Value-destructive Patents?

Jinghan Cai[1]
(University of Scranton, USA)

Yunzhi Lu
(South China Normal University, China)

Le Xia
(BBVA, Hong Kong, China)

Dazhi Zheng
(West Chester University, USA)

Kaiguo Zhou*
(Capital University of Economics and Business, China)

[1]Cai is from University of Scranton, U.S.A., email: jinghan.cai@scranton.edu; Lu is from South China Normal University, China, email: yunzhi.lu@m.scnu.edu.cn; Xia is from BBVA, Hong Kong, China, email: le.xia@bbva.com; Zheng is from West Chester University, U.S.A., email: dzheng@wcupa.edu; Zhou (Corresponding author) is from Capital University of Economics and Business, China, email: zhoukg@cueb.edu.cn.

Abstract

The quantity of patent granted, often referred to as patent count, serves as an important indicator of a firm's innovation capability and is widely used as a measure of research and development (R&D) output. However, this paper uncovers a negative relationship between patent count and the Tobin Q of Chinese listed firms. Specifically, a one-percent increase in total patent counts will lead to a 2.51 percent drop in Tobin Q, suggesting that patents can be value destructive. We argue that the observed value-destructive patents stem from China's administrative innovation system in which quantity-based incentives are pervasive in the society. When stakeholders (CEOs, head of subsidiaries, etc.) have patent-quantity-based incentives or targets (e.g., seeking government subsidies or job promotion, reputation building, peer pressure, etc.), classic agency problems occur: stakeholders may benefit from producing low-quality patents for the quantity-based incentives, which demises firm value. We call the above mechanism the "inflated patent count hypothesis" and provide supporting empirical evidence by showing that: (1) value-destructive patents are prevailing in the society; (2) when there is a stronger incentive (e.g., InnoCom program), patents are more value destructive; (3) patents from firms with higher patent-count-peer-pressure tend to be more value destructive.

Keywords: Patents, Firm value, Inflated patent count hypothesis, Value destruction

JEL code: O31, O38, G40,

1. Introduction

Since surpassing the United States in 2011, China has become the global leader in patent applications and grants. Over the decade, China's lead has consistently widened: In 2021, an impressive 607,758 patents were granted in China, far exceeding the 286,205 patents granted in the United States. Notably, China's patent dominance spanned across 29 fields, while the United States and Japan led in only 4 and 3 fields, respectively (Figure 1). This surge in patent counts reflects China's growing emphasis on innovation, intellectual property protection, and substantial investments made by domestic companies in research and development.

However, unlike in the U.S., where innovations emerge from market-oriented motives, China's innovation system features strong state direction: Starting from the early 2000's, the Chinese central government has introduced a series of policies to promote scientific and technological progress and to stimulate innovation, such as, the *National Medium- and Long-term Science and Technology Development Plan Outline* (2006) and *Revisions to the Patent Law* (2008)[2], which strengthen patent protection, emphasize enhancing national innovation capabilities, and encourage independent innovation. While emphasizing the quality of innovations, which is harder to evaluate ex-ante, most of these policies implicitly, or even explicitly, set up targets based on patent quantity: compared with quality, patent counts are much easier to quantify. For example, the *National Medium- and Long-term Science and Technology Development Plan Outline* (2006) states that "By 2020, ……The annual authorized number of domestic invention patents …… ranks among the top 5 in the world." With such guidance from the central government, there appears a cascading patent count target system which creates a multi-layered pressure environment: The provincial governments closely follow up with the central government and set quantity-based targets in their economic development plans[3]. Then, city- and county-level administrators tend to further translate national/provincial targets into specific regional quotas. Finally, firms as well as corresponding stakeholders of the firms, e.g., CEOs, heads of subsidiaries, etc., incorporate patent count targets into their performance/incentive metrics. This is the China-featured "administrative innovation system". On one hand, this cascading patent count target system has successfully promoted the

[2] Table 0 shows some important Policies introduced by the central government of China.
[3] For example, almost all the provincial five-year plans contain the number of patents per person goal for the next five-year period.

R&D development in China, and has increased China's patent output dramatically[4]. On the other hand, the patent quantity target, although sometimes without concrete numbers, has been embedded everywhere in the entire society: local governments understand that patent count is within their performance metric; firms know that their performance evaluation, access to subsidies and resources, and relationship with local governments partly depend on their contribution to the local patent statistics; stakeholders (CEOs, head of subsidiaries, etc) may also have patent counts in their performance valuation and incentive metric for job promotion, reputation building, etc. (He 2021; Kersten et al. 2022; Ang et al. 2024).

However, these quantity-incentivized actions are not necessarily value maximizing, which give rise to classic agency problems. The prevailing patent-count-based "soft targets" may lead the stakeholders, driven by quantity-based goals, to produce lower quality patents, due to the lower cost associated with producing low-quality patents, and the difficulty to identify patent qualities ex-ante. Consequently, the agency problems may result in lower firm values. To summarize, the prevailing quantity-based soft targets lead stakeholders of the firms to produce excessive low-quality patents to realize the quantity goals, but those low-quality patents may demise the market values of the firm. This mechanism is what we define as the "inflated patent count hypothesis" (IPC hereinafter).

In the current literature, there have been many discussions on Chinese administrative innovation system and concerns on quality have been raised. Among the early research endeavors, Hu and Jefferson (2009) argue that the dramatic increase in patent count stems from government indicatives, and they raise concerns about whether the volume of patents translates into substantive innovation or is more reflective of incentives to meet government targets. Li (2012) argues that alongside R&D, changes in patent laws, ownership reforms, and the cultural shift towards recognizing patenting as a measure of innovation success are pivotal. It highlights how these institutional changes led to an increase in patent filings across different sectors, not just in corporate entities but also in universities and individual inventors. The role of government incentives in driving this patent surge has been extensively debated. Hu (2010) investigates how

[4] For example, Hu and Jefferson (2009) argue that Amendments to the patent law that favor patent holders and ownership reform that has clarified the assignment of property rights also emerge as significant sources of China's patent boom.

government subsidies and rewards for patent applications have influenced the behavior of firms. His findings suggest that while these incentives have clearly increased patent filings, they might not necessarily lead to high-quality innovations. This raises questions about the strategic use of patents to secure economic benefits rather than to protect genuine innovations. More recently, there has been a growing literature on the misallocation effects caused by China's quantity-based R&D policy. Among those studies, Konig et al. (2022) construct a model to show how subsidy policy affects firms' choice between imitation and innovation and leads to a suboptimal outcome, and the R&D misallocation between innovation and imitation has a large negative effect on TFP growth. Cao et al. (2024) document that China's quantity-based innovation targets and subsidy programs seem to have induced a quantity-quality trade-off in the R&D investment. They find that quantity-based subsidies reduce the equilibrium growth rate by 0.19 percentage points, or 10% of the actual TFP growth decline from 2001–2007 to 2008–2014, and reduce the aggregate welfare by 3.31%. Wei et al. (2023) scrutinize the InnoCom program and estimate that the social return to this R&D program is -19.7%.

In Wei et al. (2023) or almost all other current literature papers, firms are considered as rational and they individually maximize their market values. The possible welfare loss is at the entire society level and it comes from the large scale of government subsidy and marginal cost of tax collection (e.g., see Wei et al 2023, for more details). Our IPC hypothesis takes one step ahead and suggests that firms may end up producing excessive low-quality patents, which hurts induvial firms' market values at individual firm levels. Empirically we use the sample period of 2008 to 2019 and find that an increase in a firm's annual patent count from zero to the sample mean of 60.02 causes a decrease in Tobin Q of the Chinese listed firms by 0.428 (the mean Tobin Q is 2.20 in our sample). It is hard to justify why rational firms want to produce a patent knowing it is going to hurt the firm value otherwise, but we argue that the classic agency problem suggested by our IPC hypothesis can well explain the phenomenon.

In the existing literature, there have been alternative explanations on why patents could lead to lower firm values, including: (i) Market under-reaction: Patents are sometimes complicated, and it takes longer for the market to understand the value of them. In other words, the market is not efficient enough to reflect the information in a timely manner (Fitzgerald et al. 2021); (ii)

Information ambiguity: high uncertainties associated with R&D programs may cause higher information ambiguity and therefore require further compensation for lower quality of information disclosure, which increases the discount rate and thus lower the market value (see Hussinger and Pacher 2019). (iii) Strategic patenting. The objective of some patents is neither to foster technological innovation nor to protect innovation from imitation, but solely to block competitors from innovating in the same technological area (Blind et al. 2006; Veihl 2022). However, we show that our results cannot be reconciled by those alternative explanations.

In comparison to that, we provide a series of tests and all the results are consistent with the agency problem story and the IPC hypothesis. First, we find that when there is a stronger incentive, firms tend to produce more patents but those patents are more value-destructive. The InnoCom program provides a good example. The InnoCom program is a tax incentive scheme that provides substantial corporate income tax cuts. We find that in the year when a firm gets its InnoCom qualification, they file a significantly higher number of patents than the two-year window before and after[5]. Also, the increase in patent count is at the cost of patent quality: in the year of InnoCom qualification, patent quality (proxied by the 5-year citation as well as the ratio of invention patents over total patents, etc. See Farre-Mensa et al, 2020, among others) is lower than the two-year window before and after. The InnoCom qualification is associated with a Tobin Q decrease of 1.21% for individual firms. In the literature, Wei et al. (2023) show that the InnoCom program alone can cause -19.8% welfare loss due to the distortion at society level. Our result implies that the social cost for quantity-based policies is even higher than Wei et al.'s (2023) estimation since firms may deviate from their value-maximizing objectives due to the agency problems.

Second, we find empirical evidence supporting that the value destructive patents are prevailing in the entire society: (1) value-destructive patents are found in both highly-patent-concentrated industries and those industries with very few patents; (2) both the State-owned enterprises (SOEs) and the private firms produce value-destructive patents; (3) For firms who are not facing InnoCom program opportunities, value-destructive patents are documented. This finding echoes the

[5] Interestingly, the average patent count around the InnoCom certification year is way higher than the InnoCom's required number, and both invention patents and utility patents increases. It is hard to attribute this finding to merely meeting the InnoCom requirements. Instead, when firms/stakeholders know that InnoCom year is the timepoint where patent counts are more important, they tend make their profiles look better by producing a higher number of patent count.

prediction that the cascading patent-quantity-based soft targets are pervasive in the society.

Third, cross-sectionally, we find that "weaker firms'" within an industry (which are defined as those firms whose annual patent count falls below the industry median) are more value destructive, since the stakeholders may face peer pressure and have stronger agency problems. Also, we find that the subsidiaries' patents will cause a larger Tobin Q drop for their parent firms than the parent firms' patents do. This seemingly counter-intuitive finding can be well-explained by the agency problems suggested by the IPC hypothesis. Subsidiaries may face stronger agency problems: they care more about their own performance metrics (which is related to patent counts) but they care less about their parent firm values. Therefore, they tend to produce more value-destructive patents.

Our paper contributes to the current literature in the following ways. First, we document a "value-destructive patents anomaly" in China: we find a robust and significant negative relationship between patent counts and firm value, which contradicts most of the existing literature that the patent counts, as a measure of R&D output, should be positively related with the firm's market values (Jaffe 1986; Hall 1993; Hall et al. 2005; Sandner and Block 2011; Fang et al. 2014; Carosi 2016; Kogan et al. 2017). It is also documented in the literature that the responses of patent counts and citation numbers (a well-accepted measure of patent quality, see Farre-Mensa, 2019, among others) to some internal and external factors are typically found to vary in the same direction (e.g., see Kong et al. 2020). Overall, the conventional wisdom on R&D and patent counts makes our empirical results novel and counter intuitive. Our empirical results suggest that this anomaly cannot be explained by the existing hypotheses, e.g., (1) market underreaction, see Fitzgerald et al. (2020); (2) information ambiguity, see Kong et al. (2022), Hussinger and Pacher (2019); or (3) strategic patenting, see Blind et al. (2006), Noel and Schankerman (2013), Veihl (2022), among others.

Second, our paper contributes to the growing literature on the misallocation effects caused by China's quantity-based R&D policy, in which firms are typically considered as rational and value maximizing at individual firm levels. Our IPC hypothesis takes one step ahead and suggests that firms may produce excessive number of low-quality patents to fulfill the quantity goals, which hurts market values at firm levels due to the agency problems. In the literature, Konig et al. (2022)

construct a model to show how subsidy policy affects firms' choice between imitation and innovation and leads to a suboptimal outcome, and the R&D misallocation between innovation and imitation has a large negative effect on TFP growth. Cao et al. (2024) document that China's quantity-based innovation targets and subsidy programs seem to have induced a quantity-quality trade-off in the R&D investment. They find that quantity-based subsidies reduce the equilibrium growth rate by 0.19 percentage points, or 10% of the actual TFP growth decline from 2001–2007 to 2008–2014, and reduce the aggregate welfare by 3.31%. Wei et al (2023) scrutinize the InnoCom program and estimate that the social return to this R&D program is -19.7%. While they focus on TFP growth, welfare and social return, in essence, our paper is complementary to these papers in that, for the first time in the literature, we test the R&D's distortion effect from the stock market reaction. We show that the stock market negatively reacts to the surge of patent number, and this observed value-destructive patent counts strengthen this stream of resource misallocation literature and are consistent with patent counts' negative impact on TFP growth, the welfare loss and the negative social return resulted from the misallocation, as documented in Konig et al. (2022), Cao et al. (2024), and Wei et al. (2023). In our case, the stock market seems to be smart enough to value the surging patent quantity negatively. Also, echoing Cao et al. (2024), we find that InnoCom qualification is accompanied with higher patent quantity but lower quality, and we further document the market response to the InnoCom: the qualification is associated with a Tobin Q decrease of -1.21%.

Our paper also has important policy implications. While government policies have been effective in enhancing China's innovation capacity, as reflected by the country's dominance of patent filings, there is a potential downside. These policies, which incentivize firms to focus on patent quantity, may inadvertently overlook patent quality. As stated in Ang et al (2023), by looking at the burgeoning patent counts in China, Western observers frequently gasp at the staggering numbers and its appearance of rapid catch-up with the United States technologically by mobilizing its bureaucracy and assigning ambitious targets to local governments, it may be only a phenomenon described as "China's Great Leap Forward in patenting" (Hu et al., 2017). Moreover, this patent quantity-driven trend in China is wide-spread. For example, in the document "*Outline of the 14th Five-Year Plan for Economic and Social Development of Hainan Province and Vision 2035*",[6] one

[6] The Chinese name of the document is: 海南省国民经济和社会发展第十四个五年规划和二〇三五年远景目标纲要,

of the main development goals (Section 4, page 7) is that the number of invention patents will go up from 4.5 patents per 10,000 people in 2020 to 6.2 per 10,000 people by 2025, which is still quantity oriented. Ironically, the goals are silent on patent quality. Under the current policies, we may legitimately envisage that firms are motivated to prioritize quantity over quality, resulting in excessive and low-quality patents. Hence, we suggest governments and policy makers to look into policies that delink incentives and patent quantity, which may weaken the above distortion and incentivize companies to focus on pursuing meaningful and impactful innovations.

The rest of the paper is arranged as follows: Section 2 reviews the literature. Section 3 shows the empirical results. Section 4 discusses the mechanism, and Section 5 concludes.

2. Literature review: Alternative explanations

2.1 Conventional Wisdom: Value-enhancing Patents

It is well known that technological innovation is a key driver of economic growth (Romer 1990). As is suggested by Schumpeter (1942)'s pioneered work, the so-called *creative destruction* depicts the critical role that innovation comes into effects: generally, technological innovation can create new products for improving the social welfares and displace the incumbents with more efficient competitors, thus enhancing the value of the innovators (Garcia-Macia et al. 2019). Following this lead, many theoretical and empirical studies try to investigate how the market value is related with innovative activities. Loosely speaking, the research and development (R&D) conducted by a firm is an investment decision (Hall and Lerner 2010), while its output is an intangible asset known as firm's "knowledge capital" (Griliches 1979; Bloom et al. 2013). If knowledge stock contributes positively to the firm's future net cash flows, then the size of a firm's knowledge stock should be reflected in the firm's observed value. In the augmented *q*-based investment model, Griliches (1981) predicts that the market value, measured by Tobin's *q*, will be higher if more knowledge capital is acquired. Many empirical researchers test this firm-side prediction using accumulated R&D stocks (Jaffe 1986; Hall 1993; Carosi 2016) and, more recently, patents[7] (Hall et al. 2005; Sandner and Block 2011; Fang et al. 2014; Kogan et al. 2017; Stoffman et al. 2022; Tseng 2022).

obtained from the website of National Development and Reform Commission (https://www.ndrc.gov.cn/fggz/fzzlgh/dffzgh/202104/P020210428646025031658.pdf)

[7] Admittedly, the final goal of innovation is the launch of new products which helps generate higher profits (Fracassi et al. 2022). However, the launch of new products contains many confounding factors such as labor and physical capital inputs. The increase in market valuation related with this may consist of those from input factors.

Belenzon (2012) further show that citations on the technology based on which a firm built before are linked to market value positively.[8]

2.2 New Wine in Old Bottles: Value Destructive Patents

Although the positive relationship between patents and market values is more intuitive, the dispute of patent system is not limited to traditional factors. In fact, some papers provide opposite evidence against the conventional wisdom.

(1) Market Under-reaction

The idea behind this theory is that the information conveyed by the patents may be neglected by some investors, leading to a lower market value. Early studies attribute this to investor's sentiment (Baker and Wurgler 2006) and short-sale constraints (Shleifer and Vishny 1997). However, Leung et al. (2020) do not find deterministic evidence supporting these channels. Recently, some scholars argue that the underreaction to complex information leads to asset mispricing, which means investors cannot realize the benefits of innovation (Eberhart et al. 2004) or they have limited attentions on the characteristics of the firm's innovation efficiency (Hirshleifer et al. 2013) and originality (Hirshleifer et al. 2018). Along with this argument, researchers link this anomaly to a broader range of patenting characteristics such as incremental innovation (Fitzgerald et al. 2020) and patent examiner's busyness (Shu et al. 2022).

(2) Information Ambiguity

Since the R&D programs are highly uncertain, conventional financial information may be insufficient for relevant investors to make correct investment decisions. For instance, Xu et al. (2007) investigate some combinations of financial and non-financial information (such as approved patents) from biotech firms and conclude that the complementarity between them is crucial to market pricing of the firm's R&D expenses.

Though some scholars argue that, in an efficient stock market, stock prices should fully reflect the firm's intangible assets including R&D and advertising (Chan et al. 2001), there is some evidence

---

[8] There has been another stream of literature which starts from investors side and explore the relationship between innovations/R&D, systematic risks, as well as the expected returns/abnormal returns (e.g., Berk et al. 2004; Garlappi 2004; Gu 2016; Hsu 2009; Li 2011; Kung and Schmid 2015; Gu 2016; Bena and Garlappi 2020).

of under-recognized incoming spillover effects of R&D even in the most developed stock markets such as the US market (Chen et al. 2013). Despite the fact that a firm's ability to innovate is easy to compute, Cohen et al. (2013) suggest that investors tend to ignore the past success of technological innovation of the firms.[9]

To explain this phenomenon, Epstein and Schneider (2008) introduce the concept of ambiguity averse investors who are pessimistic about uncertainty and take the lower bound of the possible outcomes. Thus, on top of traditional risk premium, the information ambiguity asks for further compensation for low quality of information disclosure. In line with this prediction, Hussinger and Pacher (2019) show that information ambiguity embedded in the patents may hinder the process of valuation of future profitability and thus lower the market value.

(3) Strategic Patenting

Some related research suggests that, in addition to the under-reaction theory, there are other strategical and institutional issues that could reverse the sign of innovation on market performance. Generally speaking, the patenting system grants innovators with short-term monopoly rights to appropriate the benefits from their inventions in exchange of incentives for innovation and early publication of technology-related information (Hall and MacGarvie 2010). The net effect of innovation on market value relies on the tradeoff between the benefits and costs of patenting. However, attracted by the potential monopolistic profits, some larger companies may possess a number of low-quality patents, known as the *strategic purposes* of patent application, which can lead to value destruction as well. For example, Noel and Schankerman (2013) find that the strategic patenting on firm's value such as patent thickets are detrimental to firm's value[10]. The authors show that such strategic behavior is actually a rational response, but with unintended effect, to the patent system.

3. Empirical results

[9] It is worthy point out that the prediction of market under-reaction theory on market values is opposite to that on stock returns. As is discussed by Shu et al. (2022), a positive relation between patent quality and market values implies a negative relation between patent quality and stock returns.

[10] The patent thicket is also known as the fragmentation of patent rights. The strategic innovator will divide her invention into many pieces of patents with detailed claims on specific fields related with the main invention. By doing so, the innovator establishes a "thicket" preventing any potential followers from exploring the underlying technology, which increases the enforcement costs.

3.1 Sample Selection and Variable Definition

Our dataset is compiled from multiple sources. Our main sample covers all common equity from 2008 to 2019 that are traded in A-share markets of China, including Shanghai Stock Exchange Mainboard, Shenzhen Stock Exchange Mainboard, Small and Medium Enterprise Board, and ChiNext market. We obtain the companies' and their subsidiaries' names from annual reports and use them as the applicants to search their patent application records from China National Intellectual Property Administration (CNIPA) webpage. The citation data of patents are collected from a data vendor named Chinese Research Data Services Platform (CNRDS). Trading data and financial statement data of the firms are from CSMAR dataset. Our sample contains 3,598 listed firms from China. According to CNIPA webpage,[11], there are three types of patents: invention patents, utility patents, and design patents. If there is a new technical solution relating to a product, a process, or an improvement thereof, an *invention patent* may be filed. If there is a new technical solution relating to a product's shape, structure, or a combination thereof, which is fit for practical use, a *utility patent* may be filed. If there is a new design of the shape, pattern, or a combination thereof, as well as a combination of the color, shape and pattern of the entirety or part of a product, which creates an aesthetic feeling and is fit for industrial application, a *design patent* may be filed. In our paper, letter A refers to the number of invention patents, letter U refers to that of utility patents, letter S refers to that of design patents, and letter P refers to total patent count, P=A+U+S.

The descriptive statistics of the underlying firms are shown in Table 1. We can see that in the sample period, the average patent counts increase rapidly, soaring from an average of 20.35 patents per firm in 2008 to 93.41 patents in 2019. The pooled mean total annual patent count for a listed firm in China is 60.02.

(Insert Table 1 here)

3.2 Naïve model

We first run a naïve regression of Tobin Q on firms' patent counts using the following regression:

$$UTobinQ_{it} = \theta_0 + \gamma_0 UPatNo_{it} + \nu_{0t} + \varepsilon_{it} \quad (1)$$

[11]See: https://english.cnipa.gov.cn/col/col2995/index.html

where $UTobinQ_{it}$ is the undetrended Tobin Q of firm *i* in year *t*, and $UPatNo_{it}$is the undetrended patent count, defined as the natural logarithm of (1+number of patents from firm *i* in year *t*). Letter A refers to the number of invention patents, letter U refers to utility patents, letter S refers to design patents, and letter P refers to total patent count, P=A+U+S. The estimation uses OLS model with White heteoskadasticity-adjusted standard errors and time fixed effect, and the results are shown in Table 2.

(Insert Table 2 here)

The results of the naïve regressions in Table 2 look counter intuitive. Based on the existing mainstream literature (e.g., Hall, et al, 2005), we expect to see that patent counts will propel firm value, but none of the coefficients in Table 2 are significantly possible. On contrary, all the coefficients for the undetrended patent counts are significantly negative. This documented value-destructive patent is not consistent with most current theoretical and empirical research.

3.3 The baseline model and inflated patent count hypothesis

Next, we try to run the following set of baseline regressions to have a closer look at the relationship between firm value, patent counts, and intangible assets:

$$Intang_{it} = \alpha^{Int} + \beta^{Int} PatNo_{it} + \nu_i + e_{it}^{Int} \quad (2)$$

$$TobinQ_{it} = \alpha^{Q} + \gamma_1 PatNo_{it} + \gamma_2 X_{it} + Control_{it}\delta' + \nu_i + e_{it}^{Q} \quad (3)$$

where $PatNo_{it}$ is the detrended[12] natural logarithm of (1+patent count from firm *i* in year *t*). $TobinQ_{it}$ is the detrended logged-Tobin Q value of firm i in year t[13]. X_{it} is the measures of intangible assets, including the $Intang_{it}$, which is the detrended natural logrithm of the intangible assets of firm *i* in year *t*, or $\widehat{e_{it}^{Int}}$, which is the residual value of equation (2). $Control_{it}$ contains the control variables including: (1) *R&D:* the R&D intensity, which is defined as the firm's R&D

[12] For any detrended variable in this paper, we regress the underlying variable on the calendar year, with both stock- and industry-level fixed effect.

[13] Here we follow Noel and Schankerman (2013) and Griliches (1981) and use the logged Tobin Q in the value function. We also use the levels of Tobin Q and redo all the exercises conducted in this paper and the results are highly consistent.

expenses divided by its sales, (2) *sale_miss*, a dummy variable which equals 1 if R&D intensity is missing and 0 otherwise, (3) *AnalystNo*, the detrended natural logarithm of (1+ number of analyst recommendation for firm *i* in year *t*). (4) *analyst_miss*, a dummy variable which equals 1 if *AnalystNo is* missing and 0 otherwise. (5) natural logarithm of total asset of firm *i* in year *t*-1. Equations (2) and (3) are estimated using OLS with stock- and industry-level fixed-effect. The results are shown in Table 3.

(Insert Table 3)

The results in Table 3 further confirm that the value-destructive effect of patent counts revealed in Table 2 is not by coincidence: after taking into considerations various fixed effects as well as the control variables, Tobin Q decreases significantly when the underlying firm increases its patent counts. More specifically, a one-percent increase in total patent counts will lead to a 2.51 percent drop in Tobin Q. The negative relationship between patent counts and Tobin Q holds for all types of patents (invention, utility, and design patents). This result contradicts most existing literature (see Hall et al. 2005; Sandner and Block 2011; Fang et al. 2014; Kogan et al. 2017, etc.). Interestingly, when we include R&D intensity in the regressions and the results show that the R&D intensity indeed boosts the Tobin Q, which is consistent with the literature (Jaffe 1986; Hall 1993; Carosi 2016). This result suggests that patent counts and R&D capture different dimensions of innovation. As far as we know, the existing literature typically consider patent counts and R&D intensity both economic *goods* (e.g., Custódio, et al 2019), and the current literature cannot explain why patent counts and R&D captures different dimensions.

We propose the "*inflated patent count hypothesis*" as a possible explanation for the negative link of patent counts and Tobin Q: Under the China-featured administrative innovation system, the prevailing quantity-based soft targets lead stakeholders of the firms to produce excessive low-quality patents to realize the quantity goals, but those low-quality patents may demise the market values of the firm.

Our empirical results in Table 3 support the IPC: Increased patent counts may hurt firm value. When firms want to inflate their patent counts due to some external motives, these patents will be recorded in the balance sheet as a higher amount of intangible assets (as shown in model (1) of Table 3), which appear in the denominator of Tobin Q. Meanwhile, the market does not recognize the intangible assets (since they tend to be of low quality), and the firm's market value (on the numerator of Tobin Q) does not increase as much, resulting in a lower Tobin Q. That is precisely what we observe in Table 3: First, all coefficients of *PatNo* in in models (2) through (4) are significantly negative, supporting that the patent counts are the value destructive; second, the coefficient of *PatNo* in model (1) is significantly positive, illustrating that more patent counts correspond to higher intangible assets. Moreover, after the inclusion of *Intang* into the regression, the magnitude of patent counts' impact on Tobin Q weakens. For example, in model (2), the coefficient of *PatNo* is -0.0251, while that in model (3) is -0.0156, suggesting that part of the negative relationship between patent counts and firm value is through the channel of intangible assets. Considering the multicollinearity between intangible assets and patent counts, we also use $\widehat{e_{it}^{Int}}$, the residuals of model (1), as a proxy of the fraction of intangible assets unrelated to patent counts in model (4). The results of model (4) is highly consistent with those from models (2) and (3). Furthermore, models (5) through (16) replicate the results for *invention*, *utility*, and *design* patents, and the results are highly consistent. The above empirical results all support the IPC.

A possible concern arising from Table 3 may be the relationship between patent counts and R&D. It is well known that patent counts are the output of R&D, and they are positively correlated with each other. Therefore, it is a valid concern that the negative coefficients for patent counts and the positive coefficients for R&D might come from the possible multicollinearity between the two variables. We tackle this concern by using the following regressions:

$$PatNo_{it} = \alpha^{No} + \beta^{No} R\&D_{it} + \nu_i + e_{it}^{No} \quad (4)$$

and

$$TobinQ_{it} = \alpha^{Q} + \gamma_1 PatNoResid_{it} + \gamma_2 Intang_{it} + Control_{it}\delta' + \nu_i + e_{it}^{Q} \quad (5)$$

where $PatNoResid_{it}$ is the residual value from equation (4) and all other variables are the same as in Table 3. The results are shown in Table 4.

(Insert Table 4 here)

Model (1) of Table 4 confirms the current literature results that the R&D spending is positively associated with patent counts. However, $PatNoResid_{it}$, the residual values from equation (3) which is orthogonal to R&D, still holds a negative coefficient on Tobin Q, implying that patent counts and R&D capture different dimensions of information pertaining to firm values. Panels (B) through (D) show that all three types of patents exhibit consistent results.

3.4 Alternative explanations

The *IPC* offers one possible channel to explain the negative relationship between Tobin Q and patent counts. As explained in the literature review section, there are a few alternative explanations that could possibly resolve the seemingly puzzling negative relationship. In this section, we will go through these potential explanations.

(1) Information ambiguity

Information ambiguity offers another possible channel. Hussinger and Pacher (2019) argue that innovation activities lead to information ambiguity about the future value of firms' assets, and the information ambiguity further lowers firms' market value. Hussinger and Pacher (2019) use the analyst forecast dispersion as the proxy of ambiguity, and they find out that it is the forecast dispersion, as well as the interaction term of R&D stock/Asset and the forecast dispersion that have significantly negative impact.

Following Hussinger and Pacher (2019), we test the information ambiguity hypothesis by including the analyst forecast dispersion in our baseline regressions. More specifically, we have the following regression equations (5) and (6):

$$Disperson_{it} = \theta^{Dis} + \gamma_1^{Dis} PatNo_{it} + \gamma_2^{Dis} Intang_{it} + Control_{it}\delta' + \nu_i + \varepsilon_{it}^{Dis} \quad (6)$$

$$TobinQ_{it} = \theta^{Q} + \gamma_0^{Q} Disperson_{it} + \gamma_1^{Q} PatNo_{it} + \gamma_2^{Q} Intang_{it} + Control_{it}\delta' + \nu_i + \varepsilon_{it}^{Q} \quad (7)$$

(Insert Table 5)

It can be seen from Table 5 that none of the patent counts (P, A, U, or S, see models (1)-(4)) has led to any statistically significant analyst forecast dispersion increase, meaning that the patent count increase does not necessarily lead to higher information ambiguity, which is not consistent with the information ambiguity hypothesis. Furthermore, models (5)-(8) show that analyst forecast dispersion does not result in any significant impact on firm value. The results in Table 5 suggest that the observed negative relationship between Tobin Q and patent counts is not through the channel of information ambiguity.

(2) Market under-reaction

Another stream of research argues that the market may underreact facing complex information, which means investors cannot realize the benefits of innovation in a timely manner (Eberhart et al., 2004) or they have limited attentions on the characteristics of the firm’s innovation efficiency (Hirshleifer et al., 2013) and originality (Hirshleifer et al., 2018). Following this line, the market underreaction hypothesis implies return predictability. Theoretical models also predict that limited investor attention affects stock prices and can cause market underreaction (Hirshleifer and Teoh, 2003; Hirshleifer, Lim, and Teoh, 2011; Peng and Xiong, 2006). Empirically, Hirshleifer et al (2013) find that lagged innovative efficiency (Patents/R&D is used as a proxy) can positively predict market valuation, which implies that innovations positively impact firm value with a time lag since the market needs time to understand the innovations. In order to test whether our observed negative impact from patent count is also driven by market underreaction, we add the one-year lagged patent count in our baseline regression model. If the underreaction hypothesis works, we would expect to see a significantly positive coefficient of this lagged patent count. However, according to Table 6, in which we add one-year lagged patent count as an explanatory variable, for all types of patent counts, none of the coefficients of lagged patent count is positive. We further add more lags (results are shown in the appendix) and find that the second and third lags are also insignificant. Therefore, the empirical results do not support the market underreaction hypothesis.

(Insert Table 6)

(3) Strategic patenting

It is well known that some companies may possess a number of low-quality patents due to *strategic purposes* of patent application. This strategic patenting is to protect the firms' own high-value-added patents or to dampen the competitors' value. Noel and Schankerman (2013) find that the strategic patenting such as patent thickets are detrimental to firm's value. At the first glimpse, our inflated patent count hypothesis is quite similar to the strategic patent hypothesis in the sense that both predict that firms would produce low-quality patents which hurt market values. However, we argue that the *strategic patenting hypothesis* and the *inflated patent count hypothesis* are fundamentally different: Strategic patenting is featured by large patent portfolios which "affects bargaining power in patent disputes, or patent thickets (the fragmentation of patent rights) which "increases the transaction costs of enforcement". In any case, strategic patenting is adopted by large firms who have a large number of patents. This is why Noel and Schankerman (2013) choose all large firms in their empirical analysis. In stark contrast to that, in the *inflated patent count* hypothesis, firms seek to obtain an exogeneous target of patent count, and if they find their value-maximizing high-quality patent count falls below the target, they tend to inflate their patent counts by producing more less-costly-but-no-value-added low-quality patents, therefore decreasing the firm value. This procedure is more likely to occur in small firms since they are weaker in terms of R&D, and therefore are more likely to face the need of inflating their patent counts. So, while strategic patenting hypothesis predicts that larger firms tend to have more value-destructive patents, inflated patent count hypothesis predicts that the negative relationship between firm value and patent counts is stronger in small firms (see **H2** above: the negative relationship between firm value and patent counts is stronger in small firms).

We test this motive by grouping all firms according to their market capitalizations. Larger firms have stronger incentives for strategic patenting purposes, which suggests that if strategic patenting is the explanation, we would observe stronger value-destructive patterns for large firms. Admittedly, due to the sizable magnitude of large firms, it is harder to change large firms' market cap, *ceteris paribus*, however, if strategic patenting is the solo reason, small firms should not be expected to see much value-destruction pattern of patent counts, at least.

The results from Panel B of Table 7 show that, for larger firms the coefficients of patent counts are insignificant (Groups 7, 8 and 9) or only marginally significant (Groups 6 and 10), while the coefficients of patent counts for small firms are significantly negative (except for group 4), implying that the value destruction is more prominent in small firms. This is not consistent with the strategic patenting explanation. Meanwhile, it is worth noting that the results from Table 7 supports the IPC. These two hypotheses are alternative to each other. Different types of patents, i.e., invention, utility and design patents show consistent results (see Panels B, C and D, respectively).

Overall, our empirical evidence proves the existence of the value-destructive patents, and we have also ruled out alternative possible explanations.

4. Mechanism

Our IPC hypothesis posits that the conflict of interests between the shareholders and the other stakeholders of the firms may lead to agency problems and result in value-destructive patents. An administrative innovation system has been formed in China, due to the central-government-initiated policies. The cascading patent count soft target mechanism is pervasive in the entire society: The provincial government closely follows up with the central government and sets quantity-based targets in their economic development plans. Then, city- and county-level administrators tend to further translate national/provincial targets into specific regional quotas. Finally, firms as well as corresponding stakeholders of the firms, e.g., CEOs, heads of subsidiaries, etc., incorporate patent count targets into their performance/incentive metrics. For some stakeholders the quantity of patents is in their performance metrics and reaching a desired quantity target is more important than value maximization. Therefore, they end up producing excessive low-quality patents that enhances their performance but hurts firm values. We can have the following descriptions about the about IPC hypothesis: first, only in some rare cases are there concrete quantity target (e.g., at provincial levels, each province has the average number of patent targets in the next five-year period in their Provincial Five-year Plans). For most firms' stakeholders, they know that more patents are better than less, for the purpose of pleasing local governments/obtaining KPI requirements from parent firms/obtaining promotion or repulation, etc., but they typically do not have a clear target[14]. Second, the impact of the cascading quantity-

[14] The InnoCom program does have a clear target quantity but evidence shows that the target is not binding: firms would

based soft target system is pervasive in the entire society. Third, stronger firms are less likely to be bounded by the soft target since their R&D investment and innovation activities are good enough and they don't need to cook low-quality patents. For example, ZTE (000063.SZ) is the industry leader, and it has many patents. The "soft targets" have been automatically satisfied by their routine operations. ZTE has weaker incentives to please local government. In comparison to that, the weaker firms have stronger incentives to fight for quantity. Therefore, weaker firms tend to have higher degree of agency problems, and are more likely to produce low-quality patents to meet the quantity target, but they end up hurting market values.

4.1 The InnoCom program

During periods in which patent counts are more important (compared with other periods), the IPC hypothesis predict that there should exist a stronger agency problem, and stakeholders tend to produce more low-quality patents, which tend to be more value destructive. China's InnoCom program provides a rare example to directly test the above hypothesis. The InnoCom Program, initiated at around 1990s, aims at selecting and subsidizing the most innovative firms in China every year. The selected firm will be granted a certification for three years, which could be extended for another three years if approved. The benefits of InnoCom Program are substantial, including (1) Tax credits: the corporate tax rate will be reduced to 15% from 25%; (2) Tax-deductible R&D expense: 150% of actual R&D expense (before 2017), 175% (before 2019), or 200% (since 2022); (3) Local government subsidy. In Guangzhou city, for example, a lump-sum windfall of 20,000 yuan from Guangzhou government for the first-time qualified high-tech firms, or 10,000 yuan for the re-qualified ones. Hence, the InnoCom Program attracts many firms applying for the certification.

To qualify for the InnoCom program, a firm must submit an application to the local government's Department of Science and Technology (DoS&T), which will invite experts as reviewers. Then, a committee of experts assigns a final score to each firm based on guidelines issued by the central government. Out of the 100 points, 30 are from the number of independent intellectual property rights (i.e., patent counts); 30 are from the capacity of transformation of science and technological achievements; 20 are from the level of organization and management of research and development,

---

produce much more patents than actually required by the InnoCom program. More details will follow up.

and 10 (plus 10 extra points) are from growth of sales and total assets (Zhao et al 2019). The firm are disqualified immediately if financial reporting misconducts or severe production accidents are detected. It is important to note that only patent quantity, no quality measures, is included in the evaluation procedure. Therefore, facing InnoCom application, the patent count is more important than in regular periods. Stakeholders have stronger incentives to produce more patents in the year of InnoCom.

We adopt the following method to analyze firms' behaviors surrounding their InnoCom certification granting year. For a listed firm *i*, if the firm itself (or its subsidiaries) gets the InnoCom certification in year *t*, we obtain a 5-year window from year t-2 to year t+2 as an event "*s*"[15]. We first plot the average patent counts, as well as the per patent 5-year citation in each year of the event window. As shown in Figure 2, in the year when the firm (or its subsidiaries) is awarded the InnoCom certification, the average total patent count is 108.4 per year, much higher than the years before and after. This pattern holds for all three types of patents, consistent with the hypothesis that when firms plan to obtain InnoCom certification, they inflate patent counts, and the patent count level will come back to normal levels after the firm gets InnoCom. This pattern implies that in the InnoCom certification year, firms' increased patent counts are more likely to stem from agency problem, rather than from firms' rational value-maximizing behavior by balancing the possible tax benefit and the cost of generating the (low-quality) patents. First, the cutoff number for objective patent is as low as 6, i.e., firms can get full points if they have no lower than 6 patents on average, and in our sample, the average number of patent produced in the year of InnoCom is 108.4, way above the necessary level. If InnoCom is the only goal, firms do not need to reach such a higher level. Second, only *invention patents* will be counted as useful in applying the InnoCom certification. It is therefore hard to explain why rational firms would also increase the *utility patent* counts in the InnoCom certification year. However, our IPC hypothesis links patent production to the degree of agency problems, which states that as long as patent count is more important compared with other years, stakeholders would produce more patents.

Meanwhile, patent quality, proxied by the per-patent 5-year citation, exhibits a V-shape during the

[15] It is worth noting that there is not always a full 5-year window for an event: if firm *i* (or its subsidiaries) obtains InnoCom certification in year *t*, and in year *t+1*, there is another subsidiary of *i* obtains the certification, the event window now becomes [*t–2, t*]. It means that the window length for different event varies from 1 year to 5 years.

5-year window surrounding the InnoCom award year, with the lowest patent quality occurring in the award year. The patterns shown in Figure 2 indicate that to cater for the InnoCom Program's quantity-first requirement of patents, firms would inflate their patent counts at the cost of quality, possibly through producing low-quality patents.

(Insert Figure 2)

To formally test the InnoCom's impact on firms' patent counts and patent quality, we proceed by finding the control stocks: first, a control stock must be from the same industry as the test stock; second, the firm of the control stock (or its subsidiaries) must not receive the InnoCom certification during the same 5-year window of the test stock, and third, the size difference (proxied by total asset) between the control and the test stocks in the event-window must be the smallest. Then, we use the following regression:

$$y_{is\tau} = \beta_0 + \beta_1 HT_{is\tau} + \beta_2 test_{is} \times HT_{is\tau} + control_{is}\gamma' + \alpha_i + \theta_s + \varepsilon_{is\tau} \qquad (8)$$

Where *s* is the event window, which contains [*t*-2, *t*+2] where *t* is the InnoCom certification year. $test_{is}$ equals 1 for a test stock in window *s*, and 0 for a control stock $HT_{is\tau}$ is a dummy variable which equals 1 if $\tau = t$ for stock *i* in window *s*, (in the year when InnoCom certification is awarded to firm *i* in the event-window) and 0 if $\tau \neq t$ (it is not a year in which the firm *i* gets the InnoCom certification in the event-window s. In other words, it is in the years preceding or following the certification-award year in the event-window *s*). The dependent variable $y_{is\tau}$ includes: the undetrended logged (1+number of patents), the detrended logged (1+number of patents); $P_{is\tau}$, the number of patent counts; *citation*, the 5-year citation number per patent, the undetrended 5-year citation number per patent; the skewness of 5-year citation; invention patent percentage, defined as the invention patent counts over the total patent counts, and design patent percentage, defined as the design patent counts over the total patent counts for firm *i* in event window *s* and in year τ. The control variables are the same as in previous tables. Model (3) uses Poisson regression[16], and other models use OLS fixed effect model. The results are shown in Table 8.

[16] According to Cohn, Liu and Wardlaw (2022), applying log(1+countable variable) may result in wrong coefficient signs in expectation. This is why we adopt the Poisson regression with fixed effects.

(Insert Table 8)

Table 8 shows consistent results with those from Figure 2. The coefficients of the interaction terms for models (1) through (3) are significantly positive, while that for models (4) and (5) are significantly negative, further proving that in the year when a firm fights for its InnoCom certification, it inflates patent counts at the cost of quality. Model (6) tells us that in the year of fighting for InnoCom certification, the distribution of patent quality is more positively skewed, implying that more patents are concentrated on the left side (with lower quality).

Moreover, it is typically considered that invention patents are more valuable and are of higher quality than design patents (see Fang, et al., 2017, among others). Models (7) and (8) show that in the year of InnoCom certification, the firms have a lower fraction of high-quality innovation patents granted, and higher fraction of low-quality design patents granted. This test using alternative proxies of patent quality also shows results supporting that firms tend to produce patent with lower quality when they fight for quantity. The results above are highly consistent with Cao et al. (2024) (see their online Appendix). However, we further link the InnoCom program to the stock market performance. In model (9), we show that InnoCom awarding year is associated with a significant Tobin Q decrease, confirming the market's negative evaluation on the quantity-quality distortion brought by the InnoCom program.

Under the IPC hypothesis, when the external incentives for patent counts disappear, the patent counts become "less important" and the stakeholders have weaker incentives to fight for counts so they produce less. The InnoCom program can also test this story. We define a variable *granting month* which equals 1 if the firm gets its InnoCom certification in January, 2 if in February, …, and 12 if in December. Panel A of Table 9 shows the distribution of the granting month. We can see that a majority of the firms are granted the InnoCom certification in the fourth quarter: more than 75% of the firms obtained their certification in the fourth quarter since the 25 percentile is 10. Our null hypothesis is that the distribution of granting month has no impact on firms' patent counts in the year of InnoCom. However, if firms' patent creation behaviors are indeed affected by the InnoCom certification granting month, once the firm is awarded the certification, say, in June, it does not have as strong an incentive to create patents in the second half of the year, implying that firms' patent counts in the InnoCom granting year should be positive correlated with the granting month.

Following this line of argument, we set up the following regression:

$$y_{it} = \theta \quad + \gamma_1 \ GM_{it} + control_{it}\delta' + \nu_i \quad + \varepsilon_{it} \quad (9)$$

where y_{it} is patent counts for firm *i* in year *t*, denoted as P_{it}, or log(1+P_{it}). GM_{it} is the granting month of firm *i* in year *t*, which is defined above. We use the same control variables as in Table 3. γ_1 should be significantly positive if firms are fighting for quantity. This is exactly what is shown in Panel B of Table 9: for the treatment group, both coefficients for GM_{it} granting month of firm *i* in year *t*, are significantly positive, implying that after the certification is granted, the firm has a weaker incentive to fight for patent quantity in the rest of the year.

We further conduct the same regression for the control group as a placebo test. In stark contrast to the treatment group, neither of the coefficient of GM_{it} is different from 0, suggesting that the granting month distribution has no impact on firms' patent creation behaviors if the InnoCom certification is not a goal for the firm.

(Insert Table 9)

4.2 The prevalence of value-destructive patents

One of our central predictions in the IPC hypothesis is that the cascading patent count soft targets exist everywhere in the society. It is very hard to directly identify those targets at the firm level. First, the targets are "soft" and we cannot easily find a clearly defined target number at the firm level. For example, in one policy paper promulgated by the local government of Shenzhen, namely *The Annual Report of Shenzhen Intellectual Property Administration (2022)*, it is documented that "…by the end of 2022, …, the number of patents per 10,000 people was 138.1, which is 5.8 times the national average and 3.2 times the provincial average"[17]. Clearly at the city level there is a concrete target number, and it is reasonable to assume that local firms in Shenzhen will all be subject to this target. However, as to "what is the required target number for a specific firm in Shenzhen", there is no solution to the question. Second, those soft targets may be mixed with other value-maximizing objectives. For example, in the InnoCom case, some firms may want to increase their patent counts after they *rationally* balance the profit and cost of producing low-quality patents vs the possible tax benefits.

(1) Non-InnoCom firms

In order to provide some evidence on how firms will behave under the "soft targets", we conduct the following exercise. We first drop all firm-year observations when firm *i* obtains InnoCom certificate in year *t*, and the remaining sample represents periods when InnoCom may be less likely to play a dominant role. Then we repeat our benchmark regressions in Table 3. That is, we would like to see whether there exist value-destructive patents after excluding the InnoCom incentives. The results are shown in Table 10.

(Insert Table 10)

The results of Table 10 are highly consistent with those in Table 3. That is, the negative relationship between patent counts and firm value still exists for firm-year observations unlikely to be affected by the InnoCom program, although the magnitude of coefficients is slightly lower. This result supports the idea that the misallocation brought by patent quantity-driven motivation is not only triggered by the InnoCom programs, but also exists in general, maybe everywhere in the economy (e.g., local government's short- or long-run quantity target, R&D employee job promotion incentive, etc.). Our empirical results are consistent with the IPC hypothesis that the cascading patent count target prevails in the society.

(2) Ownership structure

The state-owned enterprises (SOEs) in China are primarily led by the central government, but their management and supervision can involve multiple levels of government. The State-owned Assets

[17] See https://amr.sz.gov.cn/attachment/1/1300/1300133/10604167.pdf

Supervision and Administration Commission (SASAC) under the State Council is responsible for managing and supervising central enterprises (央企). These are SOEs directly controlled by the central government. In parallel to that, provincial SASACs manage and supervise local SOEs. Provincial governments have direct management and oversight responsibilities for SOEs within their jurisdiction. Overall, the SOEs are supervised and overseen by different layers of governments. In comparison to that, private firms in China operate within a market economy framework but under the overarching influence of the state. Unlike state-owned enterprises, private companies have more autonomy in their business operations, decision-making, and profit distribution. However, they must still navigate a complex regulatory environment where government policies, industrial strategies, and political considerations play significant roles.

Based on the difference between SOEs and private firms, it would be reasonable to claim that SOEs in China may face stronger agency problems, and private firms may be more market oriented. However, our IPC hypothesis claims that all firms, regardless of the ownership structure, may be subject to the cascading patent count soft targets. It is therefore an empirical question whether both the SOEs and private firms would produce value-destructive patents.

$$TobinQ_{it} = \alpha^{Q} + \gamma_1 PatNo_{it} + \gamma_2 PatNo_{it} * SOE_{it} + Control_{it}\delta' + \nu_i + e_{it}^{Q} \qquad (10)$$

where SOE_{it} is the matrix that measures the ownership structure of the underlying firm. It includes (1) $SOEdum_i$, which equals 1 if firm *i* is a state-owned enterprise (SOE), and 0 otherwise; and (2) $SOEshare_{it}$, which is the percentage of shares owned by government or its representatives for firm i in year t. All other variables are defined earlier.

(Insert Table 11)

Specifications (1) and (2) in Table 11 are the benchmark regression results for private firms and for SOEs, respective. We can see that the coefficients for PatNo are both significantly negative, implying that both private firms and SOEs could produce value-destructive patents. Although the magnitude of PatNo is smaller for private firms, in Specification (3), the interaction term of PatNo and SOEdum is insignificant, suggesting that there is no difference in how SOEs and private firms' patent affect the TobinQs. We further interact the PatNo with the percentage of government shares, and the coefficient of this interaction term is insignificant, either. Overall, our results are consistent with our IPC's prediction that the soft targets are pervasive in the society, and even the less-government-controlled private firms are subject to these soft constraints, ending up producing value-destructive patents.

(3) Value-destructive patents across industries

In all previous analyses, we have controlled the industry fixed effect. However, the importance of R&D varies significantly across different industries, implying that it is necessary to further break down and study the variations with different industries. For instance, technology-intensive industries like information technology and biopharmaceuticals might have a higher dependency on R&D, whereas in other sectors like services, R&D might play a relatively minor role. Therefore, stakeholders may have stronger incentives to produce low-quality value-destructive patents in more R&D intensive industries. However, due to the pervasiveness of the soft targets, even in an industry which is not R&D intensive, firms may produce excessive patents due to the agency problems discussed above. Therefore, whether firms in different industries produce value-destructive patents remains again an empirical question.

We employ the following setting to test the above story. First, we assign each firm into 79 sub-industries, then we drop the subgroup if the total number of firms is below 5[18], and 62 sub-industries and 3561 firms remain in the sample. We then sort the median annual patent counts for each sub-industry from smallest (0.405 per year) to largest (181.5 per year). Next, we categorize these sub-industries into 3 groups: lowest-/medium-/highest-patent-count groups, such that the number of firms in each group is approximately the same, based on the 33rd and 67th percentiles. We then run the benchmark regression in each group. The results are shown in Table 12.

(Insert Table 12 here)

Panel A of Table 12 shows the results for the three groups for total patent counts. Two findings are exhibited: first, in all three groups the coefficients of PatNo is significantly negative, which

[18] The reason why we do not use the primary industry group is that the primary industry of manufacturing has too many stocks: 2443 out of 3561 firms are from the manufacturing industry.

further proves the pervasiveness of the soft targets: even in an industry where the industry median of patent counts is lowest, firms still produce patents which are value destructive. Second, the magnitude of the coefficients are increasing from lowest to highest median patent count industries, although the difference is not significant. Still this evidence is consistent with the hypothesis that stakeholders may have stronger incentives to produce low-quality value-destructive patents in more R&D intensive industries.

4.3 Which firms' patents are more value-destructive?

In section 4.1, we have shown that, for the same firm, it tends to produce more value-destructive patents in some specific time periods when patent counts are more important. Following that argument, we try to deal with a parallel question: which types of firms tend to produce value-destructive patents? Our IPC hypothesis suggests that firms who face stronger agency problems are more likely to create more value-destructive patents, and we will empirically test that.

(1) Peer pressure

Firms within the same industry are inherently competitors; however, their position within the industry often dictates the pressures they face and the strategies they adopt, which can be fundamentally different. Compared to industry leaders, firms at the lower end of the industry spectrum face greater survival pressure. According to our IPC hypothesis, stakeholders (e.g., CEOs) of these downstream companies are under more pressure to demonstrate their capabilities and performance to shareholders and the market. Therefore, *ceteris paribus*, these stakeholders in downstream firms have a greater incentive to produce low-quality patents to appear more impressive in terms of quantity. Therefore, we predict that the downstream firms' patents may be more value destructive.

We define a "*BAD*" dummy variable which equals 1 if firm i's annual patent count is lower than the sub-industry median value, and 0 otherwise. The following regression is adopted:

$$TobinQ_{it} = \alpha^{Q} + \gamma_1 PatNo_{it} + \gamma_2 PatNo_{it} * BAD_i + Control_{it}\delta' + \nu_i + e_{it}^{Q} \qquad (11)$$

where all other variables are defined the same as in Table 3. The results are shown in Table 13.

We can see that for the total patent counts, as well as for each of different types of patents (invention, utility, and design), the coefficients for the interaction terms $PatNo_{it} * BAD_i$ are significantly negative, suggesting that the value-destructive patents are more likely to be produced by BAD firms, i.e., firms whose annual patent counts are below sub-industry medians. The intuition is straightforward: firms who are relatively weak and face higher peer pressure have stronger incentives to produce low-quality patents to catch up with the quantities, potentially to make their situation look better. However, their patents are more likely to be value destructive, conforming our IPC hypothesis.

(2) Parent firms vs subsidiaries: an anomaly?

In this subsection, we present some empirical results which seem to be counter-intuitive but can be well explained by the IPC hypothesis. The research question is: parent firms (listed firms) versus subsidiaries: whose patents are more value destructive?

At the first glimpse, we may expect that the patents from the listed firms themselves would have a stronger impact on the market value (i.e., are more value destructive), since the patents produced by subsidiaries are not directly coming from the firms themselves and therefore are more remotely and weakly connected to the market value for the listed firms. To formally test this prediction, we use the following regression:

$$TobinQ_{it} = \alpha^Q + \gamma_1 PatNoListed_{it} + \gamma_2 PatNoSubsidiry_{it} + Control_{it}\delta' + \nu_i + e_{it}^Q$$

(12)

where $PatNoListed_{it}$ is the total patent count for the listed firms (parent firms) for firm i in year t, while $PatNoSubsidiary_{it}$ is the total patent count for all subsidiaries of firm i in year t. All other variables are defined earlier.

Table 14 exhibits some interesting result: for the total patent counts, as well as for all three types of patents (invention, utility, and design), the magnitude of $PatNoSubsidiary_{it}$ is higher than that of $PatNoListed_{it}$, and the difference is significant in all four cases, meaning that compared with the patents produced by the listed firms themselves, the subsidiaries' patents are more value destructive. We argue that it is not an anomaly, and our IPC hypothesis can explain the phenomenon: compared with the listed firms, the stakeholders in the subsidiaries care less about the market value of the parent firm, but they care more about their own KPI, performance, etc., which are more likely to be connected with patent counts. In other words, subsidiaries on average face stronger agency problems, and they tend to produce more value-destructive patents.

4.5 Reverse causality

There may be some concern of potential reverse causality between firm value and patent counts: If a firm is not performing well, they may have stronger incentives to report more patents such that their balance sheet could look better. We use the following two instruments to tackle the endogeneity issue: first, the one-year lagged patent counts is used as the instrument variable. It is unlikely that a firm's performance can impact lagged patent counts. In the first stage, we regress the patent counts on the instrument and estimate the predicted values. In the second stage, we regress Tobin Q on the predicated patent counts value from the first stage, along with other control variables. We find highly consistent results with previous ones, and they are not likely to be driven by endogeneity. Second, from Section 3.4 we know that firms tend to increase patent counts in the year of InnoCom, so we use the InnoCom dummy as the instruments, and again obtain highly consistent results, implying that reverse causality is not a concern.

$$PatNo_{it} = \beta_0 + \beta_1 X_{it} + \nu_i + \epsilon_{it} \quad (13)$$

$$TobinQ_{it} = \gamma_0 + \gamma_1 \widehat{PatNo}_{it} + \gamma_2 X_{it} + Control_{it}\delta' + \nu_i + e_{it}^{Q} \quad (14)$$

where X_{it} is the instruments including lagged patent counts and InnoCom dummy, $\widehat{PatNo}_{it}$ is the predicted value of patent counts from equation (11). All other variables are the same as in previous tables.

(Insert Table 15)

5. Conclusion and policy implications

In this paper, we study the patent data in China, and find a negative relationship between Tobin Q and the number of patent filings for firms listed in China's stock markets. The potential explanations documented in the existing literature are unable to explain this seemingly counter-intuitive result. Therefore, we propose the "*inflated patent count hypothesis*" as a potential explanation: when facing external patent-quantity-based targets/incentives, stakeholders within a firm may choose to produce low-quality patents to seek the target/incentive, but these low-quality patents may hurt the firm value, which is a classic agency problem that causes firms to deviate from value maximization.

We further argue that China's innovation system is where the agency problem stems from. Unlike the market-based U.S. innovation system, China' innovation system features strong state direction. Since early 2000's, the Chinese central government has introduced a series of policies to promote scientific and technological progress and to stimulate innovation. While emphasizing the quality of innovations, which is hard to identify ex ante, most of the policies have implicit or even explicit patent quantity requirement or target. Following up with the central government, provincial governments set quantity-based targets in their economic development plans. Then, city- and county-level administrators further translate national/provincial targets into specific regional quotas. Finally, firms as well as corresponding stakeholders of the firms, e.g., CEOs, heads of subsidiaries, etc., incorporate patent count targets into their performance/incentive metrics. This is the China-featured "administrative innovation system", and there exists a cascading patent count target mechanism. The administrative innovation system successfully promotes the R&D development and dramatically levels up China's innovation output. However, the quantity-based target system also causes distortion and inefficient utilization of resources. The existing literature has documented the tradeoff between patent qualities and quantities. More recent research has also revealed the welfare loss of the quantity-based policies at society levels. We are among the first research who documents the distortion at firm levels. We find that the firms tend to produce value-destructive patents, and we propose the "We argue that the Chinese administrative innovation system has led to a cascading patent count target system which has the following characteristics: first, the soft quantity-based target may lead to classic agency problems: stakeholders of the firms may produce excessive low-quality patents that will benefit their own utility function at the cost of firm value, resulting in the observed value-destructive patents. Second, the soft targets of patent quantity are pervasive in the society, which implies that the value-destructive patents are not unique phenomena for only the R&D intensive firms. Instead, patents may be found value destructive in different industries/different firms/different occasions. Third, When a specific quantity-based target becomes binding, the agency problems become more severe and the patents may be more value destructive. We use the InnoCom program as a case and find supporting evidence. Fourth, for firms which are potentially have stronger agency problems, their patents tend to be more value destructive. Correspondingly, we find that the patents from firms with stronger peer pressure are more value destructive, and subsidiaries of a listed firm produce more value-destructive patents than their parent firms. All the empirical evidence is consistent with the IPC hypothesis.

Our findings have significant policy implications. While government policies have been effective in enhancing China's innovation capacity, as reflected by the country's dominance of patent filings, there is a potential downside. These policies, which incentivize firms to focus on patent quantity, may inadvertently overlook patent quality. Under the current policies, firms are motivated to prioritize quantity over quality, resulting in a large number of inefficient, low-value, or even value-destructive patents. Therefore, it is recommended that the government design policies that place greater emphasis on patent quality rather than quantity. This shift would encourage firms to pursue more meaningful and impactful innovations.

One approach could be helpful to improve the existing rating system in the InnoCom program, with a focus on evaluating the quality of applicants' patents. This could involve reducing the weight attached to the number of patents held by a firm during the certification process. Alternatively, experts in a committee could identify high-quality patents first and then prioritize them in the decision-making process. Some argue that assessing patent quality ex ante is challenging, as it is difficult to predict future measures like citation numbers. Imposing additional quality requirements on applicant firms might be seen as counterproductive. However, this challenge can be addressed by providing revocable incentives for successful InnoCom applicants. For instance, tax credits or subsidies granted to qualified applicants could be issued in phases. If a firm's patents are proved to be high quality ex post after a period of time, the authorities can reward the firm with additional benefits in the second phase. As such, the government can encourage firms to pursue more meaningful and impactful innovations.

References

Ang, Y. Y., Jia, N., Yang, B. and Huang, K. G. 2023**.** "China's Low-Productivity Innovation Drive: Evidence from Patents." *Comparative Political Studies*, 51(8), 1074–1105

Baker, M. and Wurgler, J. 2006**.** "Investor Sentiment and the Cross-Section of Stock Returns." *The Journal of Finance*, 61(4): 1645-80.

Belenzon, S. 2012**.** "Cumulative Innovation and Market Value: Evidence from Patent Citations." *The Economic Journal*, 122(559): 265-85.

Bena, J. and Garlappi, L. 2020**.** "Corporate Innovation and Returns." *The Review of Corporate Finance Studies*, 9(2): 340-83.

Berk, J. B., Green, R. C. and Naik, V. 2004**.** "Valuation and Return Dynamics of New Ventures." *Review of Financial Studies*, 17(1): 1-35.

Blind, K., Edler, J., Frietsch, R. and Schmoch, U. 2006**.** "Motives to Patent: Empirical Evidence from Germany." *Research Policy*, 35(5): 655-72.

Bloom, N., Schankerman, M. and Van Reenen, J. 2013**.** "Identifying Technology Spillovers and Product Market Rivalry." *Econometrica*, 81(4): 1347-93.

Bloom, N., Van Reenen, J. and Williams, H. 2019**.** "A Toolkit of Policies to Promote Innovation." *Journal of Economic Perspectives*, 33(3): 163-84.

Cao, L., H. Jiang, G. Li, and L. Zhu (2024) Haste makes waste? Quantity-based subsidies under heterogeneous innovations, *Journal of Monetary Economics* 142, 103517

Carosi, A. 2016**.** "Do Local Causations Matter? The Effect of Firm Location On the Relations of Roe, R&D, and Firm Size with Market-to-Book." *Journal of Corporate Finance*, 41: 388-409.

Chan, L. K., Lakonishok, J. and Sougiannis, T. 2001**.** "The Stock Market Valuation of Research and Development Expenditures." *The Journal of Finance*, 56(6): 2431-56.

Chen, S. S., Chen, Y. S. and Wang, W. L. Y. 2013**.** "R&D Spillover Effects and Firm Performance Following R&D Increases." *Journal of Financial & Quantitative Analysis*, 48(5): 1607-34.

Cochrane, J. H. 1991**.** "Production-Based Asset Pricing and the Link Between Stock Returns and Economic Fluctuations." *The Journal of Finance*, 46(1): 209-37.

Cohen, L., Diether, K. and Malloy, C. 2013**.** "Misvaluing Innovation." *The Review of Financial Studies*, 26(3): 635-66.

Eberhart, A. C., Maxwell, W. F. and Siddique, A. R. 2004**.** "An Examination of Long-Term Abnormal Stock Returns and Operating Performance Following R&D Increases." *The Journal of Finance*, 59(2): 623-50.

Epstein, L. G. and Schneider, M. 2008**.** "Ambiguity, Information Quality, and Asset Pricing." *The Journal of Finance*, 63(1): 197-228.

Fang, J., He, H. and Li, N. 2020**.** "China's Rising Iq (Innovation Quotient) and Growth: Firm-Level Evidence." *Journal of Development Economics*, 147: 102561.

Fang, V. W., Tian, X. and Tice, S. 2014**.** "Does Stock Liquidity Enhance Or Impede Firm Innovation?" *The Journal of Finance*, 69(5): 2085-125.

Farre-Mensa, J., Hedge, D. and Ljungqvist, A. 2019. "What is a Patent Worth? Evidence from the U.S. Patent Lottery" *The Journal of Finance*, 75(2): 639-682

Fitzgerald, T., Balsmeier, B., Fleming, L. and Manso, G. 2021**.** "Innovation Search Strategy and Predictable Returns." *Management Science*, 67(2): 1109–1137

Fracassi, C., Previtero, A. and Sheen, A. 2022**.** "Barbarians at the Store? Private Equity, Products, and Consumers." *The Journal of Finance*, 77(3): 1439-88.

Garcia-Macia, D., Hsieh, C. and Klenow, P. J. 2019**.** "How Destructive is Innovation?" *Econometrica*, 87(5): 1507-41.
Garlappi, L. 2004**.** "Risk Premia and Preemption in R&Amp;D Ventures." *Journal of Financial and Quantitative Analysis*, 39(4): 843-72.
González, X. and Pazó, C. 2008**.** "Do Public Subsidies Stimulate Private R&D Spending?" *Research Policy*, 37(3): 371-89.
Griliches, Z. 1979**.** "Issues in Assessing the Contribution of Research and Development to Productivity Growth." *Bell Journal of Economics*, 10(1): 92-116.
Griliches, Z. 1981**.** "Market Value, R&D, and Patents." *Economics Letters*, 7(2): 183-87.
Gu, L. 2016**.** "Product Market Competition, R&D Investment, and Stock Returns." *Journal of Financial Economics*, 119(2): 441-455.
Hall, B. H. 1993**.** "The Stock Market's Valuation of R&D Investment During the 1980'S." *The American Economic Review*, 83(2): 259-64.
Hall, B. H. and Lerner, J. "The Financing of R&D and Innovation," *Handbook of the Economics of Innovation.* Elsevier, 2010, 609-39.
Hall, B. H. and MacGarvie, M. 2010**.** "The Private Value of Software Patents." *Research Policy*, 39(7): 994-1009.
Hall, B. H., Jaffe, A. and Trajtenberg, M. 2005**.** "Market Value and Patent Citations." *Rand Journal of Economics*, 36(1): 16-38.
He, A. 2021. "What Do China's High Patent Numbers Really Mean?", Center for International Governance Innovation, https://www.cigionline.org/articles/what-do-chinas-high-patent-numbers-really-mean/#:~:text=The%20rapid%20increase%20of%20patent,to%20improve%20China's%20patent%20level..
Hirshleifer, D., Hsu, P. and Li, D. 2013**.** "Innovative Efficiency and Stock Returns." *Journal of Financial Economics*, 107(3): 632-54.
Hirshleifer, D., Hsu, P. and Li, D. 2018**.** "Innovative Originality, Profitability, and Stock Returns." *The Review of Financial Studies*, 31(7): 2553-605.
Hirshleifer, D., Lim, S. and Teoh, S.H., 2011. "Limited Investor Attention and Stock Market Misreactions to Accounting Information." *Review of Asset Pricing Studies* 1(1), 35–73.
Hirshleifer, D. and Teoh, S.H., 2003. "Limited attention, information disclo- sure, and financial reporting." *Journal of Accounting and Economics* 36(1-3), 337–386.
Hsu, D. H., Hsu, P. and Zhao, Q. 2021**.** "Rich On Paper? Chinese Firms' Academic Publications, Patents, and Market Value." *Research Policy*, 50(9): 104319.
Hsu, P. 2009**.** "Technological Innovations and Aggregate Risk Premiums." *Journal of Financial Economics*, 94(2): 264-79.
Hu, A. G. Z., Zhang, P. and Zhao, L. 2017**.** "China as Number One? Evidence from China's Most Recent Patenting Surge." *Journal of Development Economics*, 124: 107-19.
Hud, M. and Hussinger, K. 2015**.** "The Impact of R&D Subsidies During the Crisis." *Research Policy*, 44(10): 1844-55.
Hussinger, K. and Pacher, S. 2019**.** "Information Ambiguity, Patents and the Market Value of Innovative Assets." *Research Policy*, 48(3): 665-75.
Jaffe, A. B. 1986**.** "Technological Opportunity and Spillovers of R & D: Evidence from Firms' Patents, Profits, and Market Value." *The American Economic Review*, 76(5): 984-1001.
Kersten, A., Athanasia, G. and Arcuri., G. 2022**.** "What Can Patent Data Reveal About U.S.-China Technology Competition?" *Critical Questions*, https://www.csis.org/analysis/what-can-

patent-data-reveal-about-us-china-technology-competition#:~:text=WIPO%20data%20show%20that%20Chinese,applications%20in%20the%20United%20States..

Kim, J., Valentine, K. 2021**.** "The Innovation Consequences of Mandatory Patent Disclosures." *Journal of Accounting and Economics*, 71 (2-3)101381

Kogan, L., Papanikolaou, D., Seru, A. and Stoffman, N. 2017**.** "Technological Innovation, Resource Allocation, and Growth." *The Quarterly Journal of Economics*, 132(2): 665-712.

Kong, D., Lin, C., Wei, L. and Zhang, J. 2022**.** "Information Accessibility and Corporate Innovation." *Management Science*, 68(11): 7837-60.

Kong, D., Wang, Y. and Zhang, J. 2020**.** "Efficiency Wages as Gift Exchange: Evidence from Corporate Innovation in China." *Journal of Corporate Finance*, 65: 101725.

König, M., Song, Z. M., Kjetil, S. and Fabrizio, Z. 2022 "From imitation to innovation: Where is all that Chinese R&D going?" *Econometrica*, 90 (4): 1615-1654

Kung, H. and Schmid, L. 2015**.** "Innovation, Growth, and Asset Prices." *The Journal of Finance*, 70(3): 1001-37.

Lanjouw, J. O., Pakes, A. and Putnam, J. 1998**.** "How to Count Patents and Value Intellectual Property: The Uses of Patent Renewal and Application Data." *The Journal of Industrial Economics*, 46(4): 405-32.

Leung, W. S., Evans, K. P. and Mazouz, K. 2020**.** "The R&D Anomaly: Risk Or Mispricing?" *Journal of Banking & Finance*, 115: 105815.

Li, D. 2011**.** "Financial Constraints, R&D Investment, and Stock Returns." *The Review of Financial Studies*, 24(9): 2974-3007.

Marino, M., Lhuillery, S., Parrotta, P. and Sala, D. 2016**.** "Additionality Or Crowding-Out? An Overall Evaluation of Public R&D Subsidy On Private R&D Expenditure." *Research Policy*, 45(9): 1715-30.

Noel, M. and Schankerman, M. 2013**.** "Strategic Patenting and Software Innovation." *The Journal of Industrial Economics*, 61(3): 481-520.

Romer, P. M. 1990**.** "Endogenous Technological Change." *Journal of Political Economy*, 98(5, Part 2): 71-101.

Sandner, P. G. and Block, J. 2011**.** "The Market Value of R&D, Patents, and Trademarks." *Research Policy*, 40(7): 969-85.

Schumpeter, J. A.*Capitalism, Socialism and Democracy*. New York: Harper, 1942.

Shleifer, A. and Vishny, R. W. 1997**.** "The Limits of Arbitrage." *The Journal of Finance*, 52(1): 35-55.

Shu, T., Tian, X. and Zhan, X. 2022**.** "Patent Quality, Firm Value, and Investor Underreaction: Evidence from Patent Examiner Busyness." *Journal of Financial Economics*, 143(3): 1043-69.

Stoffman, N., Woeppel, M. and Yavus, M.D. 2022**.** "Small Innovators: No Risk, No Return." *Journal of Accounting and Economics*, 74: 101492

Sullivan, J. 2024. "Remarks and Q&A by National Security Advisor Jake Sullivan On the Future of U.S.-China Relations," https://www.whitehouse.gov/briefing-room/speeches-remarks/2024/01/30/remarks-and-qa-by-national-security-advisor-jake-sullivan-on-the-future-of-u-s-china-relations/

Tseng, K. 2022**.** "Learning from the Joneses: Technology Spillover, Innovation Externality, and Stock Returns," *Journal of Accounting and Economics***,** 73(2):101478.

Veihl, M. 2022**.** "The Dark Side of Patents: Strategic Patenting, Product Market Entry and Competitor Innovation." *Academy of Management Proceedings*, 2022(1): 17819.

Wei, S., X, J., Yin, G. and Zhang, X. 2023, "Mild government failure." NBER Working paper 32278

Xu, B., Magnan, M. L. and André, P. E. 2007**.** "The Stock Market Valuation of R&D Information in Biotech Firms." *Contemporary Accounting Research*, 24(4): 1291-318.

Zhao, C., Qu, X. and Luo, S. 2019, "Impact of the InnoCom program on corporate innovation performance in China: Evidence from Shanghai." *Technological Forecasting and Social Change*, 146, 103-118

Table 0:

Year	Name of Policy	Major Content	Relevant Statement
2006	**National Medium- and Long-term Science and Technology Development Plan Outline (2006-2020)[19]**	This outline emphasizes enhancing national innovation capabilities and encourages independent innovation, particularly regarding technology and patent quantities.	By 2020, ……The annual authorized number of domestic invention patents and the number of citations to international scientific papers ranks among the top 5 in the world.
2008	**Patent Law (Revised)[20]**	The revised patent law strengthens patent protection, encouraging innovation and increasing patent applications.	The 2008 amendment to China's Patent Law encouraged institutions and individuals to apply for more patents through several key measures: (1) Enhanced patent protection (Sections 1 and 11, 59-68); (2) Simplified application procedures; (3) Increased rights for design patent holders; (4) Promotion of technology transfer and application; (5) Clear rewards for employee inventions (Section 16)
2008	**National Intellectual Property Strategy Outline[21]**	The outline serves as a comprehensive framework for guiding China's intellectual property (IP) development, and the overall goals are to establish a robust IP system that supports innovation, promotes economic growth, and enhances international competitiveness, as well as achieve significant improvements in IP management and enforcement by 2020.	By 2020, China's level of intellectual property development will rank among the top in the world (Section 2.2.7: Short term 5-year goal)
2016	**Innovation-Driven Development Strategy Outline[22]**	This outline emphasizes that innovation is the primary driving force for development and supports the commercialization of high-tech and patent results.	Strengthen basic frontier and high-tech research oriented to national strategic needs. Focusing on the "stuck" issues related to long-term development and national security, strengthen the forward-looking layout of basic research, and increase the intensity of major basic research and strategic high-tech research in the fields of space, ocean, network, nuclear, materials, energy, information, life, etc.
2021	**Intellectual Property Strategy Outline (2021-2025)[23]**	This strategy aims to further promote the creation of intellectual property and strengthen support for enterprises in patent applications.	By 2025, ….., the number of high-value invention patents reaches 12 per 10,000 people.

[19] https://www.gov.cn/gongbao/content/2006/content_240244.htm
[20] https://www.gov.cn/flfg/2008-12/28/content_1189755.htm
[21] https://www.cnipa.gov.cn/art/2018/6/1/art_734_48203.html
[22] https://www.gov.cn/zhengce/2016-05/19/content_5074812.htm
[23] https://www.gov.cn/zhengce/2021-09/22/content_5638714.htm

Table 1: Descriptive statistics

Total number of firms: 3,598

Panel A: Patent counts

Statistics	Total patent counts	Invention patents	Utility patents	Design patents
Mean	60.02	27.42	26.43	6.17
Median	17.50	5.92	7.00	0.33
P25	5.00	1.42	1.36	0.00
P75	41.67	16.75	20.17	2.83

Panel B: Time-series of patent counts per firm

year	Total patent counts	Invention patents	Utility patents	Design patents
2008	20.35	9.42	7.62	3.30
2009	28.76	13.27	11.65	3.85
2010	34.19	14.75	15.07	4.38
2011	41.62	17.55	19.00	5.08
2012	48.04	20.16	22.52	5.36
2013	52.61	23.31	24.21	5.09
2014	60.69	27.82	26.82	6.04
2015	66.25	30.71	29.36	6.18
2016	73.19	35.58	31.41	6.20
2017	83.69	38.73	37.95	7.00
2018	99.75	47.49	44.06	8.19
2019	93.41	47.90	37.17	8.33

Panel C: Financial information of the underlying firms

Statistics	Tobin Q	Total Asset (mil RMB)	Intangible Asset (mil RMB)	R&D intensity
Mean	2.20	11584.25	380.68	0.0363
Median	1.95	3040.67	100.83	0.0298
P25	1.51	1579.08	43.23	0.0065
P75	2.57	6605.26	246.37	0.0471

Table 2: Naïve regression

Table 2 shows the results of the following naïve regression

$UTobinQ_{it} = \theta_0 + \gamma_0 UPatNo_{it} + \nu_{0t} + \varepsilon_{it}(1)$

where $UTobinQ_{it}$ is the undetrended Tobin Q of firm *i* in year *t*, and $UPatNo_{it}$is the undetrended natural log of (1+number of patents from firm i in year t). Letter A refers to the number of invention patent, letter U refers to that of utility patent, letter S refers to that of design patent, and letter P refers to total patent count, i.e., P=A+U+S. White heteroskadasticity-adjusted standard errors and time fixed effect are used.

Dependent var:	$UTobinQ$	$UTobinQ$	$UTobinQ$	$UTobinQ$
UPatNo, Type: P	-0.104***			
(Total patent counts, P=A+U+S)	[-20.0]			
UPatNo, Type: A		-0.0896***		
(Invention patent)		[-15.7]		
UPatNo, Type: U			-0.144***	
(Utility patent)			[-27.6]	
UPatNo, Type: S				-0.0424***
(Design patent)				[-6.24]
Constant	2.831***	2.758***	2.818***	2.682***
	[66.3]	[65.4]	[67.2]	[64.1]
N	30235	30235	30235	30235
F-value	260.8	252.6	283.1	243.7

Note: *, ** and *** represent significance levels of 10%, 5%, and 1%, respectively. t-values are in brackets.

Table 3: The baseline model of Tobin Q, intangible assets, and patent counts
This table is based on the following regressions:

$$Intang_{it} = \alpha^{Int} + \beta^{Int} PatNo_{it} + \nu_i + e_{it}^{Int} \quad (2)$$

And

$$TobinQ_{it} = \alpha^{Q} + \gamma_1 PatNo_{it} + \gamma_2 X_{it} + Control_{it}\delta' + \nu_i + e_{it}^{Q} \quad (3)$$

where $PatNo_{it}$ is the detrended natural logarithm of (1+patent count from firm *i* in year *t*). $TobinQ_{it}$ is the detrended logged-Tobin Q value of firm *i* in year *t*.X_{it} is the measures of intangible assets, including the $Intang_{it}$, which is the detrended natural logrithm of the intangible assets of firm *i* in year *t*, as well as $\widehat{e_{it}^{Int}}$, which is the residual value of equation (2). $Control_{it}$ contains the control variables including: (1) *R&D:* the R&D intensity, which is defined as the firm's R&D expenses divided by its sales, (2) *sale_miss*, a dummy variable which equals 1 if R&D intensity is missing and 0 otherwise, (3) *citation*, the natural logarithm of (1+ 5-year number of patent citations from firm *i* in year *t*). (4) *AnalystNo*, the detrended natural logarithm of (1+ number of analyst recommendation for firm *i* in year t). (5) *analyst_miss*, a dummy variable which equals 1 if *AnalystNo is* missing and 0 otherwise. (6) natural logarithm of total asset of firm *i* in year t-1. The equations are estimated using OLS stock- and industry-level fixed-effect model. The standard errors are clustered at stock level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Patent count total (P)				Panel B: Invention patent (A)			
Dependent var:	Intang	Tobin Q	Tobin Q	Tobin Q	Intang	Tobin Q	Tobin Q	Tobin Q
PatNo	0.149***	-0.0251***	-0.0156***	-0.0225***	0.162***	-0.0231***	-0.0127***	-0.0202***
	[13.6]	[-6.43]	[-4.44]	[-6.36]	[13.6]	[-5.28]	[-3.19]	[-5.08]
R&D			0.724***	0.724***			0.729***	0.729***
			[3.70]	[3.70]			[3.73]	[3.73]
Intang			-0.0461***				-0.0466***	
			[-10.4]				[-10.5]	
$e_{it}^{\widehat{Int}}$				-0.0461***				-0.0466***
				[-10.4]				[-10.5]
cons	-0.0002***	0.0000	2.406***	2.406***	-0.0001***	0.0000	2.407***	2.407***
	[-13.6]	[0.0073]	[16.9]	[16.9]	[-13.6]	[0.006]	[16.9]	[16.9]
N	29525	30142	28349	28349	29525	30142	28349	28349
F-value	184.1	41.4	106.9	106.9	185.5	27.92	105.2	105.2

Note: ** and *** represent significance levels 5%, and 1%, respectively. t-values are in brackets.

	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	Panel C: Utility patent (P)				Panel D: Design patent (S)			
Dependent var:	Intang	Tobin Q	Tobin Q	Tobin Q	Intang	Tobin Q	Tobin Q	Tobin Q
PatNo	0.127***	-0.0268***	-0.0183***	-0.0241***	0.0832***	-0.0169***	-0.0111***	-0.0150***
	[11.6]	[-7.02]	[-5.26]	[-6.95]	[7.48]	[-3.80]	[-2.79]	[-3.77]
R&D			0.720***	0.720***			0.720***	0.720***
			[3.69]	[3.69]			[3.68]	[3.68]
Intang			-0.0462***				-0.0473***	
			[-10.4]				[-10.7]	
$e_{it}^{\widehat{Int}}$				-0.0462***				-0.0473***
				[-10.4]				[-10.7]
cons	-0.00003	0.00000	2.403***	2.403***	-0.0000***	0.00000	2.417***	2.417***
	[-11.6]	[0.015]	[16.9]	[16.9]	[-7.48]	[0.012]	[17.0]	[17.0]
N	29525	30142	28349	28349	29525	30142	28349	28349
F-value	133.8	49.23	107.9	107.9	55.94	14.44	103.8	103.8

Note: ** and *** represent significance levels 5%, and 1%, respectively. t-values are in brackets.

Table 4: R&D vs patent count
This table is based on the following regressions:

$$PatNo_{it} = \alpha^{No} + \beta^{No} R\&D_{it} + \nu_i + e_{it}^{No} \quad (4)$$

and

$$TobinQ_{it} = \alpha^{Q} + \gamma_1 PatNoResid_{it} + \gamma_2 Intang_{it} + Control_{it}\delta' + \nu_i + e_{it}^{Q} (5)$$

where $PatNo_{it}$ is the detrended natural log of (1+patent count from firm *i* in year *t*). $Intang_{it}$ is the detrended natural log of the intangible assets of firm *i* in year *t*. $TobinQ_{it}$ is the detrended logged-Tobin Q value of firm *i* in year *t*.$PatNoResid_{it}$ is the residual value from equation (3).$Control_{it}$ contains the control variables including: (1) *R&D:* the R&D intensity, which is defined as the firm's R&D expenses divided by its sales, (2) *sale_miss*, a dummy variable which equals 1 if R&D intensity is missing and 0 otherwise, (3) *citation*, the natural log of (1+ 5-year number of patent citations from firm *i* in year *t*). (4) *AnalystNo*, the detrended natural log of (1+ number of analyst recommendation for firm *i* in year t). (5) *analyst_miss,* a dummy variable which equals 1 if *AnalystNo is* missing and 0 otherwise. (6) log value of total asset of firm *i* in year t-1. The equations are estimated using OLS stock- and industry-level fixed-effect model. The standard errors are clustered at stock level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Patent count total (P)				Panel B: Invention patent (A)			
Dependent var:	PatNo	Tobin Q	Tobin Q	Tobin Q	PatNo	Tobin Q	Tobin Q	Tobin Q
PatNoResid		-0.0210***	-0.0211***	-0.0156***		-0.0186***	-0.0186***	-0.0127***
		[-5.87]	[-5.89]	[-4.44]		[-4.59]	[-4.61]	[-3.19]
R&D	2.034***		0.794***	0.692***	2.434***		0.802***	0.698***
	[7.48]		[4.12]	[3.54]	[10.1]		[4.17]	[3.57]
Intang				-0.0461***				-0.0466***
				[-10.4]				[-10.5]
cons	-2.532***	3.053***	3.158***	2.446***	-2.324***	3.053***	3.153***	2.437***
	[-14.0]	[21.4]	[21.1]	[17.3]	[-14.5]	[21.3]	[21.0]	[17.2]
N	28959	28959	28959	28349	28959	28959	28959	28349
F-value	112.5	249.4	118.8	106.9	128.2	242.1	116.5	105.2

Note: ** and *** represent significance levels 5%, and 1%, respectively. t-values are in brackets.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel C: Utility patent (U)				Panel D: Design patent (S)			
Dependent var:	PatNo	Tobin Q	Tobin Q	Tobin Q	PatNo	Tobin Q	Tobin Q	Tobin Q
PatNo_resid		-0.0222***	-0.0223***	-0.0183***		-0.0130***	-0.0130***	-0.0111***
		[-6.31]	[-6.34]	[-5.26]		[-3.19]	[-3.21]	[-2.79]
R&D	1.523***		0.796***	0.693***	1.451***		0.811***	0.704***
	[5.87]		[4.15]	[3.55]	[6.91]		[4.21]	[3.59]
Intang				-0.0462***				-0.0473***
				[-10.4]				[-10.7]
cons	-2.134***	3.053***	3.157***	2.442***	-1.024***	3.053***	3.148***	2.428***
	[-12.4]	[21.4]	[21.1]	[17.2]	[-7.34]	[21.4]	[21.0]	[17.1]
N	28959	28959	28959	28349	28959	28959	28959	28349
F-value	86.96	253.8	120.2	107.9	43.51	234.8	113.4	103.8

Note: ** and *** represent significance levels 5%, and 1%, respectively. t-values are in brackets.

Table 5: Patent counts and analyst forecast dispersions

Table 5 is based on the following regressions

$$Disperson_{it} = \theta^{Dis} + \gamma_1^{Dis} PatNo_{it} + \gamma_2^{Dis} Intang_{it} + Control_{it}\delta' + \nu_i + \varepsilon_{it}^{Dis} \ (6)$$
$$TobinQ_{it} = \theta^{Q} + \ \gamma_0^{Q} Disperson_{it} + \gamma_1^{Q} PatNo_{it} + \gamma_2^{Q} Intang_{it} + Control_{it}\delta' + \nu_i + \varepsilon_{it}^{Q} \ (7)$$

Where $Disperson_{it}$ is the analyst forecast dispersions, which is defined as the standard deviation of analysts' recommendations of firm *i* in year *t*. All the other definitions of variables are the same as in the benchmark regression from Table 3.

	(1) Dispersion	(2) Dispersion	(3) Dispersion	(4) Dispersion	(5) TobinQ	(6) TobinQ	(7) TobinQ	(8) TobinQ
PatNo (P)	0.00126				-0.0162***			
	[0.72]				[-4.62]			
PatNo (A)		0.00188				-0.0138***		
		[1.01]				[-3.51]		
PatNo (U)			0.000856				-0.0190***	
			[0.48]				[-5.52]	
PatNo (S)				0.00241				-0.0118***
				[1.14]				[-2.98]
dispersion					0.00347	0.00347	0.00337	0.00341
					[0.26]	[0.26]	[0.26]	[0.26]
Cons	0.877***	0.878***	0.876***	0.877***	2.492***	2.493***	2.489***	2.503***
	[14.4]	[14.4]	[14.4]	[14.4]	[17.6]	[17.6]	[17.6]	[17.7]
N	28350	28350	28350	28350	28350	28350	28350	28350
F-value	767.2	767.7	766.9	765.3	111.8	110.6	112.3	108.7

Note: *, ** and *** represent significance levels of 10%, 5%, and 1%, respectively. t-values are in brackets.

Table 6: Patent counts and market underreaction

Table 6 uses the same benchmark regression as in Table 3, but adds the one-year lagged patent count.

Total patent counts (P)	(1)	(2)	(3)	Invention patent (A)	(4)	(5)	(6)
PatNo (P)	-0.0223***	-0.0183***	-0.0148***	**PatNo (A)**	-0.0220***	-0.0170***	-0.0124***
	[-6.14]	[-5.65]	[-4.60]		[-5.34]	[-4.58]	[-3.36]
L.PatNo (P)	-0.0202***	-0.00639**	-0.00349	**L.PatNo (A)**	-0.0157***	-0.000643	0.00165
	[-5.73]	[-2.01]	[-1.11]		[-3.97]	[-0.18]	[0.47]
R&D		0.455**	0.369*	R&D		0.453**	0.362*
		[2.42]	[1.93]			[2.41]	[1.89]
analysts		0.0712***	0.0761***	analysts		0.0710***	0.0759***
		[13.0]	[13.9]			[12.9]	[13.9]
Intang			-0.0439***	Intang			-0.0447***
			[-9.55]				[-9.73]
cons	0.0329***	4.174***	3.523***	cons	0.0329***	4.192***	3.535***
	[659.3]	[28.8]	[23.6]		[615.2]	[28.9]	[23.7]
N	26459	26458	25932	N	26459	26458	25932
F-value	28.99	205.2	168.3		19.1	203.7	166.6

Note: *, ** and *** represent significance levels of 10%, 5%, and 1%, respectively. t-values are in brackets.

Utility patent (U)	(7)	(8)	(9)	Design patent (S)	(10)	(11)	(12)
PatNo (U)	-0.0223***	-0.0188***	-0.0162***	**PatNo (S)**	-0.0138***	-0.00793**	-0.00764**
	[-6.23]	[-5.92]	[-5.14]		[-3.21]	[-2.09]	[-2.02]
L.PatNo (U)	-0.0260***	-0.0118***	-0.00948***	**L.PatNo (S)**	-0.0112***	-0.00479	-0.00313
	[-7.20]	[-3.62]	[-2.93]		[-2.77]	[-1.27]	[-0.85]
R&D		0.456**	0.374*	R&D		0.438**	0.359*
		[2.43]	[1.95]			[2.32]	[1.87]
analysts		0.0711***	0.0761***	analysts		0.0699***	0.0753***
		[12.9]	[13.9]			[12.8]	[13.8]
Intang			-0.0439***	Intang			-0.0454***
			[-9.52]				[-9.88]
cons	0.0329***	4.166***	3.508***	cons	0.0326***	4.212***	3.537***
	[854.7]	[28.7]	[23.6]		[1437.0]	[29.2]	[23.8]
N	26459	26458	25932	N	26459	26458	25932
F-value	35.79	208.6	170.4	F-value	7.218	200.3	164.8

Note: *, ** and *** represent significance levels of 10%, 5%, and 1%, respectively. t-values are in brackets.

Table 7: Patent counts and Tobin Q by firm size

In Table 7 we initially divide all firms into 10 groups based on their average annual market capitalization within the sample period. Group 1 represents the firms with the smallest market capitalization, while Group 10 represents the firms with the highest market capitalization. We then apply the benchmark model to all the 10 groups and the results are shown below.

Panel A: Patent counts and firm size

Group	Total patent (P)	Invention patent (A)	Utility patent (U)	Design patent (S)
Smallest-1	20.19	6.90	10.06	3.23
2	22.50	8.70	11.09	2.71
3	22.77	8.71	10.82	3.24
4	29.09	13.06	12.80	3.23
5	26.83	10.58	12.79	3.46
6	34.38	14.57	15.65	4.16
7	37.35	15.44	16.63	5.28
8	52.13	19.69	24.69	7.74
9	71.15	34.07	28.60	8.48
Largest-10	283.61	142.35	121.08	20.18

Note: Panel A shows the average annual patent counts for different types of patents in the 10 size groups.

Panel B: Total patent (P)

Tobin Q	Smallest-1	2	3	4	5	6	7	8	9	Largest-10
PatNo (P)	-0.0751***	-0.0553***	-0.0466***	-0.0188	-0.0437***	-0.0193*	-0.00191	-0.00823	-0.0125	-0.0114*
	[-2.92]	[-2.98]	[-3.85]	[-1.29]	[-3.83]	[-1.91]	[-0.20]	[-0.83]	[-1.45]	[-1.67]
R&D	1.081	1.071	1.187**	1.060*	0.563	1.142**	-0.357	0.878	1.115**	0.218
	[1.03]	[1.34]	[2.02]	[1.75]	[0.96]	[2.16]	[-0.76]	[1.61]	[2.09]	[0.50]
Analysts	-0.00985	-0.0356	0.0417*	0.0246	0.0216	0.0415**	0.0656***	0.0931***	0.0977***	0.0768***
	[-0.19]	[-1.07]	[1.91]	[1.11]	[1.23]	[2.46]	[4.67]	[6.07]	[8.92]	[6.91]
cons	2.847***	2.572***	2.338***	2.443***	2.912***	2.610***	3.264***	2.914***	2.405***	2.471***
	[3.20]	[2.71]	[3.69]	[3.26]	[6.57]	[5.89]	[8.65]	[7.10]	[7.38]	[7.56]
N	1008	1870	2546	2694	3150	3244	3500	3490	3653	3790
F-value	3.33	4.054	8.088	4.72	13.86	10.87	22.63	17.13	26.07	21.56

Panel C: Invention patent (A)

Tobin Q	Smallest-1	2	3	4	5	6	7	8	9	Largest-10
PatNo (A)	-0.0799***	-0.0781***	-0.0497***	-0.0141	-0.0346***	-0.0129	0.0000134	-0.00727	-0.0113	-0.00971
	[-2.75]	[-4.09]	[-3.45]	[-0.90]	[-2.79]	[-1.14]	[0.0012]	[-0.62]	[-1.16]	[-1.25]
R&D	1.024	1.127	1.190**	1.062*	0.499	1.141**	-0.363	0.885	1.121**	0.27
	[0.99]	[1.40]	[2.03]	[1.75]	[0.85]	[2.15]	[-0.78]	[1.61]	[2.10]	[0.62]
Analysts	-0.0161	-0.0384	0.0427*	0.0241	0.0193	0.0404**	0.0653***	0.0928***	0.0979***	0.0770***
	[-0.31]	[-1.15]	[1.94]	[1.09]	[1.10]	[2.40]	[4.64]	[6.03]	[8.97]	[6.94]
cons	2.843***	2.645***	2.360***	2.434***	2.957***	2.604***	3.264***	2.913***	2.398***	2.493***
	[3.03]	[2.84]	[3.72]	[3.25]	[6.63]	[5.87]	[8.66]	[7.11]	[7.36]	[7.62]
N	1008	1870	2546	2694	3150	3244	3500	3490	3653	3790
F-value	3.114	6.174	7.57	4.54	13.28	9.963	22.63	17.19	26.01	21.6

Note: *, ** and *** represent significance levels of 10%, 5%, and 1%, respectively. t-values are in brackets.

Panel D: Utility patent (U)

Tobin Q	Smallest-1	2	3	4	5	6	7	8	9	Largest-10
PatNo (U)	-0.0815***	-0.0495***	-0.0508***	-0.0134	-0.0358***	-0.0247**	-0.00757	-0.0200**	-0.0113	-0.0124*
	[-3.07]	[-2.99]	[-3.93]	[-0.94]	[-3.26]	[-2.35]	[-0.82]	[-2.08]	[-1.31]	[-1.78]
R&D	0.88	0.978	1.134*	1.042*	0.572	1.133**	-0.341	0.907*	1.108**	0.221
	[0.83]	[1.22]	[1.93]	[1.73]	[0.98]	[2.14]	[-0.73]	[1.67]	[2.08]	[0.51]
Analysts	-0.0165	-0.0347	0.0393*	0.0246	0.021	0.0421**	0.0662***	0.0941***	0.0977***	0.0772***
	[-0.34]	[-1.04]	[1.80]	[1.11]	[1.20]	[2.50]	[4.74]	[6.14]	[8.88]	[6.93]
cons	2.907***	2.589***	2.397***	2.454***	2.932***	2.615***	3.261***	2.899***	2.398***	2.478***
	[3.26]	[2.72]	[3.81]	[3.30]	[6.66]	[5.90]	[8.64]	[7.06]	[7.37]	[7.61]
N	1008	1870	2546	2694	3150	3244	3500	3490	3653	3790
F-value	3.376	3.923	8.192	4.568	13.38	11.39	23.25	17.43	25.75	21.39

Panel E: Design patent (S)

Tobin Q	Smallest-1	2	3	4	5	6	7	8	9	Largest-10
PatNo (S)	-0.0441	-0.0256	-0.0326**	0.00447	-0.0331**	-0.0266**	0.00356	0.00614	-0.0287***	0.00134
	[-1.20]	[-0.94]	[-2.01]	[0.32]	[-2.40]	[-2.33]	[0.30]	[0.57]	[-2.81]	[0.18]
R&D	0.874	0.968	1.091*	1.030*	0.477	1.162**	-0.37	0.847	1.184**	0.277
	[0.79]	[1.20]	[1.84]	[1.71]	[0.80]	[2.20]	[-0.79]	[1.55]	[2.23]	[0.65]
Analysts	-0.00266	-0.0377	0.0380*	0.0236	0.0189	0.0404**	0.0650***	0.0916***	0.0971***	0.0765***
	[-0.053]	[-1.12]	[1.73]	[1.06]	[1.08]	[2.41]	[4.66]	[5.98]	[8.94]	[6.91]
cons	3.102***	2.668***	2.513***	2.453***	2.984***	2.635***	3.266***	2.956***	2.395***	2.544***
	[2.94]	[2.75]	[3.96]	[3.32]	[6.73]	[5.91]	[8.66]	[7.11]	[7.37]	[7.77]
N	1008	1870	2546	2694	3150	3244	3500	3490	3653	3790
F-value	2.162	2.583	6.302	4.008	12.64	11.34	22.69	17.3	28.38	20.97

Note: *, ** and *** represent significance levels of 10%, 5%, and 1%, respectively. t-values are in brackets.

Table 8: The impact of the InnoCom program

For an InnoCom event *i* that comes froma list firm, if the firm itself (or its subsidiaries) obtains the InnoCom certification in year *t*, we obtain a 5-year window from year t–2 to year t+2 as an event in our regression. It is worth noting that there is not always a full 5-year window for an event: if firm *i* (or its subsidiary) obtains InnoCom certification in year *t*, and in year *t+1*, there is another subsidiary of *i* obtains the certification, the event window now becomes [*t–2*, *t*]. It means that the window length for different event varies from 1 year to 5 years. For each test group event, we use the following method to find a control event: first, the control event stock must be from the same industry as the test group stock; second, the control group must have not received InnCom certificated during the sample period, and third, the size difference (proxied by total asset) between the control group and the test group in the event-window must be the smallest. Then, we use the following regression:

$$y_{is\tau} = \beta_0 + \beta_1 HT_{is\tau} + \beta_2 test_{is} \times HT_{is\tau} + control_{is}\gamma' + \alpha_i + \theta_s + \varepsilon_{is\tau} \qquad (8)$$

Where s is the event window, which contains [t-2, t+2] where t is the InnoCom certification year. $test_{is}$ equals 1 for a test stock in window s, and 0 for a control stock. $HT_{is\tau}$ is a dummy variable which equals 1 if $\tau = t$ in window s, (in the year when InnoCom certification is awarded to firm i in the event-window) and 0 if $\tau \neq t$ (it is not a year in which the firm i gets the InnoCom certification in the event-window s. In other words, it is in the years preceding or following the certification-award year in the event-window s). The dependent variable $y_{is\tau}$ includes: the undetrended logged (1+number of patents), the detrended logged (1+number of patents); P_{is}, the number of patent counts; *citation*, the 5-year citation number per patent, the undetrended 5-year citation number per patent; the skewness of 5-year citation; invention patent percentage, defined as the invention patent counts over the total patent counts, and design patent percentage, defined as the design patent counts over the total patent counts for firm i, in event window s, and in year τ. The control variables are the same as previous tables. Model (3) uses Poisson regression[24], and other models use OLS fixed effect model. Standard errors are clustered at firm level.

[24] According to Cohn, Liu and Wardlaw (2022), applying log(1+countable variable) may result in wrong coefficient signs in expectation. This is why we adopt the Poisson regression with fixed effects.

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent var $y_{is\tau}$	ln(1+Patent No.)	Detrended ln(1+Patent No.)	Patent No.	Citation	Detrended Citation	Skewness of Citation	Invention (A) percentage	Design (S) percentage	Tobin Q
$HT_{is\tau}$	-0.00579	-0.013	0.00809	0.0893**	0.0379	-0.0367**	0.0127***	-0.00716**	-0.00775**
	[-0.56]	[-1.25]	[0.49]	[2.22]	[0.90]	[-2.44]	[3.25]	[-2.25]	[-2.00]
$test_i$*$HT_{is\tau}$	0.0640***	0.0635***	0.0389*	-0.0948*	-0.123**	0.0539***	-0.0169***	0.00820**	-0.0121**
	[4.21]	[4.11]	[1.89]	[-1.86]	[-2.28]	[2.83]	[-3.36]	[2.00]	[-2.12]
Constant	-1.968***	-0.973***	-0.48	-4.534***	-2.036***	1.930***	0.115	0.121**	5.084***
	[-9.78]	[-5.80]	[-1.21]	[-6.17]	[-3.50]	[6.74]	[1.58]	[2.02]	[67.4]
Year fixed effect	Yes	No	Yes	Yes	No	Yes	Yes	Yes	Yes
Stock fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	50371	50307	46731	34186	34186	32561	35785	35785	50307
F/Chi2	195.4	72.92	304.8	41.09	18.28	21.88	32.58	41.07	809.2

Note: *, ** and *** represent significance levels of 10%, 5%, and 1%, respectively. t-values are in brackets.

Table 9: InnoCom Certification granting month and patent counts

Panel A: Descriptive statistics of InnoCom Certification granting month

Granting month equals 1 if the firm gets its InnoCom certification in January, 2 if in February, …, and 12 if in December.

	Granting month
Mean	10.34
Median	11
Stdev	1.83
25 percentile	10
75 percentile	12
# of obs.	8,824

Panel B: InnoCom Certification granting month and patent counts

Panel B is based on the following regression:

$y_{it} = \theta \quad + \gamma_1 \ GM_{it} + control_{it}\delta' + \nu_i \quad + \varepsilon_{it}$ (9)

Where y_{it} is patent counts for firm i in year *t*, denoted as P_{it}, or log(1+P_{it}). GM_{it} is the granting month of firm *i* in year *t*, which is defined above. Models (1) and (3) are estimated using OLS with fixed effect, while models (2) and (4) are estimated using Poisson regression with fixed effect.

	Treatment group		Control group	
	(1)	(2)	(3)	(4)
	log(1+P_{it})	P_{it}	log(1+P_{it})	P_{it}
GM_{it}	0.0117*	0.0250***	-0.00171	-0.00312
	[1.80]	[2.88]	[-0.33]	[-0.40]
cons	-2.419***	-3.091***	0.466	4.907**
	[-4.59]	[-3.54]	[0.83]	[2.28]
Stock fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes
N	7790	7674	8541	7397
F/Chi2	32.86	186.6	53.14	122.7

Note: *, ** and *** represent significance levels of 10%, 5%, and 1%, respectively. t-values are in brackets.

Table 10: Value-destructive patents from Non-InnoCom firms

This table is based on the same regressions as in Table 3, but all the firm-year observations on the year of InnoCom certification awarding are deleted.

$$Intang_{it} = \alpha^{Int} + \beta^{Int} PatNo_{it} + \nu_i + e_{it}^{Int} \quad (2)$$

<u>And</u>

$$TobinQ_{it} = \alpha^{Q} + \gamma_1 PatNo_{it} + \gamma_2 X_{it} + Control_{it}\delta' + \nu_i + e_{it}^{Q} (3)$$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Patent count total (P)				Panel B: Invention patent (A)			
Dependent var:	Intang	Tobin Q	Tobin Q	Tobin Q	Intang	Tobin Q	Tobin Q	Tobin Q
PatNo	0.146***	-0.0201***	-0.0138***	-0.0203***	0.177***	-0.0201***	-0.0171***	-0.0249***
	[10.3]	[-4.07]	[-3.20]	[-4.67]	[10.1]	[-3.36]	[-3.27]	[-4.75]
R&D			0.433	0.433			0.442*	0.442*
			[1.64]	[1.64]			[1.68]	[1.68]
Intang			-0.0442***				-0.0441***	
			[-8.97]				[-8.94]	
$\widehat{e_{it}^{Int}}$				-0.0442***				-0.0441***
				[-8.97]				[-8.94]
cons	-0.0224***	0.00933***	2.857***	2.858***	-0.0222***	0.00943***	2.868***	2.869***
	[-54.8]	[64.5]	[14.7]	[14.7]	[-50.8]	[65.1]	[14.8]	[14.8]
N	16847	17413	16070	16070	16847	17413	16070	16070
F-value	106.1	16.6	82.87	82.87	101.6	11.26	83.47	83.47

Note: ** and *** represent significance levels 5%, and 1%, respectively. t-values are in brackets.

	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
		Panel C: Utility patent (P)					Panel D: Design patent (S)	
Dependent var:	Intang	Tobin Q	Tobin Q	Tobin Q	Intang	Tobin Q	Tobin Q	Tobin Q
PatNo	0.136***	-0.0213***	-0.0169***	-0.0229***	0.0795***	-0.00955	-0.00659	-0.0102*
	[8.99]	[-4.19]	[-3.71]	[-5.03]	[4.78]	[-1.45]	[-1.15]	[-1.77]
R&D			0.43	0.43			0.425	0.425
			[1.62]	[1.62]			[1.60]	[1.60]
Intang			-0.0443***				-0.0454***	
			[-8.96]				[-9.19]	
$e_{it}^{\widehat{Int}}$				-0.0443***				-0.0454***
				[-8.96]				[-9.19]
cons	-0.0229***	0.00934***	2.863***	2.864***	-0.0260***	0.00984***	2.856***	2.857***
	[-54.2]	[67.5]	[14.8]	[14.8]	[-183.2]	[170.2]	[14.7]	[14.7]
N	16847	17413	16070	16070	16847	17413	16070	16070
F-value	80.79	17.53	83.49	83.49	22.86	2.097	80.85	80.85

Note: ** and *** represent significance levels 5%, and 1%, respectively. t-values are in brackets.

Table 11: Ownership Structure

In this table, we use the following regression:

$$TobinQ_{it} = \alpha^{Q} + \gamma_1 PatNo_{it} + \gamma_2 PatNo_{it} * SOE_{it} + Control_{it}\delta' + \nu_i + e_{it}^{Q} \quad (10)$$

where SOE_{it} is the matrix that measures the ownership structure of the underlying firm. It includes (1) $SOEdum_i$, which equals 1 if firm i is a state-owned enterprise (SOE), and 0 otherwise; and (2) $SOEshare_{it}$, which is the percentage of shares owned by government or its representatives for firm i in year t. All other variables are defined earlier.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Patent count total (P)				Panel B: Invention patent (A)			
Dep. var:	Tobin Q	Tobin Q	Tobin Q	Tobin Q	Tobin Q	Tobin Q	Tobin Q	Tobin Q
	Private firms	SOEs	Full sample	Full sample	Private firms	SOEs	Full sample	Full sample
PatNo	-0.0206***	-0.0328***	-0.0220***	-0.0263***	-0.0168***	-0.0343***	-0.0181***	-0.0231***
	[-3.83]	[-6.62]	[-4.04]	[-6.18]	[-2.86]	[-5.90]	[-3.05]	[-4.86]
PatNo*SOEdum			-0.00848				-0.0135	
			[-1.14]				[-1.61]	
PatNo*SOEshare				0.0131				-0.0196
				[0.41]				[-0.52]
cons	-0.0411***	-0.0648***	-0.0597***	-0.0622***	-0.0406***	-0.0671***	-0.0602***	-0.0628***
	[-2.72]	[-5.85]	[-5.92]	[-6.18]	[-2.68]	[-6.06]	[-5.98]	[-6.23]
N	17930	11664	29689	30141	17930	11664	29689	30141
F-value	8.054	33.03	25.6	25.84	6.911	32.09	24.14	24.39

Note: ** and *** represent significance levels 5%, and 1%, respectively. t-values are in brackets.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel C: Utility patent (U)				Panel D: Design patent (S)			
Dep. var:	Tobin Q	Tobin Q	Tobin Q	Tobin Q	Tobin Q	Tobin Q	Tobin Q	Tobin Q
	Private firms	SOEs	Full sample	Full sample	Private firms	SOEs	Full sample	Full sample
PatNo	-0.0236***	-0.0342***	-0.0244***	-0.0275***	-0.0194***	-0.0156**	-0.0196***	-0.0213***
	[-4.64]	[-6.50]	[-4.74]	[-6.63]	[-3.38]	[-2.34]	[-3.38]	[-4.57]
PatNo*SOEdum			-0.0073				0.00592	
			[-0.99]				[0.67]	
PatNo*SOEshare				0.00417				0.0589
				[0.12]				[1.29]
cons	-0.0406***	-0.0648***	-0.0592***	-0.0616***	-0.0407***	-0.0681***	-0.0603***	-0.0623***
	[-2.68]	[-5.87]	[-5.88]	[-6.12]	[-2.68]	[-6.09]	[-5.96]	[-6.16]
N	17930	11664	29689	30141	17930	11664	29689	30141
F-value	9.301	32.31	26.06	26.45	7.156	25.97	20.08	21.55

Note: ** and *** represent significance levels 5%, and 1%, respectively. t-values are in brackets.

Table 12: Value-destructive patents across industries

In this table, we categorize each firm into three groups: low-/medium-/high-patent-count group based on the following: First, we assign each firm into 79 sub-industries, then we drop the subgroup if the total number of firms is below 5[25]., and 62 sub-industries and 3561 firms remain in the sample. We then sort the median annual patent counts for each sub-industry from smallest (0.405 per year) to largest (181.5 per year). Next, we categorize these sub-industries into 3 groups: lowest patent counts/medium patent counts/highest patent counts, such that the number of firms are approximately the same, based on the 33rd and 67th percentiles. We then run the benchmark regression in each group for total patents, invention patents, utility patents, and design patents, respectively.

Panel A: Total patents	(1) Low patent counts	(2) Medium patent counts	(3) High patent counts
Dep. var:	Tobin Q	Tobin Q	Tobin Q
PatNo	-0.0326***	-0.0682***	-0.0740***
	[-4.68]	[-10.2]	[-8.38]
cons	3.428***	2.570***	1.401***
	[9.10]	[10.8]	[5.18]
Controls			
N	5618	8714	8276
F-value	40.99	95.84	55.82

Panel B: Invention patents	(1) Low patent counts	(2) Medium patent counts	(3) High patent counts
Dep. Var:	Tobin Q	Tobin Q	Tobin Q
PatNo	-0.0278***	-0.0539***	-0.0584***
	[-3.60]	[-7.58]	[-6.99]
cons	3.567***	2.742***	1.431***
	[9.66]	[11.4]	[5.14]
Controls			
N	5618	8714	8276
F-value	39.19	89.66	54.49

Panel C: Utility patents	(1) Low patent counts	(2) Medium patent counts	(3) High patent counts
Dep. var:	Tobin Q	Tobin Q	Tobin Q
PatNo	-0.0256***	-0.0511***	-0.0633***
	[-4.01]	[-9.20]	[-7.93]
cons	3.535***	2.716***	1.564***
	[9.46]	[11.5]	[5.83]
Controls			
N	5618	8714	8276

Panel D: Design patents	(1) Low patent counts	(2) Medium patent counts	(3) High patent counts
Dep. Var:	Tobin Q	Tobin Q	Tobin Q
PatNo	-0.0161*	-0.0283***	-0.0325***
	[-1.85]	[-4.40]	[-4.64]
cons	3.673***	3.032***	1.867***
	[9.90]	[12.8]	[6.95]
Controls			
N	5618	8714	8276

[25] The reason why we do not use the primary industry group is that the primary industry of manufacturing has too many stocks: 2443 out of 3561 firms are from the manufacturing industry.

F-value	40.18	91.77	53.01	F-value	38.96	83.38	47.89

Note: ** and *** represent significance levels 5%, and 1%, respectively. t-values are in brackets.

Table 13: Peer pressure

In this table, we use the following regression:

$$TobinQ_{it} = \alpha^{Q} + \gamma_1 PatNo_{it} + \gamma_2 PatNo_{it} * BAD_i + Control_{it}\delta' + \nu_i + e_{it}^{Q} \qquad (11)$$

where BAD_i is a dummy variable which equals 1 if firm i's annual patent count is lower than the sub-industry median value, and 0 otherwise. All other variables are defined earlier.

	(1) Total patents (P=A+U+S)	(2) Invention patents (A)	(3) Utility patents (U)	(4) Design patents (S)
Dep. var:	Tobin Q	Tobin Q	Tobin Q	Tobin Q
PatNo	-0.0481***	-0.0360***	-0.0384***	-0.0180***
	[-9.30]	[-6.82]	[-8.48]	[-3.98]
PatNo*BAD	-0.0226***	-0.0242***	-0.0230***	-0.0288***
	[-2.94]	[-2.74]	[-3.05]	[-2.78]
cons	2.469***	2.609***	2.600***	2.847***
	[15.2]	[15.9]	[16.1]	[17.7]
Controls				
N	22879	22879	22879	22879
F-value	155.9	147.8	151.4	136.8

Note: ** and *** represent significance levels 5%, and 1%, respectively. t-values are in brackets.

Table 14: List firms and subsidiaries

In this table, we use the following regression

$$TobinQ_{it} = \alpha^{Q} + \gamma_1 PatNoListed_{it} + \gamma_2 PatNoSubsidiry_{it} + Control_{it}\delta' + \nu_i + e_{it}^{Q} \qquad (12)$$

where $PatNoListed_{it}$ is the total patent count for the listed firms (parent firms) for firm i in year t, while $PatNoSubsidiary_{it}$ is the total patent count for all subsidiaries of firm i in year t. All other variables are defined earlier.

	(1) Total patents (P=A+U+S)	(2) Invention patents (A)	(3) Utility patents (U)	(4) Design patents (S)
Dep. var:	Tobin Q	Tobin Q	Tobin Q	Tobin Q
PatNoListed	-0.0281***	-0.0210***	-0.0212***	-0.0147***
	[-7.31]	[-4.87]	[-5.15]	[-2.85]
PatNoSubsidiary	-0.0442***	-0.0417***	-0.0425***	-0.0291***
	[-12.6]	[-10.5]	[-11.8]	[-6.67]
cons	2.033***	2.088***	2.117***	2.355***
	[13.0]	[13.3]	[13.6]	[15.1]
Controls				
N	22607	22607	22607	22607
F-value	160.4	156.2	154.4	145.7
F value for: PatNoListed = PatNoSubsidiary	9.96	12.56	14.39	4.38
p value for: PatNoListed = PatNoSubsidiary	0.0016	0.0004	0.0002	0.0363

Note: ** and *** represent significance levels 5%, and 1%, respectively. t-values are in brackets

Table 15: Reverse causality

In this table, we use the following regressions

$$PatNo_{it} = \beta_0 + \beta_1 X_{it} + \nu_i + \epsilon_{it} \quad (13)$$

$$TobinQ_{it} = \gamma_0 + \gamma_1 \widehat{PatNo}_{it} + \gamma_2 X_{it} + Control_{it}\delta' + \nu_i + e^Q_{it} \quad (14)$$

where X_{it} is the instruments including lagged patent counts and InnoCom dummy, $\widehat{PatNo}_{it}$ is the predicted value of patent counts from equation (11). All other variables are the same as in previous tables.

Panel A: lagged patent counts as instrument

Total patent (P=A+U+S)				Invention patent (A)			
IV 1st stage		IV 2nd stage		IV 1st stage		IV 2nd stage	
	PatNo		TobinQ		PatNo		TobinQ
PatNo-1	0.344***	PatNo	-0.0395***	PatNo-1	0.348***	PatNo	-0.0217**
	[37.6]		[-4.63]		[39.5]		[-2.30]
F	289.4***	F	349.8***	F	313.9***	F	345.7***
N	26458			N	26458		

Utility patents (U)				Design patent (S)			
IV 1st stage		IV 2nd stage		IV 1st stage		IV 2nd stage	
	PatNo		TobinQ		PatNo		TobinQ
PatNo-1	0.309***	PatNo	-0.0596***	PatNo-1	0.224***	PatNo	-0.0323**
	[34.4]		[-6.13]		[19.3]		[-1.98]
F	233.7***	F	352.2***	F	83.7***	F	12.66***
N	26458			N	26458		

Notes: This table explores whether the relation is the outcome of endogeneity. The instruments are the lagged detrended log patent counts. N shows the number of observations. t-values are shown in brackets. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Panel B: InnoCom as instrument

Total patent counts (P=A+U+S)				Invention patent (A)			
IV 1st stage		IV 2nd stage		IV 1st stage		IV 2nd stage	
	PatNo		TobinQ		PatNo		TobinQ
InnoCom	0.0953***	PatNo	-0.315***	InnoCom	0.0762***	PatNo	-0.394***
	[7.01]		[-4.12]		[6.08]		[-3.88]
F	65.55***	F	126.9 ***	F	64.37***	F	116.9***
N	28959			N	28959		

Utility patent (U)				Design patent (S)			
IV 1st stage		IV 2nd stage		IV 1st stage		IV 2nd stage	
	PatNo		TobinQ		PatNo		TobinQ
InnoCom	0.0923***	PatNo	-0.325***	InnoCom	0.0320***	PatNo	-0.937***
	[6.90]		[-4.11]		[3.00]		[-2.59]
F	53.21***	F	129.5***	F	23.06***	F	58.71***
N	28959			N	28959		

Notes: This table explores whether the relation is the outcome of endogeneity. The instruments are the InnoCom dummies which equal 1 if firm i or its subsidiaries obtains the InnoCom qualification in year t, and 0 otherwise. N shows the number of observations. t-values are shown in brackets. *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Figure 1: Patent Grants by Origin Country and Field of Technology

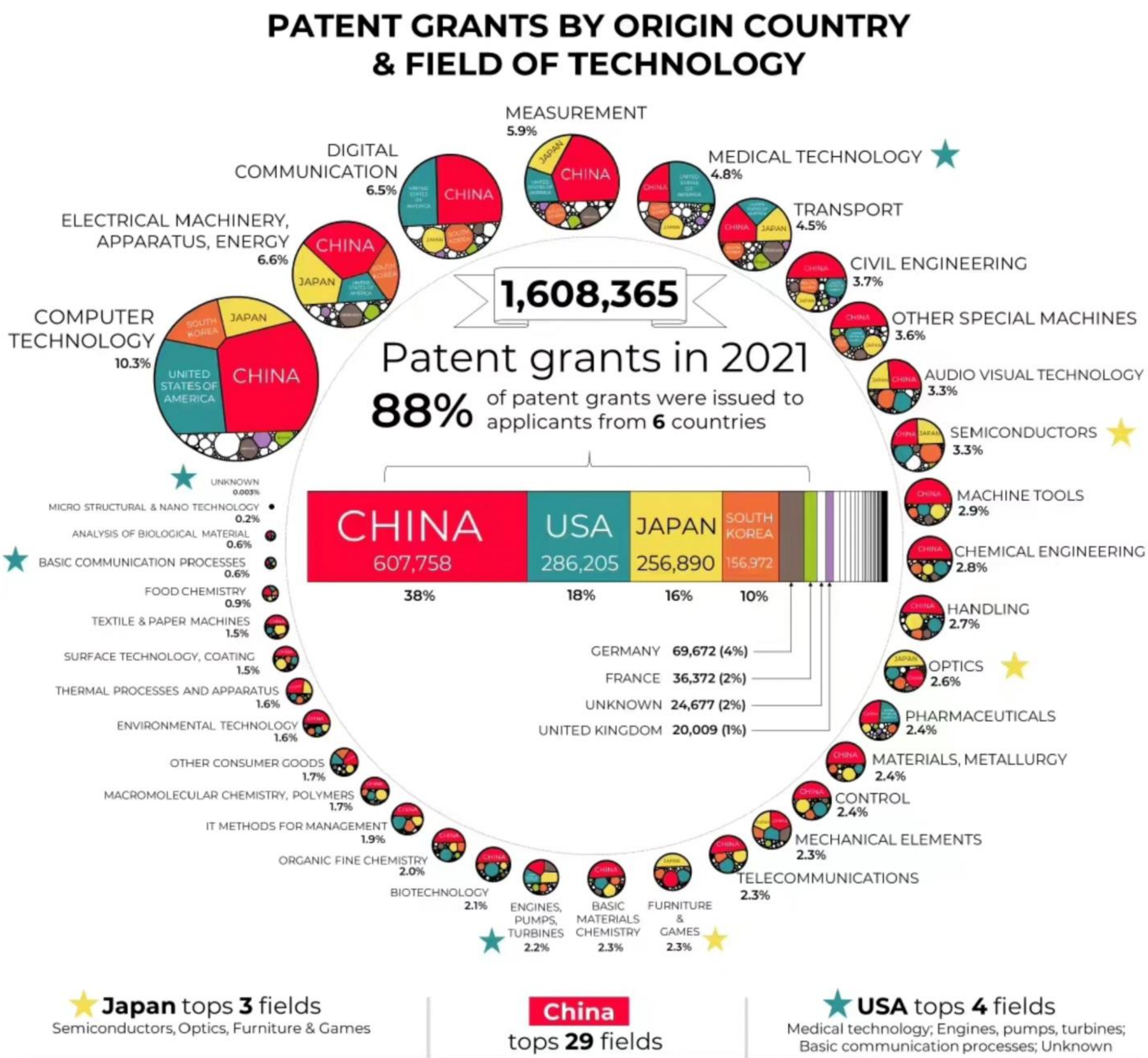
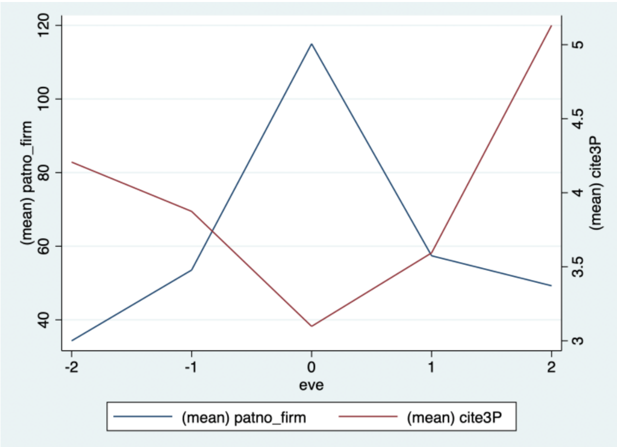
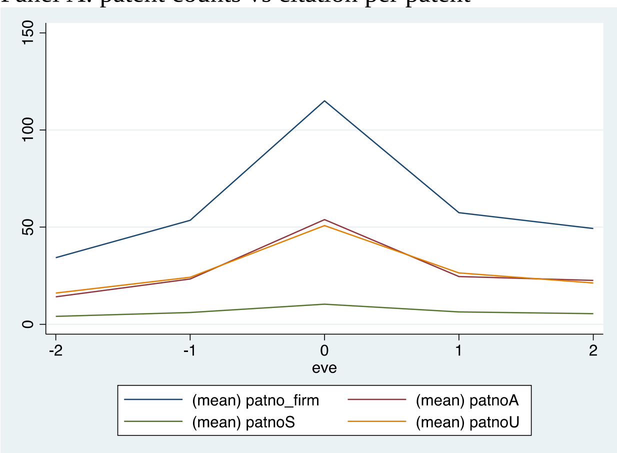


Figure source: www.wipo.int/ipstats

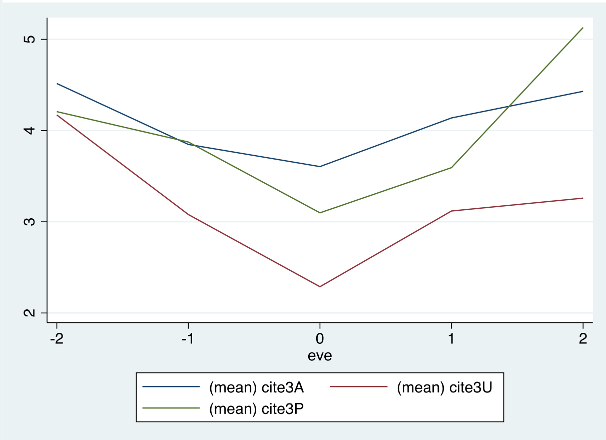
Figure 2: InnoCom, patent counts and patent citation



Panel A: patent counts vs citation per patent



Panel B: patent counts for different patent types



Panel C: Citation per patent for different patent types