Patent Litigation, Patent Value and the Direction of Innovation: evidence from China *

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Abstract

This paper investigates the role of patent litigation in patent valuation and firm innovation strategy. I take China as the institutional context and examine how its damage awards doctrine and patent remedy enhancement efforts impact patent valuation and the direction of firm innovative activities. To estimate patent value, I construct a finite-horizon stochastic dynamic model and recover key parameters of the patent litigation process. The structural estimates and counterfactual simulations show that strengthening patent enforcement by promoting damage awards significantly boosts the valuation of utility models- the type of patents that do not go through rigorous examination- while leaving the valuation of invention patents- the type of patents that go through examination and are superior to utility models- almost unchanged. To explore the implication of the asymmetric boosting effect on patent values, I run a series of difference-in-differences analyses on firm's patenting choices and performance. I find that firms with higher litigation exposure tend to patent more utility models after the patent reform enhances damage awards. The "treated" firms are more likely to switch from low-quality invention patents to utility models but meanwhile make more breakthrough invention patents. I also document that firm performance is negatively affected by the shift in innovation strategy after the patent reform. Policy simulations suggest that differentiating damage awards for invention patents and utility models might be a feasible solution to adjust the distortion in patent valuation and firms' innovation strategy.

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1 Introduction

Patent protection is crucial to the well-functioning of innovation system (Arora et al., 2004; Branstetter and Sakakibara, 2002; Hall and Ziedonis, 2001; Klemperer, 1990; Lerner, 2009; Moser, 2005; Nordhaus, 1969; Qian, 2007. The scope and efficiency of patent protection, either wide or narrow, could only be achieved via effective patent enforcement in court (Agarwal et al., 2009; Ganco et al., 2015; Lanjouw and Schankerman, 2001; Lemley and Shapiro, 2005; Shapiro, 2016; Somaya, 2012). This could be especially true for countries with relatively weak intellectual property rights (IPR) regimes, where the weak enforcement hampers knowledge spillovers and thus technological advance. As a result, innovating firms seek for alternative innovation strategy such as arbitrage to protect their inventions (Belderbos et al., 2021; Beukel and Zhao, 2018; Branstetter et al., 2006; Lamin and Ramos, 2016; Paik and Zhu, 2016; Zhao, 2006). Though patent litigation is usually a "rare" event, how the patent litigation allegations are handled in court has been closely watched by innovators, policy makers and even potential imitators; and strengthening patent enforcement has long been advocated as the right direction of innovation policy, especially in weak IPR regimes.

However, recent studies show that strong intellectual property protection might not always stimulate innovation. Strong upstream patent rights might increase the costs and risks for downstream innovations and thus hinder the inventive activities (Budish et al., 2013; Galasso and Schankerman, 2015; Murray and Stern, 2007; Scotchmer, 1991). Furthermore, well-established patent rights might exacerbate the inertia of incumbent innovators in making breakthrough innovations due to the replacement effect (Arrow, 1962; Parra, 2019). In practice, the patent enforcement system is not always effective even in Western countries (Lemley and Shapiro, 2005). Noisy enforcement, uncertain and fuzzy boundaries of patent rights might encourage speculative patenting and frivolous litigation, which potentially damage innovation ecosystem and economic growth (Bessen and Meurer, 2008; Feng and Jaravel, 2020; Lemley and Feldman, 2016; Mezzanotti, 2021).

My study contributes to the latter line of research by identifying another potential source of inefficiency of patent protection. Instead of focusing on the quantity and intensity of innovation, I investigate how strengthening intellectual property rights impacts firms' choices over different types of innovation. Put differently, does strengthened IPR enforcement equally benefit all types of innovations and innovators? From the perspective of firm strategy, decisions are typically made based on the potential value of each option (Adner and Levinthal, 2004; Dixit et al., 1994; Manso, 2011). If strengthening IPR enforcement makes certain type

of innovations more valuable and appealing, it is likely that firms will invest intensively in the more valuable type. Thus, the first part of my paper is to investigate how strengthening patent enforcement would impact the valuation of different types of patented technologies. If strengthened patent enforcement does lead to divergence in the valuation among different types of patents, then the next question would be which types of firms are most likely to shift their innovation strategy towards the more valuable type of innovation? How does the shift in innovation strategy affect the quality of innovations? And which firms will gain (or lose) from the shift of innovation strategy? These are the questions that the second part of my paper- a series of reduced-form analyses- attempts to answer.

To examine how strengthening patent enforcement influences patent valuation, I construct a stochastic finite-horizon dynamic model and structurally estimate key parameters of the model. Specifically, the patent owner has two choices- renewal and litigation- at each time period during the entire patent life cycle. The patent owner could stop paying the patent renewal fees; as a result, the patent will expire, and its value becomes zero at the focal time period. If the patent owner decides to renew the patent, she faces the second decision: whether to launch a patent litigation lawsuit if she detects infringement. The decision making is based on two state variables that the patent owner observes at the beginning of each time period: 1) per-period profit flow of the patented technology, which depreciates at a known rate over time; 2) whether infringement occurs, whose likelihood is also known. I assume the patent owner is rational in the sense that she anticipates all possible outcomes in the future given her knowledge (maybe limited) at each time period and she will choose the option to optimize her expected profits from the current and all the future periods.

I then fit the stochastic model with China's patent litigation data and recover key parameters: technology depreciation rate, infringement hazards, the distribution of patent initial value, exogenous shocks to the patent value and the share of market profits the patent owner receives if she tolerates the infringement. I choose China as the institutional context because it provides sufficient variations in both the patent enforcement and the heterogeneity of patent value. First, despite its relatively short history of modern patent system, China launched four rounds of patent reforms and strengthening patent enforcement is at the heart of almost all the reforms. Unlike Western countries, the dominant doctrine of compensating infringement loss in China is the statutory damage awards doctrine which, instead of awarding the real loss, sets a fixed range for the damage awards. This feature greatly facilitates quantification and comparison on the strength of patent enforcement over time. Second, China's patent office grants two types of patents: invention patents- the type of patents analogous to utility patents granted in the U.S.- and utility models- the type of patents whose grant is not contingent on rigorous examination and thus are inferior to the invention patents. The bifurcation in the types of patents granted provides variations that could facilitates the evaluation of the effect of patent enforcement on patent value. For the purpose of structural estimation, I compile two sets of data: one contains all lit-

igated invention patents in China whose lawsuits were decided before 2009, together with their non-litigated counterparts- a group of invention patents filed at the same day and in the same technological area but without litigation records; the other dataset contains all litigated utility models whose lawsuits were decided before 2009 and their counterparts collected in the same fashion. The richness of the data allows me to identify the decision likelihood at each time period for each patent, which motivates the maximum likelihood estimation method for parameter estimation.

The structural estimation illustrates that invention patents are much more valuable than utility models, as expected. On average, invention patents are around 18 times as large as utility models in terms of the first-period valuation. To evaluate the efficiency and effect of patent enforcement- particularly the damage awards doctrine and the amount of damage awards- I run two counterfactual analyses. First, I estimate a "benchmark" scenario in which patent owners will be compensated with their real loss from infringement. Specifically, I assume the patent owner will recover the profit flow of the focal period if she prevails in the patent litigation lawsuit. Comparing the estimates from real-world data with this "benchmark" scenario, I find that the compensation doctrine and amount of damage awards before 2009 generates similar level of patent values as the "benchmark" scenario. However, the statutory damage awards doctrine does lead to extremely low litigation rate for invention patents relative to the "benchmark" scenario whereas the litigation rate of utility models is higher than the benchmark scenario. This implies that valuable patents are less likely to be litigated, suggesting a potential "crowd-out" of valuable patents from China's patent litigation practice. Second, I investigate the effect of strengthening patent enforcement on patent valuation by simulating the scenario of 2009 patent reform which greatly enhanced the range of damage awards. While the extent to which damage awards are lifted is the same for invention patents and utility models, I document a significantly larger boosting effect of damage awards enhancement on the value of utility models than invention patents, suggesting a potential over-compensation effect of the 2009 patent reform for utility models.

These findings from the structural estimation suggests that increasing damage awards without differentiating the heterogeneity of patents might lead to over-valuation of patents with relatively low value. The back-of-the-envelope calculation illustrates that the 2009 patent reform might greatly reduce the gap of the valuation between invention patents and utility models- from 18 times (the ratio of invention value over utility models) to around 6. The over-valuation of low-value patents will potentially lead to a switch in firm innovation strategy from invention patents to utility models. To examine whether and to what extent this strategy shift occurs, I compile a comprehensive data set containing all invention patents and utility models filed by domestic Chinese firms from 2005 to 2012. I focus on the group of firms which filed both types of patents during the time period and measure their exposures to patent litigation hazards before 2009. Using a difference-in-differences

framework, I find that firms with higher litigation exposure before the patent reform tend to have higher ratio of utility models in their patent portfolio, compared to firms with lower litigation exposure. This tendency of filing more utility models is more pronounced among private firms whose financial resources are more constrained compared to publicly traded firms, as well as among firms with larger patent portfolios, relative to firms with smaller ones.

I document that the shift from invention patents towards utility models has two effects on the quality of invention patents. One is that "treated" firms- firms with high litigation exposure- tend to switch low-quality invention patents to utility models. The reason could be that after the patent reform, the value of some utility models might exceed some low-quality invention patents. By switching to utility models with similar values, firms could potentially save innovation costs and face fewer uncertainties because making utility models is usually cheaper than making invention patents. This leads to the second effect on invention quality documented by my paper: firms with high litigation exposure tend to file more inventions with top-tier qualities relative to firms with low litigation exposure.

With these two effects at work, the implication of the patent reform on firm performance could be ambiguous. On the one hand, by switching to utility models, which are still inferior to invention patents, "treated" firms might have lower performance; on the other hand, the performance of "treated" firms might be boosted by their increasing efforts in making top-tier inventions after the patent reform. To investigate the impact on firm performance, I assemble a panel data set of Chinese manufacturing companies with R&D inputs and patent records from 2005 to 2012. I find evidence that profits and industrial outputs of firms with high litigation exposure tend to decrease relative to firms with low litigation exposure, suggesting that the negative effect from patenting more utility models dominates the positive effect from investing more in top-tier invention patents. Consistent with the analysis on firm heterogeneity in the propensity of filing utility models, the negative effect on firm performance is found to be more pronounced among big firms and incumbent firms.

This paper contributes to several strains of studies on firm innovation strategy and patent policy. First, this study provides novel evidence for a growing literature on institutional context, regulatory changes and innovation activities (Claessens and Laeven, 2003; Conti, 2014; Hegde and Luo, 2018; King and Levine, 1993; Lerner and Schoar, 2005; Lin et al., 2021; Mezzanotti, 2021). Previous studies mostly focus on how government policy changes impact the rate of firm innovative activities. This paper pays attention on the direction of innovative activities and its implications on firm performance. Furthermore, by investigating the implication of strengthening IP protection in weak IPR regimes, my research also relates to the line of inquiries on innovation strategy in weak IPR regimes (Belderbos et al., 2021; Beukel and Zhao, 2018; Lamin and Ramos, 2016; Paik and Zhu, 2016; Zhao, 2006). While prior studies mostly focus on the downside of weak patent protection and thus implicitly

suggest the strengthening patent protection would be public good, this paper reveals the caveats of strengthening IP protection in weak IPR regimes.

The paper also closely relates to the well-known literature of structural estimation of patent values (Lanjouw et al., 1998; Pakes, 1984; Schankerman and Pakes, 1985; Serrano, 2018). This line of research attempts to estimate patent value via patent owners' renewal decisions, assuming that the patent owner stops renewing the patent when its expected profit flow falls below zero. Based on Schankerman and Pakes, 1985's seminal work, later studies add up more features to the original model. For instance, Lanjouw, 1998 and Marco, 2005 consider patent litigation as another key option for the patent owner. Serrano, 2018 introduces patent transaction as an option, exploring how selling out a patent impacts patent valuation. My paper extends this line of research in the following aspects. First, instead of assuming infringement happens at each time period, my model considers infringement as a stochastic event, making it possible to recover the overall infringement hazard. Second, to the best of my knowledge, this paper is the first to evaluate the effect of patent enforcement on patent valuation by comparing two types of patents. Utility model patents, though not as popular as invention patents, play an important role in many countries like Germany, Japan and South Korea. The study of utility models, however, is scarce and this paper helps to improve our understanding of this type of patents.

Finally, this paper contributes to the theoretical discussion on the potential impact of damage awards doctrines on innovation incentives (Anton and Yao, 2007; Y. Chen and Sappington, 2018; Choi, 2009; Henry and Turner, 2010; Schankerman and Scotchmer, 2001). Prior studies mostly focus on doctrines of unjust enrichment or lost profit, the types of doctrines prevalent in the U.S. or Europe. This paper examines the effect of statutory damage awards doctrine- the dominant damage awards doctrine in China which leads to "homogeneous" damage awards for patents with different values. I show that the statutory damage awards doctrine might be responsible for "crowding out" valuable patents from pursuing patent remedies in court. Furthermore, lifting the damage awards under such doctrine might narrow the gap of patents with different values and thus potentially drive the explosion in low-value patents observed in recent years in China.

2 Institutional background

2.1 China's two types of patents

China is a late comer of the modern patent regime. The current patent system was first established in 1985 and has been revised for four times in the years of 1992, 2000, 2009 and 2021. Each revision made significant changes to improve the efficiency and efficacy of the regime. The initial version of the patent law was mostly "imported" from Japan and Germany. As a result, China "inherited" the utility model patenting system from the two

countries. Compared with invention patents, utility models are usually viewed as "moderate improvement" for the reason that their inventive steps are usually smaller. Though utility models are rarely considered as equivalent to invention patents in Germany and Japan, they are widely filed in China, usually as substitutes, instead of complementary options, of invention patents.

Table 1 summarizes major differences of invention patents and utility models in China. Invention patents provide longer protection term- 20 years since the patent filing date- than utility models, which only provide 10-year protection at the most. Longer protection is based on rigorous examination: invention patents usually go through relatively rigorous examination process, taking around 400 days in China on average from the date when first request for examination is issued to the grant decision date. As a contrast, the examination of utility models is usually reduced to a formality check which typically takes less than one year. Aside from prolonging the examination cycle, rigorous examination for invention patents usually shoots down around 20% of applications[1], whereas utility models are almost surely to be granted.

Withstanding the relatively higher cost of filing an invention patent compared to utility models, the expected benefits of the invention patents are typically higher than utility models. Apart from the longer protection term an invention patent could possibly have, invention patents usually serve as signals of innovation capacity of the patent owner. The signaling function could sometimes be more beneficial for the owner than the profit extracted from the patent per se. For instance, China's central and local governments implement a battery of patent subsidy programs- usually in the form of direct cash transfer- to encourage patent filings. Beside, firms with valid patents are also eligible for a variety of policy benefits ranging from substantial corporate tax cut (e.g. InnoCom policy), higher chance to be listed in tech stock market or being funded by state institutions. For all these "patent-contingent" resources, inventions usually prove to be more useful than utility models [2].

Last but not the least, invention patents and utility models are set to protect different types of technologies. Invention patents are eligible for all technological innovations fulfilling the three criteria: novelty, non-obviousness and usefulness. On the other hand, utility models cover fewer types of innovations: only inventions with solid structures or shapes could be applied for utility models. Pharmaceutical products, process improvement, or method innovation, for instance, are only eligible for invention patents because they lack tangible structures or shapes.

However, unlike Germany and Japan where utility models are considered quite different

[1]Self-calculated from patent data provided by IncoPat.

[2]For instance, the InnoCom policy stipulates that owning 6 utility models will be evaluated as earning the same score as owning 1 invention patent grant.

from invention patents, utility models are taken as substitutes of inventions patents in China. According to my informal interviews with several Chinese patent attorneys as well as scholars studying European patent system, several factors might cause the similarity. First, these two types of patents share the same set of patent classifications (namely the IPCs), suggesting similar technological coverage of the two types of patents. More importantly, China's patent office officially recognizes the "double patenting" practice in the 2009 patent reform: patent applicants are allowed to file one invention patent and one utility model for the same innovation at the same day; but at any single time point, only one of these two patent rights could be reserved. The "double patenting" practice further narrows the difference of two types of patents in terms of inventive step and protection scope because patent applicants usually submit one filing document for the two types of patents. Finally, utility models yield similar or even bigger judicial benefits than invention patents in patent infringement lawsuits. Apart from the similar amounts of damage awards compensated for these two types of patents, infringement on utility models are usually easier to be proved because features of inventions with solid shape or structure are typically easier to be identified, whereas for certain types of invention patents, especially method inventions or process improvement, evidence on infringement could be more difficult to collect and confirm.

In sum, utility models offer an option for quicker but weaker protection, compared with invention patents. As some studies show (Cao et al., 2014; Cohen et al., 2000), utility models tend to be more popular in industries where technologies advance rapidly. That said, for owners of truly valuable inventions who seek for effective patent protection, invention patents could be a better choice if the examination process is not too long and the patent could be effectively defended in the court. But Chinese innovators tend to treat these two types of patents as similar substitutes. I will discuss the implication of these features in later parts of the paper.

2.2 Doctrines of damage awards for patent infringement lawsuits

As an established member of the World Intellectual Property Organization (WIPO), China has adopted the "unjust enrichment" (UE) and "lost profit and reasonable loyalty" doctrines (LP)- two rules that are commonly applied when deciding the damage awards compensated for the patent owner (Schankerman and Scotchmer, 2001). Besides, China's patent judges could compensate the prevailing patent owners according to the third doctrine- "statutory damages award doctrine." The 2001 Chinese patent law stipulated the statutory damages to be no less than 5000 RMB ($ 725) but no more than 300,000 RMB ($ 46,590). This range was enhanced by the 2009 patent law revision to the level from 10,000 RMB ($ 1553)

to 1,000,000 RMB ($ 155,300) [3].

China's patent law sequences these damage awards doctrines and places the statutory damage awards after the 'unjust enrichment' and 'lost profits and reasonable loyalty' doctrines, meaning statutory damage doctrine applies only when the plaintiff could not provide valid evidence on the amount of infringement loss. In practice, however, adopting the UE or LP doctrines is rare case: 98% of all infringement lawsuits in which patent owners prevailed followed the statutory damage awards doctrine, according to CIELA's patent infringement data[4]. The popularity of statutory damage awards doctrine in China is mainly driven by the difficulty of evidence collection and pressure for judges to close cases as quickly as possible. Lack of 'evidence discovery' doctrine, it usually takes enormous time and resources for patent owners to collect evidence of infringement. Moreover, as lawsuit process time is one of key performance measure for Chinese judges, they are inclined to employ an easy and quick way, such as the statutory damage awards doctrine, as the compensation decision rule.

I will leave detailed discussion on the implication of the dominance of statutory damage doctrine to later parts of this paper. For now, it is intuitive to see that if the statutory damage awards are too low compared with what the UE or LP doctrines could offer, patent owners might be reluctant to defend their patented inventions via judicial lawsuits; as a result, the valuation of patents might be discounted as well. This also implies that if the statutory damages are too big, infringed patents tend to be over-compensated and patent rights will be unnecessarily strengthened which probably will lead to inefficiency, such as amplifying monopoly market power or blocking follow-on innovations.

3 The structural model

In this section, I establish a finite-horizon stochastic dynamic model to capture key features of patent life cycle. Like other types of assets with real options, owners of patents face a variety of decisions during the entire patent life. Before the patent expires, patent owners need to decide whether to renew it, sell it out, license to others for royalty profits, or launch a litigation lawsuit in the court when infringement occurs. Each option affects profit flows of the current period and following periods. Litigation, despite of its rareness, could potentially affect patent valuation via other venues. Thus, in this model, I attempt to single out the effect of litigation decision and explore how institutions related to patent litigation, such as compensation doctrines and infringement hazards, influence patent valuation, litigation and renewal likelihoods.

[3] In 2021, China conducted the fourth patent reform which further lifted the statutory damage awards to the range of 30,000 RMB to 5 million RMB ($4660 to $776,700).

[4] https://www.ciela.cn/en/analysis/patents.

3.1 Model Set-up

Consider a granted patent with maximum periods of validity, T, which is usually stipulated by the patent law. In China's case, T is 20 years for invention patents and 10 years for utility model patents from the filing date. The patent owner could keep the patent for a maximum of T periods, as long as she pays the patent renewal fees at the beginning of each time period. Or, she could simply stop paying the renewal fees at time t (where $t \leq T$); the patent will expire in that period.

In each time period t, the patent owner has three options. The first is to sue the alleged infringer in court. This option implicitly assumes that the patent is renewed at that time period. Importantly, I assume the litigation option is only available when infringement occurs and is detected by the patent owner. Prior studies (Lanjouw, 1998; Marco, 2005) mostly assume infringement occurs at *each* time period. My model, instead, allows for stochastic occurrence of infringement, which is not only a closer mimic to the reality and but also helpful in estimating the overall infringement hazards. The second option the patent owner could choose is to renew the patent but not launch litigation lawsuits in court. This choice is available whether or not infringement is detected. If infringement occurs but the patent owner decides to tolerates the infringement, she will only receive a portion of the profit flow of the patent and the portion is denoted as θ, $\theta \in (0, 1)$. Finally, if the patent is considered as useless, or formally, with negative value, the patent owner could choose the third option- stop renewing the patent. The patent, thereafter, will expire and join the realm of public knowledge, meaning that anyone could use the patented technology free of charge.

The scheme of patent renewal fees plays an important role in this dynamic decision making process. Whether the patent is litigated or not, the patent owner needs to compare the current-period patent valuation with the renewal fee. The patent will only be renewed if the valuation exceeds renewal fees at time t. The amount of renewal fees and timing of payment are usually stipulated by the patent office. Different from the U.S. or in Europe, China's patent office requires the renewal fees to be paid annually since the year the patent application was submitted. As Table 2 shows, the amount of patent fees increase as the patent ages, implying that the cost of keeping the patent valid increases over time. Renewal fees for invention patents are typically higher than those for utility models, reflecting the widely held belief that the valuation of inventions should be higher than that of utility models.

At each time period, patent owners decide which option to choose based on two state variables they observe at the beginning of the period (but might not be observed by other people). One state variable is the current-period profit flow of the patent, x_t [5]. This

[5] x_t could be closely related to the profit flows the patent owner expects to receive from enforcing

state variable covers all expected profits from patent options other than litigation, such as licensing, transaction, or signaling [6]. I assume the evolution of x_t follows a Markov process:

$$x_t = \gamma x_{t-1} + u_t \tag{1}$$

Equation 1 assumes that x_t only depends on the profit flow from the previous period and an exogenous shock u_t, which is subject to a normal distribution $\mathcal{N}(0, \sigma^2)$. σ is known by the patent owner, which captures the stochastic component of patent's profit flows, such as unexpected policy changes, technological shocks (or opportunities) or market turbulence. Aside from these exogenous shocks, the per-period patent profit flow is assumed to decrease over time. This could be driven by a patent (technology) race in highly competitive industry or simply by the technology obsolescence. γ models the depreciation rate, $\gamma \in (0, 1)$.

The initial value of x_t is set as x_0. As mentioned in section 2, invention patents are usually more valuable than utility models. To model this difference, I assume at period 1 x_0 is randomly drawn from a known right-skewed Gamma distribution. This set-up of distribution captures the feature that most patents are of relatively low values whereas merely a very small portion of patents- the outliers- are highly valuable. To simplify the model without losing generality, I fixate the scale parameters of Gamma distributions of both utility models and invention patents to be $50,000$ RMB [7]. The only difference of these two distributions is the shape parameter, α. To visualize how α affects the Gamma distribution, I plot two Gamma distributions with $\alpha = 2$ and $\alpha = 4$ (Figure A.1); β is fixated at 5. The distribution with smaller α is employed to describe the distribution of utility models' initial values. As expected, invention patents are more valuable than utility models (higher mean) and the portion of high-value invention patents is significantly larger than that of high-value utility models (fatter tails).

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the patent. For instance, if the court enforcement is too weak to deter infringement, it is likely that the patent owner cannot negotiate a profitable license agreement or transaction contract with potential downstream users. But this type of association usually occurs at a general level, namely that x_t will be affected by the patent enforcement effectiveness of the whole system (i.e. the overall distribution of realized damage awards, not the specific amount of damage awards the patent owner expects to get for the focal patent. Therefore, in the baseline model, I assume the per-period profit flows of these two options- enforce or not enforce- are not related.

[6] In China, patents usually serve as important signals of innovation capacities to resource providers, usually the government. For instance, firms with valid patent grants are more likely to win government subsidies for innovative enterprises. The subsidies, sometimes, could be substantial. For example, the InnoCom program provides qualified firms with income tax reduction by 10 percentage points (i.e., from 25% to 15%). Only firms with valid patent grants are eligible to win the InnoCom certificate.

[7] This figure comes from estimates of another two papers on valuation of Chinese patents (Gupeng and Xiangdong, 2012; Zhang et al., 2014). $50,000$ RMB is around the median value of invention patents at the first period in their papers.

The other state variable that the patent owner observes at the beginning of each time period is whether the infringement occurs [8]. I use a dummy variable $L_t \in \{0, 1\}$ to denote the infringement occurrence. I assume the infringement occurrence to peak around the time when the patent was formally granted. Before the patent grant, patent applications are also subject to infringement but the infringement occurrence might not be high because of the uncertainty of the patent right (if the patent was not granted yet, its value for firms other than the patent owner will be uncertain). I also assume the infringement occurrence in the last period of the patent becomes zero since there will be no value left even if infringement is not held accountable. Therefore, from the year the patent was granted (normally the second year of the utility models and the fifth year of the invention patents) to the last year, I assume the infringement hazard l_t decreases at a constant rate. Finally, I assume the first-year infringement occurrence for invention patents to be zero because the invention patents will not be published after 18 months since the patent filing date [9] Finally, note that, before time period t, the patent owner (and others) will know that the likelihood for infringement to happen in time t is l_t. But whether the infringement occurs at time t is uncertain. Therefore, I assume that there is no stochastic component in the evolution of infringement hazards, simplifying the model without losing generality.

If the infringement is detected at time t, the patent owner could litigate against the infringer in court or tolerate the infringement. As stated previously, if the infringement is tolerated, the patent owner will only receive θx_t from the patent in that period. On the other hand, if the patent owner decides to litigate in court, it is not guaranteed that her loss will be compensated. For instance, a common counter-strategy of the defendant (infringer) is to challenge the validity of the disputed patent; even the patent passes the validity challenge, it is likely for the patent owner to lose the lawsuit due to a variety of reasons. Therefore, I use $p \in (0, 1)$ to capture the win rate of the patent owner in an infringement lawsuit, which is conditional on the fact that the patent has already passed validity challenge. If the patent owner prevails, she will receive $z > 0$- the damage awards- as compensation to her infringement loss. Litigation lawsuits are usually costly, even in China. Patent attorney fees, administrative payments to the court, opportunity costs from the time and resources the patent owner could have allocated to other activities all contribute to a non-trivial amount of litigation cost, which is denoted in the model as $c > 0$.

[8] In the case that infringement happens but not detected by the patent owner, the infringement is considered as not occurring.

[9] Though the patent owner could request the publication of the patent document before the end of the 18th month, most patents remain unknown by other parties at least during the first year.

3.2 Dynamic decisions

The current-period profits of the patent owner is thus clear. Formally, the reward function of time t could be written as:

$$f(t) = L_t[\ (pz - c)a_t + (1 - a_t)x_t\theta]\ + (1 - L_t)x_t - Rc_t \tag{2}$$

L_t is a dummy variable taking value 1 if the patent owner detects infringement at time t. a_t is a choice variable, taking value 1 if the patent owner decides to sue the infringer. Rc_t is the renewal cost at time t, usually increasing as t gets bigger. The first term of Equation 2 is the expected profits if the infringement occurs. The second term, then, is the expected profits if the infringement does not occur. Whether infringement happens, the renewal fees will be paid otherwise $f(t)$ would be zero; so the last term is the subtraction of patent renewal fees.

In order to make decisions, it is not sufficient for the patent owner to only calculate the current-period profits. She also needs to calculate the expected profit flows of all future periods, discount and incorporate them together with $f(t)$. This yields to the Bellman equation:

$$V(x_t, L_t) = \max_{a_t}[\ 0, f(t) + \delta E_{u,l} V(x_{t+1}, L_{t+1})] \tag{3}$$

Where $V(x, L)$ is the per-period valuation of the focal patent, accommodating all future profits. The value function V is a function of the state variables x_t and L_t, the optimal choice a_t (litigate or not) the patent owner makes at the period. It also involves stochastic components u and l, the exogenous shock to patent value and infringement hazards, which govern the evolution process of x_t and infringement occurrence L_t. δ is the discount factor. The Bellman equation states that, at each time period t, the patent owner will calculate and discount all the future profits , adding it together with the current-period profit $f(t)$ in Equation 2. The second term inside the maximization operator calculates the optimal value if the patent owner does not give up the patent. Thus the final step would be to compare it with 0, the profit the patent owner will get if she decides not to renew the patent, namely $k_t = 0$.

3.3 Numerical solutions and likelihoods

This is a finite-horizon dynamic programming problem, which does not have a closed-form solution. Following the literature (Lanjouw, 1998; Miranda and Fackler, 2004; Pakes, 1984; Schankerman and Pakes, 1985), I solve the model numerically using backward induction.

The algorithm basically assumes the value of patent at the $T+1$ period to be zero and infer the value function and optimal choice for each time period, backwardly, from period T to 1.

Several features of this dynamic model could be solved numerically. Aside from per-period patent value V_t, the model also identifies per-period thresholds for renewal and litigation decisions, $\bar{x}_{rt}$ and $\bar{x}_{lt}$, as well as the optimal action set $\Omega_t = \{a_t, k_t\}$. a_t and k_t are the indicators for litigation or renewal, which take value one when the patent owner decides to litigate or renew the patent at the focal time period. In the real-world data, however, I observe neither x_t (or their thresholds for litigation and renewal) nor the patent value V_t. The only observable element is Ω_t, the choices patent owners made. This feature motivates a maximum likelihood method for the structural estimation, for which I will introduce details in section 4. Here I simply specify the likelihoods I will need for the maximum likelihood estimation. Specifically, the litigation likelihood at time t is:

$$Pr(a_t = 1) = l_t\{\Phi(\frac{\bar{x}_{lt} - \mu_x(t)}{\sigma_x(t)}) - \Phi(\frac{\bar{x}_{rt} - \mu_x(t)}{\sigma_x(t)})\} \tag{4}$$

And the renewal likelihood is:

$$Pr(k_t = 1) = 1 - \Phi(\frac{\bar{x}_{rt} - \mu_x(t)}{\sigma_x(t)}) \tag{5}$$

Where σ_x and μ_x are standard variances and means of the distribution of x_t, and Φ denotes the *cdf* of a normal distribution. According to Equation 1, x_t follows a normal distribution because of the distribution assumption made for u_t, conditional on the assumption that x_0 is already drawn and known by the patent owner. Formally, $x_t \sim \mathcal{N}(\mu_x(t), \sigma_x(t)^2)$, where:

$$\mu_x(t) = \gamma^{t-1} x_0 \tag{6}$$

$$\sigma_x(t)^2 = \gamma^{2(t-1)} x_0 + \frac{1 - \gamma^{2(t-1)}}{1 - \gamma^2} \sigma^2 \tag{7}$$

It is straightforward to see that the patent will be renewed if x_t exceeds the threshold $\bar{x}_{rt}$, which motivates Equation 5. However, for the litigation decision, it is more complicated. Under the current setting, namely the damage awards are a fixed amount, patents will be litigated only if x_t is lower than the threshold $\bar{x}_{lt}$. The intuition is as following. When the per-period profit flow is lower than the expected infringement compensation, the patent owner will decide to litigate. The upper bound of damage awards also imposes an upper

bound to the expected profits the patent owner could get from litigation. This implies that patent owners who consider their patents are more valuable than this "upper bound" will choose to tolerate the infringement because litigation is a less profitable choice. Formally, this could be summarized as:

Proposition 1 If the damage awards are capped by an upper bound $\bar{z}$, patent will be litigated against the infringement only when its value is below $\bar{x}_{lt}$, where

$$\bar{x}_{lt} \leq \frac{p\bar{z} - c}{\theta} \tag{8}$$

It is easy to see that the threshold $\bar{x}_{lt}$ increases in the expected damage awards pz, and decreases in litigation cost c and the market share of the patent owner θ if infringement is tolerated. When it comes to the renewal threshold $\bar{x}_{rt}$, however, the implication does not seem straightforward. Unlike $\bar{x}_{lt}$, there is no closed-form solution for $\bar{x}_{rt}$, meaning the renewal likelihood depends on almost all parameters identified in this model. I will return to this point in the section of counterfactual analysis.

3.4 Empirical approach

3.4.1 Data

The primary challenge of data collection is rarity of patent litigation. The ratio of patents being litigated among all patents issued is usually very low. In the U.S., this ratio is higher than other Western jurisdiction- around 1% on average (Bessen and Meurer, 2005). In China, however, the litigation rate is extremely low- around 0.17%. The low occurrence of litigation events among all patents posts a challenge for structural modeling. If the theoretical model is fitted with a "sparse" data set- a dataset with more than 99% zeros in this case, model convergence could be difficult to achieve.

To solve this problem, I focus on a sample of litigated inventions and utility model patents and a group of non-litigated patents similar to them. To start with, I select all invention patents and utility models that have been involved in infringement lawsuits in mainland China. In 2009, China revised the patent law, making several changes to the legal practice of patent enforcement. To ensure a relatively stable regulatory environment, I focus on patents for which the infringement lawsuits were decided before 2009. Moreover, there are several types of patent infringement lawsuits, such as in-court settlements, disputes over court jurisdiction and judicial judgment on infringements. I select the last type- judicial judgment on infringements- because in-court settlements are closer to the scenario in which the patent owner decides not to sue and the jurisdiction disputes usually serve as a combatant strategy of the defendants and thus an integral part of cases with judicial judgment. Finally, to reduce the dependence among observations in my sample to the lowest, I reserve the first

patent that has been litigated by patent owners who have multiple patents being litigated. In a similar vein, for the non-litigated patents, I pick up one single patent from each patent owner. If there are multiple non-litigated patents by the same owner linked to one litigated patent, I randomly pick up one. Thereby, in the final sample, each patent is owned by one single patent owner.

The restrictions in sampling leads to a sample containing 377 litigated patents with 115 invention patents and 262 utility models. To select a "control" group which shares similar features- so that the litigation hazards are similar, I match the litigated patents with all patents filed at the same day as the litigated patent and in the same technological areas (measured by 3-digital IPC assignment) [10], following prior literature (Allison et al., 2003; Lanjouw and Schankerman, 2001). As a result, I match a group of 2247 "control" patents (726 invention patents, 1521 utility models) for the sampled litigated patents. Together with the litigated patents, the final sample contains 2624 patents with 841 invention patents and 1783 utility models.

The detailed summary statistics of the data is laid out in Appendix E. Here I briefly summarize the general pattern. First, invention patents tend to be more valuable than utility models if we focus on variables that are usually considered as proxies for patent value- the number of claims, foreign destinations of family patents and the number of inventors (Allison et al., 2003; Lanjouw et al., 1998; Lanjouw and Schankerman, 1997). However, if we compare litigated and non-litigated patents within each type of patents, the pattern differs from what prior studies have documented (Table A1). Indeed, for invention patents, valuable patents are less likely to be litigated whereas for utility models the pattern is reversed- valuable utility model patents are more likely to be litigated. These patterns are further corroborated by the distribution of patent renewal terms (Figure A.3). The summary statistics confirms the proposition 1 derived from the theoretical model. It implies that as the patent value decreases (e.g. from invention patents to utility models), the "adverse selection" pattern- namely that the valuable patents will be "crowded out" from litigation practice- might be ameliorated.

3.4.2 Maximum likelihood estimation

The empirical strategy is mostly motivated by the feature of the data. I use maximum likelihood estimation, instead of simulated moment method which has been widely employed by prior studies in this strain of research (Lanjouw, 1998; Pakes, 1984; Schankerman and Pakes, 1985; Serrano, 2018) for several reasons. First, the data of my sample is available at the individual patent level, which allows maximum likelihood method at such granular level. As a comparison, estimation by simulated moment method is usually at the aggregate

[10]Some litigated patents do not have patents registered in the same day and in the same tech area. For these patents, I extend the search into 7 days before and after its filing day.

level- in this case, the aggregate litigation and renewal rates-, which might neglect useful patterns at the micro level. Second, though the model does not produce closed-form solutions, it does yield litigation and renewal likelihoods at the individual level in an explicit way (though not in closed form either), which potentially enables the maximum likelihood estimation. Furthermore, unlike most Western countries, patents in China are renewed yearly, potentially providing sufficient moments for the MLE method.

To start with, I calculate the litigation and renewal likelihoods using Equation 4 and 5 and get the likelihood of not renewal by subtracting the litigation and renewal likelihoods from 1. For each "cell" (each individual patent at each time period), I thus obtain its likelihood based on the real-world choice [11]. After taking logarithm of each likelihood, I sum up all the log-likelihoods and maximize the sum. Formally, the log-likelihood function could be written as:

$$\max_{\gamma,\sigma,\alpha,\theta,l_0} \sum_{i=1}^{N}\sum_{t=1}^{T} Log\left(A_{it}P^i_{litigate}(t) + K_{it}P^i_{renew}(t) + (1-A_{it}-K_{it})\left(1-P^i_{litigate}(t)-P^i_{renew}(t)\right)\right) \tag{9}$$

Where i denotes patent i and t denotes patent term t. A_{it} and K_{it} are litigation and renewal decisions from the real-world data. N is the size of the sample. $P^i_{litigate}(t)$ and $P^i_{renew}(t)$ could be derived from Equation 4 and 5. In other words, I'm seeking the set of parameters that maximize the likelihood of the formal model being supported by the data.

Next, I calibrate several parameters with values from the literature or directly estimated from the data. The interest rate r is set to be 0.1, following the literature (Lanjouw, 1998; Pakes, 1984; Schankerman and Pakes, 1985; Serrano, 2018). Annual renewal costs Rc are obtained directly from official payment schedule published by China's Patent Office (Table 2). Different from most Western countries, Chinese patents are renewed annually, which potentially provides more variation to the model estimation. Patent terms, T, are stipulated by the law, which is 20 years for invention patents and 10 years for utility models[12].

For the gamma distribution of x_0, two parameters- α, the shape parameter, and β, the position parameter- are unknown. Both parameters determine the distribution; but if two gamma distributions are similar- in our case, the invention patents and utility models could

[11]For example, if the patent owner stops renewing the patent at the current period, I will assign the likelihood of stop renewing to that cell.

[12]The annual renewal fees are charged from the patent filing date. Here I assign the maximum patent life term to 20 years and 10 years, assuming that infringement might occur before patent is officially granted. The infringement could be even more severe before patent is granted because patents are not officially under patent protection during the examination process.

be substitutes for each other- fixating one parameter could greatly reduce computation loads without losing generality. Thus, I fix the position parameter, β, to be 50,000 RMB for both types of patents, which is around the median level of monetary values of patents estimated by prior studies (Gupeng and Xiangdong, 2012; Zhang et al., 2014). This leaves α to be the only unknown parameter of the distribution of initial patent values.

The rest parameters are the ones associated with infringement lawsuits: litigation costs, c, damage awards, z and win rate p. In the sample, these information are only available for litigated patents which prevail in the infringement lawsuits. The seemingly lack of data points, however, does not pose a serious challenge here because patent owners make decisions based on *expected* values of litigation cost, damage awards and win rate, instead of their real values. Therefore, it is reasonable to assume that the patent owner obtains the knowledge of the empirical distribution of damage awards, litigation costs and win rate by observing lawsuits already closed and published (i.e. the data I have collected). Thereby, I estimate the empirical distribution using all available data points on litigation costs [13] and damage awards before 2009. Usually, damage awards and litigation costs tend to increase in the patent value because the patent owner is willing to make more efforts in court to defend their valuable innovation. Therefore, I assume the damage awards and litigation cost will be at the same "position" in their empirical distributions as the patent's initial value. Specifically, I calculate the percentile of the initial value x_0 for each observation and locate the damage awards and litigation cost to be at the same percentile in their own empirical distributions. For the win rate, I use the aggregate win rate 0.7 as the value. Prior studies show that patent owners will adjust their expectation on win rate based on the aggregate average (Bessen and Meurer, 2005; Lanjouw, 1998). Informal interviews with several Chinese patent attorneys also confirm that it is not uncommon that infringement lawsuit plaintiffs will be informed by the average damage awards and litigation costs of similar cases and make litigation decisions accordingly.

Apart from parameters whose values are calibrated, there are five parameters to be estimated: technology depreciation rate γ, the shape parameter, α, of the gamma distribution of initial patent value, and the standard deviation of the random shock to per-period patent profit flows, σ, the share of profits the patent owner is supposed to extract from the patent if the patent owner does not litigate against the detected infringement, θ, as well as the peak value of the infringement hazards, l_0.

[13] Some of the disclosed patent infringement lawsuits reveal the litigation costs claimed by the patent owner (i.e. plaintiffs). I use this information as basis of estimating the empirical distribution of litigation costs. Though it is possible that the revealed litigation costs might not be representative of the population, empirical distribution inferred from this information is still reliable because these are exactly the information the patent owner could get access to when making litigation decisions. Thus the empirical distribution derived from the disclosed litigation costs should be quite close to the information set the patent owner has.

Though there are no closed-form solutions for the litigation or renewal likelihoods of each period, I provide a heuristic description of how the five key parameters could be identified by these likelihoods. γ, the technology depreciation rate, could be identified through the distribution of per-period patent flow x_t. From Equation 6 and 7, it is clear that γ governs the values of $\mu_x(t)$ and $\sigma_x(t)$. Similarly, σ could be identified through changes in $\sigma_x(t)$; but different from γ, it has no effect on $\mu_x(t)$. Furthermore, α governs the distribution of x_0, which affects $\mu_x(t)$ and $\sigma_x(t)$, as shown in Equation 6 and 7. The way θ is identified is mainly through the litigation threshold $\bar{x}_{lt}$, as stated in Equation 8. A larger θ leads to a smaller litigation threshold and thus a lower litigation likelihood if renewal threshold is held constant. Moreover, the peak infringement hazards l_0 could be identified by l_t, the per-period infringement hazards, which mainly shows in the litigation likelihood (Equation 4). Finally, due to the lack of closed-form solutions, I determine these thresholds numerically, namely via the decisions observed from the simulated data. Therefore, the five parameters might all take part, implicitly or explicitly, in the governance of the litigation threshold $\bar{x}_{lt}$ and renewal threshold $\bar{x}_{rt}$, which are key components of the litigation and renewal likelihoods shown in Equation 4 and 5.

4 Structural estimates and counterfactual analysis

In this section, I present the parameters estimated from the maximum likelihood estimation method. Using the estimated parameters, I recover the distribution of patent value of each time period as well as the aggregate litigation and renewal rates for each time period. Finally, I present several robustness checks for the MLE estimates.

4.1 Estimates on key parameters

Table 3 shows point estimates of key parameters and their confidential intervals (CIs) at the 95% level. [14] To start with, the technology depreciation rate, γ, of invention patents (γ=0.75) is larger than that of utility models (γ=0.65), reflecting the fact that utility models have shorter period of protection compared to invention patents and that utility models are more likely to be used for innovation protection in fast-moving, highly competitive industries where technologies tend to quickly become obsolescent (Cao et al., 2014). But the variation of the valuation of invention patents (σ = 20089) tends to be larger than that of utility models (σ = 5007), indicating that extremely valuable patents are more likely to be found among invention patents than among utility models. As expected, invention patents (α=4.52) have a much larger α than utility models (α=0.34), meaning that invention patents are, in general, much more valuable than utility models.

[14] Bootstrapping confidential intervals such as BC_a or ABC methods are widely used in the literature (DiCiccio and Efron, 1996). Motivated by these methods, I estimate the CIs using the 97.5 and 2.5 percentile of all the point estimates I obtain. The MLE procedure are run for 100 rounds, a process which resembles to the bootstrapping of BC_a or ABC methods.

Parameters related to infringement process, however, do not significantly differ between these two types of patents. Specifically, the owners of invention patents are expected to receive slightly larger share of the profits from patented technology ($\theta = 0.32$) than the owners of utility models ($\theta = 0.24$) if they chose not to litigate against the infringement. This might be driven by the difficulties in imitating certain invention patents such as huge infrastructure investment, organizational routines, tacit knowledge and skill endowment embedded within firms' specific human resources. These difficulties might be mitigated for most utility models whose major inventive feature are in the products' shape or structure, the imitation to which could be much easier relative to invention patents. Finally, the peak infringement hazards, l_0, are similar for these two types of patents. The similarity might reflect the trade-off of infringing valuable invention patents: on one hand, the gains will be magnificent if succeed; on the other hand, however, the cost and risk of imitating valuable patents might be proportionally (or even disproportionally) higher. The large magnitude of infringement hazards-40%- is also consistent with the widely-held impression of the prevalence of infringement in China. The peak infringement hazard, however, is strikingly high compared to the litigation rate in China- namely the ratio of patents being litigated in court over all patents filed during the same time (much lower than 1%), suggesting that the patent enforcement might be too weak to incentivize patent owners to defend their infringed innovations in court.

Next I examine the aggregate litigation and renewal rates across the entire patent life cycle and compare them with the rates calculated from the real-world data. Figure 1 shows the results of invention patents. While I do not target the per-period aggregate litigation or renewal rates when running MLE estimation [15], the estimated rates (orange lines) turn out to be reasonably close to the real-world rates (blue lines). The same pattern applies to utility models, shown in Figure 2. These patterns further corroborate the robustness of the MLE estimates. The aggregate renewal rates of both types of patents keep declining over time, reflecting the fact that the patent value decreases over time, regardless of the patent type. Specifically, around 80% of sampled invention patents are kept valid for at least 10 years and around 20% of invention patents are renewed until the end of the maximum term (i.e. 20 years). Though the proportion of utility models which are kept valid till the end of the maximum term is similar to that of invention patents (i.e. 20%), only 60% of utility models are renewed for half of the maximum term (equivalent to 10 years for invention patents), lower than that of invention patents. This might be driven by the higher depreciation rate utility models have relative to invention patents.

Figure A.4 shows the evolution of patent value over the entire patent life, simulated using the MLE estimates. The left panel reports the valuation of invention patents, with the solid line in the middle showing the median and two dash lines showing the values at 90 and 10

[15] Prior studies usually target these two aggregate rates using the simulated moment method (Lanjouw et al., 1998; Pakes, 1984; Schankerman and Pakes, 1985).

percentiles. It is evident that the value of invention patents decreases over time, consistent with the pattern of renewal rates in Figure 1 and Figure 2. More details are revealed if we look at the patent value in the first period, which is actually the sum of the first-period value and expected values from the following periods (Table 4) [16]. The first-period value of invention patents is much higher than that of utility models- almost 60 times larger at the median (Table 4). But the gap seems to narrow as we move up the distribution. For instance, the maximum value of invention patents in the first period is roughly twice of that of utility models. This pattern is also exhibited by the larger gap of first-period value between the 90 percentile and median of utility models relative to the 90%-median gap of invention patents (Figure A.4). This might partly be driven by the fact that these two types of patents share the same range of statutory damage awards.

Compared to the literature, the patent value I estimate using the model featuring patent enforcement seems to be relatively large. For instance, using a dynamic model in the similar spirit (but without the feature (option) of patent enforcement), Gupeng and Xiangdong, 2012 estimates the median value of invention patents filed before 2000 to be 2839 RMB, which is around 8746 RMB transformed to the price level in 2005. Several reasons could be behind the larger magnitude of my estimates. First, patents estimated using my model are a sub-sample with relatively high infringement hazards and thereby are probably among the most valuable patents of the population while Gupeng and Xiangdong, 2012 estimate valuation of the population of Chinese patents. The other reason could be that the omission of patent litigation as an "outside" option tends to underestimate the patent value. As mentioned before, the range of damage awards before 2009- 5000 RMB to 300,000 RMB- could be higher than the value of half of utility models in my sample; therefore, neglecting the litigation as an outside option tends to lead to downward bias in the value estimation.

4.2 Robustness checks

The maximum likelihood estimation method is particularly vulnerable to two problems (Struben et al., 2015). The first is the violation to the MLE's key assumption-observations are independent in terms of the likelihood. It is difficult to directly test the independence of both litigation and renewal likelihoods among all observations because closed-form solutions are not available. But it is still possible to reduce the dependence to a low level. Both litigation and renewal are decisions made by the patent owner; therefore, the biggest dependence of these likelihoods comes from the common patent ownership. For instance, if one patent has already been litigated, the patent owner might refuse to litigate another one due to the cost. Similarly, paying renewal fees for one of the key patents might reduce the patent owner's incentive to renew another one, especially when the latter is less important. In this sense, I reserve one patent from the same patent owner in the sample. For litigated

[16] As for each type of patents, the value decreases at a relatively stable rate. Therefore, the patent value in the first period is representative of patent values in the following time periods.

patents, I keep the first litigated one by the same patent owner; for non-litigated patents, I randomly pick one from the group of control patents owned by the same patentee. If litigated patents and non-litigated patents are owned by the same patent owner, I keep the litigated one.

The other concern of the MLE method regards its sensitivity to the initial guess of the parameters. To alleviate this concern, I generate the initial guess using a global search algorithm (e.g. "annealing" algorithm in MATLAB). The advantage of the global search algorithm is that it leaps through the entire parameter space to search for the optimal solution, thus reducing the possibility of parameter estimates being "trapped" within a local optimum.

After the initial guess being generated, the next robustness check is to ensure that MLE estimation recovers the "true" parameters as close as possible. This could be done by running a trial simulation. Specifically, I generate two data sets- 1000 utility models and 1000 inventions- using the theoretical model introduced in section 3. I employ the same MLE algorithm I plan to apply to the real data to recover the parameters. Since I know the true parameters of the simulated data sets, I could compare the estimated parameters with their true values. To control for the stochastic component of the model, I run the MLE estimation for 50 rounds. It turns out that the median value of each parameters is very close to the "true" parameters I use to generate the data. This robustness check exercise not only confirms the reliability of the MLE estimates but also helps me to identify the statistics I could use as the final estimates. Appendix B lays out the details of this robustness check.

One might also concern that it is the specific setting of the model and estimation strategy (e.g. parameter calibration) that drive the specific pattern we observed. To alleviate this concern, I employ an alternative estimation strategy to : 1) reduce the influence of stochastic components on the estimation; 2) extend the set of parameters for estimation to test the robustness of the current point estimations. To this end, I set the litigation cost c and the shape parameter of the gamma distribution of patent initial value β as parameters for estimation and construct a "seven-parameter" model for estimation. As Table A7 and Table A8 show, the estimates yielded by this alternative model are largely consistent with the main results. See Appendix D for details of this robustness check.

4.3 Counterfactual analysis

To answer the major inquiry of this paper, I perform several counterfactual analyses. One is to explore how the patent value, litigation and renewal rates change if the damage awards equal the real infringement loss, the ideal scenario I use as the benchmark. The second counterfactual exercise examines how the patent value and litigation, renewal rates react to lifted damage awards, such as the enhancement enacted by the 2009 patent reform. Finally,

I use simulated data to investigate how the key parameters of the model affect patent valuation, litigation and renewal likelihoods of each period.

4.3.1 The benchmark: damage awards doctrines compensating the real loss

To further evaluate the efficiency of patent enforcement under the "statutory damage awards doctrine", I estimate the evolution of patent value and the aggregate litigation and renewal rates of the sampled patents by running a counterfactual exercise assuming that damage awards will equal the real loss from infringement. The "unjust enrichment" or "lost profits and reasonable loyalty" doctrines (UE and LP doctrines), damage awards doctrines widely adopted by Western countries are close to this scenario. This will generate an "ideal" scenario for what the patent valuation and aggregate rates will be, thus creating benchmark for the evaluation of the statutory damage awards doctrine and the damage awards range it has imposed.

Formally, I revise the model by substituting z, the lump-sum statutory damage awards, with x_t, the per-period patent profit flow at time t. Other parameters, including those estimated in section 5.1, remain the same with the baseline model[17]. The reward function at time t is re-written as:

$$f(t) = L_t[\ (px_t - c)a_t + (1 - a_t)x_t\theta]\ + (1 - L_t)x_t - Rc_t \tag{10}$$

Figure A.5 shows the evolution of patent value for invention patents (the left panel) and utility models (the right panel) in the benchmark scenario. Surprisingly, the estimates on patent value are very close to those estimates from the baseline model. Table 4 reports the first-period patent value in the benchmark scenario. It is evident that first-period patent values estimated from the baseline model and from the benchmark scenario are similar across the entire distribution. These evidence seems to suggest that the damage awards range imposed by the statutory damage awards doctrine before 2009 are appropriate in the sense that it generates similar distribution of patent value as the benchmark.

The benchmark scenario, however, does differ greatly from the statutory damage awards doctrine in one aspect. Table A2 reports the aggregate litigation and renewal rates estimated from these two scenarios. The aggregate renewal rates of the benchmark are quite similar to

[17]One might concern that when the damage awards doctrines change, the parameters that are closely associated with infringement might be changing accordingly, such as the initial infringement hazard l_0 . I will address this concern in section 5.4 in which I investigate how the patent valuation and aggregate rates of litigation and renewal change when the key parameters change. From that exercise, we will have a reasonable expectation on how the results discussed in this part shift when parameters change.

those under the statutory damage awards doctrine, reflecting the aforementioned similarity in patent valuation. Nevertheless, aggregate litigation rates differ greatly across the two doctrines. For invention patents, the aggregate litigation rates of the benchmark are much larger than those of the statutory damage awards doctrine (Panel A of A2). For instance, the litigation rate in period 2 from the benchmark (0.0525) is more than 500 times as big as the litigate rate in the same period estimated using statutory damage awards (0.0001). The gap, however, seems to decline sharply as the patent ages. For example, in periods 14 and 15, the aggregate litigation rates of statutory damage awards doctrine are merely twice as large as the the litigation rates of the benchmark. This pattern, however, does not hold among utility models. Panel B of A2 shows that the aggregate litigation rates of utility models before 2009 (the baseline model) are larger than those estimated in the benchmark scenario.

This indicates that the pre-2009 level of damage awards might already over-compensate utility models because it seems to encourage more utility models to be litigated in court. On the other hand, the extremely low litigation rate in China before 2009 reveals the potential inefficiency of the statutory damage awards doctrine for invention patents. Patent owners, especially those with valuable patents, might be reluctant to defend their patents in litigation court because of the cap imposed on the expected amount of damage awards by the doctrine. This implication is consistent with the empirical pattern revealed by the summary statistics in section 4.2 that litigated invention patents seem not to be more valuable than non-litigated counterparts. On the other hand, in the benchmark scenario, patent owners are compensated with their real loss, thus alleviating the concern that infringed patents will be under-compensated. Though the general distribution of patent value seems not to be directly affected by the damage awards doctrine, the extremely low litigation rate implies potential welfare loss of owners with extremely valuable patents.

4.3.2 The effect of lifting statutory damage awards: China's patent reform in 2009

Another useful counterfactual exercise is to examine how the patent valuation and aggregate rates of litigation and renewal react to enhancement in damage awards under the statutory damage awards doctrine. To this end, I investigate the potential effect of China's patent law of 2009, which greatly lifted both the lower and upper bounds of statutory damage awards. Indeed, the range of damage awards increased from 5000 RMB ($725) to 300,000 RMB ($46,590) before 2009 to the range of 10,000 RMB ($1553) to 1,000,000 RMB ($155,300) after that. The expected amount of damage awards, especially the upper bound, was promoted by more than three times.

As expected, the valuation of the two types of patents increases after the enhancement in damage awards, shown by Figure A.6 (compared to Figure A.4). Specifically, for invention

patents, the lines of the median, 10 percentile and 90 percentile all move up-though slightly-compared to the invention panel in Figure A.4. The improvement in the valuation of utility models turns out to be more evident: the medians of patent value before the 2009 patent reform stay below 10,000 RMB for all time periods (the solid line in the utility model panel of Figure A.4) whereas the median line only goes below 10,000 RMB after period 7 after the reform (the solid line in the utility model panel of Figure A.6). The 10 and 90 percentiles exhibit similar patterns. Additionally, the first-period patent values across the entire distribution further illustrates the different patterns of invention patents and utility models (Table 4). For invention patents, the enhancement in damage awards does improve the patent value, but not much. At the 90 percentile, median and 10 percentile, the increases in first-period patent value are merely 4%, 5% and 6.5% relative to their pre-reform levels, respectively. As a contrast, the increases in the value of utility models at the 90 percentile, median and 10 percentile of the distribution, are 155%, 289% and 605% relative to the pre-reform levels. These patterns seem to persist through the entire life cycle of most patents.

These patterns imply that the promotion in damage awards by the 2009 patent reform bears boosting effect on both types of patents, but the effect is much bigger on utility models than invention patents. More important, the post-reform valuation of utility models are even much larger than the "benchmark" patent value estimated in the previous section whereas the post-reform valuation of invention patents are similar- or even slightly smaller than the benchmark valuation. These patterns lend suggestive evidence that the 2009 patent reform might lead to overvaluation of utility models while leaving the valuation of invention patents almost unchanged. In reality, this seems to be corroborated by the dramatic spike in utility model patenting and relatively moderate increase in invention patenting in China since 2009.

Next, I examine the aggregate rates of litigation and renewal. For both types of patents, patent renewal rate increases in all time periods (Table A2), consistent with the finding on patent valuation. However, the increase in renewal rates are dwarfed by the increase in litigation rates. For both types of patents, the aggregate litigation rate in almost all time periods experiences a remarkable increase after the patent reform. For instance, the litigation rate in the first period of utility models increases for more than 4000 times compared to the benchmark litigation rates (Table 4). Taken together, the modest increase in renewal rates and huge increase in litigation rates suggest that the enhancement in damage awards exert a much larger effect in litigation likelihood than renewal likelihood. After the expected damage awards increase, patent owners of valuable patents which would not have been litigated before are significantly encouraged to defend their patents in court. In other words, the increase in damage awards is more likely to change patentees' litigation choices, rather than their renewal choices.

4.3.3 Asymmetric effects of boosting damage awards

The enhancement of the damage awards by the 2009 patent reform might significantly narrow the gap of valuation between invention patents and utility models. This might shift firms' patenting strategy in favor of utility models- the type of inventions featuring of "baby steps"- and away from invention patents- the type of inventions that are more likely to generate "quantum leaps" and thus make significant economic contributions. This is largely because, as illustrated in section 2.1, making a utility model typically involves much lower costs and uncertainty relative to invention patents.

A back-of-the-envelope calculation helps to clarify this argument. Table A3 reports the ratio of patent values of invention patents over utility models, adjusted by the patent grant rates across the entire distribution [18]. It is evident that the gap of valuation between invention patents and utility models significantly shrinks after 2009 across the entire distribution, though utility models are still less valuable than invention patents after the patent reform. On average, the valuation of invention patents are around 18 times as large as that of utility models before the 2009 patent reform; the former, however, is merely 6 times as large as the latter after 2009. That said, after 2009, one invention patent is roughly equivalent to six utility models in terms of the expected value. This estimate is surprisingly close to the "rule-of-thumb" estimate provided by Chinese officials. For instance, the Chinese authority stipulates that six utility models are equivalent to one invention patent when evaluating firms' high-tech innovative capacity (e.g. InnoCom policy, Z. Chen et al., 2021; Wei et al., 2021). Moreover, Table 4 illustrates that patents from the lower-end of the distribution- might be affected by the enhancement in damage awards to a larger extent than their counterparts from the upper end. Indeed, changes in the ratio among patents from the upper-end of the distribution (i.e. above the median or 75%) are much smaller than changes among patents from the lower-end of the distribution. For example, the ratio of values of inventions relative to utility models among patents in the bottom 1% goes down from 88 before 2009 to merely 10 after 2009 while the ratio of patents from the top 99% moves from 4.3 to 1.6. Considering that the sample of patents I examine in this paper might be patents with relatively higher values among the entire population of Chinese patents, the overall effect of the 2009 patent reform on the population might be larger than the estimates reported Table A3.

5 The effect on innovation direction

The structural estimation and simulation show that the enhancement in damage awards by the 2009 patent reform asymmetrically impacts the valuation of invention patents and utility models. It greatly promotes the valuation of the low-value type- utility models- while

[18] The patent grant rate is the ratio of invention patents that are eventually granted over the cohort of invention applications. See Appendix C for details on the grant rate.

leaving the valuation of invention patents almost unchanged. A direct consequences of this asymmetric influence could be a shift from utility model patenting to invention patenting by innovating firms. In this section, I employ a series of firm-level difference-in-differences analyses to explore the extent to which the shift occurs and its implication on the quality of innovation output and firm heterogeneity.

5.1 Data and methodology

I compile a comprehensive panel data set of all patenting Chinese firms from 2001 to 2012. Specifically, I search in the IncoPat data- a private data provider widely used by scholars and China's patent examiners- for all firm patenting records within mainland China by domestic Chinese firms from 2001 to 2012. I tease out institutional patent owners whose identities could not be uniquely confirmed [19]. I also drop foreign patent owners because they might face different regulatory and innovation environments when filing patents [20]. This yields 219166 unique firm patent owners who make 1189738 invention patent applications and 1497799 utility model applications during the period of 2001 to 2012. Furthermore, I drop firms which only patent one type of patents because I do not observe switch between the two types of patents for these firms. The final data set comprises 48627 patenting firms.

Begin with the "treatment" measure. In principle, the 2009 patent reform affected all firms in my sample, but the extent to which they were affected could be heterogeneous across firms. Thus, I leverage this inter-firm heterogeneity in exposure to the litigation-related changes brought about by the 2009 patent reform to identify the effect on firm innovation strategy. Specifically, I assume that firms that were exposed to more patent litigation hazards before the reform will potentially be more reactive to changes in the litigation-related policy changes. Follow the procedure proposed by Mezzanotti, 2021, I construct a measure for firms' exposure to patent litigation:

$$\eta_i = \sum_{q=1}^{N} \zeta_{iq} r_q \tag{11}$$

η_i is the measure for patent litigation exposure of firm i. ζ_{iq} is the ratio of patents filed in area q (IPC classes or subclasses) by firm i over the number of all patents filed firm i, measuring the relative importance of each tech area in the focal firm's entire patent portfolio. r_q is the ratio of the number of patents being litigated in area q over the number of all patents being litigated, measuring the litigation hazards of area q. Put together,

[19] The IncoPat database standardised all institutional patent owners according to their history of patent records. I utilize this function and drop out patent owners that are not standardized.

[20] Most patents registered to China's patent office by foreign patent owners are family patents to original inventions made in foreign countries.

η_i proxies the weighted patent litigation exposure which varies across firms and different time windows. In the main analysis, I use IPC classes- technological areas widely used to classify patents- to define the area and calculate the total litigation exposure of sampled firms during the period of 2005 to 2008. Summary statistics of major variables used in this section is shown in Table A10.

5.2 The ratio of invention patenting over utility model patenting

The major outcome of interest is firms' choices over invention patenting vis-a-vis utility model patenting. Specifically, I intend to quantify how the over-compensation of utility models by the 2009 patent reform impacts firms' choices between the two types of patents across firms with heterogeneous exposures to litigation hazards. Formally, I estimate:

$$Y_{it} = \beta_0 + \beta_1 \eta_i * Post_t + Post_t + X_{it} + \delta_i + \theta_{jt} + \psi_{lt} + \epsilon_{it} \tag{12}$$

Y_{it} is the ratio of the utility model applications over all patent applications filed by firm i in year t, measuring the firms' patenting choice between the two types of patents. η_i is the litigation exposure of firm i, the treatment variable, and $Post_t$ is a dummy variable takes 1 after the patent reform year (2009, including). X_{it} are a battery of control variables, teasing out impacts from potential contributors to the dependent variable. Specifically, I use the number of patents registered in foreign countries as a measure for firms' foreign activities. Hu and Jefferson, 2009 identifies firms' exposure to foreign investment and trade will change its patenting strategy. Furthermore, it is well acknowledged by the literature that firm's R&D spending is closely associated with its patenting strategy. While I do not directly observe R&D spending from the data, I use the size of firms' patent portfolio- the number of firms' valid patents in year t- as a proxy for firms' R&D efforts and absorptive capacities. Finally, the literature also points out the extent of competitiveness of the industry (or tech area) in which the firm operates could affect its choice over invention patents and utility models (Cao et al., 2014). Thus, I compute the industry-level (or technological-area-level) herfindahl-hirschman index (HHI) of patenting at year t as another control variable.

Next, I insert fixed effects at a variety of levels. δ_i are firm fixed effects, controlling for unobserved firm-level time-invariant factors. θ_{jt} is a yearly trend of industry (or tech area) fixed effects, absorbing time-changing industry-level factors, such as changes in industry policies or shifts in market demands. ψ_{lt} are yearly trend of firm location fixed effects, absorbing time-changing province-level factors. This could be particularly relevant in China's context due to its patent subsidy programs which typically offer larger rewards for invention patents than utility models (Dang and Motohashi, 2015). I identify the industries (or tech

areas) firms belong to and their major locations using the industries or provinces where the majority of patents are registered by the focal firm in year t. Though theoretically the way I construct these measures allow them to change over time, the majority of firms in my sample patented in few years across the entire observation window, resulting in low variations. This is the reason why I multiply the industry and location fixed effects with time trends.

The major coefficient of interest is β_1, which, according to my structural estimation, is expected to be positive. The diff-in-diff estimation confirms this. Table 5 reports the results estimated using Equation 12. Column 1 uses the full sample and it indicates that one standard deviation increase (around 0.094) in the litigation exposure of a firm before 2009 will increase the ratio of utility model patenting by 2.26%. This effect is statistically significant at conventional levels. Furthermore, from columns 3 and 5, we could see that the increase in utility model ratio by firms with higher litigation exposure is mostly driven by significant increases in utility model patenting, rather than invention patenting. The invention patenting by firms with high litigation exposure slightly decreases after 2009 relative to firms with low litigation exposure, but the decrease is small and statistically insignificant. Plus, the coefficients of $Post_t$ in columns 3 and 5 indicate that both types of patents increase after the patent reform but utility models increase more. This pattern is consistent with the prediction of the structural estimation- namely that both types of patenting are expected to be incentivized due to the overall enhancement in damage awards, but the incentives for utility model patenting should be lifted to a much larger extent.

To test the key assumption of a valid difference-in-differences exercise, I estimate the treatment effect by year. Specifically, I substitute the $Post_t$ in Equation 12 with a series of year dummies and plot the coefficients of the interaction terms $Litigation_exposure * Year_t$, shown in the left panel of Figure 3. The jump in diff-in-diff estimators after 2009 is evident and it seems the positive effect on utility model ratio persists and even slightly increases over time. But the pre-shock trend is not parallel and mostly below the zero line, suggesting that firms with larger litigation exposure tend to have much lower portion of utility models in their patent portfolio before the policy change. This pre-shock trend might be driven by unobserved factors that could potentially motivate the spike we observe in the post-shock coefficients. For instance, the negative pre-shock trend could be driven by firms with low litigation exposure and no invention patenting before the policy change. These firms tend to increase the ratio of utility model patenting in the "control" group before the change but amplify the estimated increase in the utility model ratio after the change because they could only change their utility model ratio downwards. Therefore, I exclude observations with zero invention patenting from the sample and re-estimate the dynamic difference-in-differences model, shown by the right panel of Figure 3. The pre-shock trend becomes parallel and indistinguishable from zero before 2009, indicating that the restricted sample excluding firms that do not patent inventions before the change could be a better

one in terms of controlling unobservable pre-shock confounders. Therefore, I use this sample in most of the following analyses.

The restricted sample yields results similar to the full sample. Column 2 of Table 5 indicates that the ratio of utility model patenting increases by 2.36% after 2009 if the litigation exposure of firms increases by one standard deviation (0.093). This suggests that the boosting effect of strengthening patent enforcement by the patent reform might mostly concentrates among firms at the intensive margin. The estimates on the number of utility model patenting (column 4) and invention patenting (column 6) further confirm this intuition. Indeed, in the restricted sample, the number of invention patent applications decreases after 2009 for firms with higher litigation exposure relative to firms with lower exposure; the magnitude is much larger than that estimated using the full sample, and more importantly, the negative coefficient is statistically significant at conventional levels whereas the estimate using the full sample is not. Meanwhile, the estimate on the number of utility model applications is positive, statistically significant, and almost twice as large as that estimated from the full sample (column 3). Put together, these evidence indicates that for firms with patenting experiences in both types of patents (i.e. the restricted sample), they tend to switch between the two types of patents; that said, increases in utility model patenting actually "crowd out" invention patenting. This might be due to the limited resources of R&D efforts within firms or that firms simply value more of utility models than invention patents, as what the structural estimation suggests. I will return to this point in the innovation quality part.

Alternative mechanisms and robustness checks. The observed increase in utility model ratio by firms with high litigation exposure might be driven by other factors or contemporaneous policy changes. The most probable ones are from other changes introduced by the 2009 patent reform. One could be the official recognition of "double patenting" practice by the 2009 patent law. According to the 2009 patent law, patent applicants are allowed to apply one invention patent and one utility model for the same invention at the same day; at any time point later, though, the patent applicant could only preserve one of the two patent rights if both of them are approved by the patent office. Informal interviews with Chinese patent attorneys suggest that the 2009 patent reform does increase "double patenting" in practice and might, to some extent, encourage utility model patenting. To alleviate this concern, I have removed all patents that are registered as double patenting from the main analysis.

Moreover, the 2009 patent reform also enhances the criteria of granting invention patents. After 2009, Chinese patent examiners will compare invention patent applications with prior art- existing public knowledge related to the application- around the world; previously, the prior art was defined as public knowledge within mainland China. The change in the scope of prior art makes the examination of invention patents (not utility models) more rigorous and thus could potentially lead to a shift from invention patenting to utility model patenting.

One piece of evidence contrast to this argument is the fact that invention patenting increases after 2009 in the full sample, indicated by the coefficients of $Post_t$ in Table 5. This increase is mostly driven by firms at the extensive margin if we compare the negative $Post_t$ estimated from the restricted sample. If the "higher examination criteria" mechanism was at work, we would expect that firms at the intensive margin (i.e. firms without invention patenting experiences) are most unlikely to increase their invention patenting. This is inconsistent with what we observe from the data.

One might also concern the impact from policy changes other than the 2009 patent reform, such as the InnoCom policy (Z. Chen et al., 2021; Wei et al., 2021). As mentioned before, an implicit rule of evaluating the two types of patents by the InnoCom program is that one invention patent is equivalent to six utility models. Due to the large corporate tax cut (25% to 15% after 2008) enjoyed by the certificated firms, the incentive to quickly acquire the InnoCom certification could be nontrivial. Utility models appear to be a better choice than invention patents for firms to acquire for the purpose of winning the certificate because they are much easier and quicker to get. Therefore, the increase in utility model ratio could be due to the incentives to win certificates or other government subsidies in the same fashion. Several checks are ready to alleviate this concern. First, I include a yearly trend of province fixed effects in the diff-in-diff specification (Equation 12), which could control the confounding effects from province-level patent subsidy programs over time. Second, the InnoCom policy took into effect in 2008, which, if truly at work, will predict an uptake in the utility model ratio in the year of 2008. This is inconsistent with the pattern shown in Figure 3. The dynamic diff-in-diff estimators indicate that the uptake starts around the year 2010, two years after the InnoCom policy taking effect.

Finally, for all the aforementioned alternative mechanisms, it is unclear how firms with high litigation exposure will increase their utility model patenting relative to firms with low exposure if they were at work. Indeed, the influences of all these mechanisms- the flourishing double patenting practice, rigorous invention examination criteria and patent subsidy programs such as InnoCom policy- tend to target the patent application process rather than patent litigation process. In other words, firms that are more exposed to litigation hazards might make similar decisions as firms that are less exposed should these alternative mechanisms were at work here.

Table A11 reports other robustness checks I perform. The main results are shown to be robust to: 1) measuring the litigation exposure by industry (three-digit industry codes); 2) using the yearly changing measurement of litigation exposure (by IPC classes); 3) measuring the litigation exposure from 2001 to 2004; 4) winsorizing the top 1% observations by year in terms of invention applications and utility models; 5) using the sample excluding the observations with zero invention applications and the ones with zero utility models.

5.3 Quality of innovation outputs

According to the structural model, the mechanism behind the increase in utility model ratio is the asymmetric effects on utility models and invention patents by the enhancement in damage awards by the 2009 patent reform. If it is this mechanism at work, we should expect to observe the following in the quality of invention patents. Firms with high litigation exposure are more likely to reduce the low-quality inventions in their entire patent portfolio relative to firms with low litigation exposure. As a result, the group of invention patents whose value and quality most resemble to utility models is most likely to be dropped out. Meanwhile, the cost of making low-quality inventions- though they might be as valuable as utility models after 2009- could still be much higher than the cost of making utility models (e.g. patent attorney fees, patent fees etc..). Hence, the "treated" firms might use the "saved" R&D spending to invest inventions with higher quality (or even breakthrough inventions). Therefore, we would expect to see that firms with relatively high litigation exposure tend to reduce low-quality invention patenting and increase high-quality invention patenting, relative to firms with low litigation exposure.

To examine this prediction, I construct measures for the quality of invention patents made by sampled firms and substitute Y_{it} in Equation 12 with the quality measure. Specifically, following the literature, I count the number of invention patents filed in year t by the focal firm whose forward citations are among top 1 percentage, 5 percentage, 10 percentage, 25 percentage and 50 percentage (median) of all invention patents filed within the same technological area (i.e. IPC classes) in year t. This measurement has several advantages: first, by comparing the forward citations among cohorts, the measure alleviates truncation bias which tends to undervalue the importance of patents filed in later years of the observation window; second, by comparing with other Chinese invention patents, the measure also alleviates the concern on reliability of the citation data released by the China's patent office if we assume the data bias, if any, is randomly distributed across areas and over time. Moreover, I normalize the measurement for patent quality with the number of invention patents filed by the focal firm in year t, gauging the composition, rather than raw numbers, of patents with different qualities.

Table 6 report the results. Columns 1-4 show estimates on invention patents which are within top 1, 5, 10 and 25 percentages among their cohorts from the same technological areas. The coefficients of $Post_t$ are negative and statistically significant at conventional levels, indicating that firms with zero litigation exposure significantly reduce patenting in top-quality inventions after 2009. The interaction terms $Litigation_exposure_i * Post_t$ are positive and statistically significant at conventional level (columns 1-4), suggesting that firms with positive litigation exposure tend to reduce the top-quality patenting to a smaller extent and the reduction gets smaller as the litigation exposure increases. For instance, the ratio of invention patents among top 1 percentile increases by 0.15 percentage if the

litigation exposure increases by one standard deviation (column 1). The increase in the top-quality invention patenting by firms with high litigation exposure relative to firms with low exposure is likely to be driven by the reduction in low-quality invention patenting. Column 5 reports the estimated changes in the patenting of inventions whose qualities are below the median [21]. As expected, firms with high litigation exposure decreases the composition of these low-quality invention patents relative to firms with low exposure. Indeed, firms with no litigation exposure before 2009 increase patenting in inventions of below-median quality (the estimate of $Post_t$ in column 5).

Furthermore, I examine how the patenting in inventions of "middle-tier" quality changes before and after 2009. Columns 6 to 9 report the results of patenting in the "rest" inventions-invention patents whose qualities are neither among the top percentiles nor below the median. As the percentiles move down (i.e. from top 1 percentile to top 25 percentile), the differences of patenting inventions in the "middle tier" between firms with high litigation exposure and firms with low exposure become narrow and less significantly different from zero (the coefficient of the diff-in-diff estimator in column 9 is not statistically significant at any conventional level). This is also consistent with the prediction that firms with high litigation exposure tend to switch from low-quality patenting to high-quality patenting. Finally, I plot the dynamic difference-in-differences estimators (i.e. the estimates by substituting the $Post_t$ dummy with a series year dummies in Equation 12) on the ratio of invention patents whose qualities are above the median (Figure A.7). The dynamic diff-in-diff estimators not only confirm the parallel pre-shock trend- the key assumption of the diff-in-diff analysis- but also visualize the clear jump in the ratio of high-quality invention patents within the patent portfolio of firms with high litigation exposure relative to firms with low exposure. Overall, the difference-in-differences analysis on invention patent quality illustrates that the quality of patent portfolio held by firms with high litigation exposure tends to shift to the high-quality end relative to the quality of the patent portfolio held by firms with low litigation exposure.

5.4 Firm heterogeneity

The mechanism revealed in the previous section- that the "treated" firms are more likely to switch low-quality invention patents to utility models and to invest in breakthrough inventions using the cost being saved- has two implications. First, from the perspective of R&D spending, this "switch" mainly stems from limited R&D resources of innovating firms and therefore will be more pronounced among firms with financial constrains. Second, from the perspective of expected profits of making innovation, the "switch" reflects diminishing returns to increasingly larger size of the patent portfolio owned by innovating firms, especially

[21] I use median as the threshold to measure low-quality patents because non-trivial number of invention patents do not have any forward citations. This makes the measures to be the same if I use bottom 1, 5, 10 or 25 percentile as the measure for low-quality patents.

for patents of the same type. In this section, I investigate these implications by exploring firm heterogeneity in the propensity of making utility models.

To begin with, I examine whether the reactions of publicly traded companies and private firms to the changes in damage awards are different. Specifically, I split the entire sample into one sample containing publicly traded firms and another one containing the rest private firms [22]. Then I run the difference-in-differences model specified in Equation 12 on the two sub-samples, separately. Columns 1- 2 of Table 7 report the results. Consistent with the prediction, publicly traded firms with high litigation exposure do not significantly increase their ratio of utility model patenting relative to publicly traded firms with low exposure after 2009. On the other hand, private firms which, compared with publicly traded firms, usually face more difficulties in raising funding, exhibit the opposite pattern: private firms whose pre-shock litigation exposures are high tend to have higher utility model ratios relative to private firms whose exposures are low. The diff-in-diff estimator is statistically significant at conventional levels.

Furthermore, I examine the second implication by exploring the reactions of firms with large patent portfolios before the shock and firms with small ones. To this end, I define firms with zero patents in their patent portfolio in 2008- the year before the patent reform- as firms with small patent portfolios and group them into the "inexperienced patenting firms". The rest firms are defined as firms with large patent portfolios. Columns 4 to 5 of Table 7 report the results. As expected, among firms with relatively large patent portfolios (column 4), firms with high litigation exposure tends to be reactive to the patent reform- they significantly increase the utility model ratio relative to firms with low exposure. By contrast, among firms with small patent portfolios (column 5), the pattern is the opposite: firms with high litigation exposure *decrease* the utility model ratio relative to firms with low exposure. This indicates that for firms with fewer valid patents in their portfolio, they might be less constrained by the law of diminishing returns and thus less subject to the switch from low-value invention patents to utility models, compared with their counterparts with larger patent portfolios.

The split-sample regressions only focus on the impact of the patent reform *within* the subsample and thus might suffer from biases inherent in each subsamples. To alleviate this concern, I perform triple difference-in-differences regressions in which a third dummy indicating whether the firm is publicly traded company (or possesses large patent portfolios) is inserted. The third dummy is interacted with the *Litigation_exposure* terms (the interaction term in normal diff-in-diff) and with litigation exposure and post-reform dummy. Results (Columns 3 and 6 of Table 7) are aligned with the estimation using split samples. Overall, estimations that take account of firm heterogeneity in reactions to the patent re-

[22] I identify publicly traded firms by year because some firms were listed only for several years of the entire observation window.

form are largely consistent with the implications derived from the main analysis- private firms and firms with large patent portfolios are more reactive to the policy change compared with publicly traded companies and firms with small patent portfolios, respectively.

6 The effect on firm performance

6.1 Data and methods

In this section, I examine how the damage awards enhancement in 2009 affects firms' financial performance. To this end, I construct a balanced panel data comprising of R&D intensive Chinese manufacturing firms. From the Chinese Annual Survey of Manufacturing (ASM), a longitude survey conducted by Bureau of Statistics which is widely used by scholars, I select companies with positive R&D records from 2005 to 2007 [23], a sub-sample of firms that are most likely to be affected by changes in patent enforcement. I match these firms with their patent records from IncoPat. The matching is based on firms' full names and addresses; for patent applicants whose unique IDs [24] are available in the Incopat database, I also match on these unique identification numbers. Next, I exclude firms with no patenting records or firm which only patent one type of patents (utility models or invention patents), so the remaining sample could capture the effect of the switch between the two types of patents. This yields a sample of 4922 manufacturing companies with patenting and balance-sheet financial records from 2005 to 2012 (39376 firm-year observations). The summary statistics for this database is reported in the Panel B of Table A10.

To evaluate the effect of the changes in damage awards on firm performance, I employ the following specification, similar to the one I use to examine the effect on innovation output in Equation 12:

$$Y_{it} = \beta_0 + \beta_1 \eta_i * Post_t + X_{it} + \Gamma_t + \delta_i + \theta_{jt} + \psi_{lt} + \epsilon_{it} \tag{13}$$

For Y_{it}, the dependent variable, I use profits, annual sales, exports and annual industrial outputs-all normalized by the total assets of the focal firm at the same year, measuring firm financial performance from several dimensions. η_i, the litigation exposure, is defined in Equation 11. A slight change in Equation 13, compared with Equation 12, is that I use a series of year dummies, Γ_t, to substitute the post-shock dummy, $Post_t$, controlling for the unobserved time trend [25]. As defined in Equation 12, δ_i, θ_{jt} and ψ_{lt} are firm fixed effects,

[23] The R&D data is only available for years from 2005 to 2007.

[24] A unique firm identification number issued by the government for tax purpose.

[25] In Equation 12, the time trend in patenting could partly be absorbed by the time-changing patent portfolio.

time trend of industry fixed effects and time trend of province fixed effects.

I insert several time-variant variables which potentially affect firm performance as controls, X_{it}. I use the logarithm of the number of employees to control for firm size. Also, firm performance could experience sudden changes as firms adjust their major products; therefore, I insert a dummy variable indicating whether the firm changes major products in year t. Finally, I incorporate the logarithm of firm age to control for the heterogeneity in firm performance among old and young firms.

6.2 Results

It is not immediately clear whether the performance of firms that are more affected by the damage awards enhancement will improve or deteriorate after the patent reform. One the one hand, the switch from invention patents- though mostly low-quality ones- to utility models might hamper firm performance because despite of bearing similar values with invention patents after the patent reform, utility models are still inferior to invention patents in terms of their qualities, technological and economic potentials. The rigorous examination process, relatively wider protection scope and longer patent term all contribute to potentially larger importance of invention patents relative to utility models in a firm's portfolio. On the other hand, however, firms might also benefit from directing more resources towards breakthrough invention patents, as demonstrated in section 5.3. High-quality invention patents will eventually contribute to firm performance in the long run.

Consistent with these two competing forces, the difference-in-differences analysis depicts a nuanced picture of the effect of the damage awards enhancement on firm performance. Table 8 reports the baseline results estimated using Equation 13. Columns 1 and 4 show that the profits and industrial outputs seem to decrease after the patent reform for firms more exposed to litigation hazards relative to firms with less exposure. But the negative diff-in-diff estimators in these columns are merely significant at 10% level. The effects on the sales and exports (columns 2 and 3) are positive, but not statistically significant at any conventional levels. Overall, these analyses provide slightly weak evidence that the negative effect of switching from invention patents to utility models dominates the positive effect of making more breakthrough invention patents, and hence, firms with high litigation exposure tend to perform worse after the patent reform.

Furthermore, to check the pre-shock trend, I substitute the $Post_t$ dummy in the interaction term of Equation 13 with a series of year dummies and plot the corresponding coefficients. The left panel of Figure 4 shows these dynamic diff-in-diff estimators on profits. The pre-shock trend is largely flat and indistinguishable from zero, confirming the validity of the key assumption of the difference-in-differences analysis on profits. After 2009, the estimates start to drop; though it slightly bounces back in 2010, the rest diff-in-diff estimators are

largely below zero after the shock. The right panel of Figure 4 shows the dynamic diff-in-diff estimators on industrial outputs. Though the pre-shock trend is parallel and close to zero, the post-shock decreases are not significantly distinguishable from zero, suggesting the negative effect on outputs is weak. Finally, to ensure the robustness of the baseline analysis, I define the *litigation_expose* by IPC subclasses and the results resemble to those in Table 8 [26].

Last but not the least, I examine the heterogeneity in performance across different types of firms. Specifically, I examine whether the reactions of firm performance to the changes in damage awards are different across: 1) big and small firms, measured by the average annual sales before 2009; 2) financially constrained versus non-constrained firms, measured by the average ratio of debts over the total assets before 2009; 3) start-ups versus incumbents. I divide the big (small) firms and financially constrained (non-constrained) firms using the medians of correspondent measures and define start-ups as firms which were founded before 2005. Table 9 reports the results estimated from split samples, following similar procedures used in Table **??**. To begin with, Columns 1 and 2 illustrate that the difference between financially constrained firms and firms that are not constrained is negligible. It seems the pattern revealed in section 5.4 that financially constrained firms are more likely to be affected and apply for more utility models does not extend to firm performance. Furthermore, the split-sample estimation seems to suggest that big firms are negatively affected in terms of profits whereas the reduction in profits of small firms is not statistically significant (Columns 4 to 5). But the difference becomes statistically insignificant in the triple difference-in-differences analysis (Column 6 of Table 9). Finally, Columns 7 to 9 show that the pattern of start-ups is quite different from that of incumbent firms surviving for longer time: start-ups with high litigation exposure seem to benefit from the changes in damage awards relative to start-ups with low exposure; but the incumbent firms with high exposure suffer from the change. The results from triple diff-in-diff analysis also support this pattern.

Put together, these evidence suggests that small and young firms with high litigation exposure tend to benefit from the damage awards enhancement, which might be attributed to their efforts of making more breakthrough invention patents; meanwhile, big and incumbent firms with high litigation exposure tend to suffer from the damage awards enhancement, which could be attributed to the switch from invention patents towards utility models. This intuition is supported by the patterns revealed by the analysis on firm heterogeneity in terms of patent quality. Specifically, I explore how big firms and start-ups react differently in terms of the ratios of the patents whose forward citations are within top tiers (1%, 5%, 10% and 25%) among their cohorts within the same IPC classes and filed in the same year, the measure I use in section 5.3 to measure innovation quality. Following the

[26]The results are unreported which are available upon request

same procedure I utilize in Table 9, I perform a normal difference-in-differences analysis on split samples and triple difference-in-differences analysis on the full sample. The results are reported in Table A12 and Table A13. These results indicate that the tendency for firms with high litigation exposure to file top-tier patents is slightly bigger among small firms than that among big firms [27]; and similarly, this tendency of start-ups is significantly more evident than that of incumbent firms. These evidence is consistent with the pattern revealed by the firm heterogeneity analysis in Table 9, thus confirming the mechanism behind the firm performance proposed in the beginning of this section.

7 Policy suggestions

Given the asymmetric effects of lifting damage awards on invention patents and utility models and its consequences, a direct policy suggestion would be to revise the damage awards doctrine to suit different types of patents. I briefly discuss feasibility of several options of revisions in this part.

The most effective doctrine, relatively to the statutory damage awards doctrine, should be doctrines that compensate the patent owner with the real infringement loss such as the "unjust enrichment" (UE) or "lost profit and reasonable loyalty" doctrines (LP). While UE or LP doctrines have already been stipulated by China's patent law for almost two decades and been adopted in few cases in practice, they are apparently less efficient than statutory damage awards doctrine in terms of providing a quick legal remedy because determining the real loss is usually a time-consuming process, which could be a daunting task in China where there is no evidence discovery doctrine in court. Therefore, adopting a UE or LP doctrine might result in slow protection; in quickly-evolving industries, slow legal remedy could almost equal to no protection. In addition, an overall shift to the UE or LP doctrine might require a battery of experienced IP judges and other professional experts such as judicial authenticators, which might be heavily under-supplied in many areas. Thus, fully adopting UE or LP doctrine could be considered as the ultimate goal in the long run.

In the short run, small revisions to the current statutory damage awards doctrine might achieve desirable effects as well. One feasible approach is to differentiate the damage awards ranges for invention patents and utility models. Intuitively, to match the values of these two types of patents, invention patents should be bestowed with higher damage awards than utility models. Specifically, given that the range of damage awards for utility models before 2009 seems to generate a distribution of patent value similar to that generated in the benchmark scenario (see Table A2), we could leave the damage awards doctrine to its

[27] The triple diff-in-diff estimator in Table A12 is not statistically significant, suggesting that the difference between small and large firms could be trivial. This is consistent with the finding in this part that the negative effect on big firms' performance is marginal.

pre-2009 level for utility models, namely a range of 5000 RMB ($ 725) to 300,000 RMB ($ 46,590). Meanwhile, for invention patents, the range of damage awards needs to be enhanced from its pre-2009 level. Though the pre-2009 damage awards range generates patent value distributed in a similar way as the benchmark scenario, the aggregate litigation rate is much lower under the pre-2009 statutory damage awards doctrine than the benchmark scenario (Table A2).

Therefore, enhancing the pre-2009 damage awards range for invention patents while leaving that for utility models to its pre-2009 level could be a feasible policy approach to adjust the inefficiency in China's patent litigation system. Naturally, the next question should be how to enhance the damage awards range, e.g. to what extent. It is far-reaching to derive specific numbers for the ideal range for damage awards from my current model because models are only abstract of the reality no matter how delicate they are. However, simulation exercises like the ones in section 5.2 and 5.3 could provide useful clues on the general direction of the enhancement.

To start with, I explore lifting which bound- the upper bound or the lower bound- could be more efficient. Table A5 and Table A6 in Appendix A report four simulation exercises I run to this end. Specifically, I extend the upper bound of the post-2009 damage awards range to 1.1 million RMB and 1.3 million RMB for the first two exercises, leaving the lower bounds unchanged, which is 0.01 million RMB; in a similar vein, I extend the lower bound of the post-2009 damage awards range to 0.1 million RMB and 0.3 million RMB for the third and fourth exercises, leaving the upper bound unchanged, which is 1 million RMB. The baseline is the results of the 2009 patent reform presented in Table A2 and Table 4. It is evident that, as expected, the patent value increases when either bounds of the damage awards range increases. Plus, the extent to which the patent value increases is proportional to the extent to which the damage awards range is lifted. For instance, lifting the upper bound to 1.3 million RMB exerts larger boosting effect on the patent value than lifting it to 1.1 million RMB. However, what is unexpected is the asymmetric effects of lifting the upper bound and lower bound. It turns out that the enhancement in the lower bound exerts a significantly larger effect on the patent value than lifting the upper bound. This effect is pervasive across the overall distribution of the first-period patent value and also applies to aggregate litigation rates (Table A6). Intuitively, the reason could be that a lower bound above zero provides a "guaranteed" bottom line of expected profits from winning the infringement lawsuits while the upper bound, however large it is, represents the best scenario which might merely happen at a very low chance, especially for innovators whose patents are of relatively low value. The asymmetry in the effect of upper bound and lower bound of the damage awards range on the patent value indicates that policy makers might need to lift the lower bound, rather than the upper bound, if they aspire to achieve a strong, positive effect of strengthening patent protection.

8 Conclusions

This paper investigates the role of patent litigation in the valuation of patents and the direction of innovative activities under the context of weak IPR countries like China. I start with building a finite-horizon stochastic dynamic model, which captures key features of the patent litigation and renewal process. The model suggests that valuable patents are less likely to be litigated if the damage awards are capped by an upper bound. By fitting the model with China's patent litigation data, I obtain structural estimates on the technology depreciation rate, peak litigation hazards, the distribution of patent initial values, and the share of profits the patent owner is expected to receive if the infringement is tolerated. These parameters allow me to recover the valuation, aggregate litigation and renewal rates of invention patents and utility models- the two major types of patents granted by the China's patent office. As expected, the valuation of utility models- the type of patents that do not go through rigorous examination and are thus inferior to invention patents- is much lower than that of invention patents- the type of patents analogous to the utility patents granted in the U.S..

Based on the estimates on key parameters, I run two counterfactual exercises. By comparing China's statutory damage awards which are bounded by a range- with the "benchmark" scenario in which patent owners are compensated with the exact loss they suffer from infringement, I show that China's statutory damage awards before 2009 might significantly lower the aggregate litigation rates of invention patents while generating patent valuation similar to the benchmark scenario. However, the second counterfactual exercise reveals that strengthening the patent enforcement by promoting damage awards exerts a much larger boosting effect on utility models than on invention patents. As a result, China's 2009 patent reform, which greatly enhanced the general level of damage awards, might over-compensate utility models- the inferior type of patents, rather than inventions, by offering inflated level of damage awards. A back-of-the-envelope calculation and show that the 2009 patent reform significantly narrow the gap between invention patents and utility models in terms of the patent valuation.

To evaluate the implication of the patent reform on patent valuation, I perform a series of difference-in-differences analyses on firms' patenting strategy and performance. The firm-level analysis confirms the prediction that firms with high litigation exposure (and thus will be more affected by changes in patent enforcement) tend to file more utility models after the patent reform relative to firms with low exposure. The "treated" firms are more likely to reduce low-quality invention patenting while increasing the patenting efforts in top-tier invention patents. This shift in the direction of results in poorer firm performance, suggesting that the negative effect from switching to utility models dominates the potentially positive effect from making more top-tier inventions. Finally, by running another set of counterfactual exercise, I show that setting different ranges of damage awards for the two

types of patents might be a feasible solution of the distortion in patenting and raising the lower bound of the damage awards might be more effective than raising the upper bound.

Several limitations of this study could become potential venues for further exploration. First, I fit the theoretical model with a subgroup of the population of Chinese patents-though the subgroup that might potentially face highest infringement hazards. Future studies could apply the model developed in this paper to a more comprehensive sample of Chinese patents to examine the generality of major findings among the patent population. Second, an international comparison with the evolution of utility model patenting in other countries which grant utility models, such as Germany and Japan, could be very useful in investigating whether the patterns exhibited by China's patent litigation practice are applicable to other jurisdictions.

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Tables

Table 1: Main differences between inventions and utility models

	Inventions	Utility models
Protection term	20 years	10 years
Rigorous examination	yes	no
Benefit/cost	high/high	low/low
Coverage	any invention novel non-obvious and useful	invention with solid structures or shapes

Table 2: Patent renewal fee scheme in China

Years	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Inventions	144	144	144	192	192	192	320	320	320	640	640	640	960	960	960	1280	1280	1280	1280	1280
Utility models	96	96	96	144	144	192	192	192	320	320										

Note: Chinese Yuan is exchanged into USD according to recent market currency price: 1 RMB=0.16 USD

Table 3: Estimates on key parameters

	Inventions		Utility models	
	Estimates	95% CIs	Estimates	95% CIs
γ	0.748	[0.661,0.899]	0.65	[0.25,0.9]
σ	20089	[1329.321,20940.65]	5007	[1020.033,12888.44]
α	4.52	[3.792,9.983]	0.34	[0.003,1.996]
θ	0.318	[0.1,0.541]	0.243	[0.1,0.9]
l_0	0.615	[0.187,0.789]	0.61	[0.12,0.9]

Table 4: First-period patent values (in local currency, RMB)

	Inventions			Utility models		
	Before patent reform	benchmark	After patent reform	Before patent reform	Benchmark	After patent reform
Min	91166.65	104081.2	71955.01	1701.959	1786.091	13826.35
1%	175084.02	198033.7	184064.4	1725.304	1791.785	14373.17
5%	257578.63	282879.3	266990	1996.978	1962.515	16001.12
10%	310026.12	340927.7	330291.8	2460.487	2485.377	17337.78
25%	422566	450566.6	448672.6	3485.939	3368.353	24362.73
50%	590150.45	615177.6	620956	8295.944	8282.796	32245.29
75%	796095.15	830541.6	837942.2	29234.87	30212.99	79940.51
90%	1023914	1053769	1065213	73939.41	74849.56	188679.1
95%	1167655.6	1226054	1235460	116487.4	119587.2	294240.1
99%	1506869.4	1528511	1600449	305429.1	308864.4	767502.8
Max	3840061	4314056	3778141	1390615	1178542	1866687
Mean	636389.41	667373.9	670652.6	29571.3	29837.09	81728.44
SD	294561.1	303152.3	307199.7	64918.16	62930.43	134407.4
#obs	10000	10000	10000	10000	10000	10000

Table 5: The effect on the ratio of utility model patents

	(1)	(2)	(3)	(4)	(5)	(6)
	utility model ratio		log(utility model applications)		log(invention applications)	
Sample	full	positive invention	full	positive invention	full	positive invention
Litigation_exposure*Post	0.0226***	0.0236***	0.0574***	0.0981***	-0.00580	-0.0516***
	(0.00257)	(0.00279)	(0.00559)	(0.00982)	(0.00750)	(0.00921)
Post	-0.0170***	0.0132***	0.0747***	0.00971	0.0311***	-0.0208**
	(0.00360)	(0.00385)	(0.00598)	(0.0104)	(0.00741)	(0.00977)
Log(family patents)	-0.135***	-0.0432***	0.0868***	0.125***	0.660***	0.439***
	(0.00590)	(0.00377)	(0.0151)	(0.0158)	(0.0179)	(0.0141)
Log(patent portfolio)	0.209***	0.195***	0.811***	0.762***	0.0517***	0.166***
	(0.00268)	(0.00397)	(0.00776)	(0.0147)	(0.00474)	(0.00660)
HHI	1.330***	-1.209***	-1.474***	-3.614***	-3.353***	0.124
	(0.113)	(0.145)	(0.198)	(0.451)	(0.247)	(0.434)
Constant	0.319***	0.0246***	-0.319***	-0.283***	0.539***	1.008***
	(0.00605)	(0.00871)	(0.0158)	(0.0315)	(0.0114)	(0.0163)
Firm FEs	Y	Y	Y	Y	Y	Y
Industry FEs	Y	Y	Y	Y	Y	Y
Province FEs	Y	Y	Y	Y	Y	Y
Observations	157,332	62,567	157,332	62,567	157,332	62,567
R-squared	0.585	0.716	0.775	0.822	0.675	0.778
#Firms	48627	21608	48627	21608	48627	21608

Note: All specifications use OLS model. The sample used in columns 2,4 and 6 is the one containing firms filing positive number of invention patents at year t. *Litigation_exposure* is measured at the firm level during the period of 2005 to 2008. $Post_t$ takes 1 if the year is after 2009 (including). Family patents and patent portfolio are counted at the firm level at year t. HHI is computed for each year at the 2-digit IPC code level. The dependent variables for columns 1-2 are the ratio of utility model applications over all patent applications taken by the focal firm at year t. The dependent variables for columns 3-4 and columns 5-6 are the number of utility models and invention applications taken by the focal firm at year t. All logarithm transformation is taken after adding one to the original value for all observations. Robust standard errors are clustered at the firm level, shown in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 6: The effect on the quality of invention patents

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variables	top 1%	top 5 %	top 10 %	top 25 %	below-median	between top 1% and median	between top 5 %and median	between top 10 %and median	between top 25 %and median
Litigation_exposure*Post$_t$	0.00152**	0.00294*	0.00400*	0.00987***	-0.0111***	0.00956***	0.00842**	0.00741**	0.00139
	(0.000672)	(0.00160)	(0.00213)	(0.00328)	(0.00350)	(0.00352)	(0.00358)	(0.00358)	(0.00356)
Post	-0.00307**	-0.00686**	-0.0195***	-0.0523***	0.0985***	-0.0952***	-0.0910***	-0.0772***	-0.0415***
	(0.00145)	(0.00318)	(0.00430)	(0.00620)	(0.00654)	(0.00660)	(0.00677)	(0.00688)	(0.00681)
Log(family patents)	-0.000816	-0.00436**	-0.00658***	-0.0157***	0.00384	-0.00301	0.000577	0.00262	0.0119***
	(0.000974)	(0.00197)	(0.00246)	(0.00357)	(0.00395)	(0.00401)	(0.00409)	(0.00414)	(0.00430)
Log(patent portfolio)	0.000665	0.00238*	0.00347**	0.0104***	-0.0155***	0.0149***	0.0132***	0.0121***	0.00509*
	(0.000549)	(0.00129)	(0.00175)	(0.00253)	(0.00234)	(0.00238)	(0.00250)	(0.00262)	(0.00280)
HHI	-0.0270	-0.0547	-0.162	-0.205	-2.451***	2.481***	2.498***	2.598***	2.607***
	(0.0421)	(0.104)	(0.144)	(0.196)	(0.242)	(0.244)	(0.258)	(0.265)	(0.264)
Constant	0.0120***	0.0551***	0.113***	0.269***	0.158***	0.830***	0.787***	0.728***	0.571***
	(0.00171)	(0.00390)	(0.00517)	(0.00749)	(0.00756)	(0.00767)	(0.00793)	(0.00811)	(0.00820)
Firm FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y
Province FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	62,567	62,567	62,567	62,567	62,567	62,567	62,567	62,567	62,567
R-squared	0.403	0.425	0.432	0.429	0.566	0.557	0.535	0.522	0.499
#Firms	21608	21608	21608	21608	21608	21608	21608	21608	21608

Note: All specifications use OLS model. All dependent variables are the ratio of the patents specified within all invention patents filed by the focal firm in year t. *Litigation_exposure* is measured at the firm level during the period of 2005 to 2008. $Post_t$ takes 1 if the year is after 2009 (including). Family patents and patent portfolio are counted at the firm level at year t. HHI is computed for each year at the 2-digit IPC code level. All logarithm transformation is taken after adding one to the original value for all observations. Robust standard errors are clustered at the firm level, shown in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 7: Firm heterogeneity on utility model ratio

Dependent variable	utility model ratio					
Samples	(1) publicly traded firms	(2) private firms	(3) Full	(4) firms with large patent portfolios	(5) firms with small patent portfolios	(6) Full
Litigation_exposure*Post	0.0100	0.0268***		0.0398***	-0.0211*	
	(0.00666)	(0.00313)		(0.00280)	(0.0121)	
Publicly_traded*Litigation_exposure*Post			-0.00870			
			(0.00660)			
Large_portfolio*Litigation_exposure*Post						0.0637***
						(0.00970)
Controls	Y	Y	Y	Y	Y	Y
Firm FEs	Y	Y	Y	Y	Y	Y
Indutry FEs	Y	Y	Y	Y	Y	Y
Province FEs	Y	Y	Y	Y	Y	Y
Observations	7,961	51,344	62,567	32,017	30,548	62,567
R-squared	0.738	0.723	0.716	0.691	0.745	0.720
#Firms	2595	18671	21266	9615	11993	21608

Note: All specifications use OLS model. *Litigation_exposure* is measured at the firm level during the period of 2005 to 2008. $Post_t$ takes 1 if the year is after 2009 (including). *Publicly_traded* takes 1 if the firm is publicly listed in year t; $Private_firm$ is the opposite. $Large_portfolio$ takes 1 if the firm has zero patents in the portfolio in year 2008. Family patents and patent portfolio are counted at the firm level at year t. HHI is computed for each year at the 2-digit IPC code level. All logarithm transformation is taken after adding one to the original value for all observations. Robust standard errors are clustered at the firm level, shown in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 8: The effect on firm performance

Dependent variables	(1) Profits	(2) Sales	(3) Exports	(4) Outputs
Litigation_exposure*Post	-0.00174*	0.0102	0.00241	-0.0365*
	(0.000990)	(0.0101)	(0.00342)	(0.0204)
Log(employees)	0.00515***	0.0228**	0.0190***	0.00289
	(0.00115)	(0.0103)	(0.00324)	(0.0215)
Change_product	-0.000869	-0.0563***	-0.0116***	-0.143***
	(0.00135)	(0.0135)	(0.00389)	(0.0392)
Log(age)	-0.00240	-0.0517**	0.00756	-0.152***
	(0.00234)	(0.0205)	(0.00571)	(0.0398)
Constant	0.0605***	1.894	0.0477*	1.944***
	(0.00865)	(97.45)	(0.0254)	(0.154)
Firm FEs	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y
Indutry FEs	Y	Y	Y	Y
Province FEs	Y	Y	Y	Y
Observations	35,498	35,191	33,630	35,199
R-squared	0.602	0.573	0.741	0.457
#Firms	4911	4910	4900	4900

Note: All specifications use OLS model. *Litigation_exposure* is measured at the firm level during the period of 2005 to 2008. $Post_t$ takes 1 if the year is after 2009 (including). $Change_product$ takes 1 if the focal firm changes its major product in year t. All logarithm transformation (except for age) is taken after adding one to the original value for all observations. Robust standard errors are clustered at the firm level, shown in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 9: Firm heterogeneity in performance

Dependent variable	Profits/assets								
Sample	(1) Financial con-strained	(2) Financial non-constrained	(3) Full	(4) Big	(5) Small	(6) Full	(7) Start-ups	(8) Incumbents	(9) Full
Litigation_exposure*Post	-0.00106	-0.00109		-0.00339**	-0.000168		0.00325	-0.00292***	
	(0.00141)	(0.00164)		(0.00158)	(0.00126)		(0.00303)	(0.00101)	
Financial_constrained*Litigation_exposure*Post			-0.00252						
			(0.00221)						
Big*Litigation_exposure*Post						-0.00219			
						(0.00204)			
Start-ups*Litigation_exposure*Post									0.00582*
									(0.00316)
Firm FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y
Province FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	16,033	15,975	32,008	17,718	17,777	35,495	5,610	29,888	35,498
R-squared	0.570	0.629	0.625	0.620	0.591	0.602	0.593	0.607	0.602
#Firms	2455	2456	4911	2419	2492	4911	775	4136	4911

Note: All specifications use OLS model. *Litigation_exposure* is measured at the firm level during the period of 2005 to 2008. $Financial_constrained$ takes 1 if the ratio of debt over total asset before 2009 of the firm is above median. *Big* takes 1 if the firm is above median in terms of the average annual sales before 2009. $Start-up$ takes 1 if the firm was founded after 2005. $Post_t$ takes 1 if the year is after 2009 (including). Controls containing $log(age)$, $Change_product$ and $log(employees)$. Robust standard errors are clustered at the firm level, shown in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Figures

Figure 1: Aggregate litigation and renewal rates of invention patents

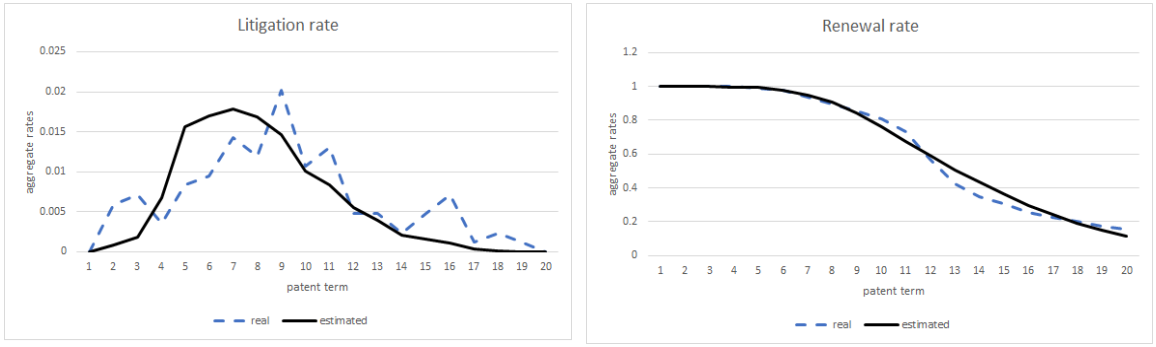


Figure 2: Aggregate rates of litigation and renewal of utility models

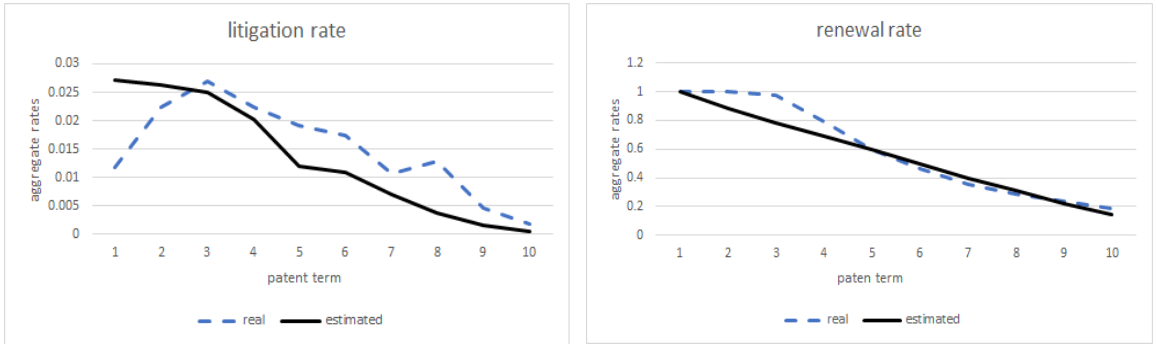
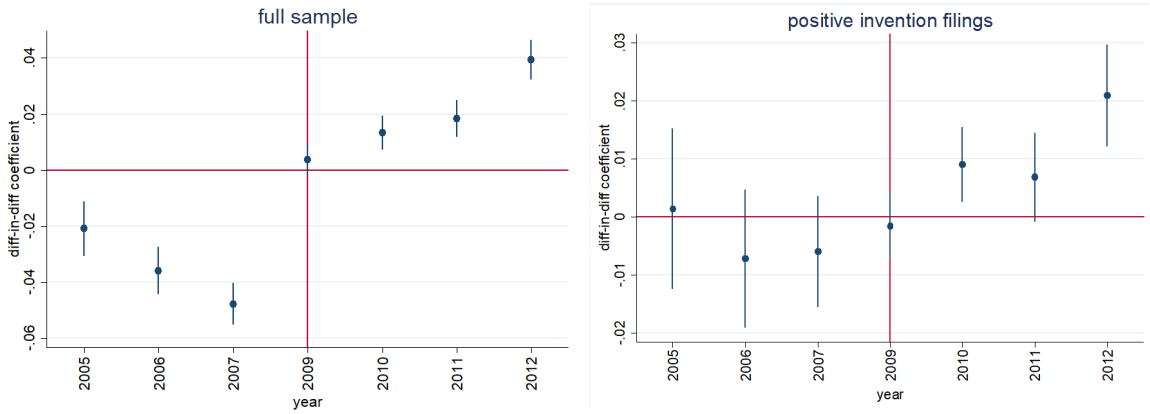
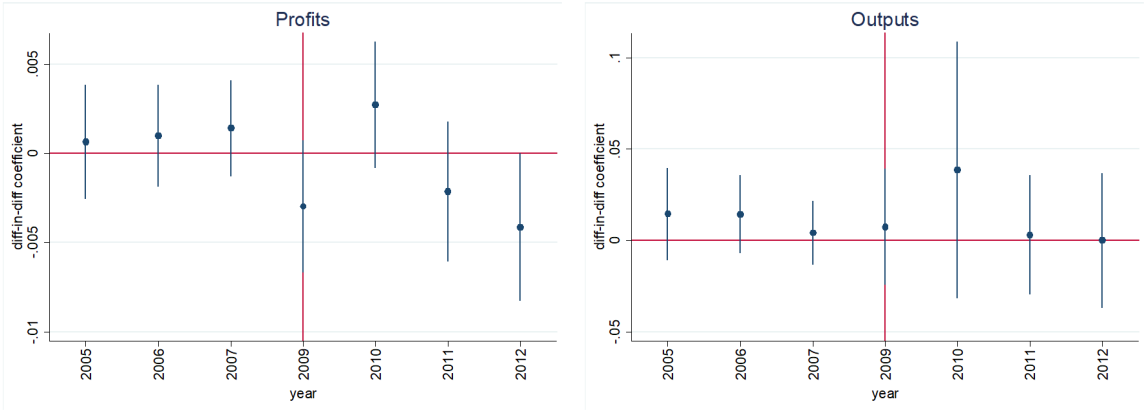


Figure 3: The effect on firms' utility model ratio (dynamic diff-in-diff)



Note: The x-axis shows the year; Y-axis shows the coefficients of the dynamic difference-in-differences estimation. "Treated" group is the group of industries with higher-than median ratio of litigation occurrence before 2009. The dependent variables is the ratio of the number of utility model applications over the number of invention patent applications at year t of industry i. 2008 is set as the baseline year, thus omitted. Vertical lines show the 95% confidence intervals for point estimates.

Figure 4: The effect on firm performance



Note: The x-axis shows the year; y-axis shows the coefficients of the dynamic difference-in-differences estimation. The dependent variables are profits in the left panel and outputs in the right panel, both normalized with total assets. 2008 is set as the baseline year, thus omitted. Vertical lines show the 95% confidence intervals for point estimates.

Appendices

A Appendix tables and figures

Table A1: Summary statistics of sampled inventions and utility models

	#Obs	Mean	Std. Dev.	Min	Max
Panel A Litigated invention patents					
#claims	115	13.31	17.75	1	107
#foreign destinations of family patents	115	16.79	37.56	1	241
#IPC	115	1.94	1.13	1	6
#applicants	115	1.01	0.09	1	2
#inventors	115	1.97	1.55	1	8
transaction	115	0.33	0.47	0	1
invalidation	115	0.57	0.50	0	1
Panel B non-litigated invention patents					
#claims	726	23.54	22.68	1	223
#foreign destinations of family patents	726	26.56	37.00	1	241
#IPC	726	2.41	1.92	1	18
#applicants	726	1.04	0.23	1	3
#inventors	726	2.10	1.90	1	14
transaction	726	0.45	0.50	0	1
invalidation	726	0.01	0.11	0	1
Panel C litigated utility models					
#claims	262	4.47	2.88	1	23
#foreign destinations of family patents	262	1.16	1.19	1	16
#IPC	262	1.40	0.70	1	5
#applicants	262	1.08	0.50	1	8
#inventors	262	1.41	1.16	1	13
transaction	262	0.16	0.37	0	1
invalidation	262	0.53	0.50	0	1
Panel D non-litigated utility models					
#claims	1,521	4.30	3.17	1	29
#foreign destinations of family patents	1,521	1.03	0.34	1	9
#IPC	1,521	1.54	0.82	1	7
#applicants	1,521	1.13	0.42	1	4
#inventors	1,521	1.76	1.77	1	27
transaction	1,521	0.04	0.19	0	1
invalidation	1,521	0.00	0.07	0	1

Table A2: Aggregate litigation and renewal rates of simulated data

Panel A Inventions						
	Before patent reform		Benchmark		After patent reform	
Term	litigate rate	renew rate	litigate rate	renew rate	litigate rate	renew rate
1	0	1	0	1	0	1
2	0.0008	0.9999	0.0801	0.9998	0.0382	0.9998
3	0.0018	0.9987	0.1217	0.9992	0.14	0.9991
4	0.0068	0.9966	0.1218	0.9967	0.2472	0.9982
5	0.0156	0.9925	0.1129	0.9899	0.3491	0.9973
6	0.017	0.9777	0.0762	0.9757	0.3365	0.9935
7	0.0179	0.9482	0.0582	0.9474	0.319	0.9816
8	0.0169	0.9041	0.0437	0.9007	0.2967	0.9606
9	0.0147	0.8454	0.0378	0.8438	0.2749	0.9238
10	0.0101	0.7594	0.0292	0.7626	0.2392	0.8642
11	0.0084	0.6758	0.0231	0.6756	0.2139	0.7958
12	0.0055	0.5941	0.0186	0.5946	0.1727	0.7203
13	0.0039	0.5059	0.0143	0.5116	0.1432	0.6349
14	0.0021	0.4361	0.0102	0.441	0.1137	0.554
15	0.0016	0.3665	0.0072	0.3746	0.086	0.4709
16	0.0011	0.2982	0.0041	0.3071	0.0601	0.3889
17	0.0003	0.2439	0.0045	0.25	0.0426	0.321
18	0.0001	0.1911	0.0024	0.1997	0.0261	0.2566
19	0	0.1529	0.0008	0.1554	0.013	0.1982
20	0	0.1163	0.0007	0.1163	0.0047	0.1461
Panel B Utility models						
	Before patent reform		Benchmark		After patent reform	
Term	litigation rate	renew rate	litigation rate	renew rate	litigation rate	renew rate
1	0.0218	1	0.0001	1	0.4526	1
2	0.029	0.9089	0.0062	0.8762	0.5271	0.996
3	0.0282	0.8144	0.0068	0.7741	0.6038	0.9859
4	0.0221	0.702	0.0072	0.6782	0.5176	0.9612
5	0.0147	0.5893	0.0053	0.587	0.4373	0.9129
6	0.0112	0.487	0.0035	0.4907	0.3407	0.8472
7	0.0074	0.3998	0.0024	0.3956	0.2578	0.7549
8	0.0048	0.31	0.0011	0.3151	0.1733	0.6441
9	0.0036	0.2204	0.0006	0.2215	0.1002	0.4963
10	0.0012	0.1465	0.0003	0.1508	0.0374	0.3032

Table A3: Grant-rate adjusted ratio of valuation of individual patent (inventions/utility models)

	before 2009	after 2009
Min	46.60	4.22
1%	88.29	10.37
5%	112.22	13.52
10%	109.62	15.43
25%	105.46	14.92
50%	61.89	15.60
75%	23.69	8.49
90%	12.05	4.57
95%	8.72	3.40
99%	4.29	1.69
Max	2.40	1.64
Mean	18.72	6.65

Table A4: Ratio of total value of all granted patents (inventions/utility models)

	Number of granted patents	Total value of all granted patents	Value of inventions/value of utility models
2005-2008			
invention	520304	3.3e+11	19.34
utility models	578819	1.7e+10	
2009-2012			
invention	945462	6.3e+11	4.50
utility models	1725174	1.4e+11	
2013-2016			
invention	1677827	1.1e+12	4.04
utility models	3410354	2.8e+11	

Table A5: First-period patent value of differentiated ranges of damage awards

Range of damage awards (RMB)	10k-1100k	10k-1300k	110k-100k	310k-1000k
Min	82448.56	91864.59	242780.5	638737.19
1%	184703	187459.4	347329	723297.3
5%	274294	272452.7	435207.5	811258.5
10%	343832	344569.8	503328.4	872691.2
25%	479941.6	493859.5	635475.9	975086.2
50%	654182.3	672412.9	741270.6	1036768.0
75%	801600.3	800725.9	805810.4	1118315.5
90%	1032284	1103021	1017396	1252668.9
95%	1213326	1390110	1220050	1398300.2
99%	1574522	1779857	1592686	1712180.3
Max	3395633	4506284	4109116	4312429
Mean	676182.3	703084.1	761743.6	1062424.9
SD	302114.8	345459.6	249592.8	194762.15
#obs	10000	10000	10000	10000

Table A6: Aggregate litigation and renewal rates of simulated inventions with different range of damage awards

Damage awards range (RMB)	10k-1100k		10k-1300k		110k-100k		310k-1000k	
term	litigate rate	renew rate	litigate rate	renew rate	litigate rate	renew rate	litigate rate	renew rate
1	0	1	0	1	0	1	0	1
2	0.0659	0.9999	0.0942	0.9999	0.0949	1	0.1558	1
3	0.1531	0.9995	0.1925	0.9994	0.1925	1	0.3006	1
4	0.2546	0.9987	0.313	0.9979	0.2887	1	0.459	1
5	0.3899	0.9969	0.4207	0.9961	0.4238	0.9999	0.6194	1
6	0.373	0.9934	0.4094	0.9931	0.4068	0.9992	0.5747	1
7	0.3623	0.9823	0.3878	0.9829	0.3847	0.9969	0.5393	1
8	0.3395	0.963	0.3567	0.9646	0.3839	0.9896	0.4915	1
9	0.3017	0.931	0.3252	0.9375	0.3414	0.9718	0.4545	1
10	0.2725	0.8767	0.2944	0.8933	0.3069	0.9478	0.4129	0.9997
11	0.2306	0.813	0.2635	0.8391	0.2779	0.9145	0.3891	0.9989
12	0.1969	0.7395	0.2254	0.7776	0.2468	0.8673	0.3452	0.9958
13	0.1637	0.6554	0.1818	0.6982	0.216	0.8073	0.3026	0.9877
14	0.1297	0.5767	0.1508	0.623	0.1783	0.7377	0.2677	0.9706
15	0.0991	0.4987	0.1184	0.5406	0.1443	0.6659	0.2252	0.936
16	0.0725	0.4186	0.0794	0.4558	0.1112	0.5768	0.1785	0.8749
17	0.0486	0.3452	0.055	0.3795	0.0727	0.4865	0.1349	0.7837
18	0.0315	0.2824	0.0354	0.3078	0.0522	0.3962	0.0909	0.6608
19	0.017	0.2131	0.0184	0.238	0.0247	0.3069	0.053	0.5194
20	0.0069	0.1566	0.0072	0.1741	0.0099	0.2161	0.0187	0.3346

Table A7: Parameter estimates from alternative modeling and empirical strategy

	inventions		utility models	
	point estimate	95% CI	point estimate	95% CI
γ	0.70	[0.1,0.9]	0.57	[0.19,0.9]
σ	20172.70	[1000.41,20916.1]	5005.29	[1000.1,7819.55]
α	2.41	[1.39,23.03]	0.60	[0.44,21.7]
θ	0.63	[0.1,0.9]	0.48	[0.1,0.9]
l_0	0.59	[0.1,0.9]	0.57	[0.1,0.9]
c	200070.00	[183649,220715]	170002.30	[125689,193118]
β	49934.00	[33141.3,70900.4]	50007.01	[39038.7,95965.6]

Table A8: The first-period patent values from alternative modeling and empirical strategy (in local currency, RMB)

	Inventions			Utility models		
	Before the patent reform	benchmark	After patent reform	Before the patent reform	Benchmark	After patent reform
Min	30278.09	29038.09	30027.49	2113.346	2016.181	4369.46
1%	59380.39	57812.41	74004.63	4510.692	4458.094	5127.859
5%	85318.14	85973.02	134780.3	5406.095	5166.669	8214.481
10%	107876.1	107460.6	185593.3	6470.582	5996.896	18601.89
25%	163773.7	162232.9	341124.9	11866.3	9925.139	113925.8
50%	255723.3	254594.4	730867.1	32364.35	24941.09	546423.7
75%	380777.6	382135.6	1253914	76953.1	61182.55	1034851
90%	535409.9	539792	1625684	131457.1	115991	1394020
95%	636760.4	645344.5	1797278	186547.8	180590.8	1586218
99%	867307.2	891747.5	2022839	530520.4	524222.1	1731568
Max	2404957	2048585	2786481	1492770	1743376	2382141
Mean	295246.2	295652.7	824584.7	61676.93	54892.3	622779.4
SD	181261.9	181660.4	541844.6	95851.72	98686.19	519386.2
N	10000	10000	10000	10000	10000	10000

Table A9: Robustness checks on MLE's parameter capture

	inventions			**utility models**		
	true value	estimates	95% CI	true value	estimates	95% CI
γ	0.71	0.709	[0.103,0.899]	0.5	0.508	[0.201,0.898]
σ	20089	20088.997	[1000.18,21384.719]	4990	4990.000	[1335.962,71852.953]
α	4	4.000	[2.189,9.987]	0.35	0.350	[0.003,2]
θ	0.32	0.320	[0.101,0.9]	0.57	0.574	[0.1,0.9]
l_0	0.76	0.760	[0.1,0.9]	0.51	0.510	[0.209,0.9]

Table A10: Summary statistics on data used for reduced-form analyses

Panel A Patent data								
	Min	25%	50%	75%	Max	Mean	SD	N
Invention applications	1	1	2	4	7624	8.847513	101.2716	82381
Utility model applications	0	0	2	6	10557	7.886552	65.88457	82381
Utility model ratio	0	0	0.5	0.710526	0.997059	0.427874	0.323071	82381
Family patents	0	0	0	0	4767	1.202353	44.64329	82381
Patent portfolio	0	2	5	13	19137	30.40553	282.6616	82381
HHI	0.000794	0.002612	0.004939	0.008172	0.198724	0.007174	0.009381	82381
Litigation exposure	0	0	0.03931	0.108621	0.515862	0.073497	0.100224	82381
Top 1% patents	0	0	0	0	1	0.010242	0.081346	82381
Top 5% patents	0	0	0	0	1	0.051582	0.180714	82381
Top 10% patents	0	0	0	0	1	0.100475	0.247318	82381
Top 25% patents	0	0	0	0.433333	1	0.242719	0.354452	82381
Big firm	0	0	1	1	1	0.669477	0.470405	70328
Start-ups	0	0	0	1	1	0.330523	0.470405	70328
Publicly traded firms	0	0	0	0	1	0.138709	0.345645	82381
Panel B Performance data								
	Min	25%	50%	75%	Max	Mean	SD	N
Litigation exposure	0	0	0	0	0.128966	0.017445	0.034926	39376
Profits	-9284682	1781	9580	38282	1.35E+08	117208.7	1748663	35879
Debts	-3273561	33198	103779	345024	1.54E+08	957994.5	4783454	32379
Sales	0	55140	167807	532637	3.58E+08	1399498	7509016	35882
Exports	0	0	1945	50231	1.87E+08	232171.9	2810006	34246
Assets	0	62432	186086	592327	2.68E+08	1570637	8258640	35885
Industrial outputs	0	63290	191113	602680	3.62E+08	1559817	8173343	35881
Employees	0	173	420	1032	188151	1590.382	6366.004	35668
Age	0	7	11	18	100	16.65902	15.58935	39249
Change in main products	0	0	0	1	1	0.282355	0.450151	39376
Financially constrained	0	0	1	1	1	0.500911	0.500007	32379
Big firm	0	0	0	1	1	0.499972	0.500007	35882
Start-ups	0	0	0	0	1	0.157456	0.364235	39376

Table A11: Robustness checks for the difference-in-differences analysis on utility model ratio

dependent variable: utility model ratio					
	(1) Industry	(2) Yearly changing exposure	(3) exposure (2001-2004)	(4) positive inventions and utility models	(5) winsorized
Litigation_exposure*Post	0.0306***	0.0161***	0.0395***	0.0242***	0.0231***
	(0.00256)	(0.00218)	(0.00255)	(0.00263)	(0.00338)
Post	0.0165***	0.0297***	0.0173***	0.0173***	0.0219***
	(0.00379)	(0.00360)	(0.00358)	-0.00379	(0.00411)
Log(family patents)	-0.0425***	-0.0408***	-0.0449***	-0.0562***	-0.0454***
	(0.00386)	(0.00380)	(0.00376)	(0.00345)	(0.00573)
Log(patent portfolio)	0.203***	0.192***	0.199***	0.0983***	0.257***
	(0.00403)	(0.00385)	(0.00406)	(0.00432)	(0.00258)
HHI	-1.050***	-1.241***	-1.190***	-0.906***	-1.023***
	(0.126)	(0.147)	(0.144)	(0.124)	(0.201)
Constant	0.00639	0.0180**	0.0141	0.327***	-0.0500***
	(0.00912)	(0.00879)	(0.00910)	(0.0114)	(0.00622)
Firm FEs	Y	Y	Y	Y	Y
Industry FEs	N	Y	Y	Y	Y
Province FEs	Y	Y	Y	Y	Y
Observations	62,569	62,567	62,567	38,966	53,986
R-squared	0.704	0.716	0.718	0.697	0.726
#Firms	21609	21608	21608	13899	20248

Note: All specifications use OLS models and utility model ratio as dependent variables. Column 1 uses litigation exposure measured by industry. Column 2 uses yearly changing measures for litigation exposure (computed by IPC classes). Column 3 measures the exposure during 2001 to 2004 (computed by IPC classes). Column 4 uses a sample containing observations with positive number of invention patents and utility models. Column 5 excludes observations with extremely large number of invention applications or utility models (top 1%). HHI is computed at the industry level for column 1 and at the IPC class level for the rest columns. Robust standard errors are clustered at the firm level, shown in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A12: Big versus small firms on patent quality

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent variables	top1			top 5			top 10			top 25		
Sample	Big	Small	Full	Big	Small	Full	Big	Small	Full	Big	Small	Full
Litigation_exposure*Post	0.000988	0.00111		0.000751	0.00313		0.000797	0.00298		0.00773**	-0.00402	
	(0.000720)	(0.00180)		(0.00175)	(0.00476)		(0.00235)	(0.00593)		(0.00359)	(0.00940)	
Big*Litigation_exposure*Post			-0.000184			0.000589			0.00320			0.0224**
			(0.00169)			(0.00440)			(0.00572)			(0.00892)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Province FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	32,017	30,548	62,567	32,017	30,548	62,567	32,017	30,548	62,567	32,017	30,548	62,567
R-squared	0.345	0.446	0.403	0.373	0.467	0.425	0.387	0.472	0.433	0.399	0.457	0.429
#Firms	9615	11993	21608	9615	11993	21608	9615	11993	21608	9615	11993	21608

Note: All specifications use OLS models. Top 1, top 5, top 10 and top 25 are the number of patents filed by the firm in year t that received forward citations that are within the top percentile among all patents filed in the same IPC classes and the same year. *Litigation_exposure* is measured at the firm level during the period of 2005 to 2008. *Big* takes 1 if the firm has zero patents in the portfolio in 2008. $Post_t$ takes 1 if the year is after 2009 (including). Controls containing $log(familypatents)$, $log(patentportfolio)$ and HHI. Robust standard errors are clustered at the firm level, shown in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A13: Start-ups versus Incumbent on patent quality

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent variables	top1			top 5			top 10			top 25		
Sample	Start-up	Incumbent	Full	Start-up	Incumbent	Full	Start-up	Incumbent	Full	Start-up	Incumbent	Full
Litigation_exposure*Post	0.00297	0.00100		0.0142**	0.000814		0.0206**	-0.000496		0.0255**	0.00461	
	(0.00222)	(0.000779)		(0.00597)	(0.00188)		(0.00813)	(0.00254)		(0.0111)	(0.00384)	
Start-up*Litigation_exposure*Post			0.00318			0.0141**			0.0233***			0.0245**
			(0.00227)			(0.00595)			(0.00793)			(0.0108)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Province FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	16,183	37,506	53,690	16,183	37,506	53,690	16,183	37,506	53,690	16,183	37,506	53,690
R-squared	0.438	0.385	0.403	0.472	0.397	0.424	0.477	0.403	0.427	0.459	0.406	0.422
#Firms	6332	12125	18457	6332	12125	18457	6332	12125	18457	6332	12125	18457

Note: All specifications use OLS models. Top 1, top 5, top 10 and top 25 are the number of patents filed by the firm in year t that received forward citations that are within the top percentile among all patents filed in the same IPC classes and the same year. $Litigation_exposure$ is measured at the firm level during the period of 2005 to 2008. $Start-up$ takes 1 if the firm was founded before 2005. $Post_t$ takes 1 if the year is after 2009 (including). Controls containing $log(familypatents)$, $log(patentportfolio)$ and HHI. Robust standard errors are clustered at the firm level, shown in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Figure A.1: The PDF of Gamma distributions

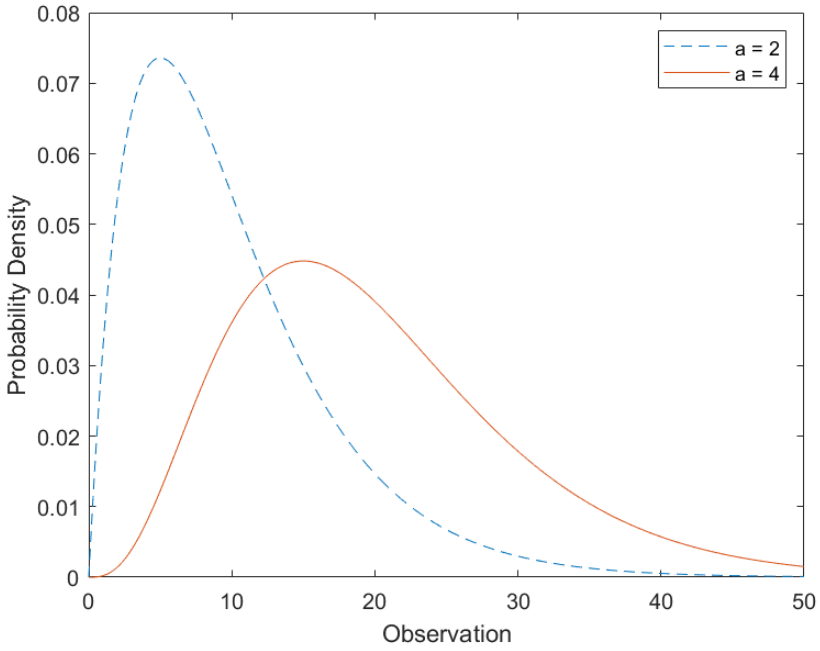


Figure A.2: Distribution of years from patent filing to patent litigation

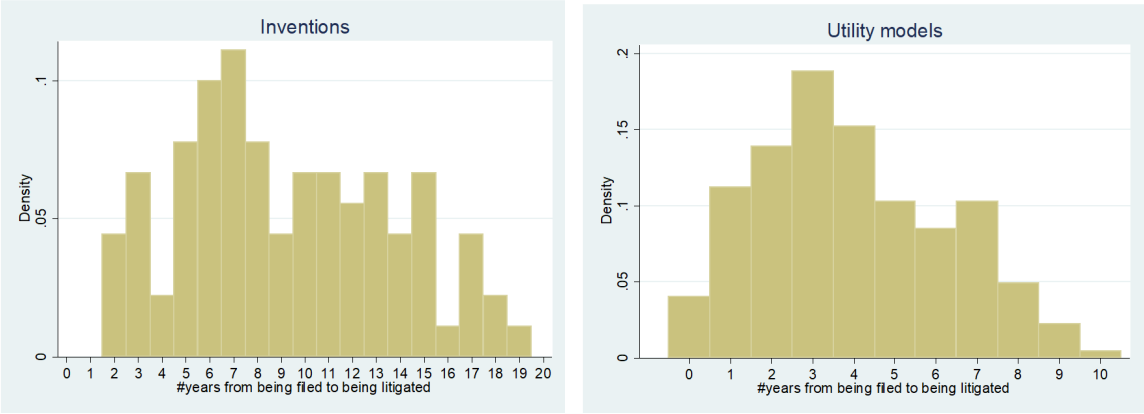


Figure A.3: Distribution of patent renewal terms (kernel density)

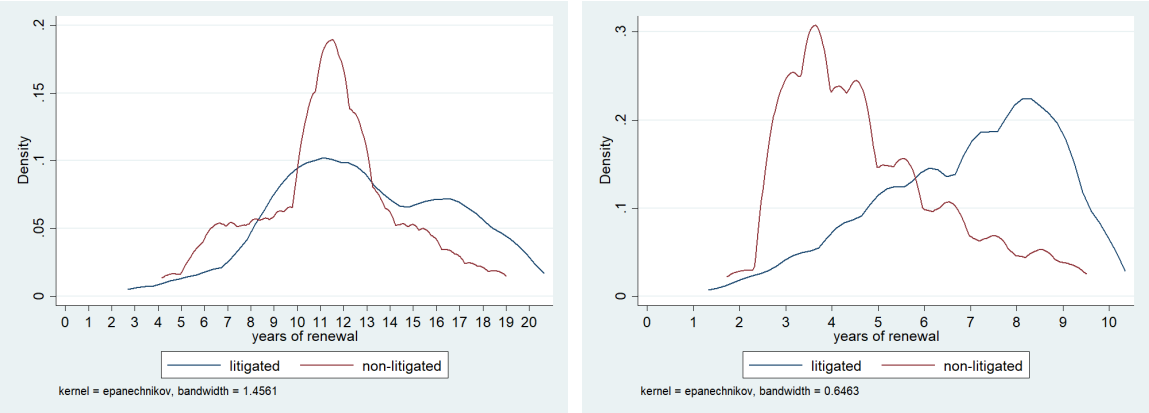


Figure A.4: Patent values at 10p, median and 90p

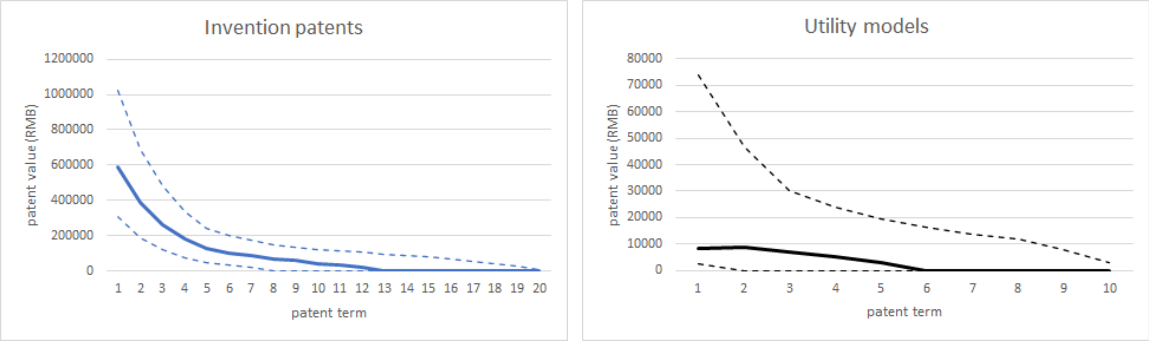


Figure A.5: Patent values at 10p, median and 90p in the benchmark scenario

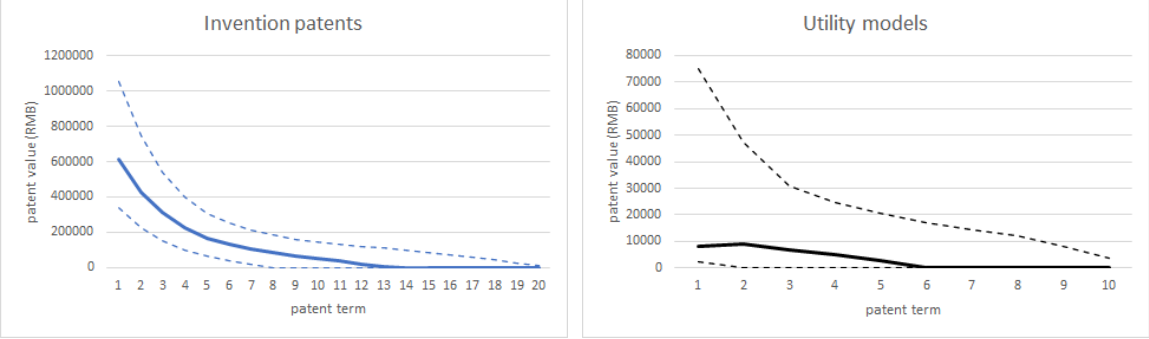


Figure A.6: Patent values at 10p, median and 90p after the patent reform

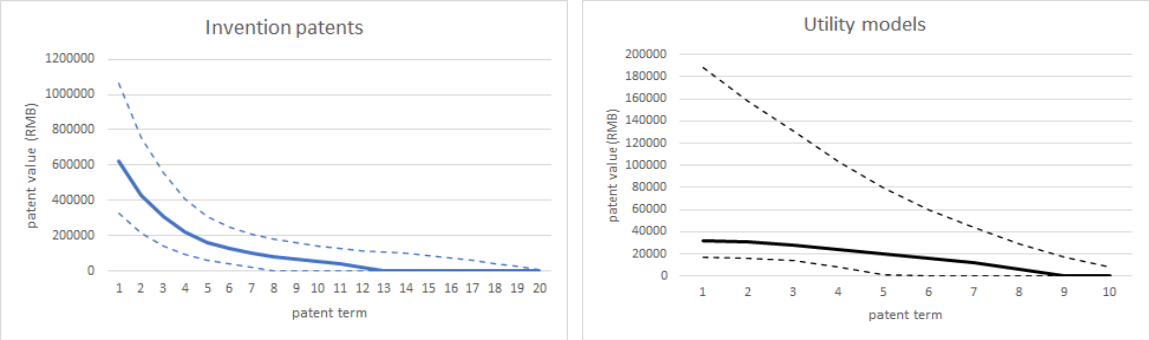
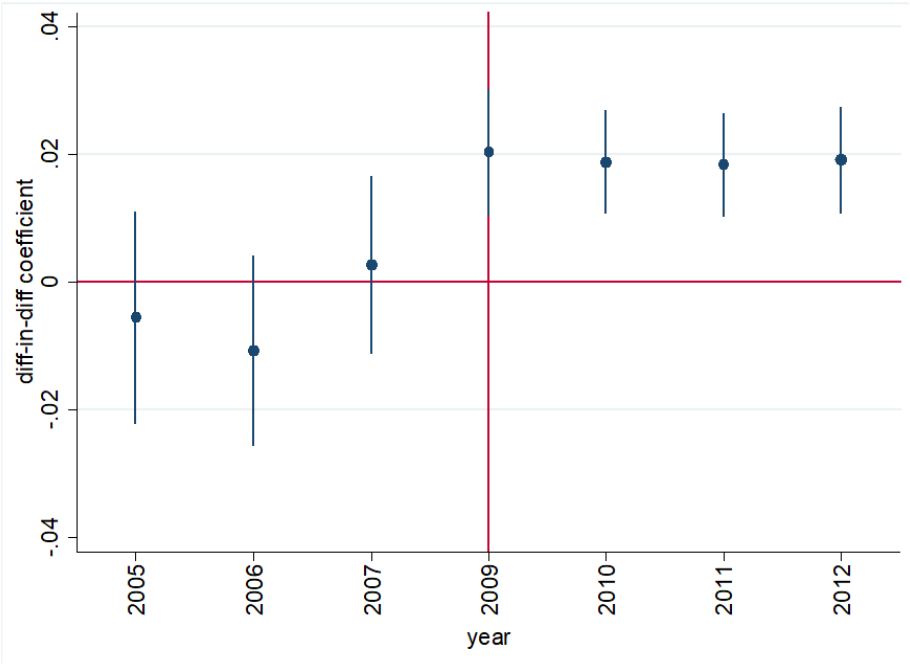


Figure A.7: The effect on the quality of invention patents (above-median)



Note: The x-axis shows the year; Y-axis shows the coefficients of the dynamic difference-in-differences estimation. "Treated" group is the group of industries with higher-than median ratio of litigation occurrence before 2009. The dependent variables is the ratio of the number of invention patents whose quality is above median by filing year and IPC classes over the number of invention patent applications filed by the focal firm at year t. 2008 is set as the baseline year, thus omitted. Vertical lines show the 95% confidence intervals for point estimates.

B Robustness check on the MLE method

To ensure the maximum likelihood estimation could produce robust results, I run a simulation exercise to test how accurate the estimated parameters could be using this method. Specifically, I generate two sets of key parameters- γ,σ,α,θ, l_0- for invention patents and utility models, respectively (Table A9). Then I simulate 1000 utility models and 1000 invention patents with these parameters. The rest parameters of the model are calibrated following the same procedure introduced in section 4. After getting the two simulated data sets, I employ the same MLE method described in section 4 to estimate the key parameters. Given the stochastic components of the model, I run the estimation for 50 rounds for each data set [28].

Results are shown in Table A9. First of all, for the two types of patents, the medians of all parameters are almost the same to the true parameters I use to generate the data sets, suggesting that medians could be the statistics for parameter estimation. Furthermore, the 95% confidential intervals of estimated parameters seem not to be too far away from the median. This suggests that the parameter estimates by the maximum likelihood method yields numbers sitting at the center of the distribution of the estimated parameters, even for a small sample. In sum, this robustness exercise helps to confirm the reliability of the maximum likelihood method, at least for the sample and formal model I develop in section 3.

C Patent grant ratio adjustment

I introduce the method of calculating the grant rate which is used to estimate the expected patent value in Table A3. Typically, innovators make this type of comparison when they need to decide which type of patents to patent [29]. That said, the comparison on patent valuation needs to consider the possible failure of being rejected by the patent examiner [30]. Specifically, since utility models do not go through rigorous examination process, I assume their grant rate is 1. By contrast, filing an invention patent bears certain risk of being rejected. I calculate the invention grant rates using IncoPat dataset for the period of

[28] More rounds of simulation will certainly produce more accurate results. Therefore, the results from 50-round estimation provide a "lower-bound" for our judgment on the accuracy of the estimates.

[29] In China, utility models are typically considered as "small inventions"- a substitute for invention patents with fewer inventive features. Therefore, innovators who decide to patent their inventions usually face the choice of filing an invention patent (slow, uncertain but broad) or a utility model (quick but narrow).

[30] I assume that the invention has already been done when innovators make the decision of which type of patents to choose. Therefore, the innovation cost is sunk and not included into this back-of-envelope calculation.

2001 to 2008 (before patent reform) and the period of 2009 to 2012 (after patent reform). To mitigate the potential truncation problem [31], I calculate the patent grant rate among patents that have already been granted. While the composition of renewed patents might be very different among patents filed in early years and patents filed in latter years, I could still observe all rejection decisions made on these patents. Thus, I calculate the grant rate as $\frac{\%rejected}{(\%rejected+\%renewed+\%expired)}$, where $\%rejected$ are the percentage points of rejected patents among all patents and $\%renewed$ and $\%expired$ are defined in similar way. The grant rates of invention patents are 0.13 and 0.19 for patents filed during 2001 to 2008 and patents filed from 2009 to 2012, respectively. The slightly higher patent rejection rate after 2009 reflects the tightening in patent examination criteria imposed by the 2009 patent reform.

D Alternative model and parameter calibration

To test the sensibility of the major results to the modeling and parameter estimation strategy, I explore an alternative empirical approach in this section. For the modeling part, it mostly resembles the model introduced in section 3. Most changes are in the parameter estimation part. Instead of estimating five parameters, I estimate seven in this alternative setting. Apart from the parameters for estimated in the model from the main text- γ, the tech depreciation rate, σ, the variance of exogenous shock to patent value, α, the position parameter of the distribution of patent initial value, θ, the share of profits extracted by the patent owner if the infringement is tolerated and l_0, the peak infringement hazards- I incorporate c, the litigation cost, and β, the shape parameter of the distribution of patent initial value, into the vector of parameters for estimation. Moving the litigation cost from the parameter for calibration to the parameter for estimation reduces stochastic component of the model but tends to average off heterogeneity of litigation cost among patents. The rest part of the empirical strategy is the same as the one in the main text, including the robustness test to confirm the feasibility of the MLE method, using global search algorithm to find the initials and the way to construct confidential intervals. I run 300 rounds of MLE estimation to pin down the final values of the parameters.

Table A7 reports the point estimates and the 95% confidential intervals. For γ, σ and l_0, both the magnitude and pattern of the estimates from this alternative model resemble those estimated from the five-parameter model of the main text (Table 3), which confirms the robustness of the main results for these three parameters. As for α, the parameter governing the distribution of initial patent value, the estimate of invention patents from the

[31] Patents in later batch of cohorts are less likely to exhibit the full patent life cycle in the data I collect. For example, patents filed in 2012 tend to have fewer patents not renewed than patents filed in 2001

seven-parameter model is lower than that estimated from the five-parameter model, but the parameter estimate of utility models is larger compared to the five-parameter model. Put differently, the gap of the initial patent value between invention patents and utility models seems to be narrower in the seven-parameter model, which could be driven by the fact that this model fixates the litigation cost to a parameter and thus reduces the potential variation within the patent valuation. The other difference in the parameter estimates resides in θ, the share of profits extracted by the patent owner when the infringement is tolerated. The estimates of the seven-parameter model are around two times as large as those of the five-parameter model, for both invention patents and utility models. Though the magnitudes of these parameters are bigger, the general pattern- the relative ratio of θ among invention patents to θ among utility models- remains.

There are two parameters not estimated by the five-parameter model- litigation cost c and the shape parameter of the gamma distribution β. For litigation cost, the invention patents bear higher cost than utility models, as expected; however, the magnitude of the litigation cost is around two-third of the upper bound of the range for damage awards. This implies that the litigation costs could be too high relative to the expected awards from patent remedy, which are consistent with the extremely low litigation rate observed in China. Moreover, the estimates of β for invention patents and utility models are close and resemble to the level I set up in the five-parameter model, further corroborating the robustness of this parameter in the main-text model.

Table A8 shows the simulated first-period patent value of the *de facto* statutory damage awards doctrine, the "benchmark" scenario of UE or LP doctrines and scenario after the 2009 patent reform. Comparing with the results in Table 4, main findings of the five-parameter model still hold. First, the valuation of patents under the statutory damage awards and benchmark scenario are similar in the seven-parameter model, confirming the main finding that the statutory damage awards doctrine before 2009 seems to generate appropriate level of patent value. With a closer look, though, the valuation of utility models seems to be slightly higher than that from the benchmark scenario, suggesting that the utility models have already been over-compensated, though slightly, before 2009. This is consistent with the main finding from the five-parameter model that the litigation rates of utility models before 2009 are higher than those estimated from the benchmark scenario but the litigation rates of invention patents before 2009 are lower than the benchmark level. Second, when comparing the valuation under the scenario before 2009 and that after 2009, the general pattern from the five-parameter model still holds- the valuation of utility models is enhanced to a larger extent than that of invention patents, though the valuation of invention patents is also boosted according to this seven-parameter model. Specifically,

the average value of utility models after the 2009 patent reform is almost 10 times as big as that before 2009 whereas the average value of invention patents after the 2009 patent reform is merely 2.8 times as big as that before 2009. Taken together, both the parameter estimates and simulation exercises on patent valuation using the seven-parameter model generates results largely consistent with the findings of the five-parameter model reported in the main text. Therefore, I confirm that the main findings are not sensitive to the modeling and estimation strategy.

E Descriptive Statistics of data used for structural estimation

Table A1 shows the summary statistics of sampled patents. Prior studies usually consider the number of claims, technological areas (usually identified by IPCs), foreign destinations of family patents and inventors as measures for patent value (Allison et al., 2003; Lanjouw et al., 1998; Lanjouw and Schankerman, 1997). From this perspective, invention patents seem to be more valuable than utility models: both litigated and non-litigated invention patents have significantly larger number of claims, foreign destinations of family patents, inventors and IPCs than utility models, litigated or non-litigated. This pattern is featured, in the model, of the positions of distributions of initial value of the two types of patents: the gamma distribution of invention patents is to the right of that of utility models (Figure A.1).

If we compare litigated and non-litigated patents within each type of patents, however, the summary statistics provide a nuanced picture. Prior studies (Allison et al., 2003; Harhoff and Reitzig, 2004; Lanjouw and Schankerman, 2001), which mostly focus on mature patent systems in the Europe and U.S., illustrate that litigated patents tend to be more valuable compared with non-litigated patents. For instance, litigated patents are featured of wider legal breadth (larger number of claims), bigger international influence (more foreign destinations of family patents) and more intellectual inputs (more inventors). My sample of invention patents, however, exhibits a different pattern: litigated invention patents tend to have *narrower* legal breadth and international coverage (fewer claims and foreign destinations of family patents), and they are produced by *fewer* inventors. Plus, the likelihood for litigated invention patents to be traded (33%) is lower than that of non-litigated invention patents (45%) on average. Normally, patents of external value will be more likely to be traded. Therefore, these patterns indicate that invention patents that have actually been defended against infringement in court might *not* be the most valuable patents. This seems to be consistent with proposition 1: when the damage awards are limited within a range,

patents with values beyond a certain range are less likely to be litigated.

The model also implies that as patent value decreases, this "adverse selection" pattern might be ameliorated. This intuition seems to be supported by the summary statistics of utility models. Being less valuable than invention patents, utility models will, as the model predicts, be more likely to exhibit the pattern consistent with the literature that valuable patents will be more likely to be litigated. This is because it is likely the entire distribution of the valuation of utility models falls below the threshold imposed by the upper bound of the damage awards so that the pattern is not distorted by the truncation. Panel C and D of table A1 confirms this prediction. Both the number of claims and the number of foreign destinations of family patents for litigated utility models are slightly larger, rather than smaller, than non-litigated utility models. The likelihood of patents being traded for litigated utility models (16%) is significantly higher than that of non-litigated utility models (4%). Though litigated utility models still have fewer IPCs and inventors than non-litigated counterparts, the gap is much smaller than the gap between litigated and non-litigated invention patents.

It is not surprising that the invalidation likelihoods of litigated patents, of both types, are significantly higher than those of non-litigated patents. Invalidation is a legal procedure that allows any individual or organization to challenge the validity of a patent granted. Thus, invalidating the disputed patents is a common strategy employed by the defendant in patent infringement lawsuits, which, in return, leads to a high invalidation likelihoods of litigated patents.

Figure A.2 shows distributions of the number of years from litigated patents being filed to the time the first infringement lawsuits was issued. The graph on the left is the distribution of litigated invention patents: most litigated inventions was litigated within 15 years since the patent filing year; and 7 years is the mode. On the other hand, litigated utility models have a much shorter cycle (graph on the right): most cases were filed within 6 years since the patent filing year and the mode is 3 year.

Figure A.3 shows the distributions of patent renewal terms for sampled patents. Red lines are litigated patents and blue lines are non-litigated patents. The literature suggests that the longer a patent is renewed, the more valuable the patent tends to be (Lanjouw and Schankerman, 1997; Pakes, 1984; Schankerman and Pakes, 1985). Thus, Figure A.3 also indicates the distribution of patent value. The graph on the left illustrates the pattern of invention patents. Litigated invention patents do have a slightly "thicker" tail than non-litigated inventions, indicating that more litigated patents were renewed for longer time than non-litigated patents. However, it is also evident that more non-litigated patents are

seen around the hump of the distribution than litigated patents. This seems to suggest that the litigated and non-litigated invention patents are different in renewal term but the difference is not significant. Nevertheless, the pattern of utility model renewal is different. The graph on the right shows that the distribution of litigated utility models is to the right of that of non-litigated utility models. This indicates that the majority of litigated utility models are more valuable than the majority of non-litigated utility models. Therefore, Figure A.3 further corroborates the pattern we have observed in the summary statistics: for the type of patents that tend to be more valuable (e.g. inventions), valuable patents are less likely to be litigated.