application and the other is with citations, because it takes several years to find out the outcome in both cases. Following Hall et al. (2001) suggestions, I only consider successful applications until 2016, given the patent data ends in 2018, and it generally takes 2 to 3 years (half a year) for an invention patent (utility model patent) application to be approved. In addition, I divide the raw number of citations by the average number of citations received by patents applied for in the same technology class-year to address the citation truncation problem. Notice that the 12$^{th}$ Five-Year Plan was enacted in 2011, far from the patent data's end dates. Therefore, the truncation bias is less likely to affect our findings (see Dass et al., 2017).

### 1.3.3 Control variables

I incorporate a set of firm characteristics identified in the prior studies that affect innovation outputs (e.g., Fang et al., 2017; Tan et al., 2020). The logarithm of total assets measures firm size. Book-to-Market is the ratio of book equity divided by equity's market value at the fiscal year-end. Leverage is the total liabilities divided by total assets. R&D is the ratio of R&D expenditure over total assets (missing values are replaced with zero). Cash is the cash and cash equivalents divided by total assets. Tangibility is the net fixed assets divided by total assets. ROA is the ratio of net income over total assets. Firm age is the logarithm of the number of months from the listing date to the fiscal year-end.

Aghion et al. (2013) show that institutional investors can ease managerial career concerns and promote corporate innovation. I thus incorporate the institutional ownership, computed as the percentage of shares outstanding held by professional investors. Apart from firm-level controls, I also consider the product market competition. Aghion et al. (2005) document an inverted-U relationship between competition and innovation in British firms. However, Lin et al. (2010) find that corporate R&D among Chinese firms is negatively related to product market competition. I define competition as one minus the Herfindahl index in each industry and add the squared term of competition into the control variables[15].

### 1.3.4 Sample and summary statistics

I begin my sample selection by looking at all A-share listed firms from 2007 to 2016. The rationale is that the Chinese Generally Accepted Accounting Principles in 2006 requires public firms to disclose R&D expense in financial statements since then. To generate the sample for empirical investigation, a set of screening criteria is applied. Firstly, I remove firm-year observations if the firm is under ST (Special Treatment) status

[15] We adopt the Guidelines for the Industry Classification of Listed Companies issued by China Securities Regulatory Commission (CSRC) in 2012. We group manufacturing firms by the first two digits of the CSRC industry code and identify the industry to which other firms belong by the first digit of their code. In total, there are 20 unique industries.

due to ST firms face a higher delisting risk. Secondly, I exclude firms from the financial services (industry code: D) and utilities (industry code: J) industry. Thirdly, I discard companies during the entire sample period without successful patent applications. In this regard, I want to ensure that the innovation activities across firms are comparable. As noted in Atanassov (2013), patenting might not be a good measure of innovation for firms that do not have patents. Finally, we have 14,613 firm-year observations from 2,140 unique firms based on these screening criteria.

I extract financial information and registration address from the China Stock Market & Accounting Research Database (CSMAR). Information about the ultimate controller and R&D expenditures are hand-collected from the annual reports. A firm is categorized as a state-owned enterprise (SOE) if its ultimate controller is a government agency. Appendix A.1 provides a detailed description of the variable definition. To mitigate the impact of outliers, I winsorize all continuous variables at the $1^{st}$ and $99^{th}$ percentiles.

[Insert Table 1.5 here]

Table 1.5 reports the summary statistics of variables in the baseline analysis. On average, a firm has filed around 30.79 patents each year. Among them, 17.83 patents either get zero citations until the end of 2018 or fall into the bottom $30^{th}$ percentile of the citation distribution. Since the estimation of economic value requires non-missing price data, the sample size used to rank patent value is reduced by 10%. Consequently, the mean value of $LnPatLowValue_{i,t}$ and $LnPatTopValue_{i,t}$ are relatively smaller. A typical firm has 2.51 patents in the top tenth percentile of the value distribution. 33.7% of the observations are subject to more policy pressure or incentives. The average R&D intensity is 1.57%, and the institutional ownership is 7.18%. Overall, the descriptive statistics are comparable with existing studies (see, e.g., Fang et al., 2017; Tan et al., 2020).

## 1.4 **Empirical Analyses**

### 1.4.1 Univariate tests

This section performs a univariate difference-in-differences (DiD) analysis to understand a per-capita policy target on firms' innovation outputs. In particular, I compare the firms' innovation outputs from 2007-2010 to 2011-2016 and examine whether the change in patenting outputs is associated with their location (in lagging or leading provinces). Table 1.6 presents the results. As shown in Panel A, firms from the leading regions have more patents both before and after the $12^{th}$ Five-Year Plan. However, the increase in the total number of patents is 31.72% (0.814/0.618-1) higher in firms from lagging regions than firms from leading regions after the policy shock.

Panels B and C show the change in the total number of less-cited patents and low-value patents, respectively. Consistent with the results in Panel A, the DiD estimates of both measures are significantly positive, which indicates that firms in lagging regions generate more low-quality patents in the post-policy period. More importantly, these low-quality patents make up the majority of increased innovation. For instance, the DiD estimate of low-value patents is 0.187, accounting for 95.41% of the total patent counts (0.196). On the other hand, neither highly cited patents nor high-value patents, as shown in Panel D and E, see more rise in the treatment group.

[Insert Table 1.6 here]

### 1.4.2 Multivariate tests

To formally identify the causal effects of policy push on corporate innovation, I perform a standard difference-in-differences analysis by estimating the following regression:

$$Innovation_{i,t} = \alpha_i + \alpha_t + \beta Treat_{i,t} + \gamma X_{i,t-1} + \varepsilon_{i,t}. \quad (1)$$

Where $Innovation_{i,t}$ is one of the five innovation measures described in Section 3.2, which captures the quantity and quality of patents applied by (and ultimately granted to) firm $i$ in year $t$. $\alpha_i$ and $\alpha_t$ denote the firm fixed effects and year fixed effects separately. $Treat_{i,t}$ is our variable of interest, which equals one for firm $i$ in the 2011-2016 period if firm $i$ is located in a lagging province (i.e., one with fewer invention patents per 10,000 people than the national average in 2010), and zero otherwise. $X_{i,t-1}$ is a vector of control variables measured at the end of year $t-1$: firm size (*Size*), book-to-market ratio (*BTM*), R&D expenditures over total assets (*R&D*), total debts scaled by total assets (*Leverage*), cash holdings over total assets (*Cash*), asset tangibility (*Tangibility*), institutional ownership (*IO*), profitability (*ROA*), log value of firm age (*Age*), product market competition (*Competition*), and the squared term of competition (*Competition^2*). I cluster standard errors by province because the treatment is defined at the provincial level (see Atanassov, 2013; Fang et al., 2017).

I present the estimated coefficients of the DiD regression in Table 1.7. In Column (1), for which the dependent variable is $LnPatent$, the coefficient estimate on the dummy indicator $Treat$ is 0.245 and significant at the 1% level, indicating that the policy push has a positive effect on firm innovation after the passage of $12^{th}$ Five-Year Plan. In terms of economic magnitude, the enactment of the 12th Five-Year Plan leads to a[16] 28.68% larger increase in the number of patents among firms in lagging provinces compared to firms in leading provinces.

In Columns (2) to (4), I examine the relationship between the policy push and innovation quality. Consistent with the results in univariate tests, the policy pressure increases the number of low-quality patents. When the dependent variable is $LnPatLowCited$ ($LnPatLowValue$), the coefficient on the dummy indicator $Treat$ is 0.200 (0.234) and significant at the 1% level, which means that the application of less cited patents (low-value patents) is more active by 23.38% (30.09%) among firms in high government intervention regions. In contrast, the effect of government intervention on breakthrough innovation (measured by $LnPatTopCited$ and $LnPatTopValue$) is not significant at the conventional level.

[Insert Table 1.7 here]

When I look at the control variables, I find that firm size, R&D intensity, and return on assets are positively related to the innovation outputs, which is consistent with the prior research (see Pakes and Griliches, 1980; Hall and Ziedonis, 2001). Although institutional ownership is unrelated to patent counts, it positively affects the number of

[16] We use the formula $[1 + Mean(Patent)] \times (exp(\beta) - 1)$ to determine the change in patent number for a treated firm. Given the DiD model specification: $Ln(1 + Patent) = \beta Treat + Controls$, the number of patents for a treated firm can be denoted as $exp(\beta + Controls) - 1$, while that of the control firm is $exp(Controls) - 1$.We derive the size of the treatment effect by taking the differences of the two equations above and get: $exp(controls) \times [exp(\beta) - 1]$. Consider the case in which $Treat = 0$, then $1 + Mean(Patent) = exp(Controls)$. As a result, we may estimate the magnitude of treatment effect using $[1 + Mean(Patent)] \times (exp(\beta) - 1)$. When we plug the value into the equation, we get: $(1 + 30.79) \times (e^{0.245} - 1) = 8.83$, which corresponds to 28.68% of the sample mean of *Patent*.

high-value patents, suggesting that institutional investors are better at discovering innovation that generates economic profits. In agreement with Lin et al. (2010), there is a negative relation between firm innovation and product market competition. Although the squared term of competition is positive, the U-shaped relation between competition and firm innovation is only statistically significant for the number of low-value patents and highly cited patents.

### 1.4.3 The Pre-treatment trends assumption

The DiD approach, as explained by Imbens and Woodridge (2009), assumes parallel trends in the outcome variable prior to the exogenous shock. That is, in the absence of the 12th Five-Year Plan, firm innovation should evolve in a similar way between the treatment and control groups. To test this assumption, I follow Bertrand and Mullainathan (2003) and Atanassov (2013) and test the dynamics of innovation surrounding the enactment of the 12th Five-Year Plan by the following Equation:

$$Innovation_{i,t} = \alpha_i + \alpha_t + \beta_1 Before_{i,t}^{-2} + \beta_2 Before_{i,t}^{-1} + \beta_3 Current_{i,t} + \beta_4 After_{i,t}^{1} + \beta_5 After_{i,t}^{2} + \beta_6 After_{i,t}^{3} + \beta_7 After_{i,t}^{4+} + \gamma X_{i,t-1} + \varepsilon_{i,t} \text{ . (2)}$$

Where $Before_{i,t}^{-n}$ is a dummy variable that takes the value of one in $n^{th}$ year before 2011 if firm $i$ is in a lagging province and zero otherwise. $Current_{i,t}$ is a dummy variable equal to one in 2011 if an observation is from the treatment group and zero otherwise. $After_{i,t}^{n}$ is a dummy variable that equals one for treated firms in $n^{th}$ year after 2011 and zero otherwise. $After_{i,t}^{4+}$ is equal to one for treated firms in the fourth year and beyond and zero otherwise. All other control variables are identical to that in Equation (1).

If the pre-treatment trends assumption is valid, I expect $\beta_1$ and $\beta_2$ to be small in magnitude and insignificant. In addition, coefficients on dummies indicating the post-policy years should be statistically significant for the number of patents, the number of less cited patents, and the number of low-value patents, as I only document a significant impact of government intervention on these three measures in the baseline DiD regression.

[Insert Table 1.8 here]

The results presented in Table 1.8 confirm our predictions. First, there is no trend of increasing innovation before the passage of the 12$^{\text{th}}$ Five-Year Plan. The coefficient of $\beta_1$ and $\beta_2$ are statistically insignificant across all regressions. Second, there is no change in the radical innovations captured by highly cited patents and high-value patents in the post-policy period. Third, government intervention has a persistent and positive impact on patent counts and incremental innovations, as shown by the significant and large coefficients of $\beta_3$ to $\beta_7$ in Columns (1) to (3).

Interestingly, the magnitude of $\beta_3$ to $\beta_7$ are almost the same in magnitude for which the dependent variables are $LnPatent$, $LnPatLowCited$, and $LnPatLowValue$, suggesting an immediate and long-lasting effect of the 12$^{\text{th}}$ Five-Year Plan. The significant coefficient on $\beta_3$ for 2011, however, warrants further discussion. Such a surge in 2011 seems to be against a common belief that it takes time for any changes in inputs or incentives to be converted into corresponding changes in outputs. For example, Fang et al. (2017) find the differences in innovation between the treated firms and control firms become significant two years after privatizations. Atanassov (2013) find that antitakeover laws affect U.S. firms' innovation two or more years after passing. Given technological change is a long-term process (Holmstrom 1989; Manso, 2011; Cong and Howell, 2021), my findings indicate that government pressure rather than the risk-taking incentive is behind the patent surge of firms located in less innovative regions after the $12^{th}$ Five-Year Plan.

### 1.4.4 Propensity score matching analysis

My identification strategy treats the before-after changes in control firms' innovation as the counterfactual outcome of treated firms. One concern is the comparability between these two groups, owing to the fact that control firms are more innovative, as evidenced by the univariate tests. To address this concern, I apply the Propensity Score Matching method to construct a matched sample. More specifically, I first estimate a logistic regression to model the probability of being a treatment firm before the policy shock. Aside from the control variables in Equation (1), I also include the patent growth rate as a predictor to ensure the parallel trend of DiD approach (see Fang et al., 2017; Tan et al., 2020). Here the patent growth rate is defined as the mean value of ($LnPatent_{i,t}$-$LnPatent_{i,t-1}$) in the prior 4-year. Next, I match every treatment firm to a control firm with the closest score estimated from the logit regression (without replacement), using a caliper distance of 0.005.

[Insert Table 1.9 here]

I present the covariate balance test in Panel A of Table 1.9. As shown, the firm characteristics between the treated firms and control firms are almost identical, with none of the t-statistics of mean difference test significant at the 10% level. After assessing the matching quality, I then re-estimate the baseline DiD regression using this matched sample. Panel B of Table 1.9 presents the results. The coefficient on the dummy indicator

$Treat$ is statistically and economically significant in Columns (1) to (3) with $LnPatent$, $LnPatLowCited$, and $LnPatLowValue$ as the dependent variable, separately. Even after accounting for sample selection issues, the per-capita policy target has a considerable impact on corporate innovation. For example, the treatment effect on the number of patents is 33.91% in this alternative sample, whereas it is only 28.68% in the baseline sample. Further, the dummy variable $Treat$ is statistically insignificant in Columns (4) and (5), which indicates that the policy push does not influence highly cited and high-value patents.

### 1.4.5 Placebo tests

Although the 12th Five-Year Plan is the first to propose a specific target for patents, it also covers a wide range of socio-economic issues (Hu, 2013). Every Five-Year Plan's particular focus is industry policies. Cen et al. (2020) find that industries encouraged and supported in the Five-Year Plans expand faster. If treatment firms in my study mainly from the Five-Year Plans' targeted industries, industrial preference could potentially drive the increased innovations. Meanwhile, I rely on a single shock that happened in 2011 to establish causality, which may raise the concern that potential omitted variables coinciding with the shock directly affect firm innovation. To rule out these explanations, I conduct two placebo tests: one is exploiting the Eleventh Five-Year Plan's enactment, and the other is randomly assigning treated firms to construct pseudo samples.

As most of the industries supported in the Five-Year Plans are emerging and high-tech industries, two consecutive plans would have considerable overlap in the industry policies. Suppose the industry policies or other planned targets are the driving forces of our baseline results. In that case, I should observe a similar effect to the 11th Five-Year

Plan. To test this proposition, I select a sample following the procedures listed in Section 3.4. The treated firms are defined as those registered in provinces that lag behind the national level in terms of invention patents per 10,000 people in 2006, the year $11^{th}$ Five-Year Plan passed. I restrict the sample period to 2000-2011, so the $12^{th}$ Five-Year Plan does not affect the findings. Panel A of Table 1.10 presents estimates from the baseline DiD regression. As shown, none of coefficients on the dummy variable $Pseudo\ Treat$ are statistically different from zero, implying the shared features of Five-Year Plans do not have a systematic influence on firms' innovation outcomes.

[Insert Table 1.10 here]

If other concurrent events in 2011 are the underlying causes of baseline results, I should detect the treatment effect even in pseudo treatment firms. Following prior studies (see Tan et al., 2020), I run simulations that artificially assign the sample firms to the treatment and control groups. For each simulation, I randomly draw 24 provinces as regions with weak innovation capacity in 2010[17], so firms located there suffer increased policy pressure and fall into the pseudo treatment group. Then, I assign firms in the remaining seven provinces to the pseudo control group. Next, I define a dummy indicator of policy push in the same way as described in Section 3.1 and estimate the baseline DiD regression in this simulated sample. Finally, I repeat this procedure 5,000 times.

[Insert Table 1.11 here]

[17] In 2010, only seven provinces are above the national level in terms of invention patents per 10,000 people: Beijing, Shanghai, Tianjin, Guangdong, Zhejiang, Jiangsu, and Liaoning. The other 24 provinces lag behind the national level, and so their government are more likely to intervene in innovation activities following the $12^{th}$ Five-Year Plan in 2011.

In Table 1.11, I summarize the coefficient estimate of dummy variable $Treat$ and the corresponding t-statistics. I only report the mean, $5^{th}$ percentile, $25^{th}$ percentile, median, $75^{th}$ percentile, and $95^{th}$ percentile for brevity. As shown in the table, the mean and median of simulated DiD estimates are all near to zero and statistically negligible. Moreover, the actual DiD estimate is above the $95^{th}$ percentile of the simulated DiD estimate when the dependent variables are the patent counts, less cited patents, and low-value patents, respectively. This finding suggests that shocks other than the Twelfth FYP are very unlikely to provoke government intervention in firm innovation during our sample period. Thus, the baseline results reported in Table 1.7 are not purely driven by chance.

## 1.5 **Additional Tests**

### 1.5.1 R&D expenditures

The findings reported so far suggest that the per-capita policy target stimulates technological innovation measured by patent counts. However, increased innovations mainly reflect incremental progress rather than technological breakthroughs. To study the channel through which the policy push affects corporate innovation, I look at firm investment in innovation activities. According to Pakes and Griliches (1980), there is a high correlation between the number of patents and R&D spending. Because of government intervention, firms may invest more capital in R&D activities.

I construct four measures of R&D inputs, with missing values set to zero. The first one is natural logarithm of 1 plus a firm's R&D expenditure in a year. The second one is R&D intensity, defined as R&D expenditures divided by total assets. In the third measure, I replace the scaling variable from total assets to the total number of employees. Hall

(2002) mentions that more than half of R&D spending is used to compensate the highly educated scientists and engineers. Therefore, I measure R&D inputs by R&D expenditures per inventor[18]. To examine the relationship between policy push and R&D inputs, I re-estimate the baseline specification with the above four measures as the dependent variable.

[Insert Table 1.12 here]

Column (1) of Table 1.12 shows the impact of government intervention on the size of R&D investment. Although the coefficient on $Treat$ is positive, it is not significant at the conventional level. Columns (2) to (4) also find insignificant coefficients on the dummy variable $Treat$. Overall, the treated firms did not increase their R&D spending relative to that of control firms after the 12th Five-Year Plan. Besides, I find that the lagged R&D intensity has a strong positive relationship with all measures of R&D inputs, consistent with the idea that innovation projects are multi-stage and long-term (see Holmstrom, 1989; Manso, 2011; Cong and Howell, 2021).

The lack of significant positive relationship between the policy push and firm's R&D expenditure warrants further discussion. Our results suggest that government policies aiming to promote innovation could offset by other factors, such as managers' choices and firms' rent-seeking behaviors. Specifically, managers under short-term earnings pressure are unwilling to increase their R&D investment because of its high

[18] Although the data on inventors is publicly available in the U.S., this is not the case in China. Moreover, the rigorous disambiguation of patent inventors is beyond the scope of this research. Hence, I apply a straightforward but conservative method to count the number of inventors in each firm. Specifically, I collect the inventors' Chinese name for patents applied by a firm in a given year. Then, I define the number of inventors as the total amount of unique name in a firm. A potential issue is the duplication of Chinese name, i.e., two or more inventors have the same name. Without other information, I cannot fully solve this problem. Nonetheless, each firm, on average, has 79 inventors every year during our sample period, so the probability of this case is arguably low.

adjustment cost (Hall, 2002). The misaligned incentives between bureaucrats and managers is another impediment to R&D investment. Since government officials are concerned about meeting their patent targets, they may not use the net present value rile to evaluate R&D projects as managers do. Furthermore, The Intellectual Property Rights protection index in Fang et al. (2017) shows that the bottom 14 provinces are in our treatment group[19], while the top 3 regions are all in the control group. Consequently, firms in less innovative regions face a higher risk of piracy and imitation, which could reduce their motivation to pursue R&D.

### 1.5.2 Labor inputs

Labor and human capital are critical inputs of innovation. Holmstrom (1989) points out that all stages of innovation projects involve intensive human efforts. Bhaskarabhatla et al. (2021) compare the relative importance of firm capabilities and the inventor's human capital in firm innovation. They find that inventor-specific skills are 5 to 10 times more important than firm-specific capabilities. Therefore, even without any material changes to R&D investments, manager can encourage more employees to apply for patents. This can prevent companies from reducing their reported income while at the same time acquiring more patents.

To test this proposition, I examine the impact of policy push on the number of inventors and inventor productivity. In particular, I calculate the natural logarithm of one plus the number of inventors who applied for a patent at the firm in the current year. In

[19] See the Table 1: summary statistics on IPR protection index in Fang et al. (2017). Among the provinces ranked in the bottom 14 in terms of average IPR score, only Liaoning has the invention patents (in force) per 10,000 residents exceeding the national average in 2010.

addition, I scale the number of inventors with the total number of employees (in thousands) to ensure the change is not driven by firm size. Following Mukherjee et al. (2017), I generate two measures of inventor productivity. The first one is defined as a logarithm of one plus the number of patents per 1,000 firm employees. The other is the logarithm of one plus the number of patents per inventor.

[Insert Table 1.13 here]

In Columns (1) and (2) of Table 1.13, I find that treated firms indeed have more employees as inventors than control firms do in the post-policy period. Furthermore, Columns (3) and (4) show that each employee produces more patents in the treated firms, and inventors' average innovative productivity is statistically different between the treated and control firms. The economic magnitude of these effects is large. Following the 12$^{th}$ Five-Year Plan, treated firms had a 23% higher percentage of inventors per 1,000 employees and a 15% greater rise in the number of patents per 1,000 employees than control firms did.

These findings corroborate our claim that under government pressure, managers encourage employees to apply for more patents. This, together with the results of R&D expenditures, suggests that firms prefer to trade quality for quantity, thereby increasing the total number of patents to help government officials meet the target. However, because this strategy relies more on employees' tacit knowledge, the increased patents are primarily reflective of incremental innovation. Manso (2011) suggests that breakthrough innovation origins from exploring unknown areas that are likely to fail. The commitment of resource and tolerance of early failure is vital to motivate exploration. In my setting, treated firms are reluctant to invest more in R&D activities. The government sets targets on patents that are often seen as successful discovery outcomes. As a result, managers and employees have little incentive to pursue risky R&D projects.

## 1.6 **Extensions and Robustness Check**

### 1.6.1 SOEs vs non-SOEs

Although less innovative provinces are more likely to interfere with corporate innovation as a result of the $12^{th}$ Five-Year Plan, this intervention should vary with the ownership. In China's stock market, state-owned enterprises (SOEs) account for around two-thirds of the market capitalization (Jiang et al., 2020). Moreover, state ownership allows the government to influence firm behavior for political reasons, such as vote and social stability (see, e.g., Shleifer and Vishny, 1994; Djankov et al., 2003). Existing studies find that Chinese SOEs are more likely than their private counterparts to comply with government incentives[20]. Given the theoretical and empirical evidence that SOEs contribute to government goals, I expect the baseline results to be stronger for SOEs than non-SOEs.

Following the suggestions of Jiang et al. (2020), who argue that the government's mechanisms to intervene in SOEs and non-SOEs are entirely different, I perform the baseline regression in two subsamples. In particular, the SOEs group comprises all firm-year observations in which government entities are the ultimate controller, while the non-SOEs group includes all other observations. To be consistent with the baseline results, I

[20] Chen et al. (2011) show that the investment efficiency is lower among SOEs because government intervenes in them for social and political reasons. Gu et al. (2020) document that the labor cost is stickier in SOEs due to government's concern on unemployment. Chen et al. (2020) find that SOEs are more likely to manage earnings in response to the GDP growth incentives of provincial government.

only include three dependent variables: $LnPatent$, $LnPatLowCited$, and $LnPatLowValue$. Table 1.14 reports the coefficient estimates.

[Insert Table 1.14 here]

Column (1) shows that the dummy indicator $Treat$ is only statistically significant in SOEs' subsample, indicating that government pressure has a greater impact on SOEs' patenting decision than private firms. Interestingly, the coefficient on $Treat$ is 0.299 and significant at 1% level, which means treated SOEs apply for 34% more patents than control firms do in less innovative provinces during the 12th Five-Year Plan. In untabulated results, I verify that this pattern exists for both local and central SOEs.

As shown in Columns (2) and (3), most SOEs' increased innovation is of low quality. When the dependent variable is $LnPatLowCited$, the coefficient on the dummy variable $Treat$ is 0.249 and significant in the SOEs group, but it is not statistically different from zero in the non-SOEs group. This result suggests that around 82.97% (=$(e^{0.254}-1)/(e^{0.299}-1)$) of the additional patents filed by SOEs receive very few citations. After I change the dependent variable to $LnPatLowValue$, the coefficient on $Treat$ is larger and more significant among SOEs than that of non-SOEs. Overall, these results are consistent with our expectation that government interferes with SOEs to file for more patents.

### 1.6.2 The size of employees

In the additional tests, I find that firms commit greater labor force to firm innovation in response to the policy push. Furthermore, there appears to be no major improvement in the quality of R&D personnel for two reasons. First, the analysis in Section 5.1 reveals that treated firms did not raise the R&D expenditures per inventor following the 12th Five-Year Plan. Since the remuneration of highly educated scientists and engineers makes up more than half of R&D spending (Hall, 2002), it is less likely that firms hire more talents to perform R&D while keeping per capita expenses constant. Second, the inventor's productivity seems differ a little between the treatment and control group in the post-policy period, as shown in Section 5.2.

To further distinguish between the quality and quantity of labor contributions, I conduct a subsample analysis based on the size of employees. Every year, I divide all firms into two groups by the median of employees, as recorded in CSMAR. Assume that in companies under government pressure, more employees are encouraged to apply for patents. In that situation, I should only find the baseline results in firms with a huge workforce. I rerun the baseline DiD regression in these two subsamples and present the estimates in Table 1.15.

Consistent with my predictions, the surge in patents counts and low-quality patents only appears in treated firms with more employees following the 12th Five-Year Plan. In particular, the coefficient on the dummy indicator $Treat$ is significant at the 1% level in all subsamples with large employee size but not in firms with fewer employees. Note that I already control log total assets, so this difference is not due to firm size. Meanwhile, the economic magnitude is comparable with the baseline results. Take $LnPatent$ as an example, firms with more employees file for 40% more patents in less innovative provinces during the 12th FYP period.

[Insert Table 1.15 here]

### 1.6.3 Benefits of more patent application

So far, the findings suggest that firms, especially SOEs, favor government officials in patents. The natural question is whether these firms benefit from doing so. Several studies find that government frequently rewards compliant firms with tax deductions, bank loan preferences, and subsidies[21]. In this study, I focus on government subsidy for two reasons. Starting from 2007, all publicly traded companies need to disclose the details of government subsidies they have received. Moreover, the subsidy has been an important policy tool used by the Chinese government to promote technological innovation. Fang et al. (2018) show that R&D subsidies make up around 1% of Chinese GDP over 2005-2015. I collect information on government subsidies from CSMAR and then examine whether treated firms receive more grants using the following regression model:

$$Subsidy_{i,t} = \alpha_i + \alpha_t + \beta_1 LnPatent_{i,t} \times Treat_{i,t} + \beta_2 LnPatent_{i,t} + \beta_3 Treat_{i,t} + \gamma' X_{i,t-1} + \varepsilon_{i,t}. \quad (3)$$

Where $Subsidy_{i,t}$ is the natural logarithm of government subsidies divided by total assets and the missing value is set to zero. The definition of dependent variables is similar to Equation (1). The variable of interest is the interaction term, which captures the extra government subsidies granted to treated firms with more patent applications. In addition, I undertake a subsample analysis by ownership to examine whether this relationship varies between SOEs and non-SOEs.

[Insert Table 1.16 here]

[21] Gu et al. (2020) show that government officials subsidize SOEs with more asymmetric labor cost adjustment to sales changes, i.e., firms increase labor faster when the business expands and reduce the labor slower when business shrinks. Chen et al. (2020) find that provincial governments give higher subsidies and allot more loans to firms with boosted earnings that helps officials to meet GDP growth targets.

Table 1.16 reports the regression results. In the pooled sample, I find that the interaction term is significantly positive (*t-statistics*=3.88), suggesting that treated firms indeed receive more subsidies for their increased patenting. When I divide the sample into two groups, the documented positive relationship is positive and statically significant among SOEs. For non-SOEs, there is a positive relationship, although it is not statistically significant.

These findings shed new light on the allocation of innovation resources in China. Wei et al. (2017) show that state-owned firms get more subsidies yet are less effective in innovation activities than private firms, which they point to the government's discretion in subsidies for research and development. My study further suggests that the reciprocal relationship between government officials and firm managers in SOEs is a potential source of resource misallocation. Consistent with this idea, Fang et al. (2018) document that the anticorruption campaign begun in 2012 has reduced the distortions in government subsidies for innovation, as the influence of innovative efficiency (defined as the ratio of patent counts to R&D expenditures) on government subsidies increased following the campaign. Nonetheless, in response to the government intervention outlined in 12$^{th}$ Five-Year Plan, some firms have increased their number of patent filings, while keeping their R&D inputs relatively unchanged, which naturally results in more low-quality patent outputs. The fact these firms are able to receive more government subsidies than others suggests that the per-capita policy target has not only shifted firms' patenting activities toward low-quality outputs but has also led to a misallocation of government funding.

### 1.6.4 Robustness checks

In this section, I undertake several robustness tests to demonstrate that our primary conclusions are not affected by other confounding factors. First, lagging provinces with rapid economic growth and a large number of research institutes may see greater innovation activity, which could be the driving forces behind the patterns we observe. I consider several additional control variables related to provincial economic conditions: GDP per capita, GDP growth rate, population, and university density. I estimate the baseline DiD specification by including these additional control variables and present the results in Table 1.17. After considering the variations in local business conditions, my major conclusions remain mostly intact. In particular, the coefficients on dummy variable $Treat$ are positive and highly significant, for which the dependent variable is $LnPatent$, $LnPatLowCited$, and $LnPatLowValue$, respectively. These results indicate that policy push caused by the patent target in 12$^{th}$ Five-Year Plan is per se a significant factor driving the increased firm innovation.

In the second robustness check, I change the cutoffs used to rank patents. Given the scarcity of technology breakthroughs, prior studies only use the top 1% of most-cited patents to measure breakthrough innovation (see, e.g., Balsmeier et al., 2017; Byun et al., 2021). Therefore, we redefine the $LnPatTopCited$ ($LnPatTopValue$) as the logarithm of one plus the number of patents falls into the 99$^{th}$ percentile of the citation (value) distribution within their type-technology class-year. I also use a lower cutoff-the bottom 20%-to construct the measures of incremental innovation: $LnPatLowCited$ and $LnPatLowValue$. Notice that $LnPatLowCited$ includes patents never received forward citations until 2018. Using these four newly developed measures, I find that the baseline results remain the same, as shown in Table 1.18.

In the last check for robustness, I consider a different notion of policy push. In the baseline analysis, I characterize policy push as a dummy variable of one for firms located in lagging provinces that were behind the national average (1.72) in invention patents per 10,000 people in 2010. As the per capita policy target puts more pressure on provinces that lack infrastructure and human capital for science and technology, government incentives to increase patent counts should be stronger among more lagging regions. In this test, I define the policy push for firms located in lagging provinces that had fewer invention patents per 10,000 people than the national median (0.89) in 2010. Table 1.19 gives the empirical results using this modified definition of treatment and the findings are the same as in the baseline study.

## 1.7 **Conclusions**

This paper exploits an exogenous shock to establish a causal relationship between policy push and corporate innovation. The Chinese 12$^{th}$ Five-Year Plan, which was enacted in 2011, sets a target to double the invention patents per 10,000 people by 2015, encouraging less innovative provinces to catch up with their peers. I posit and verify that the incentive to fulfil planned targets increases government intervention in firms' innovation activities. Using a DiD approach, I find a positive and sizable increases in the number of patents generated by Chinese firms in lagging provinces. However, the majority of these increased patents are incremental innovations rather than technological breakthroughs. A more intriguing pattern is that firms do not increase their R&D investment but devote more workforce to file patent applications. The subsample analyses reveal that the baseline results are more pronounced among SOEs and firms with more employees. Finally, I show that treated firms, especially SOEs, receive more government subsidies.

Given the critical role of technological innovation in economic development and the positive externalities of R&D investment, it is unsurprising that central and local governments are responsible for science and technology policies. However, some specific policy targets may be ill-designed and trigger unintended consequences, because government officials perform insufficient policy analysis and are subject to bureaucracies and corruption. My findings suggest that firms adapt their innovation activities to help local official meet the planned targets and earn rewards from local governments. Given the absence of influential patents generated by these policy inducements, Chinese government's goal to stimulate indigenous innovation and economic growth may turn out leading local leaders and businesses in the wrong direction. More importantly, when government officials allocate subsidies based on firms' patent counts, they may misallocate resources and distort the distribution of human capital.

# Chapter 2 Local Inventors and Corporate Innovation

## 2.1 Introduction

Corporate innovation is vital to companies' long-term growth and competitive advantage (Solow, 1957; Porter, 1992). In the risky and multi-stage process of innovation projects, inventors' human capital contributes far greater to innovation performance than firm capabilities, such as organizational capital (Liu et al., 2017; Bhaskarabhatla et al., 2021). As a result, a firm's innovativeness depends on its ability to access and hire talented workers (see Bhaskarabhatla et al., 2021). Throughout 1975-2000, a typical private firm in the U.S. has inventors located in only 1.5 commuting zones[22], while public firms, on average, have inventors located in 12 different commuting zones (Matray, 2021). This sharp contrast suggests that, for firms with less geographically diversified R&D activities, the headquarter location would affect their ability to screen and attract inventors.

Extant literature often implicitly assumes that there is a national market for talents, and so labor mobility can eliminate the effect of firm location. However, inventors are inclined to stay in the same geographical region when they change jobs, and this tendency further accelerates the localization of knowledge spillovers (Carlino and Kerr, 2015; Lychagin et al., 2016). The clusters of innovation also complicate the impact of location. Notably, the geographical concentration of innovation activities intensifies the pressure for innovation production within a cluster (Porter and Stern, 2001). If firms have no R&D

[22] A commuting zone is a cluster of counties with strong commuting ties. It is the lowest level of geography for local labor markets. In 2000, there were 709 commuting zones delineated for the U.S. See Matray (2021) for more information about the Commuting Zone.

facilities elsewhere, they would be more sensitive to innovation inputs contest like inventors both within and outside of a cluster. Overall, regarding the role of headquarter location on inventors and firm innovation, the ambiguous theoretical predictions warrant a thorough empirical investigation.

Given the challenge to collect the financial and patenting information of U.S. private firms, I turn to public firms in China. According to the data, Chinese public firms have a mean value of 1.5 provinces[23] to host their inventors over 2000-2012, compared to the 31 provinces in mainland China. The concentrated R&D activity among Chinese listed firms is analogous to that of U.S. private firms in the early days. Furthermore, the inventor mobility is restricted by the household registration (*hukou*) system that attaches most social welfare to a person's *hukou* status instead of the psychical location. As a result, an inventor who changes job to another place may risk losing public services, including education benefits, health care, housing subsidies, and social security coverage (Song, 2014). This kind of policy is prevalent in many developing countries but is less common in developed nations, where the immigration policy may affect the flow of foreign inventors[24]. Combining the two unique features mentioned above, I believe China provides a desirable context to explore the influence of location on inventors and firm innovation.

I assemble two newly developed datasets to construct a sample for the empirical analysis. The geographic location for inventors is retrieved from the Geocoding of

[23] A province is equivalent to a state in the U.S. Usually, a province encompasses prefectures and counties, but the four provincial-level municipalities-Beijing, Tianjin, Shanghai and Chongqing-only have district-level divisions. As of 2020, mainland China has 31 provinces.

[24] See Kerr and Kerr (2020) for a discussion about the immigration policy and U.S. innovation.

Worldwide Patent Data (GWPD) project. de Rassenfosse et al. (2019) devise a uniform algorithm to identify inventors' address from the patent documents in nine national, regional, and international patent databases and then use it to allocate the precise geographic coordinates. Their approach only counts the first filing of a patent family that protects the same invention in many jurisdictions. In doing so, inventors' patenting activity is not limited within their homeland, and the information of inventor location strictly corresponds to the unique invention. Compared to the U.S. patent inventor database (Li et al., 2014), the GWPD project does not disambiguate individual inventors over time. Instead, it contains the information on individual inventors shown on the original patent documents. The patent information of Chinese public firms is collected from Lin and Yu (2020). Their data project covers all invention and utility model patents granted to listed firms and their subsidiaries from 1990 to 2018. This dataset's advantages are twofold: First, it includes the number of inventors and citation counts for all patents, both backward and forward. Second, Lin and Yu (2020) estimate each patent's economic value, which offers an ex-ante measure of a new invention's quality.

To link the firm location with inventors, I calculate the number of inventors around the corporate headquarter. Specifically, I construct a new variable by taking the natural logarithm of one plus the number of local inventors, defined as those located within a 100-km radius centered on the corporate headquarter in a given year. Inventors from the focal firm are excluded so that this measure only reflects the pool of skilled labor out of the firm. In this work, I focus on innovation measured by the patent quality because of its widespread interest[25], yet my results hold even if raw patent counts model innovation[26]. Following Almeida et al. (2021), I construct the first measure of patent quality, which is calculated by summing up the value of invention and utility model patents filed by (and eventually granted) a firm in the year then scaled by lagged total assets. The second measure of patent quality is the logarithm of one plus the total number of citations received by these patents. I also use the fixed-effects approach recommended by Hall et al. (2001) to alleviate citations' truncation bias.

During the sample period of 2000-2013, a representative firm has around 2,500 inventors nearby, and there is a wide variation of local inventors across provinces. The economically developed regions, their neighbors, and several inland provinces have more local inventors, but Guangdong is the exception. Its five neighboring provinces, including the coastal one-Fujian, all fall into the bottom half in terms of local inventors, suggesting the existence of an innovation cluster and competition for talents. I then adopt the pooled OLS model to examine the effect of local inventors on firm innovation. The baseline results show that local inventors' coefficients are positive and significant after controlling for a vector of covariates, meaning more inventors near headquarters enhance patent quality. Not only is this relationship statistically significant at the 1% level, but the economic magnitude is also sizeable. Specifically, a one-standard-deviation increase in local inventors is associated with a 20% (14.6%) increases in the patent value (patent citations). Furthermore, I verify that neither industrial-technological breakthroughs nor

[25] China's official news agency, China Daily, published an article titled "High quantity, low quality: China's patent boom" on June 23, 2014. Meanwhile, the 2014 U.S. Special 301 Report claimed that the large numbers of Chinese utility model/design patents are of low quality. In 2018, a Bloomberg news article contended that most Chinese patents are worthless despite China holds the largest number of patents in the world.

[26] The empirical results is attached in the Table 2.12 for reference.

government policies cause the documented positive effect, even after considering the location's fixed effects.

I also examine the effect of local inventors on a firm's innovative search strategy captured by the breakthrough innovation. Compared to incremental innovations, breakthrough innovations involves more exploration and a combination of diverse ideas, so firms pursuing them face a greater risk of failure and need long-term commitment of resources (e.g., Manso, 2011, Acemoglu et al., 2020). By providing professional services and facilitating knowledge flows, local inventors can decrease these adverse effects and stimulate breakthroughs. I measure breakthrough innovation by the number of patents that fall into the top 1 (10) percentile of the citations distribution in the same type-technology class-year (see Bhattacharya et al.,2017; Balsmeier et al., 2017; Byun et al., 2021). Consistent with my conjecture, the results from pooled OLS and Poisson regressions show a significant positive effect of local inventors on the number of impactful patents. Meanwhile, I find that mature firms produce fewer breakthrough innovations.

To establish the causality, I implement a two-stage least squares regression by instrumenting local inventors with per capita mining output in each province. Chinitz (1961) argues that areas endowed with rich mineral and coal deposits often lack entrepreneurship. This argument receives empirical support from Glaeser et al. (2015), who find that cities close to historical mining deposits experience diminished entrepreneurship in industries unrelated to mining. In a recent study, Guo et al. (2020) show that per capita mining output is negatively correlated with industrial clusters and private firms' portion in the clusters. Because most inventors are employees of firms, I expect the number of outside inventors should relate to per capita mining output. Besides, each province's mining deposits are geographically determined, so they are exogenous to firm innovation. Consistent with the notion that the mining industry dampens entrepreneurship and innovation, the first stage regression demonstrates a significantly negative correlation between local inventors and per capita mining output. In the second stage, I find similar results as the baseline study. Particularly, the coefficient on instrumented local inventors is 0.023 (*t-statistics* = 2.41) for patent value and 0.269 (*t-statistics* = 3.63) for patent citations. In terms of breakthrough innovations, the coefficients on instrumented local inventors are significant at the 1 per cent level.

I propose two possible channels to justify the baseline findings: skilled labor supply and the escape of market competition. Carlino and Kerr (2015) suggest that inventors' spatial cluster improves the match between inventors and firms. I expect the labor supply is more critical for firms in industries demanding skilled workers. To test this proposition, I partition the baseline sample into two groups based on the status of innovative firms and the number of inventors in the industry. The subsample analysis reveals that the baseline results are more robust and pronounced for firms from innovative sectors, and the Chi-square test significantly refuses the equivalence of coefficients in the innovative- and non-innovative group. The second channel is the escape of market competition. Firms can invest more in R&D to alleviate the competitive threats (Aghion et al., 2005; Hombert and Matray, 2018), and so via which local inventors can promote innovation. I use two measures of product market competition (HHI index and the four-firm concentration ratio) to split the baseline sample. If my conjecture is true, the baseline result should be significant among subsamples with more market competition. Indeed, the positive relationship between local inventors and firm innovation mainly exist in these groups, suggesting that the spatial cluster of inventors help firms to escape innovation through R&D.

In the robustness checks, I conduct a battery of tests to address the sample selection and model specification concerns. The baseline results between local inventors and firm innovation remain significant and valid across these tests. To shed more light on local inventors' effect, I take advantage of the patent family data to gauge inventor quality. Prior studies point out that inventor quality is an essential determinant of firm innovation (see Liu et al., 2017; Bhaskarabhatla et al., 2021; Yoon, 2020). Putnam (1996) finds that applicants often protect their valuable inventions in foreign countries. In line with this finding, I define inventors with first filing abroad as high-quality ones. For robustness, I restrict the high-quality inventors to those who made the first filing in the U.S. Patent and Trademark Office (USPTO) or World Intellectual Property Organization (WIPO) because they are the major destinations of the foreign application. I then use the proportion of high-quality local inventors to examine the effect of inventor quality on firm innovation. The empirical results demonstrate that inventor quality significantly strengthens the effect of local inventors on firm innovation. For example, with a one-standard-deviation increase in the proportion of high-quality inventors, the effect of local inventors on patent value rises by 50%.

A natural implication of my findings is that firms should accumulate more talents to benefit from local inventors. Ultimately, it is R&D personnel inside the firm who invent and develop the patents. On the one hand, a sufficient supply of local inventors allows firms to choose the best match for innovation projects. On the other hand, to absorb knowledge spillovers from local inventors, firms need to hire more workers that are educated. Using the proportion and number of innovators (educated employees) to reflect human capital accumulation, I find that firms indeed have more innovators and workers with a bachelor's degree or above if surrounded by more outside inventors. This result lends support to my argument at the beginning that firm location affects their access to inventors.

I also compare local inventors' effect with that of remote inventors, who are those situated 100-200 km (200-300 km) away from the corporate headquarter. Interestingly, the average number of remote inventors is less than that of local inventors, regardless of the broader spatial coverage of the former. Given that firms benefit from local inventors through the regional labor market for inventors and the localization of knowledge spillovers while suffering from competition for innovation production, I expect a different impact of remote inventors. This expectation receives empirical support, as firm innovation is negatively correlated with remote inventors located in 100-200 km, but this relationship is insignificant when I change the definition of remote inventors to those located in 200-300 km. These findings imply that the competition for innovation production dominates knowledge spillovers and job matching among remote inventors, while the sparsity of inventors in distant area weakens this competitive threat.

To get more insights on the overall effect of local inventors, I finally examine whether and how the economic value of patents transforms into operating performance, which is measured by the earnings before interest, tax, depreciation, and amortization (EBITDA). I document a positive association between patent value and earnings growth. Furthermore, after decomposing the EBITDA change to the changes in market share, market size, and profit margin, I find that the underlying driving forces are the increased market share and profit margin. These results indicate that less local inventors could indirectly undermine firm performance and market share through the innovation channel. Because firms rarely relocate their headquarters, the geographical diversification of a firm's R&D facilities helps overcome the disadvantage of location.

This study contributes to several strands of the literature. First, my work belongs to a growing body of research that examines the impact of human capital, especially inventors, on firm innovation. Liu et al. (2017) and Bhaskarabhatla et al. (2021) compare the relative importance of inventors' human capital and firm capabilities on corporate innovation. They find that inventors' effect is 5-10 times larger than that of firms in accounting for the difference in innovation performance. Yoon (2020) study how the loss of inventors caused by the WWI draft affects firm innovation and finds that the loss of high-quality inventors decreases the knowledge production within the focal firm and other firms in the same county. Islam and Zein (2020) examine CEOs' role with experience as inventors in a firm's innovation activities. Their results show that firms generate high-quality innovation if led by inventor CEOs. Chemmanur et al. (2019) show that top management quality positively affects firm innovation and exploration. These studies have uncovered various interplays between innovation and insiders' human capital, but I extend this line of investigation beyond the firm boundary. By looking at external inventors, I reveal that local inventors enhance the patent quality and spur breakthrough innovation, while their effect varies with the geographical distance.

Second, my findings add new evidence to the existing literature on geography's relevance for firm behaviour. In particular, I show that, for firms with concentrated R&D

facilities, the headquarter location might limit their access to inventors and impede firm innovation. In a related paper, Jia and Tian (2018) find that the headquarter location affects a firm's access to the United State Patent and Trademark Office, further delays the time-to-grant-patent and materialization of the innovation output. Lychagin et al. (2016) demonstrate that geographic location matters to a firm's productivity and R&D spillovers. Nonetheless, its researchers' location is more important than the headquarter location because large firms often have research labs in many regions. Chen et al. (2020) explore the impact of headquarter relocation in China and show that firm productivity and innovation improve after moving to Shanghai and Shenzhen but worsen after relocating to Beijing.

Third, this study offers a new perspective to understand the impact of labor on the rise of China's innovation. "The advantage for companies pursuing innovation in China is the abundance of young, relatively cheap talent," said a report by Financial Times in 2013. This viewpoint echoes the finding by Kong et al. (2020). They show that the higher education expansion policy in 1999 pumped out college-educated labors and increased firm innovation in skilled sectors. However, I demonstrate that the distribution of inventors is uneven across the country so that the benefits may be concentrated among a small group of firms. Besides, Chen et al. (2020) examine the effect of rural-urban migration on innovation by exploiting the staggered loosening of the city-level household registration system. They show that the migration of low-skilled labors from rural areas to urban centers hurts firm innovation. On the contrary, my findings imply that the relaxation of the household registration system could facilitate the mobility of high-skilled inventors and improve innovation quality.

The rest of the paper is organized as follows. The next section introduces data and presents descriptive statistics. Section 2.3 reports the main empirical results. In section 2.4, I examine the possible channels through which local inventors affect firm innovation. Section 2.5 provides a series of robustness checks and further analysis. The last section concludes the paper.

## 2.2 **Data and Descriptive Statistics**

### 2.2.1 Measuring local inventors

I collect the geographic coordinates for inventors from the "Geocoding of Worldwide Patent Data" (GWPD) at the Harvard Dataverse repository[27] (de Rassenfosse et al., 2019). This dataset contains the location information of 7 million inventors and applicants for 18.8 million first filing of invention patents across 46 countries between 1980 and 2014. de Rassenfosse et al. (2019) collect the data from nine major patent databases in the world, such as the PATSTAT, WIPO, and REGPAT.

Because of the restriction on accessing the official database in China, they resort to another data source[28] for the first applicant's address and use it to locate inventors if the first filing is in China. Notice that the Chinese patent office does not require the applicants to declare the address of inventors, so most inventors share the location with their applicant. For those patents invented in China but file the first application in foreign countries, the address information of inventors is available in PATSTAT and REGPAT.

[27] The data can be accessed through https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/OTTBDX

[28] Yin. D. Y., Motohashi, K., Dang, J. W. (2020). Large-scale Name Disambiguation of Chinese Patent Inventors (1985-2016), Scientometrics, 122, 765–790.

The coverage of this dataset is quite extensive, as 91% of the first filings by Chinese inventors during 2000-2009 has detailed location information.

Since the data generation process relies on the address information shown on the original patent document, each observation represents an inventor who contributes to the patent rather than the innovator per se. In other words, an inventor who appears in ten patent documents would be recorded in ten observations. Equivalently, a patent document with ten inventors would also generate ten observations. As a result, I can regard each observation as a quality-adjusted measure of inventors.

To construct a proxy for local inventors (used interchangeably with the number of local inventors), I focus on those inventors located near the firm's headquarter. We retrieve the latitude and longitude of headquarters from CSMAR. The geodesic distance between inventors and the corporate headquarter is calculated using the Vincenty equations (Vincenty, 1975). Empirically, I define a local inventor as one whose location is within a 100-km radius centered on the corporate headquarter in a given year[29]. Furthermore, I deduct innovators of invention patents in the focal firm from local inventors so that this measure merely reflect the pool of skilled labor out of the firm. I then take a natural logarithm transformation to make it closer to a normal distribution.

[Insert Figure 2.1 here]

Figure 2.1 shows a provincial map of China and demonstrates regional variations of local inventors. I use the raw number of local inventors averaged across the sample period for all firms with headquarter in the same province for ease of presentation. The

[29] My results are robust to the choice of length of radius. For example, the results are robust if I shrink the radius to 80-km.

differences across provinces are considerable, despite that local inventors' definition does not rest on the administrative border. Consistent with the perception that economically developed regions attract talents, the number of local inventors is much higher in Guangdong, Shanghai, Jiangsu, Beijing, and Tianjin. Provinces near these regions and some inland provinces also have more inventors. One exception is Guangdong, four neighboring provinces including the coastal one-Fujian, all fall into the bottom half in terms of local inventors.

### 2.2.2 Measuring innovation

Existing studies mainly use patent counts to measure corporate innovation in China (see Fang et al., 2017, Tan et al., 2020). In this work, I am more interested in the patent quality, which has been a pressing issue as it has attracted much attention at home and abroad. To this end, I use two standard indicators of patent quality, namely, patent value and patent citations.

In particular, I follow Almeida et al. (2021) to construct a measure of patent value- $PatVal_{i,t}$, which is calculated by summing up the value of invention and utility model patents filed by (and eventually granted to) firm $i$ in year $t$ and then scaled by lagged total assets. I generate another metric using citation count- $LnCit_{i,t}$, which is defined as the logarithm of one plus the total number of citations received by these patents. Since patent accumulates citations for a long time, the latest patent cohort is inevitably getting smaller citations and thus suffering a truncation problem. To address this bias, I divide the raw number of citations by the average number of citations received by patents in the same technology class and application year (see Hall et al., 2001).

The patent information used in this work is retrieved from the data project developed by Lin and Yu (2020), who merge Chinese listed firms and their subsidiaries with patent data from two official sources: the CNIPA and SIPOP[30]. This dataset covers all patents granted to public firms from 1990 to 2018 and contains rich information about patents, such as backward and forward citations. One unique feature of this dataset is the economic value of invention and utility model patents, which they estimate, in the same spirit of Kogan et al. (2017), by the appreciation of market value around patent grants.

### 2.2.3 Other variables

Following Almeida et al. (2021), I construct a set of firm-level control variables, with all data from the China Stock Market & Accounting Research Database (CSMAR). Size is the natural logarithm of total assets. Book-to-Market is the book value of equity divided by the market value of equity at the end of each fiscal year. R&D is research and development expenditure scaled by total assets (missing values are replaced with zero). Leverage is the book debt divided by total assets. Cash is the ratio of cash and cash equivalents to total assets. Tangibility is the net fixed assets divided by total assets. ROA is net income divided by total assets. Firm age is the natural logarithm of the number of months since it has been listed on the exchange. Moreover, I include two additional factors affecting the innovation outputs: institutional ownership and product market competition (see Aghion et al. 2005; Aghion et al., 2013). I incorporate several province-level variables in the regression analysis to control the regional difference in social-economic features, such as the university density and GDP growth rate.

[30] CNIPA stands for the National Intellectual Property Administration, which is the official intellectual property administrator in China. SIPOP is the State Intellectual Property Operating Platform, a website sponsored by CNIPA to facilitate the IP rights trading, which can be accessed through http://www.sipop.cn/.

### 2.2.4 Sample selection and descriptive statistics

I select the sample period based on the coverage of the inventor location. As mentioned earlier, the inventor location is widely available since 2000, so I start from this year. Meanwhile, given the examination of invention patent applications in China involves two rounds lasting for 18 to 36 months (see Fang et al., 2017), I assume it takes two years on average to grant an invention patent. Indeed, the number of inventor locations in the GWPD database drops dramatically after 2012. Since all explanatory variables are lagged by one year, the sample period ended in 2013.

Following prior studies, I drop firms with ST (special treatment) status as they bear the risk of delisting. Firms from financial service and utilities are also obsoleted, which I identify using the industry classification implemented by the China Security Regulatory Commission (CSRC) in 2012[31]. After the sample selection, I get 17,211 firm-year observations from 2,428 unique firms over 2000-2013.

[Insert Table 2.1 here]

Table 2.1 gives the summary statistics of the variables used in the baseline analysis. I winsorize all continuous variables at the 1$^{st}$ and 99$^{th}$ percentile to alleviate the impact of outliers. On average, the patent value is equivalent to 6.4% of total assets. A typical firm has roughly 2,500 (exp(7.824)) inventors within 100-km of its headquarter, and local inventors' distribution is well balanced as the mean is close to the median. Since listed firms are required to disclose the R&D expenses only after 2006, and I replace the missing

[31] The industry classification of listed companies promulgated by CSRC in 2012 contains 17 industries, which is coded with Latin letters A, B, C… Each industry is further decomposed into different classes that are indicated by two-digit Arabic numerals like 01. I use the first digit to identify the industry. For example, letter "D" and "J" represent the financial service and utility industry respectively. Because most firms are in the manufacturing industry, I use the first two digits of the CSRC industry code for these firms to keep the industry size comparable.

value with zero, the average R&D-to-assets is only 0.58% for the whole sample, while this value has increased to 1% during 2007 to 2012.

## 2.3 **Main Empirical Results**

### 2.3.1 Patent quality

I begin the empirical analysis by exploring how firm innovation varies with local inventors. In the next section, I examine the effect of local inventors on the innovative search strategy. Finally, I solve the endogeneity problem with an instrumental variable approach. The baseline model specification is as follows.

$$Y_{i,t+1} = \alpha + \beta Inventors_{i,t} + \gamma' Contorls_{i,t} + \Lambda_{i,t} + \varepsilon_{i,t+1}. \quad (4)$$

In which $i$ indicates a firm, and $t$ indicates the year. $Y_{i,t+1}$ is one of the two measures of innovation. The variable of interest is $Inventor_{i,t}$, the log number of inventors near the corporate headquarter. $Contorls_{i,t}$ is a vector of control variables, including firm characteristics as well as two provincial socio-economic features. In the baseline regression, $\Lambda_{i,t}$ includes the year, industry, and province fixed effects. To mitigate the concern of omitted variables, I also include two other sets of fixed effects in varying specifications.

[Insert Table 2.2 here]

Table 2.2 reports the estimated results. In Column (1), I find that the coefficient of local inventors is significantly positive at the 1% level, indicating more inventors near headquarter enhance patent value. The magnitude of this effect is sizable, as a one-standard-deviation change of local inventors increases the patent value by 0.013 (0.006*2.154), which accounts for about 20% of the sample mean (0.064). When I set the dependent variable to patent citations in column (4), the positive effect of local inventors is still significant and large. A one-standard-deviation increase of local inventors is accompanied by 0.15 (0.068*2.154) additional forward citations, 14.6% of the sample mean (1.029).

The above results reveal a positive relationship between local inventors and the quality of firm's innovation outputs. However, industrial-technological breakthroughs could attract skilled labors to conduct R&D, and the resulted innovative outcomes could worth more. Alternatively, local governments may stimulate specific industries through policies such as tax breaks, subsidy, or preferential treatment. Therefore, these industries would experience a change in both inventors and patents. To rule out these possibilities, I include year by industry and year by province fixed effects in the second specification. The results in Columns (2) and (5) suggest that they do not drive the documented effect. In the third specification, I further control time-invariant firm attributes by firm fixed effects, and the baseline results still hold.

Among the control variables, the estimated results are generally consistent with existing studies. For example, there is a positive relationship between institutional ownership and firm innovation, which is similar to Aghion et al. (2013). Moreover, I document an inverted-U relationship between patent value (patent citations) and product market competition, which is firstly reported by Aghion et al. (2005).

### 2.3.2 Innovative search strategy

In this section, I examine the impact of local inventors on a firm's innovative search strategy. In particular, I investigate whether local inventors promote breakthrough innovation. This type of innovation breaks new ground for future innovation and thus is critical to firm growth and economic development. Unlike the incremental innovation that exploits existing knowledge, breakthrough innovation involves more exploration into new areas and a combination of diverse ideas (see Benner and Tushman, 2002; Manso et al., 2011; Acemoglu et al., 2020). Accordingly, firms pursuing it face a greater risk of failure and need a long-term commitment of resources. Local inventors could play a significant role in mitigating these adverse effects by providing professional services and facilitating knowledge flows.

As breakthrough innovation opens new avenues for future research, the corresponding patents would frequently get citations. Following Balsmeier et al. (2017) and Bhattacharya et al. (2017), I measure breakthrough innovation by the number of radical patents that fall into the top 1$^{st}$ (10$^{th}$) percentile of the citations distribution in the same patent type, 3-digit IPC class, and application year. I adopt the baseline specification to estimate the relationship between local inventors and breakthrough innovation. The dependent variable is the natural logarithm of one plus the impactful patents (LnPatTop1 and LnPatTop10). To ensure the results are not sensitive to the skewness of patent counts' distribution, I estimate the regression using both the pooled OLS and Poisson models.

[Insert Table 2.3 here]

Table 2.3 presents the empirical results. I find that the number of radical patents is positively correlated with local inventors in all specifications, suggesting that local inventors promote breakthrough innovation. Among the control variables, firm size, R&D expenditure, and institutional ownership all positively affect breakthrough innovation. However, firms with more tangible assets and cash holding and older firms have less radical patents, indicating that mature firms undertake less risky R&D projects.

### 2.3.3 Identification strategy

Although the number of local inventors is largely exogenous to firm innovation, the usual endogenous concerns may impede us from establishing a causal relationship. First, other firms located nearby hire most outside inventors, and these firms may have a supplier-customer link with the focal firm. Chu et al. (2019) document that supplier-customer geographic proximity has a positive effect on supplier innovation. As the connection between the focal firm and their neighboring corporations is unobservable, the results may suffer the omitted variable problem. Second, inventors in the neighborhood could be talents whom focal firms cultivated with valuable technological opportunities, so reverse causality surfaces.

I implement a two-stage least squares regression by instrumenting local inventors with per capita mining output in each province to address these issues. The idea behinds this IV can be traced back to Chinitz (1961), who argues that areas endowed with rich mineral and coal deposits often lack entrepreneurship. Glasser et al. (2015) empirically test this hypothesis and find that cities close to historical mining deposits experience diminished entrepreneurship in industries unrelated to mining. Furthermore, Guo et al. (2020) show that per capita mining output is negatively correlated with industrial clusters and private firms' portion in the clusters. Since most inventors are employees of firms, the number of outside inventors should also relate to per capita mining output. By contrast, a province's mining deposits are geographically determined and thus are exogenous to firm innovation.

I retrieve the mining output of each province from the China Mining Yearbook, which publishes this data since 2001, so the sample period is from 2001 to 2013. I estimate the following 2SLS model.

[1st stage] $Inventors_{ijpt} = \alpha + \beta Per\ capita\ mining\ output_{pt} + \gamma' Z_{ijpt} + \lambda' K_{pt} + \mu_j + \upsilon_t + \varepsilon_{ijpt}$,

[2nd stage] $Y_{ijpt+1} = \alpha + \beta Inventors\ (IV)_{ijpt} + \gamma' Z_{ijpt} + \lambda' K_{pt} + \mu_j + \upsilon_t + \varepsilon_{ijpt+1}$. (5)

Where $i$ indicates a firm, $j$ indicates the industry, $p$ indicates the province where the corporate headquarter locates, and $t$ indicates the year. I include the same set of firm-level control variables as the baseline regression. Since the identification relies on the continuous variation in mining deposits, I do not control for province fixed effects. Instead, I add two additional provincial variables-population and GDP per capita- to account for time-varying socio-economic factors that may affect firm innovation.

[Insert Table 2.4 here]

Panel A of Table 2.4 gives the results of the first-stage regression. I find that the number of local inventors has a strong and negative relationship with per capita mining output in each province, supporting the notion that the mining industry dampens entrepreneurship and innovation. The Kleibergen-Paap Wald F-test for instrument strength is highly significant (F-statistic = 103.80, p-value < 0.001), so the weak identification is refused. In panel B of Table 4, I estimate the second-stage regression. The results show that the coefficient on instrumented number of local inventors is 0.023 (*t-statistics* = 2.41) for patent value and 0.269 (*t-statistics* = 3.63) for patent citations. The positive relationship between the instrumented local inventors and breakthrough innovations is also significant at the 1 per cent level. Collectively, these findings are consistent with the baseline results, confirming that the number of local inventors has a significantly positive influence on the patent quality and exploratory patents.

## 2.4 **Possible Channels**

### 2.4.1 Skilled labor supply

Intuitively, the spatial cluster of inventors generates a thicker labor market around corporate headquarters, which would improve the match between inventors and firms (see Carlino and Kerr, 2015). On the one hand, inventors can easily find new jobs in local companies, avoiding the loss of the family's *hukou* and the need to relocate. On the other hand, a rich pool of talent allows firms to hire competent inventors at lower costs, especially for these firms in the knowledge-intensive industry. In a recent study, Kong et al. (2020) find that the expansion of higher education in China increases the supply of educated workers, which significantly affects firm innovation in skilled industries. If labor supply is a channel through which local inventors affect firm innovation, I should expect a more robust baseline result among firms in industries demanding skilled workers.

To test this conjecture, I conduct a subsample analysis on innovative industry and industries with more inventors, respectively. In particular, I follow Fang et al. (2018) to select innovative firms from the following sectors (industry code from the 2012 CSRC industrial classification guideline is in parentheses): petro-chemicals (C25-C26), pharmaceuticals (C27), metals and materials (C28-C33), machinery and equipment (C34-C37), electronics (C38-C40), and information technology (I63-I65). Thus, firms not in these sectors fall into the non-innovative industries. The process of identifying industries with more inventors is divided into three stages. First, due to the patent document records each inventor's Chinese name, I define the number of inventors as the total amount of unique name in a firm every year[32]. Second, I calculate the average number of inventors across all firms (within an industry) as a proxy for the industry's inventor counts. At last, I partition all industries into two groups by the median of this measure per year and estimate the baseline specification for each of these subsamples.

[Insert Table 2.5 here]

In Panel A of Table 2.5, where the grouping variable is the innovative industry, I find that local inventors positively affect patent quality, but only for firms from innovative sectors. The coefficient on local inventors is significant at the 1% level in the innovative group. Yet, it is insignificantly different from zero in the non-innovative group. Moreover, the difference in the magnitude of coefficients is remarkable. For example, the coefficient in Column (1) is 0.008, while it is only 0.001 in Column (2), and the Chi-square test refuses the equivalence of them at the 5% level. Panel B of Table 2.5 gives the results of subsample analysis based on industry's inventor counts. Similarly, I document a strong positive relationship between local inventors and firm innovation in groups with more inventors. Overall, the empirical results provide evidence to the conjecture that increased supply of skilled labor helps firms to benefit from more local inventors.

### 2.4.2 Escape-competition

Despite the comparative advantages provided by successful innovation, firms could underinvest in R&D for other reasons and thus reducing the importance of local inventors.

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[32] A potential issue is the duplication of Chinese name, i.e., two or more inventors with a same name. Without other information available, I cannot distinguish inventors with the identical name. However, each firm, on average, has 26 inventors every year over the sample period, so the probability of this case is arguably low.

When faced with severe product market rivalry, this type of underinvestment may have negative effects. For example, Hombert and Matray (2018) find that US firms that have invested less amounts in R&D are more vulnerable to the rising import competition from China. Aghion et al. (2005) argue that firms can innovate more to escape competition and gain greater profits. If this is the case, local inventors should have a bigger role to play among firms under greater competitive pressure. Therefore, I propose that the second avenue via which local inventors promote firm innovation is by escaping competition.

Following the industrial organization literature, I develop two commonly accepted indices of product market competition. The first one is the Herfindahl-Hirschman Index, computed by squaring the market share of each firm competing in the same industry and then summing the numbers. The second one is the four-firm concentration ratio, which is the sum of the market shares of the top four companies in a given industry. Both measures reflect the degree of market concentration, so a larger value means that the market is less competitive[33]. To test my proposition, I split the whole sample into two groups by the median of each indicator per year and then estimate the baseline regression in the subsamples.

I expect a more pronounced relationship between local inventors and firm innovation in subsamples with more market competition, because the spatial cluster of inventors help firms to escape competition through R&D. Indeed, I find that the baseline results are more substantial and significant among firms that fall into the group with greater market

[33] I acknowledge that these two measures only capture competitive pressure in the product market. As Porter and Stern (2001) point out, firms within a cluster face various pressure to innovate, such as the peer pressure, customer pressure and constant comparison. In other words, these factors could also be the channel through which local inventors stimulate firm innovation.

competition. When the dependent variable is patent value, local inventors' coefficient is around 0.008 and significant at the 1% level in both panels. A similar pattern appears when the dependent variable changes to patent citations, and I find the coefficient of local inventors is 0.074 and significant at the 1% level. Furthermore, the Chi-square test indicates that these results become weaker among firms face less competition. Overall, the empirical findings support my claim that local inventors stimulate firm innovation through competitive pressure.

## 2.5 **Robustness and Further Analyses**

### 2.5.1 Robustness checks

In this section, I conduct a battery of test to check the robustness of my findings. First, I change the screening criteria of the baseline sample to address the sample selection problem. Second, I check whether the baseline results are robust to different model specifications. Table 2.7 presents the estimated results, where I only list the coefficient of local inventors on the patent quality and its *t-statistics*. All regressions are based on the model in Column (1) of Table 2.2. I cluster the standard errors at the firm level and report results from the baseline study to facilitate comparison.

In Row (1) of Table 2.7, I consider the impact of leading technology and innovation hubs in China: Beijing, Shanghai, and Shenzhen. Arguably, firms located in these cities are more innovative and surrounded by plenty of innovators. To ensure firms in these three cities do not drive the baseline results, I exclude them from the sample and find that the baseline results still hold. Firms may relocate their headquarters for the desired resources. For example, Chen et al. (2020) find that firms with headquarter relocated to Beijing receive increased political favors. Likewise, the relocation can help firms access the skilled labor market. To deal with this self-selection bias, I drop firms with headquarter moved across cities during the sample period. Results in Row (2) of Table 2.7 show that the prior finding is robust to this concern.

The baseline sample involves firms without patents, which may raise the concern that these firms adopt other mechanisms to protect inventions, such as secrecy and lead-time (see Cohen et al., 2000). Thus, the baseline results may overestimate the effect of local inventors. I address this concern by removing firms never patented during the sample period, and the results in Row (3) of Table 2.7 reveal that the effect of local inventors does not change.

Due to the lack of patent citations and patent value, prior studies capture patent quality difference by distinguishing invention and utility model patents (see Fang et al., 2017; Tan et al., 2020). Even though my study measures patent quality directly, I re-estimate the baseline model using invention (utility model) patents for robustness check. Row (4) and (5) show that the baseline findings exist regardless of the patent type. In the last check of sample selection, I deal with the R&D expenses required to disclose since 2007. After I restrict the sample period to 2007-2013, the sample size drops by around 40%, yet the coefficient of local inventors is still significant in Row (6) of Table 2.7.

[Insert Table 2.7 here]

Next, I show that the baseline results are robust to a series of model specifications. Prior studies suggest that the geographic distribution and incentive for innovation differ between state-owned enterprises and private firms (see Fang et al., 2017). In the baseline regression, the control variables do not include a dummy variable of state ownership. In

Row (7) of Table 2.7, I include the state ownership[34] in controls and find a consistent result with the baseline study.

It is well documented that innovation and production activities are clustered spatially (Audretsch and Feldman, 1996), while this clustering may mean a correlation of R&D activity geographically. As Petersen (2009) points out, the residuals correlated across a particular direction would underestimate the standard errors of OLS estimation, and the clustered standard errors can correct this bias. Following his suggestion, I check the robustness of the baseline result by clustering the standard errors at the firm- and city-level. Results in Row (8) of Table 2.7 show that the baseline finding is robust to this clustering.

Since the industrial cluster affects the number of local inventors and the focal firm's innovation through knowledge spillovers (Audretsch and Feldman, 1996), I consider its effects in Row (9) of Table 2.7. In particular, I follow Engelberg et al. (2018) to identify clustered-firm with a dummy variable, which equals one if the city includes five or more firms in the same industry and zero otherwise[35]. I find that controlling for industrial cluster does not alter the results.

Finally, I present results for different definitions of the primary explanatory variable. To reflect the extent of a firm's exposure to local inventors, I generate a dummy variable by partitioning local inventors into two groups using the sample median. Row (10) of Table 2.7 shows that the coefficients of the dummy indicator are significant at 5% or

[34] The sample size decreases because the data is only available in CSMAR since 2003.

[35] Engelberg et al. (2018) identify the clustered-firm using a binary variable, which takes a value of 1 if a firm's MSA includes 10 or more firms with the same 3-digit SIC, and 0 otherwise. I do not choose 10 as threshold because the number of Chinese listed firm is around 2,000 during 2000-2013.

better. Moreover, the size of the coefficient suggests that having a large number of local inventors boosts the patent value by 1.9 percent, which is about one-quarter of the sample mean. I also change the geodesic distance from 100-km to 80-km when calculating the number of local inventors, and the results in the last row of Table 2.7 remain equally strong.

### 2.5.2 The Effect of local inventors' quality

Innovation is a process mainly driven by a few inventors' talents and inherent characteristics (Liu et al., 2017). Bhaskarabhatla et al. (2021) find that the importance of inventors' human capital is 5-10 times larger than firm capabilities in accounting for the difference in inventor output. Yoon (2020) show that the innovation rates of firms suffer more from losing high-quality inventors than the loss of other inventors. In this study, I document the positive effect of local inventors on firm innovation. Since the primary explanatory variable only measures the number of inventor-patent pairs outside the firm, the baseline results shed little light on the effect of inventor quality.

In addition, the dearth of information about inventors prevents us from constructing conventional proxies, which relies on the idea that citations per patent are a good indicator of innovation quality. For example, Byun et al. (2021) define a U.S. inventor as a superstar inventor if her patents receive an average number of citations per patent that fall into the 99$^{th}$ percentile among all inventors. Chemmanur et al. (2019) directly measure inventors' quality by the citations per patent for the patents filed by (and eventually granted to) them.

Fortunately, the GWPD database collects geographic coordinates for every inventor who appeared in the first filing of a patent family, including all patents granted to the same invention from different jurisdictions. In the innovation literature, the patent family size is one of the widely used patent quality measures because patents that are more valuable tend to seek protection in many countries (see Putnam, 1996, Lanjouw et al., 1998). Although the GWPD database does not provide information about the patent family size, it shows the jurisdiction where the first filing is made. I exploit this feature to construct two measures of inventor quality by the following procedures.

Firstly, I count the number of inventors whose first filing is not in China's National Intellectual Property Administration but placed within 100-km around the corporate headquarter. Similarly, I compute the number of inventors whose first filing is made to the U.S. Patent and Trademark Office (USPTO) or World Intellectual Property Organization (WIPO), as they are the major destinations. Secondly, to remove the double-counting bias from foreign applications by the firm per se, I deduct the number of inventors who locate within 10-km of the corporate headquarter. Thirdly, I define the first measure of inventor quality-*Foreign*-as the ratio of inventors with first filing abroad to total outside local inventors. The second measure is defined as inventors with first filing in USPTO or WIPO scaled by total outside local inventors, and I denote it by *US&WIPO*. I believe these two measures capture inventor quality because filing the first application in the foreign patent office means the patent is comparable with its counterparts in technologically advanced countries like the U.S.

To examine the effect of local inventors' quality on firm innovation, I create an interaction term between local inventors and the above two measures. Specifically, I estimate the following model.

$$Y_{i,t+1} = \alpha + \beta Inventors_{i,t} + \gamma Foreign_{i,t} + \mu Inventors_{i,t} \times Foreign_{i,t} + \rho' Contorls_{i,t} + \Lambda_{i,t} + \varepsilon_{i,t+1}. \quad (6)$$

Where $Y_{i,t+1}$ is either the patent value or patent citations, $Inventors_{i,t}$ is the logarithm of one plus the number of local inventors. $Foreign_{i,t}$ is the measure of inventor quality, yet I also change it to *US&WIPO* in the empirical tests. All the control variables and fixed effects are identical to the baseline specification.

[Insert Table 2.8 here]

Table 2.8 reports the estimated results. The dependent variable is patent value in Columns (1) and (2), while it changes to patent citations in Columns (3) and (4). I find that the interaction term is all positive and significant at the 1% level except for two specification, indicating that the inventor quality enhances the effect of local inventors on firm innovation. Moreover, when I restrict the inventors to those files for the first application in USPTO or WIPO, the marginal effect of inventor quality becomes even larger. This comparison is evident with the patent value as an instance. During the sample period, the mean value of *Foreign* and *US&WIPO* are 0.025 and 0.022, respectively. The coefficients of $Inventors$ and the $Inventors \times Foreign$ interaction term indicate that the average effect of local inventors is 0.006 (0.003+0.111*0.025). With a one-standard-deviation increase in $Foreign$ (0.027), the effect of local inventors increases to 0.009 (0.003+0.111*(0.025+0.027)), which is equal to a 50% rise in the magnitude. By contrast, with a one-standard-deviation increase in *US&WIPO* (0.024), the effect of local inventors would increase by 66%. As *US&WIPO* is a refined measure of inventor quality, this comparison means that improving the quality of local inventors matters to the firm innovation. Although the detailed computation is not reported for patent citations, a similar pattern exists as well. Taken together, I conclude that inventor quality strengthens the effect of local inventors.

### 2.5.3 Local inventors and human capital accumulation

Although I document a positive relationship between firm innovation and local inventors in the baseline, it is R&D personnel inside the firm invent and develop the patent[36]. Moreover, during the long process of innovation projects, intensive labor inputs are indispensable for all stages, including invention, development, and completion (Holmstrom, 1989). Hall (2002) mention that half or more of R&D expenditure is the compensation to highly educated scientists and engineers. Given the importance of skilled labor in firm innovation, I expect a firm's human capital accumulation has a positive relationship with the number of local inventors.

As discussed in the channel tests, firms can screen local inventors to choose the matched personnel for innovation projects, which would lead to more inventor mobility. At the same time, they can hire educated workers who can join the R&D group and learn from local inventors. Ideally, I can capture inventors' movement if I know their employment history, just like the net inflow of inventors used by Chemmunar et al. (2019). However, the GWPD database does not provide inventors' working experience, and the disambiguating inventors are out of the scope of this study. Therefore, following Kong et al. (2020), I use employees' education level and inventors to reflect the human capital accumulation of firms.

[36] Some firms could outsource the R&D activities to other agencies nearby. This possibility may bias us from finding significant relationship between local inventors and firm's human capital accumulation.

In particular, I collect the employees' education background from the Resset database, which is also the source used by Kong et al. (2020). I set the value as missing if the data is not available for a given firm in a year. The total number of employees of each firm is collected from CSMAR, which has a more exhaustive coverage than Resset. I then calculate the number (*Bachelor*) and share (*Bportion*) of employees with a bachelor degree or above, as well as the number (*Innovator*) and share (*Iportion*) of innovators. To examine the relationship between local inventors and firms' human capital accumulation, I re-estimate the baseline regression but change the dependent variable to one of these four measures.

[Insert Table 2.9 here]

Table 2.9 reports the empirical results. In all four specifications, the coefficient on local inventors is positive and significant at the 1% level, confirming my conjecture that firms tend to benefit from local inventors by recruiting more talents. I also find that R&D intensity has a significantly positive effect on the employee's education level and innovators, which indicates that skilled workers are the critical driver of firm innovation.

### 2.5.4 Local inventors versus remote inventors

It is interesting to compare the effect of local inventors with that of remote inventors, as this comparison would further uncover the impact of firm location. There are several reasons for a remarkable difference. First, the inventor mobility is more likely to occur locally. Lychagin et al. (2016) suggest that inventors tend to find new jobs in the same geographical region. This phenomenon is especially prevailing in China, where the residence registration (*hukou*) system binds the residential address with social welfare, including housing, health care, and education benefit (Song et al., 2014). Second, the localization of knowledge spillovers rests on local inventors rather than remote ones. Third, these two groups may compete for innovation production. Consequently, the competition in technological opportunities and skilled labors, such as college graduates, would undermine the focal firm's innovation.

I generate two measures of remote inventors. The first one is equal to the natural logarithm of one plus the number of inventors located between 100-km and 200-km around the firm headquarter. The second one is equal to the natural logarithm of one plus the number of inventors located between 200-km and 300-km. Following the same procedure in measuring local inventors, I compute the number of inventors within 200-km and 300-km of corporate headquarters separately. It is worthwhile to mention that I count inventors in circles of different radius, so the spatial coverage of remote inventors is more extensive than that of local inventors. Interestingly, the average number of inventors located within 100-200 km (200-300 km) from headquarters is 1,825 (1,789), while the number of local inventors is around 2,500. This stark disparity indicates a concentration of inventors.

[Insert Table 2.10 here]

I use the baseline model to test the effect of remote inventors on firm innovation, and the empirical results are shown in Table 2.10. Columns (1) and (4) compare local inventors with remote inventors based on 100-200 km. I find a negative and highly significant relationship between remote inventors and patent value, which is opposite to the relationship between local inventors and firm innovation. A similar relationship exists between patent citations and remote inventors, though it is marginally significant at the 10% level. To test whether the adverse effect hold in longer distance, I change the definition of remote inventors to those situated in 200-300 km. As shown in Columns (2) and (5), the negative relationship between remote inventors and firm innovation is statistically insignificant. In sum, these findings show that the competition for innovation production dominates the supply of skilled labor and the escape of market competition among remote inventors, who undermine the innovation quality of focal firms. Nonetheless, the sparsity of inventors in distant area weakens this competitive threat.

### 2.5.5 Innovation and firm operating performance

Thus far, my findings show that local inventors, even though they are external to the firm, can increase both the economic and scientific value of patents. A further question is whether the economic value of patents transforms into operating performance. The answer to this question is important in two aspects. By linking patent value with performance, I provide more evidence to the argument that the headquarter location matters to a firm because of its exposure to local inventors. Besides, this work uses the newly developed patent value to measure innovation quality. Lin and Yu (2020) have established a strong correlation between patent value and forward citation counts, but they do not examine whether patent value affects firm performance. The results here can supplement their estimation and add confidence to my argument.

I use earnings before interest, tax, depreciation, and amortization (EBITDA) to measure firm performance. To figure out the driving force of performance changes, I follow Becker and Ivashina (2019) to decompose EBITDA into three components as follows.

$$\Delta EBITDA_{ijt} = \Delta\left(Revenue_{ijt} \times Margin_{ijt}\right) = \Delta(Market\ Size_{ijt} \times Market\ Share_{ijt} \times Margin_{ijt}) \approx \Delta Market\ Size_{ijt} + \Delta Market\ Share_{ijt} + \Delta Margin_{ijt}. \quad (7)$$

Where $i$ indicates the firm, $j$ indicates the industry, and $t$ indicate the year. $Market\ Size_{ijt}$ is the sum of operating income of all firms in the same industry, and $Market\ Share_{ijt}$ is the share of a firm's revenue in its industry. I adopt a new model specification to identify the effect.

$$\Delta Y_{it+1} = \alpha + \beta PatVal_{it} + \gamma' Controls_{it} + \mu_i + \upsilon_t + \varepsilon_{it+1}. \quad (8)$$

Where $Y$ is one of the four measures of firm performance, and $Patval$ is the sum of patent value scaled by lagged assets. All regression models include the lagged dependent variable in the controls to account for the serial correlation. Table 2.11 gives the empirical results.

[Insert Table 2.11 here]

In Column (1), I find a significant positive association between patent value and earnings growth, indicating that firms achieve better performance from high-quality innovation. The results in Columns (2) to (4) further show that the increase in market share and profit margin are the main drivers of this positive relationship. Surprisingly, I find that patent value is negatively related to the change in market size, although the relation is not statistically significant. This result could happen when most patents comprise process innovation that helps the firm to reduce production costs. Even without market expansion, innovative firms can occupy a broader market and earn more profits. Accordingly, based on these results, local inventors could have a far-reaching effect on firm performance through the innovation channel.

## 2.6 **Concluding Remarks**

This study investigates the relationship between firm innovation and local inventors, defined as the ones located near the corporate headquarter. My research focuses on China- the largest developing country, with institutional barriers to labor mobility and concentrated corporate R&D activities. Exploiting a unique dataset on inventors' geographic coordinates and newly developed measure of patent value, I find that the quality of firm innovation outputs is positively correlated with the number of local inventors, indicating that they enhance the focal firm's R&D activity. Moreover, this result is robust to a battery of tests, and the instrumental variable regression using per capita mining output in each province suggests that this positive relationship is causal. In the channel test, I reveal that the baseline results mainly exist among innovative and competitive industries. Further analysis also finds compatible results in several extensions of the baseline study. In conclusion, this paper contributes to our understanding of the role of local inventors in corporate innovation as well as how the location of a firm's headquarter influences its creativity.

The findings of this paper also has several implications for firms and governments. First, R&D-intensive firms could enhance their innovation performance by establishing research and development facilities in regions with more inventors, thus maximizing the benefits of accessing talents. Second, to counteract the negative impact of *hukou* system on inventor mobility, the government might provide subsidies to firms to help them attract high-skilled workers. Lastly, the government can encourage firms to utilize local human capital by increasing market competition.

# Appendices

### Appendix. 1. A Variable Definition

| Variable | Definition and data source |
| --- | --- |
| **Panel A: Dependent variables** | |
| LnPatent | Natural logarithm of one plus the number of utility models and invention patents filed by (and eventually granted to) firm $i$ in year $t$. Source: CNIPA. |
| LnPatLowCited | Natural logarithm of one plus the number of patents with zero forward citation or in the bottom 30$^{th}$ percentile of the adjusted nonself-citation distribution among all patents with the same 3-digit IPC technology class, patent category, and application year. Source: SIPOP. |
| LnPatLowValue | Natural logarithm of one plus the number of patents that fall into the bottom 30$^{th}$ percentile of the economic value distribution among all patents with the same 3-digit IPC technology class, patent category, and application year. Source: Lin and Yu (2020). |
| LnPatTopCited | Natural logarithm of one plus the number of patents in the top 10$^{th}$ percentile of the adjusted nonself-citation distribution among all patents with the same 3-digit IPC technology class, patent category, and application year. Patents with zero citations are excluded. Source: SIPOP. |
| LnPatTopValue | Natural logarithm of one plus the number of patents that fall into the top 10$^{th}$ of the economic value distribution among all patents with the same 3-digit technology class, patent category, and application year. Source: Lin and Yu (2020). |
| Inventors | Natural logarithm of one plus inventors appeared in the patent documents filed in a given year. Source: CNIPA |
| Iportion | The proportion of inventors among the whole employees of a firm (in thousands). Source: CNIPA and Resset. |
| Ln(1+R&D) | Natural logarithm of one plus the research and development (R&D) expenditure (in millions of RMB) of firm $i$ in year $t$. Source: Annual Reports and CSMAR. |
| R&D per Inventor | The ratio of R&D expenditures to inventors. I set the missing variable into zero. Source: CNIPA and CSMAR. |
| R&D per Employee | The ratio of R&D expenditure to employees. I set the missing variable into zero. Source: CSMAR and Resset. |
| Patent per Inventor | The ratio of total number of utility model and invention patents over the number of inventors. Source: CNIPA |

| | |
|---|---|
| Patent per Employee | The ratio of total number of utility model and invention patents over the number of employees (in thousands). Source: CNIPA and CSMAR. |
| Subsidy | Natural logarithm of the ratio of government subsidy to total assets. I set the missing variable to zero. Source: CSMAR. |
| R&D/GDP | The ratio of R&D expenditure in a given province divided by the gross domestic product (GDP). Source: China Statistical Yearbook. |
| ΔPatent | The growth rate of patent applied and provided with a material examination in a province. Source: China Statistical Yearbook. |
| ΔInvention | The growth rate of invention patent applied and provided with a material examination in a province. Source: China Statistical Yearbook. |
| ΔUtility | The growth rate of utility models applied and provided with a material examination in a province. Source: China Statistical Yearbook. |
| ΔDesign | The growth rate of design patent applied and provided with a material examination in a province. Source: China Statistical Yearbook. |
| **Panel B: Independent variables** | |
| Treat | Dummy variable that equals one in 2011-2016 if a firm is registered in provinces with fewer invention patents per 10,000 people than the national average in 2010, and zero otherwise. Source: China Statistical Yearbook and CSMAR. |
| Size | Natural logarithm of total assets. Source: CSMAR. |
| BTM | The book value of equity divided by the market value of equity at the end of each fiscal year. Source: CSMAR. |
| R&D | The ratio of R&D expenditure to total assets (missing values are set to zero). Source: Annual Reports and CSMAR. |
| Leverage | Total liabilities over total assets. Source: CSMAR. |
| Cash | Cash and cash equivalents divided by book assets. Source: CSMAR. |
| Tangibility | Property, plant, and equipment divided by book assets. Source: CSMAR. |
| IO | The percentage of shares outstanding owned by institutional investors at the end of the fiscal year. Source: CSMAR. |
| ROA | Return on assets is defined as net income divided by total assets for each fiscal year in percentage. Source: CSMAR. |
| SOE | Dummy variable that is equal to one if the ultimate controller of a firm is a government-owned entity or a government agency, and zero otherwise. Source: Annual Reports and CSMAR. |

| | |
|---|---|
| Age | The natural logarithm of one plus the number of months the firm has been listed on the exchanges. Source: CSMAR. |
| Competition | One minus the Herfindahl index by total sales within the firm's CSRC (2012) industry classification. Source: CSMAR. |
| GDP growth rate | The nominal growth rate of gross domestic product (GDP) of each province. Source: China Statistical Yearbook. |
| Population | Natural logarithm of the resident population in each province, where the unit of the resident population is 100,000. Source: China Statistical Yearbook. |
| GDP per capita | Natural logarithm of the ratio of GDP to the number of residents. Source: China Statistical Yearbook. |
| University density | The ratio of four-year universities to the number of residents. Source: China Statistical Yearbook. |
| Industrial output/GDP | The ratio of industrial output to GDP. Source: China Statistical Yearbook. |

**Appendix. 2. A Variable Definition**

| Variable | Definition and data source |
|---|---|
| **Panel A: Dependent variables** | |
| PatVal | Sum of the economic value of patents filed in year t (eventually granted) scaled by lagged total assets. Source: Yu and Lin (2020). |
| LnCit | Natural logarithm of one plus the sum of citation counts across all patents filed in year t. I adjust the forward citations by removing the technology-year fixed effects. Source: SIPOP. |
| LnTop1 | Natural logarithm of one plus the number of patents falls into the top 1$^{st}$ percentile of the citation distribution among all patents within the same patent type, 3-digit technology class, and application year. |
| Lntop10 | Natural logarithm of one plus the number of patents falls into the top 10$^{th}$ percentile of the citation distribution among all patents within the same patent type, 3-digit technology class and application year. |
| Bachelor | Natural logarithm of employees with a bachelor degree or above. I set the value as missing if the data is not available. Source: Resset. |
| Bportion | The proportion of employees with a bachelor degree or above. I set the value as missing if the data is not available. |
| Innovator | The natural logarithm of inventors appeared in the patent documents filed in a given year. |

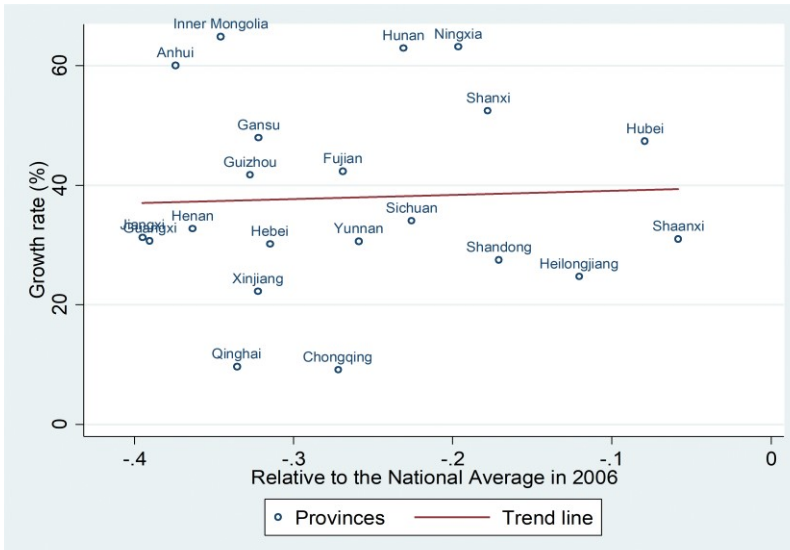
| | |
|---|---|
| Iportion | The proportion of inventors among the whole employees of a firm. |
| Chg_ebitda | The growth rate of earnings before interest, tax, depreciation and amortization from year t-1 to year t. Source: CSMAR. |
| Chg_mktsize | The growth rate of EBITDA in the industry that the focal firm belongs to. Source: CSMAR. |
| Chg_share | The growth rate of the market share of the focal firm in the industry that it belongs to. Source: CSMAR. |
| Chg_margin | The growth rate of the profit margin of the focal firm from year t-1 to year t. Source: CSMAR. |
| **Panel B: Independent variables** | |
| Inventors | The difference between the number of inventors around 100KM of the corporate headquarter and the number of inventor in the focal firm. I then take the natural logarithm of it plus one. Source: de Rassenfosse et al. (2019). |
| Inventors_dummy | I sort the number of inventors into two groups by the sample median and set the dummy variable equal to one for the top half and zero for the bottom half. |
| Inventors (100-200km) | The difference between the number of inventors around 100KM of the corporate headquarter and that of inventors around 200KM of the corporate headquarter. I then take the natural logarithm of it plus one. Source: de Rassenfosse et al. (2019). |
| Inventors (200-300km) | The difference between the number of inventors around 200KM of the corporate headquarter and that of inventors around 300KM of the corporate headquarter. I then take the natural logarithm of it plus one. Source: de Rassenfosse et al. (2019). |
| Size | The natural logarithm of total assets. Source: CSMAR |
| BTM | The book value of equity divided by the market value of equity at the end of each fiscal year. Source: CSMAR. |
| R&D | The ratio of R&D expenditure over total assets and the missing value is replaced with zero. Source: CSMAR. |
| Leverage | Total liabilities over total assets. Source: CSMAR. |
| Cash | Cash and cash equivalents divided by book assets. Source: CSMAR. |
| Tangibility | Property, plant, and equipment divided by book assets. Source: CSMAR. |
| IO | The percentage of shares outstanding owned by institutional investors at the end of the fiscal year. Source: CSMAR. |
| ROA | Return on assets is defined as net income divided by total assets for each fiscal year in percentage. Source: CSMAR. |
| Firm age | The natural logarithm of one plus the number of months the firm has been listed on the exchange. Source: CSMAR. |
| SOE | A dummy variable that equals one if the ultimate controller of a firm is a government-owned entity or a government agency, and zero otherwise. The government agency includes the central government, local government at the provincial, municipal, county, and other institutions. Source: CSMAR. |

| | |
|---|---|
| Competition | One minus the Herfindahl index by total sales within the firm's CSRC(2012) industry. Source: CSMAR. |
| Population | The natural logarithm of the resident population in each province and the resident population unit is 100,000. Source: China Statistical Yearbook. |
| GDP growth | The nominal growth rate of gross domestic product (GDP) of each province. Source: China Statistical Yearbook |
| GDP per capita | Natural logarithm of the ratio of GDP to the number of residents. Source: China Statistical Yearbook. |
| University density | The number of four-year colleges divided by the number of the resident population. Source: China Statistical Yearbook |
| Per capita mining outputs | The per capita mining outputs in each province and the unit is 100. Source: China Mining Yearbook. |

**Figure 1.1 Gap to the National Average and Growth Rate of Patent Application**

The following two graphs display the relationship between the growth rates in the number of all patents filed by industrial enterprises in each province during the 11th Five Year Plan (FYP) and the 12th FYP periods. We only include provinces that lag behind the national average in the number of invention patents per 10,000 people in 2006 (Panel A) and 2010 (Panel B). The x-axis denotes each province's invention patents per 10,000 people relative to national average (0.49 and 1.7) in 2006 and 2010 in Panel A and Panel B, respectively. The following outlier provinces are excluded: Panel A [Hainan (173.89%) and Tibet (-25.84%)]; and Panel B ([Tibet (386.89%)]. Data source: China Statistical Yearbook of Science and Technology.

**Panel A. Growth Rates in Numbers of All Patents in 2006-2010**




**Panel B. Growth Rates in Numbers of All Patents in 2011-2015**

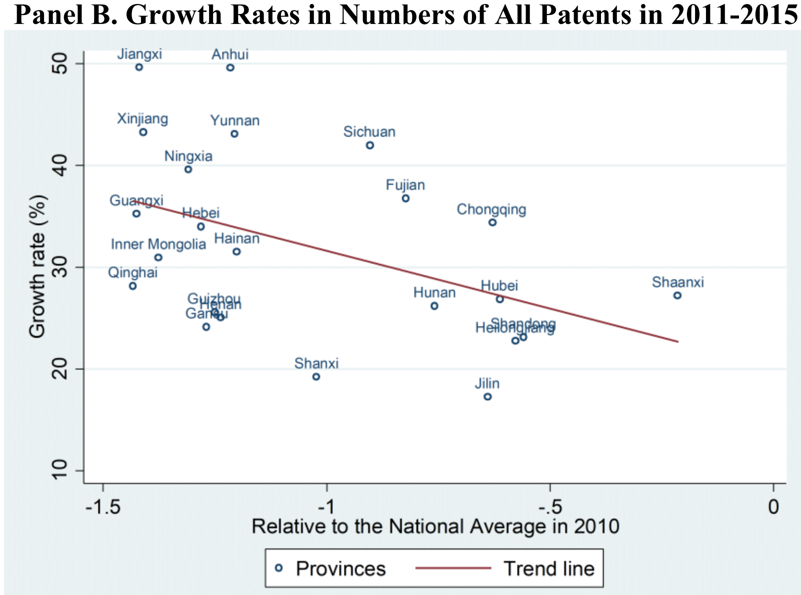
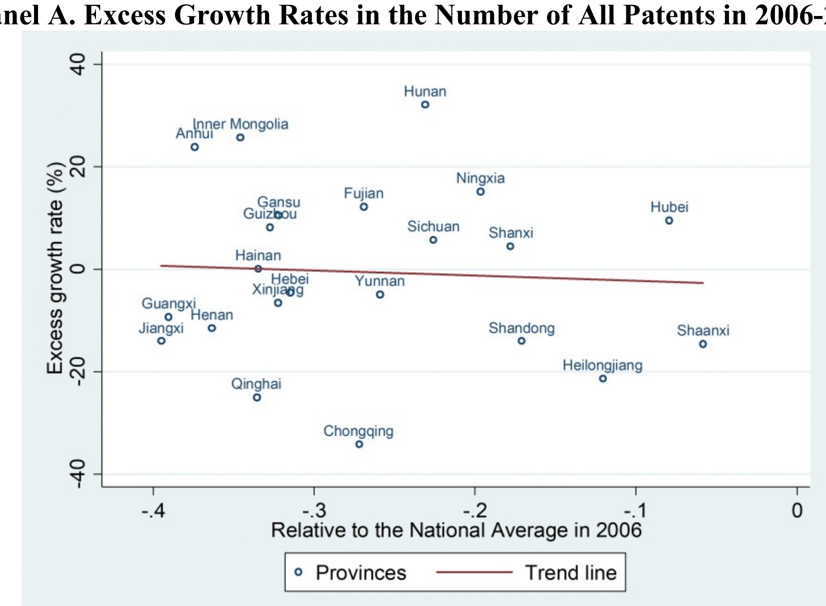


**Figure 1.2 Gap to the National Average and Excess Growth Rate of Patent Application**

The following two graphs display the relationship between the excess growth rates in the number of all patents filed by industrial enterprises in each province during the 11th Five-Year Plan (FYP) and the 12th FYP periods. We only include provinces that lag behind the national average in the number of invention patents per 10,000 people in 2006 (Panel A) and 2010 (Panel B). We first calculate the patent growth rates for each province in 2006-2010 (2011-2015) in the 11th (12th) FYP period, and then calculate the difference between each province's growth rate and those of its adjacent provinces. The x-axis denotes each province's invention patents per 10,000 people relative to national average (0.49 and 1.7) in 2006 and 2010 in Panels A and B, respectively. Both panels exclude one outlier (Tibet). Data source: China Statistical Yearbook of Science and Technology.

**Panel A. Excess Growth Rates in the Number of All Patents in 2006-2010**




**Panel B. Excess Growth Rates in the Number of All Patents in 2011-2015**

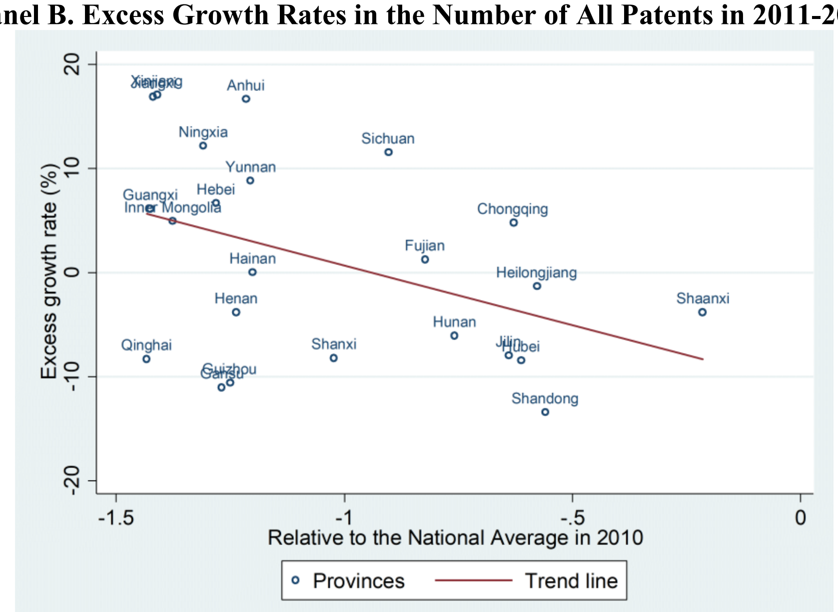


**Figure 2.1 The Distribution of Local Inventors across China**

The following provincial map demonstrates the distribution of local inventors across the country from 2000 to 2012. Local inventors are defined as outside inventors located within 100-km of the corporate headquarter. I first calculate the annual average of local inventors for all listed firms headquartered in the same province and then graph the time-series averages of each province. Notice that the sample only includes firms listed on the Shanghai and Shenzhen stock exchanges, and the province-level results are divided into four groups that are based on quartiles.

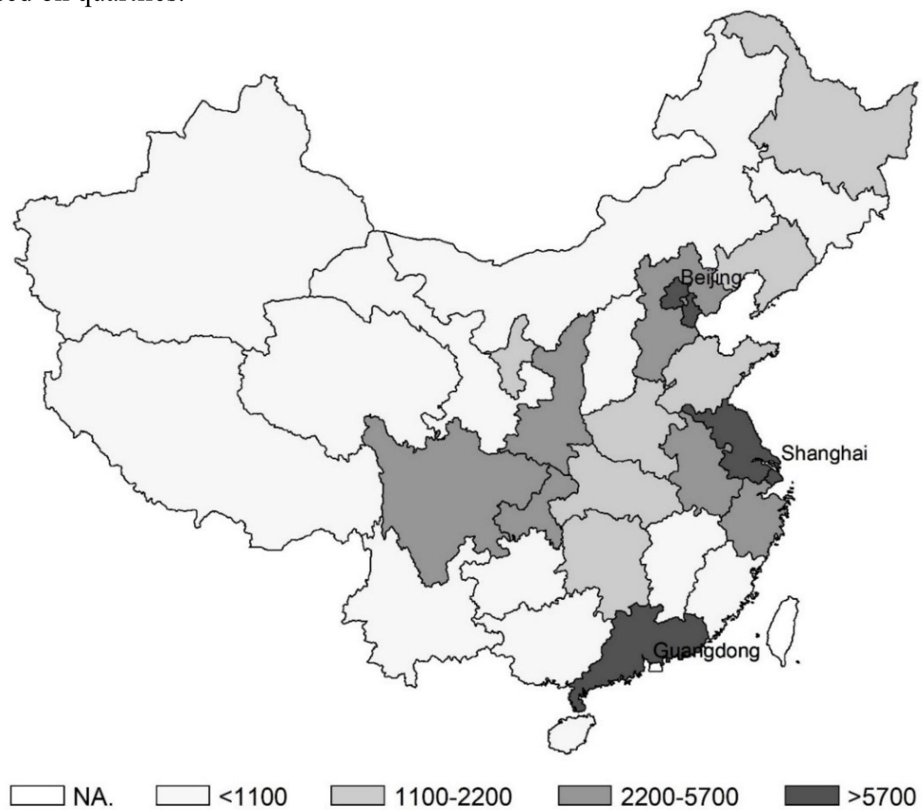


**Table 1.1 Policy Targets Related to Science and Technology in the Five-Year Plans**

This table lists the policy targets related to the development of science and technology in the 11th and 12th Five-Year Plans (FYPs). The 11th FYP has one target: a specific R&D expenditure-to-GDP ratio. In contrast, the 12th FYP also sets a certain number of invention patents per 10,000 people as a target. The targets and achieved values in this table are those for the end of each plan, i.e., 2010 and 2015, respectively. The data are retrieved from the official documents of each FYP, and "-" indicates a missing value.

| | R&D expenditure to GDP ratio | Number of invention patents per 10,000 people |
|---|---|---|
| Panel A: 11th FYP (2006-2010) | | |
| Target | 2% | - |
| Achieved | 1.75% | 1.7 |
| Panel B: 12th FYP (2011-2015) | | |
| Target | 2.2% | 3.3 |
| Achieved | 2.1% | 6.3 |

**Table 1.2 Patent-related Policy Targets in Provincial 12th Five-Year Plan**

This table shows patent-related policy targets in the provincial 12th Five-Year Plans. All data are retrieved from the official documents, and "-" indicates a missing value. The benchmark value for 2010 and the target value for 2015 are from the provincial 12th FYPs, whereas the corresponding achieved value is from the provincial 13th FYPs, as they summarize the achievements of the 12th FYPs. *The 2010 benchmark number of invention patents per 10,000 people may differ from that in the China Statistical Yearbook of Science and Technology (2011 edition), because some provincial governments used estimated values when they compiled their 12th FYP.*

| No. | Indicator | Province | 2010 | 2015 | |
|---|---|---|---|---|---|
| | | | Benchmark | Target | Achieved |
| 1 | Number of invention patents per 10,000 people | Anhui | 0.66 | 3.4 | 4.3 |
| 2 | | Guangxi | 0.29 | 3 | 2 |
| 3 | | Hainan | 0.22 | 0.44 | 2.2 |
| 4 | | Hebei | 0.4 | 0.77 | 1.65 |
| 5 | | Heilongjiang | 1.15 | 2.1 | 3.3 |
| 6 | | Henan | 0.4 | 1 | 1.88 |
| 7 | | Hubei | 0.7 | 1.5 | 4.3 |
| 8 | | Hunan | 0.8 | 1.6 | 2.8 |
| 9 | | Liaoning | 0.5 | 0.8 | 5 |
| 10 | | Shandong | 0.4 | 0.8 | 4.9 |
| 11 | | Sichuan | 0.62 | 1.24 | 3.5 |
| 12 | | Tianjin | 5.1 | 9 | 10 |
| 13 | | Xinjiang | 0.54 | 1.09 | 1.32 |
| 14 | Number of new invention patents per 10,000 people in an FYP period | Beijing | - | 8 | - |
| 15 | | Fujian | 0.3 | 0.6 | - |
| 16 | | Inner Mongolia | 0.11 | 1.5 | 0.32 |
| 17 | | Shaanxi | 0.5 | 2.5 | 1.5 |
| 18 | | Yunnan | 0.47 | 0.53 | 1.61 |
| 19 | Number of invention patent applications per 100,000 people | Shanxi | 23.1 | 35 | 39.6 |
| 20 | Number of invention patent applications per million people | Guangdong | 380 | 520 | 846 |
| 21 | Number of invention patents granted | Chongqing | 1000 | 4000 | - |
| 22 | Number of invention patents granted per 10 billion GDP | Jiangsu | 346 | 400 | 341 |
| 23 | Number of invention patents granted per million people | Ningxia | 9.6 | 15 | 67 |
| 24 | | Shanghai | - | 600 | - |
| 25 | Nil | Gansu | - | - | - |
| 26 | | Guizhou | - | - | - |
| 27 | | Jiangxi | - | - | - |
| 28 | | Jilin | - | - | - |
| 29 | | Qinghai | - | - | - |
| 30 | | Tibet | - | - | - |
| 31 | | Zhejiang | - | - | - |

**Table 1.3 Distribution of Invention Patents per 10,000 People in 2010**

This table presents the number of invention patents in each province in 2010. Patent data are from the China Statistical Yearbook of Science and Technology (2011 edition), and population data are from the China Statistical Yearbook (2011 edition). Here, the total number of invention patents represents the number of invention patents in force in each province at the end of 2010. The lagging province column indicates whether a province's number of invention patents per 10,000 people is *less* than the national average (1.72).

| Province | Total Number of Invention Patents | Population (10,000) | Invention Patents per 10,000 People | Lagging Province (Y/N) |
|---|---|---|---|---|
| Beijing | 38,996 | 1,961 | 19.89 | N |
| Shanghai | 23,843 | 2,302 | 10.36 | N |
| Tianjin | 6,516 | 1,294 | 5.04 | N |
| Guangdong | 41,891 | 10,430 | 4.02 | N |
| Zhejiang | 17,955 | 5,443 | 3.30 | N |
| Jiangsu | 19,682 | 7,866 | 2.50 | N |
| Liaoning | 8,155 | 4,375 | 1.86 | N |
| Shaanxi | 5,604 | 3,733 | 1.50 | Y |
| Shandong | 11,080 | 9,579 | 1.16 | Y |
| Heilongjiang | 4,362 | 3,831 | 1.14 | Y |
| Hubei | 6,315 | 5,724 | 1.10 | Y |
| Chongqing | 3,136 | 2,885 | 1.09 | Y |
| Jilin | 2,954 | 2,746 | 1.08 | Y |
| Hunan | 6,289 | 6,568 | 0.96 | Y |
| Fujian | 3,295 | 3,689 | 0.89 | Y |
| Sichuan | 6,533 | 8,042 | 0.81 | Y |
| Shanxi | 2,473 | 3,571 | 0.69 | Y |
| Hainan | 446 | 867 | 0.51 | Y |
| Yunnan | 2,344 | 4,597 | 0.51 | Y |
| Anhui | 2,972 | 5,950 | 0.50 | Y |
| Henan | 4,501 | 9,402 | 0.48 | Y |
| Guizhou | 1,616 | 3,475 | 0.47 | Y |
| Gansu | 1,143 | 2,558 | 0.45 | Y |
| Hebei | 3,122 | 7,185 | 0.43 | Y |
| Ningxia | 256 | 630 | 0.41 | Y |
| Inner Mongolia | 838 | 2,471 | 0.34 | Y |
| Xinjiang | 665 | 2,181 | 0.30 | Y |
| Jiangxi | 1,322 | 4,457 | 0.30 | Y |
| Guangxi | 1,332 | 4,603 | 0.29 | Y |
| Qinghai | 159 | 563 | 0.28 | Y |
| Tibet | 60 | 300 | 0.20 | Y |

**Table 1.4 12th Five-Year Plan and Provincial Innovation Activity**

This table reports the results from regressing provincial-level innovation inputs and outputs on the dummy variable-Treat, which is equal to one in 2011-2016 if a province is lagged behind the national level in terms of the invention patents per 10,000 people in 2010 and zero otherwise. All provincial and firm characteristics are lagged by one year. Appendix 1.A gives the details of variable definition. All regressions include the province and year fixed effects. The *t*-statistics reported in parentheses are based on standard errors clustered at the provincial level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

| | (1)<br>R&D/GDP | (2)<br>ΔPatent | (3)<br>ΔInvention | (4)<br>ΔUtility | (5)<br>ΔDesign |
|---|---|---|---|---|---|
| *Treat* | -0.359** | 0.133** | 0.051 | 0.105** | 0.316*** |
| | (-2.14) | (2.19) | (0.69) | (2.27) | (2.90) |
| *GDP per capita* | -0.446 | 0.052 | 0.206 | 0.138 | -0.189 |
| | (-1.59) | (0.33) | (0.82) | (1.12) | (-0.72) |
| *GDP growth* | -0.005 | 0.008 | -0.002 | 0.022** | -0.002 |
| | (-0.53) | (1.67) | (-0.24) | (2.12) | (-0.16) |
| *Population* | 0.684 | 0.232 | -0.674 | 0.786** | 0.345 |
| | (0.94) | (1.02) | (-1.53) | (2.16) | (0.59) |
| *University density* | 0.240 | -0.004 | -0.191 | 0.077 | 0.150 |
| | (1.25) | (-0.03) | (-1.29) | (1.24) | (0.63) |
| *Industrial output/GDP* | -0.004 | 0.004 | 0.001 | 0.005 | 0.001 |
| | (-0.51) | (1.45) | (0.28) | (1.29) | (0.07) |
| *Constant* | -0.272 | -2.473 | 4.262 | -8.226* | -1.250 |
| | (-0.04) | (-1.06) | (0.94) | (-2.02) | (-0.25) |
| Province fixed effects | Yes | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes |
| Observations | 494 | 494 | 494 | 494 | 494 |
| R-squared | 0.970 | 0.206 | 0.147 | 0.325 | 0.107 |

**Table 1.5 Summary Statistics**

This table presents the summary statistics of the variables used in the baseline analysis. I construct five firm innovation measures: LnPatent equals the natural logarithm of one plus the utility model and invention patents. LnPatLowCited (LnPatLowValue) equals the natural logarithm of one plus the number of patents with zero forward citation or in the bottom 30th percentile of adjusted nonself-citations (economic value) of all patents within the same 3-digit IPC class, patent category, and application year. I also measure the number of patents that fall into the top 10th percentile of the citation distribution (LnPatTopCited) or the value distribution (LnPatTopValue). A set of control variables identified by prior literature is incorporated. The sample contains 14,613 firm-year observations from 2,140 unique firms that successfully filed at least one patent from 2007 to 2016. Appendix 1.A gives the details of variable definition. All continuous variables are winsorized at the 1st and 99th percentiles.

| Variables | Obs. | Mean | S.D. | P10 | P25 | Median | P75 | P90 |
|---|---|---|---|---|---|---|---|---|
| Patent | 14,613 | 30.790 | 75.890 | 0 | 1 | 8 | 24 | 69 |
| LnPatent | 14,613 | 2.147 | 1.590 | 0 | 0.693 | 2.197 | 3.219 | 4.248 |
| PatLowCited | 14,613 | 17.830 | 44.830 | 0 | 0 | 4 | 14 | 40 |
| LnPatLowCited | 14,613 | 1.691 | 1.474 | 0 | 0 | 1.609 | 2.708 | 3.714 |
| PatLowValue | 14,613 | 7.079 | 20.970 | 0 | 0 | 0 | 4 | 16 |
| LnPatLowValue | 14,613 | 0.908 | 1.272 | 0 | 0 | 0 | 1.609 | 2.833 |
| PatTopCited | 14,613 | 4.842 | 12.380 | 0 | 0 | 1 | 4 | 11 |
| LnPatTopCited | 14,613 | 0.951 | 1.082 | 0 | 0 | 0.693 | 1.609 | 2.485 |
| PatTopValue | 14,613 | 2.505 | 7.663 | 0 | 0 | 0 | 1 | 6 |
| LnPatTopValue | 14,613 | 0.515 | 0.932 | 0 | 0 | 0 | 0.693 | 1.946 |
| Treat | 14,613 | 0.337 | 0.473 | 0 | 0 | 0 | 1 | 1 |
| Size | 14,613 | 1.290 | 1.234 | -0.127 | 0.400 | 1.105 | 1.971 | 2.981 |
| BTM | 14,611 | 0.404 | 0.264 | 0.138 | 0.214 | 0.341 | 0.523 | 0.755 |
| R&D | 14,613 | 1.565 | 1.699 | 0 | 0.107 | 1.177 | 2.337 | 3.676 |
| Leverage | 14,613 | 0.435 | 0.206 | 0.155 | 0.272 | 0.433 | 0.595 | 0.712 |
| Cash | 14,613 | 0.190 | 0.134 | 0.059 | 0.095 | 0.153 | 0.247 | 0.376 |
| Tangibility | 14,613 | 0.230 | 0.155 | 0.052 | 0.110 | 0.201 | 0.324 | 0.459 |
| IO | 14,613 | 7.176 | 7.788 | 0.226 | 1.208 | 4.552 | 10.480 | 18.220 |
| ROA | 14,613 | 0.039 | 0.052 | 0.001 | 0.013 | 0.035 | 0.065 | 0.099 |
| SOE | 14,601 | 0.427 | 0.495 | 0 | 0 | 0 | 1 | 1 |
| Age | 14,613 | 4.489 | 0.785 | 3.320 | 3.946 | 4.633 | 5.164 | 5.393 |
| Competition | 14,613 | 0.939 | 0.103 | 0.824 | 0.954 | 0.984 | 0.985 | 0.988 |
| Competition^2 | 14,613 | 0.892 | 0.166 | 0.678 | 0.910 | 0.968 | 0.971 | 0.975 |

**Table 1.6 Univariate Analysis**

This table reports the results of univariate DiD analysis designed for investigating the impact of policy push on firm innovation. Appendix 1.A gives detailed variable definitions. The numbers tabulated are the average patent number in the four years before and the six years after the enactment of the 12th Five-Year Plan in 2011. A lagging (leading) province indicates that a province's invention patents per 10,000 people are below (above) the national average in 2010. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

| *A. Total number of utility and invention patent ($LnPatent$)* | | | | |
|---|---|---|---|---|
| | Treatment (lagging provinces) | Control (leading provinces) | Difference (treatment-control) | Diff-in-Diff |
| Before | 1.397 | 1.773 | -0.376*** | |
| After | 2.211 | 2.391 | -0.180*** | |
| After-before | 0.814*** | 0.618*** | | 0.196*** |
| *B. Total number of less cited patent ($LnPatLowCited$)* | | | | |
| | Treatment (lagging provinces) | Control (leading provinces) | Difference (treatment-control) | Diff-in-Diff |
| Before | 0.898 | 1.182 | -0.284*** | |
| After | 1.806 | 1.942 | -0.135*** | |
| After-before | 0.908*** | 0.760*** | | 0.149*** |
| *C. Total number of low-value patent ($LnPatLowValue$)* | | | | |
| | Treatment (lagging provinces) | Control (leading provinces) | Difference (treatment-control) | Diff-in-Diff |
| Before | 0.503 | 0.698 | -0.195*** | |
| After | 0.993 | 1.001 | -0.008** | |
| After-before | 0.490*** | 0.303*** | | 0.187*** |
| *D. Total number of highly cited patent ($LnPatTopCited$)* | | | | |
| | Treatment (lagging provinces) | Control (leading provinces) | Difference (treatment-control) | Diff-in-Diff |
| Before | 0.501 | 0.702 | -0.201*** | |
| After | 0.974 | 1.116 | -0.142*** | |
| After-before | 0.473*** | 0.414*** | | 0.059 |
| *E. Total number of high-value patent ($LnPatTopValue$)* | | | | |
| | Treatment (lagging provinces) | Control (leading provinces) | Difference (treatment-control) | Diff-in-Diff |
| Before | 0.310 | 0.493 | -0.183*** | |
| After | 0.477 | 0.603 | -0.126*** | |
| After-before | 0.167*** | 0.110*** | | 0.057 |

**Table 1.7 Multivariate Regression Analysis**

This table reports multivariate DiD analysis results for investigating the impact of government intervention on firm innovation. *Treat* is an indicator equals to one for firms registered in a lagging provinces (that had fewer invention patents per 10,000 people than the national average in 2010) in the 2011-2016 period, and zero otherwise. Firm characteristics are lagged by one year. Appendix 1.A reports the variable definition. All regressions include firm and year fixed effects. The *t-statistics* reported in parentheses are based on standard errors clustered at the provincial level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

| | (1)<br>LnPatent | (2)<br>LnPatLowCited | (3)<br>LnPatLowValue | (4)<br>LnPatTopCited | (5)<br>LnPatTopValue |
|---|---|---|---|---|---|
| *Treat* | 0.245*** | 0.200*** | 0.234*** | 0.078 | 0.024 |
| | (3.86) | (3.09) | (3.50) | (1.60) | (0.94) |
| *Size* | 0.338*** | 0.360*** | 0.181*** | 0.225*** | 0.237*** |
| | (8.20) | (8.63) | (4.81) | (7.40) | (7.34) |
| *BTM* | -0.040 | -0.041 | 0.150** | 0.021 | -0.049 |
| | (-0.46) | (-0.50) | (2.56) | (0.32) | (-0.89) |
| *R&D* | 0.060*** | 0.073*** | 0.058*** | 0.054*** | 0.026*** |
| | (4.75) | (6.08) | (5.33) | (5.26) | (2.85) |
| *Leverage* | -0.046 | -0.026 | -0.016 | -0.084 | 0.007 |
| | (-0.39) | (-0.21) | (-0.14) | (-1.12) | (0.12) |
| *Cash* | 0.063 | 0.052 | -0.175 | 0.044 | 0.045 |
| | (0.41) | (0.36) | (-1.46) | (0.50) | (0.78) |
| *Tangibility* | 0.335* | 0.398** | 0.287** | 0.140 | 0.192** |
| | (1.74) | (2.53) | (2.23) | (1.09) | (2.44) |
| *IO* | 0.002 | 0.001 | -0.003 | 0.002 | 0.005*** |
| | (0.99) | (0.40) | (-1.51) | (1.31) | (3.21) |
| *ROA* | 1.076*** | 0.993*** | 0.596*** | 0.576** | 0.536*** |
| | (4.33) | (4.27) | (3.67) | (2.68) | (3.37) |
| *Age* | 0.049* | 0.069*** | -0.139*** | 0.030* | 0.063*** |
| | (1.75) | (2.77) | (-5.68) | (1.96) | (5.07) |
| *Competition* | -1.955 | -1.098 | -4.048** | -2.831** | -1.444 |
| | (-1.02) | (-0.55) | (-2.18) | (-2.49) | (-1.54) |
| *Competition^2* | 1.586 | 0.987 | 2.773** | 1.849** | 0.901 |
| | (1.27) | (0.76) | (2.21) | (2.44) | (1.49) |
| *Constant* | 1.691** | 0.844 | 2.367*** | 1.421*** | 0.389 |
| | (2.62) | (1.25) | (4.08) | (3.60) | (1.05) |
| Firm fixed effects | Yes | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes |
| Observations | 14,613 | 14,613 | 14,613 | 14,613 | 14,613 |
| R-squared | 0.802 | 0.791 | 0.641 | 0.755 | 0.787 |

**Table 1.8 Dynamic Regression Analysis**

This table reports the results of the dynamic DID analysis designed for testing the parallel pre-treatment trends assumption. Firm characteristics are lagged by one year. Appendix 1.A reports the variable definitions. All regressions include firm and year fixed effects. Coefficients on the similar control variables of the baseline study are omitted for brevity. The *t-statistics* reported in parentheses are based on standard errors clustered at the provincial level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | LnPatent | LnPatLowCited | LnPatLowValue | LnPatTopCited | LnPatTopValue |
| $Before^{-2}$ | 0.049 | 0.043 | 0.009 | -0.022 | -0.032 |
| | (1.08) | (1.17) | (0.18) | (-0.83) | (-1.19) |
| $Before^{-1}$ | 0.109 | 0.096 | 0.056 | -0.007 | -0.035 |
| | (1.50) | (1.51) | (1.34) | (-0.15) | (-1.44) |
| $Current$ | 0.274*** | 0.261*** | 0.217*** | 0.036 | 0.019 |
| | (3.48) | (3.91) | (3.80) | (0.72) | (0.56) |
| $After^{1}$ | 0.236** | 0.215** | 0.223*** | 0.062 | -0.009 |
| | (2.70) | (2.51) | (3.20) | (1.09) | (-0.23) |
| $After^{2}$ | 0.293*** | 0.252** | 0.277*** | 0.088 | -0.010 |
| | (3.00) | (2.74) | (3.42) | (1.42) | (-0.31) |
| $After^{3}$ | 0.282*** | 0.217** | 0.272*** | 0.046 | -0.009 |
| | (3.12) | (2.29) | (3.54) | (0.88) | (-0.29) |
| $After^{4+}$ | 0.360*** | 0.273** | 0.277*** | 0.093 | 0.009 |
| | (3.44) | (2.47) | (2.90) | (1.09) | (0.27) |
| | | | | | |
| Controls | Yes | Yes | Yes | Yes | Yes |
| Firm fixed effects | Yes | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes |
| Observations | 14,613 | 14,613 | 14,613 | 14,613 | 14,613 |
| R-squared | 0.803 | 0.792 | 0.641 | 0.755 | 0.787 |

**Table 1.9 Propensity Score Matching Analysis**

This table presents the propensity score matching analysis over the effect of policy push on firm innovation. Panel A compares the mean differences in firm characteristics of treatment firms and control firms. Panel B presents the multivariate analysis results based on the matched sample using the propensity score matching approach. Control variables in Table 1.7 are also included in the regression, but their coefficients are unreported for brevity. All regressions include firm and year fixed effects. The *t-statistics* reported in parentheses are based on standard errors clustered at the provincial level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

| Panel A: Covariate balance test | | | | | |
|---|---|---|---|---|---|
| | Treatment | Control | Diff. | T-test | P-value |
| Size | 1.019 | 1.003 | 0.016 | 0.490 | 0.622 |
| BTM | 0.480 | 0.469 | 0.011 | 1.090 | 0.277 |
| R&D | 0.328 | 0.348 | -0.020 | -0.740 | 0.458 |
| Leverage | 0.508 | 0.505 | 0.003 | 0.540 | 0.587 |
| Cash | 0.158 | 0.158 | 0.000 | 0.120 | 0.902 |
| Tangibility | 0.279 | 0.281 | -0.002 | -0.460 | 0.646 |
| ROA | 0.032 | 0.031 | 0.001 | 0.290 | 0.771 |
| IO | 6.568 | 6.856 | -0.288 | -1.000 | 0.318 |
| Age | 4.699 | 4.700 | -0.001 | -0.120 | 0.901 |
| Patent growth | 0.129 | 0.126 | 0.003 | 0.310 | 0.757 |

| Panel B: DiD test using the matched sample | | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | LnPatent | LnPatLowCited | LnPatLowValue | LnPatTopCited | LnPatTopValue |
| *Treat* | 0.284*** | 0.233*** | 0.258*** | 0.095 | 0.032 |
| | (4.63) | (3.62) | (3.10) | (1.60) | (1.00) |
| Controls | Yes | Yes | Yes | Yes | Yes |
| Firm fixed effects | Yes | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes |
| Observations | 7,772 | 7,772 | 7,772 | 7,772 | 7,772 |
| R-squared | 0.818 | 0.805 | 0.646 | 0.768 | 0.769 |

**Table 1.10 Placebo Shock using the 11th Five-Year Plan**

This table reports the placebo tests for DiD analysis by changing the treatment year to 2006 when the 11th Five-Year Plan was promulgated. The sample contains firms with at least one successful patent application during 2000-2011. *Pseudo Treat* is a dummy variable equals one in years 2006-2011 if a firm locates in provinces that lag behind the national level in invention patents per 10,000 people in 2006 and zero otherwise. All continuous variables are winsorized at the 1st and 99th percentile to alleviate the impact of outliers. Appendix 1.A gives detailed variable definitions. All regressions include firm and year fixed effects. The *t-statistics* reported in parentheses are based on standard errors clustered at the provincial level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | LnPatent | LnPatLowCited | LnPatLowValue | LnPatTopCited | LnPatTopValue |
| *Pseudo Treat* | 0.014 | 0.012 | 0.024 | -0.017 | -0.05 |
| | (0.20) | (0.22) | (0.34) | (-0.48) | (-1.32) |
| *Size* | 0.403*** | 0.345*** | 0.109** | 0.240*** | 0.301*** |
| | (6.02) | (6.22) | (2.18) | (5.98) | (9.75) |
| *BTM* | -0.070 | -0.052 | 0.113 | -0.054 | -0.159*** |
| | (-0.82) | (-0.76) | (1.32) | (-0.97) | (-3.44) |
| *R&D* | 0.134*** | 0.120*** | 0.039** | 0.082*** | 0.059*** |
| | (7.17) | (6.70) | (2.13) | (4.71) | (3.45) |
| *Leverage* | -0.189 | -0.189 | 0.103 | -0.108 | -0.312*** |
| | (-1.28) | (-1.53) | (0.70) | (-1.27) | (-3.72) |
| *Cash* | 0.025 | 0.032 | 0.031 | 0.045 | -0.084 |
| | (0.16) | (0.28) | (0.21) | (0.65) | (-0.98) |
| *Tangibility* | 0.315* | 0.219 | 0.183* | 0.182 | 0.143 |
| | (1.77) | (1.53) | (1.77) | (1.61) | (1.22) |
| *IO* | -0.000 | -0.000 | -0.004 | 0.001 | 0.005*** |
| | (-0.01) | (-0.13) | (-1.69) | (0.41) | (3.13) |
| *ROA* | 0.698*** | 0.466* | 0.393* | 0.137 | -0.010 |
| | (3.14) | (2.04) | (1.72) | (0.98) | (-0.06) |
| *Age* | 0.015 | 0.001 | -0.036 | -0.006 | -0.009 |
| | (0.50) | (0.02) | (-1.21) | (-0.38) | (-0.79) |
| *Competition* | 0.129 | 0.296 | 0.055 | -0.584 | 1.316 |
| | (0.05) | (0.15) | (0.05) | (-0.54) | (0.50) |
| *Competition^2* | -0.359 | -0.402 | -0.087 | 0.273 | -1.031 |
| | (-0.23) | (-0.31) | (-0.11) | (0.39) | (-0.59) |
| *Constant* | 1.037 | 0.608 | 0.433 | 0.592 | -0.041 |
| | (1.22) | (0.83) | (1.12) | (1.37) | (-0.05) |
| Firm fixed effects | Yes | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes |
| Observations | 9,598 | 9,598 | 9,598 | 9,598 | 9,598 |
| R-squared | 0.741 | 0.712 | 0.595 | 0.684 | 0.691 |

**Table 1.11 Placebo Tests with Random Treatment**

This table summarizes the coefficients' distribution and the corresponding *t-statistics* on the dummy indicator *Treat,* estimated by the baseline DiD regression on the simulated sample. I first randomly chose 24 provinces as regions with weak innovation capacity in 2010, and firms registered in there receive the pseudo treatment. I then assign firms in the remaining seven provinces to the pseudo control group. Next, I define a dummy variable of policy push and perform the DiD regression in this simulated sample. Finally, I repeat this process 5,000 times. For comparative purposes, I present the coefficient estimates of the actual effect in the first column.

| | Actual | Mean | P5 | P25 | Median | P75 | P95 |
|---|---|---|---|---|---|---|---|
| $LnPatent_{i,t}$ | 0.245*** | -0.013 | -0.214 | -0.078 | -0.002 | 0.065 | 0.140 |
| | (3.86) | (-0.01) | (-1.92) | (-0.79) | (-0.02) | (0.80) | (1.90) |
| $LnPatLowCited_{i,t}$ | 0.200*** | -0.010 | -0.192 | -0.068 | 0.000 | 0.060 | 0.132 |
| | (3.09) | (-0.03) | (-1.76) | (-0.75) | (0.01) | (0.81) | (1.88) |
| $LnPatLowValue_{i,t}$ | 0.234*** | -0.013 | -0.216 | -0.085 | -0.005 | 0.072 | 0.156 |
| | (3.50) | (-0.06) | (-2.03) | (-0.97) | (-0.05) | (0.76) | (1.98) |
| $LnPatTopCited_{i,t}$ | 0.078 | -0.003 | -0.129 | -0.041 | 0.008 | 0.043 | 0.086 |
| | (1.60) | (0.17) | (-1.51) | (-0.62) | (0.15) | (0.89) | (2.03) |
| $LnPatTopValue_{i,t}$ | 0.024 | -0.002 | -0.060 | -0.022 | 0.000 | 0.021 | 0.049 |
| | (0.94) | (-0.02) | (-1.52) | (-0.64) | (0.01) | (0.67) | (1.64) |

**Table 1.12 Effect on R&D Expenditures**

This table reports the results of the relationship between policy push and R&D expenditure. *Treat* is an indicator equals to one for firms registered in a lagging provinces (that had fewer invention patents per 10,000 people than the national average in 2010) in the 2011-2016 period, and zero otherwise. Firm characteristics are lagged by one year. Appendix 1.A reports the variable definition. All regressions include the firm and year fixed effects. The *t-statistics* reported in parentheses are based on standard errors clustered at the provincial level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

| | (1)<br>Ln(1+R&D) | (2)<br>R&D to Assets | (3)<br>R&D per Employee | (4)<br>R&D per Inventor |
|---|---|---|---|---|
| *Treat* | 0.116 | 0.040 | -0.002 | -0.081 |
| | (1.11) | (0.66) | (-1.24) | (-0.43) |
| *Size* | 0.522*** | -0.014 | 0.006*** | 1.118*** |
| | (8.17) | (-0.40) | (7.17) | (5.03) |
| *BTM* | 0.146 | -0.193*** | -0.006*** | -0.050 |
| | (1.31) | (-3.38) | (-3.70) | (-0.08) |
| *R&D* | 0.301*** | 0.415*** | 0.006*** | 0.560*** |
| | (12.08) | (26.49) | (13.26) | (6.81) |
| *Leverage* | 0.060 | 0.019 | -0.004 | -0.676 |
| | (0.26) | (0.11) | (-0.98) | (-0.59) |
| *Cash* | -0.038 | 0.078 | 0.001 | -1.797** |
| | (-0.34) | (0.73) | (0.24) | (-2.51) |
| *Tangibility* | 0.463** | 0.226* | -0.001 | 0.319 |
| | (2.44) | (1.90) | (-0.18) | (0.30) |
| *IO* | -0.000 | -0.001 | -0.000 | 0.002 |
| | (-0.22) | (-0.40) | (-1.01) | (0.27) |
| *ROA* | 1.196*** | 0.697*** | 0.004 | 0.238 |
| | (4.16) | (3.23) | (0.81) | (0.19) |
| *Age* | -0.232*** | -0.131*** | -0.001* | -0.433*** |
| | (-7.50) | (-5.94) | (-1.79) | (-3.16) |
| *Competition* | 0.613 | -3.531* | 0.033 | 14.844 |
| | (0.24) | (-1.72) | (0.59) | (0.94) |
| *Competition^2* | -0.348 | 2.086 | -0.021 | -9.632 |
| | (-0.21) | (1.57) | (-0.60) | (-0.97) |
| *Constant* | 2.436** | 2.946*** | 0.006 | -2.071 |
| | (2.36) | (3.67) | (0.25) | (-0.34) |
| Firm fixed effects | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes |
| Observations | 14,613 | 14,613 | 14,613 | 14,613 |
| R-squared | 0.813 | 0.827 | 0.761 | 0.451 |

**Table 1.13 Effect on Labor Inputs**

This table reports the results of the relationship between policy push and labor inputs in innovative activities. *Treat* is an indicator equals to one for firms registered in a lagging provinces (that had fewer invention patents per 10,000 people than the national average in 2010) in the 2011-2016 period, and zero otherwise. Firm characteristics are lagged by one year. Appendix 1.A reports the variable definition. All regressions include the firm and year fixed effects. The *t-statistics* reported in parentheses are based on standard errors clustered at the provincial level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

| | (1) Inventors | (2) Iportion | (3) Patent per Employee | (4) Patent per Inventor |
|---|---|---|---|---|
| *Treat* | 0.318*** | 0.208*** | 0.151*** | 0.026* |
| | (5.21) | (4.27) | (3.07) | (1.75) |
| *Size* | 0.338*** | -0.040 | -0.007 | 0.026** |
| | (7.89) | (-1.01) | (-0.19) | (2.73) |
| *BTM* | 0.043 | 0.012 | -0.083 | -0.028 |
| | (0.47) | (0.14) | (-1.16) | (-1.13) |
| *R&D* | 0.059*** | 0.030*** | 0.028*** | -0.001 |
| | (5.30) | (3.03) | (3.04) | (-0.29) |
| *Leverage* | -0.047 | -0.066 | -0.089 | -0.001 |
| | (-0.40) | (-0.49) | (-0.74) | (-0.01) |
| *Cash* | -0.061 | 0.125 | 0.210* | 0.050 |
| | (-0.38) | (1.05) | (1.76) | (1.17) |
| *Tangibility* | 0.437* | 0.061 | -0.007 | 0.001 |
| | (1.72) | (0.34) | (-0.05) | (0.03) |
| *IO* | 0.002 | 0.003 | 0.003 | 0.000 |
| | (0.89) | (1.29) | (1.24) | (0.29) |
| *ROA* | 0.762** | 0.166 | 0.384* | 0.145* |
| | (2.72) | (0.75) | (1.90) | (1.76) |
| *Age* | 0.035 | 0.032 | 0.039 | 0.000 |
| | (1.33) | (1.61) | (1.69) | (0.04) |
| *Competition* | -1.020 | -0.062 | -1.420 | -0.807 |
| | (-0.72) | (-0.04) | (-0.74) | (-1.39) |
| *Competition^2* | 1.074 | 0.231 | 1.028 | 0.577 |
| | (1.15) | (0.21) | (0.81) | (1.47) |
| *Constant* | 1.711*** | 1.503** | 1.693** | 0.598*** |
| | (3.40) | (2.47) | (2.68) | (3.15) |
| Firm fixed effects | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes |
| Observations | 14,613 | 14,613 | 14,613 | 14,613 |
| R-squared | 0.793 | 0.718 | 0.727 | 0.571 |

**Table 1.14 Subsample Analysis of State-Owned Enterprises**

This table reports the subsample analysis on the ownership. I partition the whole sample into two groups each year: state-owned enterprises and non-state-owned enterprises. *Treat* is an indicator equals to one for firms registered in a lagging provinces (that had fewer invention patents per 10,000 people than the national average in 2010) in the 2011-2016 period, and zero otherwise. Firm characteristics are lagged by one year. Appendix 1.A reports the variable definition. All regressions include the firm and year fixed effects. The *t-statistics* reported in parentheses are based on standard errors clustered at the provincial level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

| | (1) | | (2) | | (3) | |
|---|---|---|---|---|---|---|
| | LnPatent | | LnPatLowCited | | LnPatLowValue | |
| | SOE | NSOE | SOE | NSOE | SOE | NSOE |
| *Treat* | 0.299*** | 0.091 | 0.254*** | 0.064 | 0.266** | 0.133* |
| | (3.34) | (1.32) | (3.01) | (0.89) | (2.56) | (1.93) |
| *Size* | 0.324*** | 0.329*** | 0.360*** | 0.355*** | 0.249*** | 0.208*** |
| | (4.79) | (4.57) | (5.62) | (4.56) | (3.96) | (3.97) |
| *BTM* | -0.078 | -0.159 | -0.116 | -0.109 | 0.043 | 0.022 |
| | (-0.81) | (-1.33) | (-1.12) | (-1.05) | (0.53) | (0.20) |
| *R&D* | 0.039** | 0.039* | 0.065*** | 0.048** | 0.064** | 0.044** |
| | (2.11) | (1.88) | (3.60) | (2.51) | (2.14) | (2.34) |
| *Leverage* | -0.126 | -0.138 | -0.110 | -0.090 | -0.455** | 0.015 |
| | (-0.56) | (-0.65) | (-0.53) | (-0.47) | (-2.16) | (0.07) |
| *Cash* | -0.248 | 0.250 | -0.241 | 0.384* | -0.366* | -0.191 |
| | (-1.27) | (1.09) | (-1.35) | (1.77) | (-1.79) | (-0.97) |
| *Tangibility* | 0.252 | 0.417* | 0.369* | 0.466** | 0.163 | 0.310 |
| | (1.00) | (1.89) | (2.01) | (2.25) | (0.84) | (1.30) |
| *IO* | 0.002 | 0.003 | 0.000 | 0.001 | -0.003 | -0.003 |
| | (0.61) | (1.12) | (0.05) | (0.51) | (-0.89) | (-1.58) |
| *ROA* | 0.972 | 1.096*** | 0.864* | 1.221*** | -0.113 | 0.714** |
| | (1.69) | (3.37) | (1.89) | (4.05) | (-0.25) | (2.17) |
| *Age* | 0.205** | 0.149* | 0.226** | 0.258*** | -0.195 | -0.135** |
| | (2.06) | (1.93) | (2.45) | (3.63) | (-1.44) | (-2.16) |
| *Competition* | -6.492 | -0.400 | -5.487 | -0.173 | -4.478* | -7.581** |
| | (-1.67) | (-0.13) | (-1.42) | (-0.05) | (-1.93) | (-2.42) |
| *Competition^2* | 4.611* | 0.506 | 3.792 | 0.442 | 3.155** | 5.092** |
| | (1.79) | (0.24) | (1.48) | (0.21) | (2.13) | (2.36) |
| *Constant* | 2.538* | 1.036 | 1.703 | -0.113 | 2.869** | 3.704*** |
| | (1.76) | (0.93) | (1.21) | (-0.10) | (2.69) | (3.77) |
| Firm fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 5,197 | 6,992 | 5,197 | 6,992 | 5,197 | 6,992 |
| R-squared | 0.858 | 0.786 | 0.851 | 0.775 | 0.712 | 0.623 |

**Table 1.15 Subsample Analysis of the Size of Employee**

This table reports the subsample analysis of the employee size. I partition the whole sample into two groups by the sample median each year. *Treat* is an indicator equals to one for firms registered in a lagging provinces (that had fewer invention patents per 10,000 people than the national average in 2010) in the 2011-2016 period, and zero otherwise. Firm characteristics are lagged by one year. Appendix 1.A reports the variable definition. All regressions include the firm and year fixed effects. The *t-statistics* reported in parentheses are based on standard errors clustered at the provincial level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

| | (1) | | (2) | | (3) | |
|---|---|---|---|---|---|---|
| | LnPatent | | LnPatLowCited | | LnPatLowValue | |
| | Large | Small | Large | Small | Large | Small |
| *Treat* | 0.338*** | 0.107 | 0.259*** | 0.140 | 0.353*** | 0.093 |
| | (4.61) | (1.14) | (3.71) | (1.39) | (4.35) | (0.99) |
| *Size* | 0.331*** | 0.236*** | 0.357*** | 0.281*** | 0.294*** | 0.120** |
| | (6.25) | (4.08) | (6.01) | (4.22) | (4.27) | (2.18) |
| *BTM* | -0.109 | -0.130 | -0.139 | -0.165 | 0.019 | -0.041 |
| | (-1.06) | (-1.03) | (-1.36) | (-1.60) | (0.19) | (-0.28) |
| *R&D* | 0.039** | 0.035* | 0.052*** | 0.054*** | 0.070*** | 0.019 |
| | (2.31) | (1.84) | (2.76) | (3.16) | (3.37) | (1.33) |
| *Leverage* | -0.230 | 0.028 | -0.194 | 0.049 | -0.517*** | 0.148 |
| | (-1.20) | (0.13) | (-1.09) | (0.25) | (-2.91) | (0.73) |
| *Cash* | -0.071 | 0.210 | -0.056 | 0.264 | -0.530** | -0.081 |
| | (-0.28) | (0.83) | (-0.22) | (1.05) | (-2.35) | (-0.39) |
| *Tangibility* | 0.295 | 0.078 | 0.383* | 0.212 | 0.271 | 0.020 |
| | (1.15) | (0.34) | (1.97) | (0.80) | (1.10) | (0.13) |
| *IO* | 0.002 | 0.003 | 0.001 | -0.000 | -0.004 | -0.003 |
| | (0.61) | (0.86) | (0.37) | (-0.07) | (-1.33) | (-0.97) |
| *ROA* | 1.015** | 0.645 | 1.216** | 0.532 | 0.479 | 0.168 |
| | (2.39) | (1.62) | (2.71) | (1.58) | (1.06) | (0.65) |
| *Age* | 0.108 | 0.122* | 0.182** | 0.255*** | -0.252** | -0.132 |
| | (1.63) | (1.72) | (2.27) | (3.66) | (-2.39) | (-1.61) |
| *Competition* | -2.357 | -0.748 | -0.650 | -0.776 | -5.890** | -5.464* |
| | (-0.88) | (-0.23) | (-0.25) | (-0.29) | (-2.06) | (-1.90) |
| *Competition^2* | 1.906 | 0.696 | 0.803 | 0.644 | 4.309** | 3.482* |
| | (1.11) | (0.33) | (0.48) | (0.37) | (2.27) | (1.84) |
| *Constant* | 1.906* | 1.019 | 0.399 | 0.043 | 3.389** | 3.185*** |
| | (1.79) | (0.81) | (0.38) | (0.04) | (2.74) | (2.82) |
| Firm fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 6,333 | 5,693 | 6,333 | 5,693 | 6,333 | 5,693 |
| R-squared | 0.858 | 0.741 | 0.848 | 0.724 | 0.706 | 0.618 |

**Table 1.16 Benefits of More Patent Applications**

This table reports the OLS regression of government subsidies on the interaction term of government intervention and patent counts. *Treat* is an indicator equals to one for firms registered in a lagging provinces (that had fewer invention patents per 10,000 people than the national average in 2010) in the 2011-2016 period, and zero otherwise. Firm characteristics are lagged by one year. Appendix 1.A reports the variable definition. All regressions include the firm and year fixed effects. The *t-statistics* reported in parentheses are based on standard errors clustered at the provincial level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

| | (1)<br>Full sample | (2)<br>SOE sample | (3)<br>Non-SOE sample |
|---|---|---|---|
| *Treat× LnPatent* | 0.121*** | 0.138*** | 0.065 |
| | (3.88) | (2.87) | (1.68) |
| *Treat* | -0.278** | -0.389* | -0.045 |
| | (-2.42) | (-1.98) | (-0.32) |
| *LnPatent* | 0.007 | 0.004 | 0.002 |
| | (0.25) | (0.11) | (0.07) |
| *Size* | -0.158* | -0.154 | -0.125 |
| | (-1.75) | (-1.34) | (-1.34) |
| *BTM* | -0.199 | -0.262 | -0.279* |
| | (-1.49) | (-1.20) | (-1.92) |
| *Leverage* | -0.055 | -0.578 | 0.214 |
| | (-0.21) | (-1.21) | (0.87) |
| *Cash* | -0.019 | -0.112 | -0.106 |
| | (-0.09) | (-0.20) | (-0.62) |
| *R&D* | 0.046*** | 0.046 | 0.044** |
| | (3.48) | (1.41) | (2.65) |
| *Tangibility* | 0.582 | 0.888 | 0.474 |
| | (1.56) | (1.43) | (1.33) |
| *IO* | -0.002 | -0.001 | -0.003 |
| | (-0.81) | (-0.31) | (-0.97) |
| *ROA* | -0.077 | -0.637 | 0.024 |
| | (-0.16) | (-0.66) | (0.05) |
| *Age* | -0.016 | 0.081 | -0.011 |
| | (-0.35) | (0.80) | (-0.25) |
| *Constant* | -5.484*** | -5.710*** | -5.553*** |
| | (-22.87) | (-9.89) | (-24.92) |
| Firm fixed effects | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes |
| Observations | 14,613 | 6,065 | 8,497 |
| R-squared | 0.500 | 0.508 | 0.507 |

**Table 1.17 Robustness – Confounding Local Business Conditions**

This table reports the results of the robustness check for DiD analysis by controlling for local business conditions. I include four measures: the logarithm of GDP per capita, GDP growth rate, the logarithm of population, and the university density. All provincial and firm characteristics are lagged by one year. Appendix 1.A reports the variable definition. Coefficients on the similar control variables of the baseline study are omitted for brevity. All regressions include firm and year fixed effects. The *t-statistics* reported in parentheses are based on standard errors clustered at the provincial level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

| | (1)<br>LnPatent | (2)<br>LnPatLowCited | (3)<br>LnPatLowValue | (4)<br>LnPatTopCited | (5)<br>LnPatTopValue |
|---|---|---|---|---|---|
| *Treat* | 0.226*** | 0.193*** | 0.203*** | 0.056 | 0.029 |
| | (3.95) | (3.45) | (3.51) | (1.23) | (0.81) |
| *GDP per capita* | -0.071 | -0.111 | 0.016 | 0.003 | -0.108 |
| | (-0.40) | (-0.61) | (0.10) | (0.03) | (-1.06) |
| *GDP growth* | 0.013 | 0.012 | 0.012 | 0.008 | 0.000 |
| | (1.51) | (1.36) | (1.35) | (1.12) | (0.04) |
| *Population* | 0.185 | 0.200 | -0.014 | 0.059 | 0.172 |
| | (0.92) | (1.07) | (-0.10) | (0.44) | (1.39) |
| *University density* | 1.794 | 1.674* | 1.009 | 1.049 | 1.355* |
| | (1.60) | (1.80) | (1.22) | (1.59) | (1.94) |
| *Constant* | 0.780 | 0.310 | 1.945 | 0.702 | 0.166 |
| | (0.36) | (0.15) | (1.30) | (0.56) | (0.16) |
| | | | | | |
| Controls | Yes | Yes | Yes | Yes | Yes |
| Firm fixed effects | Yes | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes |
| Observations | 14,613 | 14,613 | 14,613 | 14,613 | 14,613 |
| R-squared | 0.803 | 0.792 | 0.641 | 0.755 | 0.787 |

**Table 1.18 Robustness – Ranking Patent by Different Cutoffs**

This table reports the robustness check results where I change the cutoff to 20th percentile and 99th percentile. LnPatLowCited (LnPatLowValue) is defined as the logarithm of one plus the number of patents with zero forward citation or in the bottom 20th percentile of the adjusted nonself-citations (economic value) of all patents within the same patent category, 3-digit IPC class, and application year. LnPatTopCited (LnPatTopValue) is defined as the logarithm of one plus the number of patents that fall into the 99th percentile of all adjusted nonself-citations (economic value) patents within the patent category, 3-digit IPC class, and application year. All firm characteristics are lagged by one year. Appendix 1.A gives detailed variable definitions. All regressions include firm and year fixed effects. The *t-statistics* reported in parentheses are based on standard errors clustered at the provincial level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

| | (1)<br>LnPatLowCited | (2)<br>LnPatLowValue | (3)<br>LnPatTopCited | (4)<br>LnPatTopValue |
|---|---|---|---|---|
| *Treat* | 0.193*** | 0.164*** | 0.019 | 0.014 |
| | (3.07) | (2.78) | (0.95) | (1.34) |
| *Size* | 0.373*** | 0.166*** | 0.114*** | 0.039** |
| | (8.72) | (4.54) | (6.86) | (2.36) |
| *BTM* | -0.053 | 0.107** | 0.044 | 0.006 |
| | (-0.63) | (2.14) | (1.02) | (0.18) |
| *R&D* | 0.081*** | 0.053*** | 0.019*** | 0.005 |
| | (6.56) | (5.59) | (3.61) | (1.08) |
| *Leverage* | -0.060 | -0.043 | -0.029 | 0.008 |
| | (-0.48) | (-0.40) | (-0.72) | (0.25) |
| *Cash* | 0.020 | -0.145* | -0.042 | 0.065** |
| | (0.14) | (-1.76) | (-1.01) | (2.46) |
| *Tangibility* | 0.411** | 0.215** | -0.006 | 0.048 |
| | (2.60) | (2.19) | (-0.10) | (1.34) |
| *IO* | 0.001 | -0.004** | -0.000 | 0.001 |
| | (0.24) | (-2.19) | (-0.41) | (1.19) |
| *ROA* | 0.979*** | 0.359** | 0.427*** | 0.201* |
| | (4.43) | (2.43) | (6.14) | (1.92) |
| *Age* | 0.064** | -0.144*** | 0.006 | 0.019*** |
| | (2.72) | (-6.35) | (0.75) | (2.85) |
| *Competition* | -1.544 | -2.937 | -2.532*** | -0.749* |
| | (-0.81) | (-1.53) | (-2.78) | (-1.91) |
| *Competition^2* | 1.294 | 2.016 | 1.632*** | 0.491* |
| | (1.06) | (1.56) | (2.85) | (1.71) |
| *Constant* | 0.975 | 1.863*** | 0.975*** | 0.181 |
| | (1.52) | (3.10) | (2.77) | (1.49) |
| Firm fixed effects | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes |
| Observations | 14,613 | 14,613 | 14,613 | 14,613 |
| R-squared | 0.792 | 0.595 | 0.605 | 0.703 |

**Table 1.19 Robustness – Alternative Definition of Treatment Group**

This table reports multivariate DiD analysis results for investigating the impact of per capita policy target on firm innovation. *Treat* is an indicator equals to one for firms located in a lagging province (that had fewer invention patents per 10,000 people than the national *median* in 2010) in the 2011-2016 period, and zero otherwise. Firm characteristics are lagged by one year. Appendix 1.A reports the variable definition. All regressions include firm and year fixed effects. The *t-statistics* reported in parentheses are based on standard errors clustered at the provincial level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

| | (1)<br>LnPatent | (2)<br>LnPatLowCited | (3)<br>LnPatLowValue | (4)<br>LnPatTopCited | (5)<br>LnPatTopValue |
|---|---|---|---|---|---|
| *Treat* | 0.270*** | 0.230*** | 0.197** | 0.100 | 0.031 |
| | (3.36) | (2.86) | (2.12) | (1.35) | (0.86) |
| *Size* | 0.336*** | 0.358*** | 0.181*** | 0.224*** | 0.237*** |
| | (8.40) | (8.80) | (4.84) | (7.48) | (7.35) |
| *BTM* | -0.044 | -0.044 | 0.148** | 0.019 | -0.049 |
| | (-0.51) | (-0.55) | (2.59) | (0.30) | (-0.90) |
| *R&D* | 0.061*** | 0.074*** | 0.059*** | 0.054*** | 0.026*** |
| | (4.87) | (6.16) | (5.49) | (5.23) | (2.86) |
| *Leverage* | -0.030 | -0.013 | -0.003 | -0.078 | 0.009 |
| | (-0.26) | (-0.11) | (-0.02) | (-1.05) | (0.15) |
| *Cash* | 0.059 | 0.049 | -0.178 | 0.042 | 0.045 |
| | (0.38) | (0.33) | (-1.51) | (0.48) | (0.77) |
| *Tangibility* | 0.345* | 0.406** | 0.295** | 0.144 | 0.194** |
| | (1.76) | (2.55) | (2.27) | (1.12) | (2.44) |
| *IO* | 0.002 | 0.001 | -0.003 | 0.002 | 0.005*** |
| | (0.93) | (0.35) | (-1.56) | (1.29) | (3.20) |
| *ROA* | 1.076*** | 0.995*** | 0.586*** | 0.578** | 0.536*** |
| | (4.33) | (4.29) | (3.49) | (2.70) | (3.37) |
| *Age* | 0.044 | 0.065** | -0.144*** | 0.028* | 0.063*** |
| | (1.59) | (2.65) | (-5.96) | (1.85) | (4.97) |
| *Competition* | -1.874 | -1.029 | -3.990** | -2.801** | -1.435 |
| | (-0.96) | (-0.51) | (-2.13) | (-2.44) | (-1.53) |
| *Competition^2* | 1.514 | 0.925 | 2.718** | 1.823** | 0.893 |
| | (1.19) | (0.70) | (2.14) | (2.38) | (1.47) |
| *Constant* | 1.731** | 0.873 | 2.424*** | 1.429*** | 0.392 |
| | (2.64) | (1.27) | (4.15) | (3.56) | (1.06) |
| Firm fixed effects | Yes | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes |
| Observations | 14,613 | 14,613 | 14,613 | 14,613 | 14,613 |
| R-squared | 0.802 | 0.792 | 0.640 | 0.755 | 0.787 |

**Table 2.1 Summary Statistics**

This table presents the summary statistics of variables used in the empirical analysis. I construct two measures of firm innovation: the sum of patent value scaled by lagged assets (PatVal) and the natural logarithm of one plus the adjusted citations received by all patents of a given firm (LnCit). The primary variable of interest is the local inventors (Inventors), which is defined as the number of outside inventors located within 100-km of the corporate headquarter. Bunches of control variables identified by prior literature are also incorporated. The sample contains 2,428 unique firms from 2000 to 2013. Variable definitions are in Appendix A.2. All continuous variables are winsorized at the 1st and 99th percentiles.

| Variables | Obs. | Mean | S.D. | P10 | P25 | Median | P75 | P90 |
|---|---|---|---|---|---|---|---|---|
| PatVal | 17,211 | 0.064 | 0.169 | 0 | 0 | 0 | 0.040 | 0.178 |
| LnCit | 17,211 | 1.045 | 1.404 | 0 | 0 | 0 | 1.982 | 3.180 |
| Inventors | 17,211 | 7.824 | 2.154 | 4.754 | 6.335 | 8.027 | 9.562 | 10.68 |
| Inventors_dummy | 17,211 | 0.504 | 0.500 | 0 | 0 | 1 | 1 | 1 |
| Size | 17,211 | 0.771 | 1.101 | -0.469 | -0.005 | 0.612 | 1.371 | 2.231 |
| BTM | 17,211 | 0.437 | 0.270 | 0.155 | 0.234 | 0.375 | 0.570 | 0.808 |
| R&D | 17,211 | 0.580 | 1.189 | 0 | 0 | 0 | 0.562 | 2.186 |
| Leverage | 17,211 | 0.447 | 0.195 | 0.169 | 0.303 | 0.457 | 0.597 | 0.696 |
| Cash | 17,211 | 0.201 | 0.153 | 0.054 | 0.093 | 0.157 | 0.265 | 0.425 |
| Tangibility | 17,211 | 0.259 | 0.173 | 0.054 | 0.124 | 0.228 | 0.369 | 0.512 |
| IO | 17,211 | 5.213 | 7.770 | 0 | 0.148 | 1.713 | 6.931 | 16.020 |
| ROA | 17,211 | 0.040 | 0.049 | 0.003 | 0.016 | 0.038 | 0.064 | 0.095 |
| Firm age | 17,211 | 4.095 | 1.071 | 2.571 | 3.570 | 4.395 | 4.891 | 5.166 |
| Competition | 17,211 | 0.936 | 0.103 | 0.832 | 0.939 | 0.977 | 0.985 | 0.987 |
| Competition^2 | 17,211 | 0.886 | 0.163 | 0.691 | 0.882 | 0.955 | 0.971 | 0.975 |
| University density | 17,211 | 0.190 | 0.105 | 0.093 | 0.125 | 0.155 | 0.211 | 0.317 |
| GDP growth rate | 17,211 | 11.670 | 2.213 | 8.500 | 10.000 | 11.800 | 13.400 | 14.800 |
| Population | 17,211 | 6.091 | 0.688 | 5.174 | 5.478 | 6.256 | 6.675 | 6.866 |
| GDP per capita | 17,211 | 10.170 | 0.776 | 9.026 | 9.581 | 10.270 | 10.840 | 11.130 |
| SOE | 14,308 | 0.558 | 0.497 | 0 | 0 | 1 | 1 | 1 |
| PCM | 16,286 | 4.848 | 7.223 | 0.487 | 1.105 | 2.458 | 5.559 | 12.130 |

**Table 2.2 The Effects of Local Inventors on Firm Innovation**

The table reports the pooled OLS regression results of the relationship between local inventors and firm innovation. The dependent variables are two measures built on patent value and patent citations, respectively. The main explanatory variable is the proxy for local inventors. Variable definitions are provided in the Appendix A.2, and all dependent variables are lagged by one year. I include a different set of fixed effects to control for common trend and other time-invariant firm, industry, and provincial characteristics. I denote the year, firm, industry, and provincial fixed effects by Y, F, I, and P, separately. The *t-statistics* based on standard errors clustered at the firm level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

| | Dep.Var. = PatVal | | | Dep.Var. = LnCit | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Inventors* | 0.006*** | 0.006*** | 0.009*** | 0.068*** | 0.059*** | 0.035 |
| | (3.30) | (2.82) | (2.69) | (4.73) | (3.91) | (1.45) |
| *Size* | 0.012*** | 0.013*** | -0.017*** | 0.408*** | 0.409*** | 0.329*** |
| | (3.76) | (4.01) | (-2.86) | (13.50) | (13.12) | (8.95) |
| *BTM* | -0.102*** | -0.111*** | -0.033*** | -0.077 | -0.039 | -0.107* |
| | (-10.09) | (-10.18) | (-3.77) | (-0.84) | (-0.40) | (-1.68) |
| *R&D* | 0.053*** | 0.046*** | 0.035*** | 0.292*** | 0.243*** | 0.182*** |
| | (13.84) | (11.27) | (9.18) | (17.51) | (13.65) | (11.00) |
| *Leverage* | -0.071*** | -0.071*** | -0.006 | -0.231** | -0.186 | -0.173 |
| | (-4.93) | (-4.71) | (-0.33) | (-2.00) | (-1.56) | (-1.51) |
| *Cash* | -0.025 | -0.028 | -0.032** | -0.453*** | -0.451*** | -0.015 |
| | (-1.27) | (-1.36) | (-2.00) | (-3.31) | (-3.23) | (-0.13) |
| *Tangibility* | -0.041*** | -0.053*** | 0.039*** | -0.493*** | -0.606*** | 0.530*** |
| | (-3.05) | (-3.76) | (2.87) | (-3.97) | (-4.75) | (5.06) |
| *IO* | 0.003*** | 0.003*** | 0.002*** | 0.008*** | 0.008*** | 0.002 |
| | (6.58) | (6.67) | (5.08) | (3.31) | (3.38) | (1.01) |
| *ROA* | 0.161*** | 0.189*** | 0.104*** | 0.794*** | 1.049*** | 0.092 |
| | (3.70) | (4.22) | (3.46) | (2.68) | (3.49) | (0.44) |
| *Firm age* | 0.009*** | 0.011*** | 0.020*** | -0.045** | -0.035* | 0.041* |
| | (3.90) | (4.37) | (5.65) | (-2.53) | (-1.93) | (1.91) |
| *Competition* | 0.939*** | | 0.276 | 8.484*** | | -0.764 |
| | (2.61) | | (0.87) | (3.23) | | (-0.40) |
| *Competition^2* | -0.659*** | | -0.180 | -6.012*** | | 0.620 |
| | (-2.79) | | (-0.89) | (-3.46) | | (0.50) |
| *University density* | -0.321*** | | -0.041 | -0.240 | | 0.012 |
| | (-2.97) | | (-0.54) | (-0.37) | | (0.03) |
| *GDP growth* | 0.000 | | -0.001 | 0.024*** | | 0.020** |
| | (0.31) | | (-0.52) | (2.98) | | (2.48) |
| *Constant* | -0.209 | 0.036* | -0.161 | -2.222** | 0.658*** | 0.267 |
| | (-1.56) | (1.69) | (-1.26) | (-2.33) | (3.92) | (0.35) |
| Fixed effects | Y | Y×I | Y | Y | Y×I | Y |
| | I | Y×P | F | I | Y×P | F |
| | P | | | P | | |
| Observations | 17,211 | 17,209 | 17,041 | 17,211 | 17,209 | 17,041 |
| R-squared | 0.313 | 0.342 | 0.684 | 0.476 | 0.507 | 0.766 |

**Table 2.3 The Effect of Local Inventors on Innovative Search Strategy**

The table reports estimated results of the effect of local inventors on innovative search strategy captured by breakthrough innovation. The dependent variable is LnTop1 (LnTop10), which is defined as the number of patent that falls into the top 1th (10th) percentile of the citation distribution. Variable of interest is the proxy for local inventors. I run both the pooled OLS and Poisson regression to accommodate the skewness of the patent number. All explanatory variables are lagged by one year, and their definitions are given in the Appendix. Y, I, and P denote the year, industry, and provincial fixed effects separately. The *t-statistics* based on standard errors clustered at the firm level are reported in the parentheses. *, **, *** represent the statistical significance at the 10%, 5%, and 1% level, respectively.

| | Pooled OLS | | Poisson | |
|---|---|---|---|---|
| | LnTop1 | LnTop10 | Top1 | Top10 |
| | (1) | (2) | (3) | (4) |
| *Inventors* | 0.010*** | 0.035*** | 0.066** | 0.084*** |
| | (2.73) | (4.43) | (2.13) | (2.89) |
| *Size* | 0.099*** | 0.248*** | 0.545*** | 0.602*** |
| | (9.57) | (12.51) | (15.44) | (16.41) |
| *BTM* | 0.018 | -0.041 | 0.414*** | 0.230* |
| | (0.61) | (-0.71) | (3.01) | (1.67) |
| *R&D* | 0.041*** | 0.162*** | 0.117*** | 0.134*** |
| | (7.67) | (14.85) | (4.23) | (4.59) |
| *Leverage* | -0.003 | -0.074 | 0.052 | -0.190 |
| | (-0.09) | (-1.13) | (0.22) | (-0.79) |
| *Cash* | -0.088** | -0.233*** | -0.772*** | -0.643*** |
| | (-2.10) | (-2.83) | (-2.76) | (-2.73) |
| *Tangibility* | -0.117*** | -0.285*** | -1.406*** | -1.316*** |
| | (-3.32) | (-3.94) | (-4.87) | (-4.22) |
| *IO* | 0.002*** | 0.004*** | 0.018*** | 0.016*** |
| | (2.65) | (2.67) | (4.89) | (4.86) |
| *ROA* | 0.171** | 0.293* | 2.586*** | 2.045*** |
| | (2.08) | (1.74) | (3.36) | (2.74) |
| *Firm age* | -0.008 | -0.019* | -0.094*** | -0.070** |
| | (-1.42) | (-1.71) | (-2.85) | (-2.37) |
| *Competition* | 1.000 | 6.495*** | -3.262 | -1.813 |
| | (1.29) | (4.15) | (-0.59) | (-0.21) |
| *Competition^2* | -0.746 | -4.573*** | 1.555 | 0.119 |
| | (-1.46) | (-4.47) | (0.41) | (0.02) |
| *University density* | -0.019 | -0.336 | 3.411** | 2.550 |
| | (-0.11) | (-0.87) | (2.42) | (1.61) |
| *GDP growth* | 0.003 | 0.008* | 0.044** | 0.072*** |
| | (1.27) | (1.68) | (2.17) | (3.36) |
| *Constant* | -0.279 | -1.912*** | -2.528 | -2.328 |
| | (-1.01) | (-3.35) | (-1.30) | (-0.72) |
| Fixed effects | Y | Y | Y | Y |
| | I | I | I | I |
| | P | P | P | P |
| Observations | 17,211 | 17,211 | 17,211 | 17,211 |
| R-squared | 0.195 | 0.392 | | |

**Table 2.4 Instrumental Variables Regression**

This table presents the two-stage least squares regression results for local inventors' effect on focal firm's innovation. Due to the data availability of per capita mining output, the sample period is from 2001 to 2013. The empirical model is:

[1st stage]: $Inventors_{ijpt} = \alpha Per\ capita\ mining\ output_{pt} + \beta Z_{ijpt} + \gamma K_{pt} + \lambda\mu_j + \varphi\upsilon_t + \varepsilon_{ijpt}$

[2nd stage]: $Y_{ijpt+1} = \alpha Inventors\ (IV)_{ijpt} + \beta Z_{ijpt} + \gamma K_{pt} + \lambda\mu_j + \varphi\upsilon_t + \varepsilon_{ijpt+1}$

Where $Z_{ijpt}$ is a vector of firm-specific variables, which I do not report the coefficients for brevity. $K_{pt}$ is a set of provincial characteristics, including population, GDP per capita, GDP growth rate, and university density. $\mu_j$ and $\upsilon_t$ are industry and year fixed effects, respectively. The *t-statistics* based on standard errors adjusting for heteroscedasticity and within-firm clustering are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, separately.

| *A. First-stage results* | |
|---|---|
| Dep. Var. = | Inventors |
| *Per capita mining output* | -0.038*** |
| | (-10.19) |
| *Population* | 1.105*** |
| | (19.46) |
| *GDP per capita* | 1.724*** |
| | (25.59) |
| *GDP growth* | -0.088*** |
| | (-9.60) |
| *University density* | 5.919*** |
| | (15.50) |
| Observations | 16,286 |
| R-squared | 0.695 |
| Kleibergen-Paap Wald F statistic | 103.8 |
| | (P=0.000) |

| *B. Second-stage results* | | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | PatVal | LnCit | LnTop1 | LnTop10 |
| *Inventors (IV)* | 0.023** | 0.269*** | 0.080*** | 0.155*** |
| | (2.41) | (3.63) | (4.68) | (3.69) |
| Observations | 16,286 | 16,286 | 16,286 | 16,286 |
| R-squared | 0.151 | 0.157 | 0.065 | 0.148 |

**Table 2.5 Labor Supply and the Effect of Local Inventors**

This table presents the result of subsample analyses based on the innovative industry and the number of industry inventors, which are used to reflect the demand of skilled workers. I partition the whole sample into two groups each year and then adopt the baseline specification to identify the effect. The dependent variables are two measures built on patent value and patent citations, respectively. Variable of interest is a proxy for local inventors within 100km of the corporate headquarter. All dependent variables are lagged by one year, and their coefficients are omitted for brevity. Panel A gives the result of subsample analysis based on innovative industry, while panel B reports that of industry inventors. Y, I, and P denote the year, industry, and provincial fixed effects separately. The *t-statistics* based on standard errors clustered at the firm level are reported in the parentheses. *, **, *** represent the statistical significance at the 10%, 5%, and 1% level, respectively.

| | PatVal | PatVal | LnCit | LnCit |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | Panel A: Innovative Industry | | | |
| | Yes | No | Yes | No |
| *Inventors* | 0.008*** | 0.001 | 0.081*** | 0.011 |
| | (2.68) | (0.51) | (4.16) | (0.67) |
| | | | | |
| Controls | Included | Included | Included | Included |
| Fixed effects | Y | Y | Y | Y |
| | I | I | I | I |
| | P | P | P | P |
| Observations | 9,800 | 7,402 | 9,800 | 7,402 |
| R-squared | 0.300 | 0.234 | 0.451 | 0.407 |
| $\chi^2$ test | 4.11 | | 7.42 | |
| P-Value | 0.043 | | 0.007 | |
| | Panel B: Industry's Inventor Counts | | | |
| | More | Less | More | Less |
| *Inventors* | 0.008*** | 0.001 | 0.078*** | 0.029* |
| | (3.12) | (0.51) | (4.02) | (1.85) |
| | | | | |
| Controls | Included | Included | Included | Included |
| Fixed effects | Y | Y | Y | Y |
| | I | I | I | I |
| | P | P | P | P |
| Observations | 10,292 | 6,910 | 10,292 | 6,910 |
| R-squared | 0.306 | 0.276 | 0.464 | 0.381 |
| $\chi^2$ test | 5.85 | | 4.19 | |
| P-Value | 0.016 | | 0.041 | |

**Table 2.6 Competitive Pressure and the Effect of Local Inventors**

This table presents the result of subsample analyses based on the product market competition, which I measure by the Herfindahl Hirschman Index and the four-firm concentration ratio. I then partition the whole sample into two groups – low and high group – by the sample median each year and adopt the baseline specification to identify the effect. The dependent variable are two measures built on patent value and patent citations, respectively. Variable of interest is a proxy for local inventors within 100km of the corporate headquarter. All dependent variables are lagged by one year, and their coefficients are omitted for brevity. Panel A gives the result of subsample analysis based on the Herfindahl Hirschman Index, while panel B reports that of four-firm concentration ratio. Y, I, and P denote the year, industry, and provincial fixed effects separately. The *t-statistics* based on standard errors clustered at the firm level are reported in the parentheses. *, **, *** represent the statistical significance at the 10%, 5%, and 1% level, respectively.

| | PatVal | PatVal | LnCit | LnCit |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | Panel A: Herfindahl Hirschman Index | | | |
| | Low | High | Low | High |
| *Inventors* | 0.008*** | 0.000 | 0.074*** | 0.025 |
| | (2.98) | (0.21) | (4.02) | (1.34) |
| | | | | |
| Controls | Included | Included | Included | Included |
| Fixed effects | Y | Y | Y | Y |
| | I | I | I | I |
| | P | P | P | P |
| Observations | 9,584 | 7,627 | 9,584 | 7,627 |
| R-squared | 0.323 | 0.276 | 0.473 | 0.394 |
| $\chi^2$ test | 4.88 | | 3.56 | |
| P-Value | 0.027 | | 0.059 | |
| | Panel B: Four-Firm Concentration Ratio | | | |
| | Low | High | Low | High |
| *Inventors* | 0.008*** | 0.000 | 0.074*** | 0.021 |
| | (3.04) | (0.15) | (4.13) | (1.06) |
| | | | | |
| Controls | Included | Included | Included | Included |
| Fixed effects | Y | Y | Y | Y |
| | I | I | I | I |
| | P | P | P | P |
| Observations | 9,957 | 7,254 | 9,957 | 7,254 |
| R-squared | 0.327 | 0.275 | 0.481 | 0.4 |
| $\chi^2$ test | 4.68 | | 4.28 | |
| P-Value | 0.031 | | 0.039 | |

**Table 2.7 Robustness Checks**

This table reports the results of several tests performed on the regressions of PatVal and LnCit. The main specification shows the estimate from the regression on the full sample. For brevity, this table only reports the coefficient on local inventors. Unless otherwise stipulated, the regressions include year, industry, and provincial fixed effects, and standard errors are corrected for clustering of observations at the firm level.

| | Dependent Variable | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | PatVal | | | | LnCit | | | |
| | Coeff. | t-Stat | No. of Obs. | R2 | Coeff. | t-Stat | No. of Obs. | R2 |
| Main specification | 0.006 | 3.30 | 17211 | 0.31 | 0.068 | 4.73 | 17211 | 0.48 |
| *General robustness* | | | | | | | | |
| (1) Exclude firms in Beijing, Shanghai and Shenzhen | 0.005 | 2.66 | 12859 | 0.3 | 0.063 | 4.46 | 12859 | 0.46 |
| (2) Exclude firms with headquarter moved across cities | 0.007 | 3.34 | 15325 | 0.31 | 0.069 | 4.46 | 15325 | 0.47 |
| (3) Exclude firms never patented during the sample period | 0.007 | 2.89 | 13903 | 0.31 | 0.068 | 4.24 | 13903 | 0.45 |
| (4) Use the invention patents only | 0.004 | 2.59 | 17211 | 0.28 | 0.042 | 3.70 | 17211 | 0.36 |
| (5) Use the utility model patent only | 0.003 | 3.81 | 17211 | 0.28 | 0.058 | 4.28 | 17211 | 0.45 |
| (6) Change the sample period from 2007 to 2013 | 0.007 | 2.48 | 9924 | 0.3 | 0.058 | 3.20 | 9924 | 0.47 |
| *Model specification* | | | | | | | | |
| (7) Control for the state ownership | 0.007 | 3.01 | 14308 | 0.3 | 0.066 | 4.21 | 14308 | 0.47 |
| (8) Cluster the standard error at the firm and city level | 0.006 | 2.82 | 17211 | 0.31 | 0.068 | 4.73 | 17211 | 0.47 |
| (9) Control for the industry cluster effect | 0.006 | 3.30 | 17211 | 0.31 | 0.062 | 4.24 | 17211 | 0.48 |
| (10) Dummy indicator of local inventors | 0.019 | 2.65 | 17211 | 0.31 | 0.143 | 3.42 | 17211 | 0.47 |
| (11) Change the geodesic distance to 80-km | 0.006 | 3.37 | 17186 | 0.31 | 0.075 | 5.57 | 17186 | 0.48 |

**Table 2.8 The Effect of Inventor Quality on Firm Innovation**

This table shows the results of the test on the relationship between inventor quality and firm innovation. I construct two measures to calibrate the ratio of inventors who file for the first application in foreign patent offices among the total number of local inventors: *foreign and US&WIPO*. The dependent variables are two measures of firm innovation built on patent value and patent citations, respectively. Variables of interest are the intersection term of inventors and inventor quality. All control variables are lagged by one year, and their coefficients are omitted for brevity. Y, I, and P denote the year, industry, and provincial fixed effects separately. The *t-statistics* based on standard errors clustered at the firm level are reported in the parentheses. *, **, *** represent the statistical significance at the 10%, 5%, and 1% level, respectively.

| | PatVal | PatVal | LnCit | LnCit |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *Inventors* | 0.003 | 0.002 | 0.060*** | 0.057*** |
| | (1.32) | (1.09) | (3.66) | (3.55) |
| *Inventors × Foreign* | 0.111*** | | 0.253 | |
| | (3.64) | | (1.23) | |
| *Foreign* | -0.553*** | | -1.327 | |
| | (-3.39) | | (-1.04) | |
| *Inventors × US&WIPO* | | 0.140*** | | 0.361 |
| | | (4.02) | | (1.56) |
| *US&WIPO* | | -0.777*** | | -2.168 |
| | | (-3.84) | | (-1.37) |
| | | | | |
| Controls | Included | Included | Included | Included |
| Fixed effects | Y | Y | Y | Y |
| | I | I | I | I |
| | P | P | P | P |
| Observations | 17,211 | 17,211 | 17,211 | 17,211 |
| R-squared | 0.315 | 0.315 | 0.476 | 0.476 |

### Table 2.9 Local Inventors and Firm Employee Structure

This table gives the empirical results of the relationship between local inventors and firm employee structure. I construct two measures to reflect employees' education background and the other two measures to capture the size and proportion of inventors in the employees. The dependent variable in column (1) and (2) represent the number and proportion of employees with a bachelor degree or above. The dependent variable in column (3) and (4) is the number and proportion of inventors respectively. All explanatory variables are lagged by one year, and their definitions are given in the Appendix. Y, I, and P denote the year, industry, and provincial fixed effects separately. The *t-statistics* based on standard errors clustered at the firm level are reported in the parentheses. *, **, *** represent the statistical significance at the 10%, 5%, and 1% level, respectively.

| | Bachelor<br>(1) | Bportion<br>(2) | Innovator<br>(3) | Iportion<br>(4) |
|---|---|---|---|---|
| *Inventors* | 0.056*** | 0.007*** | 0.049*** | 0.060*** |
| | (3.18) | (3.51) | (2.77) | (4.50) |
| *Size* | 0.817*** | 0.007* | 0.506*** | 0.016 |
| | (30.71) | (1.82) | (15.14) | (0.57) |
| *BTM* | -0.237*** | -0.046*** | -0.139 | -0.151* |
| | (-2.72) | (-3.63) | (-1.35) | (-1.82) |
| *R&D* | 0.148*** | 0.023*** | 0.326*** | 0.280*** |
| | (11.37) | (8.55) | (18.77) | (10.30) |
| *Leverage* | 0.148 | -0.022 | -0.206 | -0.314** |
| | (1.07) | (-1.09) | (-1.51) | (-2.47) |
| *Cash* | 0.233 | 0.089*** | -0.566*** | 0.061 |
| | (1.55) | (3.63) | (-3.68) | (0.35) |
| *Tangibility* | -0.149 | -0.218*** | -0.458*** | -0.828*** |
| | (-0.96) | (-8.94) | (-3.22) | (-6.53) |
| *IO* | 0.012*** | 0.000 | 0.008*** | 0.006** |
| | (4.77) | (0.68) | (2.81) | (2.09) |
| *ROA* | 1.124*** | -0.011 | 0.966*** | -0.129 |
| | (3.54) | (-0.22) | (2.86) | (-0.38) |
| *Firm age* | 0.033* | 0.010*** | -0.001 | -0.033 |
| | (1.84) | (3.40) | (-0.07) | (-1.64) |
| *Competition* | 3.006 | 0.097 | 6.363** | 5.685** |
| | (1.16) | (0.25) | (2.05) | (2.10) |
| *Competition^2* | -2.356 | -0.031 | -4.577** | -4.089** |
| | (-1.34) | (-0.12) | (-2.23) | (-2.26) |
| *University density* | -2.752*** | -0.366*** | -0.108 | -0.343 |
| | (-3.61) | (-3.04) | (-0.14) | (-0.44) |
| *GDP growth* | 0.015 | 0.004*** | 0.040*** | 0.033*** |
| | (1.43) | (3.26) | (4.28) | (3.51) |
| *Constant* | 3.662*** | 0.113 | -1.545 | -1.416 |
| | (3.87) | (0.75) | (-1.37) | (-1.44) |
| Fixed effects | Y | Y | Y | Y |
| | I | I | I | I |
| | P | P | P | P |
| Observations | 13,121 | 13,121 | 17,156 | 17,156 |
| R-squared | 0.510 | 0.380 | 0.479 | 0.241 |

**Table 2.10 The Effect of Local versus Remote Inventors on Firm Innovation**

This table shows the empirical results of the relationship between remote inventors and firm innovation. I calculate the number of inventors located within 200-km, but 100-km away from the corporate headquarter and then take the natural logarithm of one plus it. Similarly, I get the number of inventors located 200-300 km away from the corporate headquarter. The dependent variables are two proxies built on patent value and patent citations, respectively. All explanatory variables are lagged by one year, and their definitions are given in the Appendix A.2. Y, I, and P denote the year, industry, and provincial fixed effects separately. The *t-statistics* based on standard errors clustered at the firm level are reported in the parentheses. *, **, *** represent the statistical significance at the 10%, 5%, and 1% level, respectively.

| | Dep.Var. = PatVal | | | Dep. Var. = LnCit | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Inventors* | 0.006*** | 0.006*** | 0.005*** | 0.066*** | 0.066*** | 0.064*** |
| | (3.08) | (3.03) | (2.72) | (4.58) | (4.43) | (4.22) |
| *Inventors (100-200km)* | -0.008*** | | -0.008*** | -0.035* | | -0.036* |
| | (-3.01) | | (-3.09) | (-1.85) | | (-1.91) |
| *Inventors (200-300km)* | | -0.002 | -0.003 | | -0.010 | -0.014 |
| | | (-0.74) | (-1.09) | | (-0.47) | (-0.67) |
| Controls | Included | Included | Included | Included | Included | Included |
| Fixed effects | Y | Y | Y | Y | Y | Y |
| | I | I | I | I | I | I |
| | P | P | P | P | P | P |
| Observations | 17,211 | 17,211 | 17,211 | 17,211 | 17,211 | 17,211 |
| R-squared | 0.314 | 0.313 | 0.314 | 0.477 | 0.476 | 0.477 |

**Table 2.11 Patent Value and Firm Performance**

This table shows the empirical results of the relationship between patent value and the focal firm's performance. The main dependent variable is the percentage change of earnings before interest, taxes, depreciation and amortization (EBITDA). I then decompose the change in EBITDA to changes in market size, market share, and profit margin. The lagged dependent variable is included in each specification, but its coefficient are not reported for brevity. All independent variables are lagged by one year, and their definitions are in the Appendix A.2. I include the year (Y) and firm (F) fixed effects to control common trends and time-invariant firm characteristics. The *t-statistics* based on standard errors clustered at the firm level are reported in the parentheses. *, **, *** denote the statistical significance at the 10%, 5%, and 1% level.

| | Chg_ebitda<br>(1) | Chg_mktsize<br>(2) | Chg_share<br>(3) | Chg_margin<br>(4) |
|---|---|---|---|---|
| *PatVal* | 0.508*** | -0.058 | 0.307*** | 0.189*** |
| | (5.21) | (-1.61) | (5.74) | (2.79) |
| *Size* | -0.273*** | -0.033** | -0.105*** | -0.113*** |
| | (-6.75) | (-2.38) | (-5.91) | (-2.99) |
| *Book-to-market* | -0.190** | -0.015 | -0.128*** | -0.100 |
| | (-2.26) | (-0.51) | (-3.94) | (-1.26) |
| *R&D* | -0.020 | -0.009 | -0.017** | -0.010 |
| | (-1.17) | (-1.62) | (-2.35) | (-0.77) |
| *Leverage* | 0.893*** | 0.052 | 0.176** | 0.645*** |
| | (5.69) | (1.11) | (2.32) | (4.50) |
| *Cash* | -0.095 | 0.030 | -0.132* | 0.104 |
| | (-0.59) | (0.51) | (-1.79) | (0.65) |
| *Tangibility* | -0.183 | 0.051 | -0.154** | 0.072 |
| | (-1.21) | (0.91) | (-2.41) | (0.48) |
| *Institutional ownership* | 0.001 | 0.001 | 0.001 | -0.002 |
| | (0.75) | (1.33) | (1.09) | (-1.04) |
| *ROA* | 1.213** | -0.084 | -0.038 | 2.210*** |
| | (2.56) | (-0.81) | (-0.26) | (4.87) |
| *Firm age* | -0.155*** | -0.030* | -0.074*** | -0.103** |
| | (-3.47) | (-1.76) | (-4.07) | (-2.44) |
| *Competition* | -0.002 | 0.149 | 0.055 | 0.032 |
| | (-0.00) | (0.59) | (0.33) | (0.10) |
| *Constant* | 0.602 | 0.283 | 0.395** | -0.043 |
| | (1.61) | (1.17) | (2.37) | (-0.12) |
| Fixed effects | Y | Y | Y | Y |
| | F | F | F | F |
| Observations | 15,636 | 15,636 | 15,636 | 15,636 |
| R-squared | 0.193 | 0.205 | 0.154 | 0.190 |

**Table 2.12 The Effects of Local Inventors on Patent Counts**

This table presents the results from pooled OLS regression of the relationship between local inventors and firm innovation measured by raw patent counts. The dependent variables are three measures built on the number of patents that a firm filed for (eventually granted) in a given year. I consider only invention and utility model patents. Variable of interest is the proxy for local inventors. Variable definitions are provided in the Appendix A.2, and all dependent variables are lagged by one year. I include a different set of fixed effects to control for common trend and other time-invariant firm, industry, and provincial characteristics. I denote the year, firm, industry, and provincial fixed effects by Y, F, I, and P separately. The *t-statistics* based on standard errors clustered at the firm level are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

| | Ln(1+Patent) | Ln(1+Invention) | Ln(1+Utility) | Ln(1+Patent) | Ln(1+Invention) | Ln(1+Utility) |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Inventors* | 0.063*** | 0.044*** | 0.055*** | 0.040 | 0.040** | 0.029 |
| | (4.44) | (3.95) | (3.96) | (1.60) | (2.22) | (1.25) |
| *Size* | 0.406*** | 0.371*** | 0.367*** | 0.354*** | 0.260*** | 0.366*** |
| | (13.64) | (11.99) | (12.21) | (9.63) | (7.82) | (9.73) |
| *BTM* | -0.052 | -0.234*** | 0.074 | -0.122* | -0.044 | -0.133** |
| | (-0.58) | (-2.86) | (0.84) | (-1.92) | (-0.83) | (-2.13) |
| *R&D* | 0.288*** | 0.250*** | 0.216*** | 0.187*** | 0.157*** | 0.178*** |
| | (18.03) | (14.86) | (12.67) | (11.55) | (11.89) | (11.54) |
| *Leverage* | -0.209* | -0.343*** | -0.031 | -0.206* | -0.149 | -0.240** |
| | (-1.85) | (-3.57) | (-0.29) | (-1.80) | (-1.59) | (-2.11) |
| *Cash* | -0.366*** | -0.331*** | -0.284** | 0.054 | -0.010 | 0.133 |
| | (-2.75) | (-2.78) | (-2.22) | (0.48) | (-0.12) | (1.22) |
| *Tangibility* | -0.440*** | -0.330*** | -0.326*** | 0.532*** | 0.470*** | 0.392*** |
| | (-3.59) | (-3.11) | (-2.80) | (5.21) | (5.65) | (4.11) |
| *IO* | 0.007*** | 0.006*** | 0.003 | 0.001 | 0.003** | -0.001 |
| | (3.06) | (2.88) | (1.37) | (0.42) | (2.21) | (-0.67) |
| *ROA* | 0.833*** | 0.174 | 0.695** | 0.075 | -0.029 | -0.041 |
| | (2.88) | (0.71) | (2.56) | (0.37) | (-0.19) | (-0.21) |
| *Firm age* | -0.033* | -0.006 | -0.036** | 0.051** | 0.013 | 0.041** |
| | (-1.90) | (-0.40) | (-2.13) | (2.40) | (0.71) | (2.02) |
| *Competition* | 8.127*** | 3.861 | 11.840*** | -0.668 | -1.642 | 2.119 |
| | (3.09) | (1.64) | (5.03) | (-0.36) | (-1.08) | (1.12) |
| *Competition^2* | -5.720*** | -2.735* | -8.219*** | 0.525 | 1.166 | -1.303 |
| | (-3.29) | (-1.78) | (-5.28) | (0.43) | (1.19) | (-1.06) |
| *University density* | -0.127 | -1.543*** | 0.301 | 0.095 | -0.484 | 0.091 |
| | (-0.20) | (-2.76) | (0.49) | (0.21) | (-1.50) | (0.22) |
| *GDP growth* | 0.025*** | 0.022*** | 0.011 | 0.023*** | 0.010 | 0.017** |
| | (3.20) | (3.47) | (1.42) | (2.78) | (1.51) | (2.19) |
| *Constant* | -2.204** | -0.814 | -3.647*** | 0.172 | 0.496 | -0.842 |
| | (-2.31) | (-0.95) | (-4.29) | (0.23) | (0.82) | (-1.12) |
| Fixed effects | Y | Y | Y | Y | Y | Y |
| | I | I | I | I | I | I |
| | P | P | P | P | P | P |
| Observations | 17,211 | 17,202 | 17,202 | 17,041 | 17,032 | 17,032 |
| R-squared | 0.503 | 0.393 | 0.469 | 0.784 | 0.753 | 0.775 |

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