# Losses from Trade: The Case of China's Pro-innovation Subsidy Program

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**Abstract**

The largest subsidy program for industrial innovation in China (InnoCom) appears to raise the quantity of patents but lowers patent quality. Importantly, gains from patent trade - emphasized in the existing literature - appear to be more than offset by trade-enabled losses in welfare. Patent trade creates two sources of efficiency loss: (a) firms not eligible for subsidy may produce low-quality patterns which they sell to subsidy-eligible firms, and (b) firms that are subsidy-eligible but low-value users of patents may buy them from high-value but subsidy-ineligible users. The estimation of our structural model suggests that the overall welfare effect of the program is negative, and the trade-enabled welfare losses are substantially greater than the direct loss from subsidy-eligible firms producing low-quality patents.

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# 1 Introduction

The idea that patent trade improves welfare seems intuitive and is an application of an old and powerful ideas in economics that trade generally improves welfare. In particular, when initial innovators and best users of a patent are not the same entities, patent trade can eliminate the initial mis-allocation of innovations (see Akcigit et al. (2016); Serrano (2010)). Separately, recognizing that offering a temporary monopoly through patent protection may not be sufficient, most countries also provide a direct subsidy to innovation including tax deduction for patentable innovations.[1] In this paper, we study possible welfare losses enabled by patent trade in such subsidy programs targeting patents and other innovation outcomes directly. With the 2008 policy shock as an important source of our identification, we pay attention to how different types of firms react differently to the policy shock. We use data from the largest pro-innovation program in China, the InnoCom program, to quantify these effects.[2]

The InnoCom program offers a reduction in the corporate income tax by 40 percent (or a reduction in the corporate income rate from 25 percent to 15 percent) to eligible firms in eight designated industries that the government regards as "industries of future".[3] A major change in 2008 places an explicit link between the count of an applicant firm's patents and other IPRs to its success in receiving a subsidy. An important feature of the program is that subsidy-competing firms can use patents bought from other innovators to qualify for the subsidy, including those from outside the designated industries. Since the subsidy aims to promote commercializable innovation, it appears to be beneficial that the program can inspire many more firms to pursue innovation including those not directly applying for the

[1] A type of subsidy with growing popularity is called "patent box", which is a term for the application of a lower corporate tax rate to the income derived from the ownership of patents. This instrument has been introduced by more than 50 countries since 2000. This tool is different with the widely used instrument: R&D tax credit. The latter one is an ex-ante incentive targeting a firm's innovation input, whereas the first one is ex-post and will only be used when innovation has been patented.

[2] Figure 1 plots the central government's annual budgets of various Chinese pro-innovation policies in 2015. As we can see, the budget of InnoCom program dwarfs other pro-innovation programs.

[3] These eight industries are the pharmaceutical manufacture (CSIC 27), the special equipment manufacture (CSIC 36), the transportation equipment manufacture (CSIC 37), the communication equipment & computer manufacture (CSIC 40), the precision instrument manufacture (CSIC 41), computer service (CSIC 61), software service (CSIC 62) and environmental protection industry (CSIC 80).

subsidy, which is considered a desirable outcome of the program.[4]

In this paper, we show that such feature may introduce a significant welfare loss since bureaucrats usually can only count patents but cannot differentiate quality. Importantly, allowing patents acquired through patent trade may amplify the welfare loss by spreading subsidy-induced production of low quality patents from subsidy-competing firms to a bigger set of firms.

It is generally hard for government officials to discern the true quality of an innovation. Subsidy programs targeting ex-post innovation outcome (i.e. patents) in practice are often conditional on some quantity indicators such as the number of patents a firm holds.[5] The InnoCom program design is inline with this argument. The bureaucrats use a grading system to decide which firms to subsidize. Regardless of the source of innovations (in-house or externally acquired), the more IPRs a firm holds, the greater the likelihood of receiving a subsidy.[6] However, once the IPRs count reaches 6, additional IPRs would not increase the grade any more. We show in our data that the chance a firm can get the subsidy crucially depends on whether its IPRs reaches to 6, rather than IPRs quality.

We are able to obtain several unique firm-level and patent-level data sets associated with the InnoCom program in a large city and will focus our empirical work on that city. We separate all IPRs (patents/software) holders into two groups: subsidy-competing-enterprises (SCEs), which satisfy the basic eligibility of the InnoCom program (such as having a sufficiently high ratio of R&D expenditure to total expenditure and within eight targeted industries), and non-competing-entities (NCEs), which are firms, individual innovators, or other institutions that are not eligible for the program (such as with a low ratio of R&D/total expenditure or outside the eight designated industries). For each type of entities, we construct their IPRs portfolio and merge it with their financial information (conditional on their being

[4]This is not the unique feature of InnoCom program. When subsidizing patents, it is common to allow for acquired patents through patent trade to also qualify for subsidy as those developed in house. For example, the patent box policy in more than 10 countries do not distinguished purchased versus self-developed patents for the purpose of subsidy.

[5]For instance, since the patent box subsidizes revenues generated from patents, it may encourage firms to patent solely in order to receive subsidy. As Klemens (2016) points out, "The patent box gives new life to zombie patents".

[6]In the designated industries, IPRs generally include patents and software copyrights.

firms). We know more information about patents than software copyrights, such as whether patents have been traded (including both buyer and seller information) or renewed. Given the relative lack of information on software, we focus on patents throughout the paper.

From the data, we document several salient facts about the subsidy program. First, while the growth in the quantity of patents accelerated after 2008, the quality of patents declines significantly. We measure patent quality by patent renewal decision by firms, forward citation count, and an estimated contribution of patents to firm productivity. All three proxies points to a decline in patent quality after the 2008 policy shock.

Second, an analysis of the proprietary data on bureaucrats' scores on InnoCom applicant firms reveals that the bureaucrats count the number of patents and other IPRs but cannot tell the difference in the quality of the patents. That is, while a higher number of patents pushes up the firm score, a proxy for patent quality by their ex post citation count or ex post renewal rate does not predict a higher score. In addition, we confirm that the bureaucrats do not discount patents purchased through patent trade. That is, whether a patent is purchased or developed in house does not affect the score.

Third, for firms competing for the InnoCom subsidy, there is an increase in the number of patents they hold (beyond a linear trend predicted from the pre-2008 data). Importantly, the increase is especially great for those firms whose initial number of the IPRs is fewer than six. Our identification will explore this feature of the program: since the InnoCom has a numerical kink in the evaluation scoring formula - the subsidy does not increase for firms with the IPRs count going beyond six. (The last point is also confirmed in our analysis of the bureaucrats' scores on subsidy applicant firms.)

Fourth, the average quality of the patents held by subsidy-competing firms has declined following the InnoCom program. In addition, we find that the quality decline is more pronounced for those firms with a low pre-2008 IPR count. This suggests that such firms acquire low-quality patents in order to compete for a subsidy.

Fifth, the InnoCom program has changed the patterns of patent trade. After the 2008 policy shock, the annual patent trade has increased by 18%. Patents sold by the non-subsidy-competing firms to those competing for a subsidy, especially those with an initially low IPR count has risen as a proportion of all patent sales. The quality of the traded patents has declined. The quality decline is especially pronounced for those patents developed by non-subsidy-competing firms sold to subsidy-competing firms. This suggests that the subsidy program, together with patent trade, has altered the incentives faced by firms not directly competing for the subsidy.

Inspired by these facts, we build a structural model to quantify the welfare impact of the InnoCom program. There are three channels that the subsidy policy can affect the welfare (besides a knowledge spillover from innovations). The first is a direct effect - the SCEs may be induced to devote resources to produce low-quality patents for subsidy competition that do not otherwise raise productivity. The second is a trade-induced spillover effect - the subsidy program has encouraged NCEs to also devote resources to produce low-quality patents that can be sold to SCEs. In other words, patent trade helps to spread a wasteful incentive to firms not otherwise competing for a pro-innovation subsidy. The third is a trade-enabled mis-allocation effect - the subsidy may induce a socially inefficient trade that assigns a patent from a high-value NCE user to a low-value SCE user. Both the second and third welfare loss are enabled by patent trade.

From the calibration of the structural model, we find that InnoCom has greatly increased low-quality patents as a share of total patents. The program has created a welfare loss by more than 2 billion RMB per year in our sample city, which is about 59% of the subsidy budget. (That is, every dollar spent on subsidizing innovation through this program yields a loss of 59 cents for the society.) Our model also suggests that trade-enabled welfare loss is quantitatively important - augmenting the total welfare loss without patent trade by 50%.

In the last two decades, very few countries can rival China in terms of the rate of growth in patent count. Even though China's income per capita is still below the world average, its annual count of new patents, granted by domestic patent office, has exceeded all countries in the world since 2019.[7] Thus success or distortions in China's pro-innovation program can have a significant aggregate implication for the world as well as for China.

Our paper contributes to three sets of literature. First, While the existing literature on patent trade focuses on its benefit, this paper highlights a potentially "dark" side of the

[7]https://www.reuters.com/article/us-usa-china-patents/in-a-first-china-knocks-u-s-from-top-spot-in-global-patent-race-idUSKBN21P1P9.

trade. In the existing literature, patent trade improves welfare as it allows firms to specialize in what they are best at. For instance, Gans and Stern (2000) and Serrano (2010) analyze the gains from patent trade when different firms have a different ability to commercialise the patents. Galasso et al. (2013) study the potential of patent trade to resolve commercial disputes without resorting to courts. Since there are gains from trade, frictions in trade may reduce welfare. Shapiro (2010) and Lemley and Shapiro (2005) argue that patents are reallocated to entities that have the capacity to extract excessive royalty fees by holding up rivals. Akcigit et al. (2016) and Serrano (2018) highlight search frictions in the patent trade market. In most cases, lower frictions in trade raise welfare. In our case, lower frictions in patent trade reduce welfare due to distortions in patent subsidy programs.

Second, the paper contributes to the literature on the design of pro-innovation subsidy programs. Bloom et al. (2019) reviews a menu of common policy incentives and argues that the efficiency of various policies are very different. Subsidies in the tax code is common, especially for R&D activities. Bloom et al. (2002) and Wilson (2009) study the impact of the tax credit on the level of R&D investment in US. A special feature of the InnoCom policy is that it targets patents and other IPRs directly not just R&D expenditure shares. Interestingly, many EU countries use patent boxes (a tax cut on revenue linked to a patent), which bears some resemblance to the InnoCom policy. Although different countries have various designs of patent boxes, the literature find that the subsidy program provides a chance for firms manipulate stated revenues from patents to minimize their tax burden and may not be efficient (Griffith et al. (2014); Gaessler et al. (2021)). Our paper shows that patent trade can augment a welfare loss in this context by incentivizing resource waste in producing low-quality patents by firms not otherwise competing for a subsidy. [8]

Third, we enrich the literature on Chinese pro-innovation industrial policy by highlighting important new channels for welfare losses from the subsidy programs. Wei et al. (2017) emphasize a direct channel of welfare loss: while innovation come mostly from non-state-owned firms, the pro-innovation subsidies go mostly to state-owned firms. Chen et al. (2021) document the direct resource waste by firms competing for subsidies from re-relabelling non-

[8] Bösenberg and Egger (2017), Ciaramella (2017) and Gaessler et al. (2021) find that the patent box policy generally stimulates patent trade. Importantly, they do not study possible welfare loss arising from patent trade.

innovation expenditures as R&D expenditure. König et al. (2020) study how frictions in input markets affect innovation. While these channels are important, we analyze new channels that are also important in such programs but not yet studies in the literature: given a lack of ability by bureaucrats to distinguish patents quality, patent trade can significantly amplify the loss. Since linking subsidy to some quantity indicator of innovation and a lack of ability by bureaucrats to differential quality are common features to many pro-innovation subsidy programs around the world, our analysis might inspire a fresh examination of pro-innovation industrial policy from this new angle.

The paper is organized as follows: Section 2 introduces the background of the InnoCom program, especially the 2008 policy shock, and the data sets used in the paper. Section 3 documents five salient features of the subsidy program. These data patterns will motivate the setup of our model that is laid out in Section 4. Using the calibrated result, Section 5 performs a number of counterfactual analyses. Finally, Section 6 concludes the paper.

# 2 Background and Data

## 2.1 The Chinese InnoCom Program

The InnoCom program is designed to encourage innovation in what the Chinese government considers the "industries of future." A major change in the program design introduced in January of 2008 makes an explicit connection between the number of patents and other significant intellectual property rights of an applicant firm and the chance of obtaining a subsidy. A successful applicant firm receives a subsidy in the form of a substantial reduction in corporate income tax (from 25% to 15% for three years). Firms can apply for a new award once an existing one expires.

Firms in eight qualified industries with high R&D intensities (which we call SCEs) can apply to the program.[9] A major policy change in 2008 makes an explicit link between the number of patents and other IPRs an applicant firm owns at the time of application and its success in receiving a subsidy. Importantly, these patents can be acquired through patent

[9] Appendix A lists all the eligibility conditions to participate this program.

trade. The motivation by the architect of the policy may be to inspire more innovation not only in the targeted industry but in other industries as well. In other words, it may be considered desirable for a subsidy program in some targeted industries to spill over to innovation activities in other industries. (The patent box policy - a pro-innovation subsidy program in the European Union, Australia, Britain, Canada, and other countries - also permits patents acquired by subsidy-eligible firms through patent trade.)

In determining which firms will receive a subsidy, a government committee (an office jointly established by local tax department and local bureau of science and technology) evaluates applicants by assigning numerical scores based on a count of patents and other IPRs (up to 30 points), an ability to manage R&D (30 points), an ability to commercialize science and technology innovations (20 points), and growth potential (20 points). A subsidy (tax reduction) is awarded to a firm if it receives at least 70 points. While the last three categories are subjectively assessed, the patent count appears objective. Table A3 in Appendix A explains the grading scheme in this category. For the scoring purpose, one invention patent is considered equivalent to 6 utility or design patents. If the firm has one invention pattern or 6 non-invention patents (or other IPRs), the firm will get an "A" in this category, and receive 24-30 points. When the IPRs count decreases, its score will be marked down from letter grade "B" to letter grade "E". Importantly, an applicant firm would receive the full 30 points when its IPRs count reaches 6. Any higher count would not improve its chance of receiving the subsidy. On the other hand, fewer than 6 IPRs can noticeably reduce its chance of receiving a subsidy. A patent used in the application needs to be relatively new; bureaucrat only counts those granted within 3 years.

On average, the program each year provides a subsidy to over over 5,000 firms, about 60% of all SCEs, or 20% of all firms in the eight industries. The subsidy (tax reduction) is about 0.62 million RMB per firm-year, or a total subsidy budget of 3.4 billion RMBs for that city in our sample.

We conjecture that bureaucrats are not able to tell the quality of the patents used in application. Some anecdotal evidence suggests that due to the InnoCom subsidy, many agents have emerged to sell service to help firms applying for a subsidy. These agents advertise that they will not only prepare the application documents but also help to find additional patents and other IPRs to boost the chance of obtaining a subsidy. Using our data on bureaucrats' scores on applicant firms in a large city, we will confirm that the bureaucrats do not give high quality patent a higher score. We will also confirm that bureaucrats do not value in-house patents more than externally purchased ones.

### Comparison with patent box policy

One of the most popular and significant pro-innovation programs in other countries, including most European Union nations, Australia, Britain and Canada is a patent box. Similar to InnoCom, the subsidy in a patent box program also takes the form of a reduction in the tax rate. Furthermore, it is also linked to some outcome indicators of local innovation activities. The details between the two programs and across different patent box countries can differ. In general, a patent box program would offer a reduced tax rate to the part of a firm's value added that can be attributed to a patent that the firm owns.

The link of a patent to a part of a firm value added in the subsidy program can be interpreted as an attempt to ascertain the quality of a patent (i.e., a higher level of firm profit is thought to be associated with a higher quality of patent). However, any partition of a firm value added to a part attributed to a patent and a remainder involves some arbitrariness and is potentially subject to manipulation. This has been pointed out by (Griffith et al. (2014)). In addition, the level of firm profit linked to a patent can also reflect the degree of industry concentration and other factors not related to patent quality. For this and other reasons, Bloom et al. (2019) does not regard patent box as a socially efficient tool to incentivize innovations.

Importantly, Gaessler et al. (2021) report that in ten out of their 15-country sample, patents acquired through patent trade are equally eligible for a patent box subsidy. Bösenberg and Egger (2017) and Ciaramella (2017) find that a 1% increase in the tax subsidy in the patent box induces a 10% increase in patent trade. When a country imposes additional restrictions on externally acquired patents, such as in-house augmentation of the invention, the effect on patent trade is smaller or not significant. If the goal of a subsidy program is to encourage local innovation in general, rather than innovation of a particular firm or industry, this feature seems sensible. How this feature or patent trade in general may exacerbate distortions has not been studies in the literature.

The Chinese program's link of a subsidy to the number of patents and other IPRs owned by an applicant firm rather than firm profit may be motivated by a desire to avoid ambiguity or manipulation in how to partition firm profit. Its requirement that only relatively new patents (those granted within three years) will be counted in the subsidy application review may be designed to encourage new innovation and avoid potential zombie patents that could be present in a patent box program.

The Chinese program treats local patents acquired by the applicant firms through patent trade in the same way as in-house patents. Similar to other countries with a similar program design feature, it is likely motivated by a desire to encourage local innovation in general, beyond those by particular firms or industries. One novel contribution of our paper is to study possible efficiency losses that are augmented by patent trade.

## 2.2 Data

While InnoCom is a national program, its implementation is carried by local governments. We study the program in a city for which we have the requisite data. We utilize three data sets: administrative data about the firms from their tax records, patent assignment data and software assignment data. The first data records firm-year level financial information (such as sales, employees, assets and etc.) and the industrial classification of the firms. The second and third data record the ownership of patents and software copyrights and any transfer (i.e., assignment) of the ownership through trade. Using this information, we construct the IPRs portfolio for each firm in each year. Importantly, we know more information about each patent, including whether it is renewed or not, its citation count, and identities of the buyer and the seller if a patent is sold.[10] Unfortunately, we do not have similar information on trade in software.

We use firm names to link up firm-level records in different data sets. To clean and standardize firm names, we follow these steps: (1) We trim all special symbols and punctuation marks that are not letters, characters or numbers. (2) We remove various corporate

[10]In China, the patent needs to pay a renewal fee every year before the invalidation date. The fee depends on patent age. Overall, it is about 1,000 RMB per year.

form, such as "limited corporation" or "subsidiary". (3) We convert all full-width letters and numbers into half-width ones. (4) All lower cases are changed in to upper cases.

Using the firm names filtered by the above steps, we merge the IPRs assignment information with the list of the subsidized firms. The overall matching performance is good. In particular, we can find 94% of firms that receive an InnoCom subsidy in 2008 in the patent assignment data. This ratio is comparable to Hu and Jefferson (2009). In the end, we have 90,539 IPRs holders (including patent holders and software copyright holders) in the sample city from 2005 to 2012. In addition, if holders are firms, we have their financial information from 2007 to 2011.

We then separate the IPRs holders into two groups: subsidy-competing-enterprises (SCEs), which satisfy the basic eligibility of the InnoCom program, and non-competing-entities (NCEs), which are firms, individual innovators, or other institutions that are not eligible for the program. Overall, IPRs holders in our sample can be grouped as Figure 2.

# 3 Salient Data Patterns

In this section, we document a number of salient facts related to the InnoCom program, which will guide our subsequent model development. Since the InnoCom program treats an invention as equivalent to six other IPRs, we convert every invention patent to six other patents in our analysis.

## 3.1 While the quantity of patents has increased, the quality has declined

The growth of patents in China can be seen from the blue-circle line in figure 3, which plots the number of new patents per firm by year (left y-axis). The growth rate accelerates after 2008. The new patent count per firm includes both self-developed and purchased patents. The red-square line plots the share of external purchased patents (right y-axis). There is a noticeable jump in the share in 2008 from 1.2% to 2.8%. This figure suggests that the quantity of patents has not only been growing but has accelerated since 2008. Furthermore, patent trade is likely to have grown faster since 2008 as well.

We now look at patent quality which we gauge in several ways. Our baseline measure is the fraction of patents that are renewed three years after they are granted. Since renewing a patent requires an annual fee, the decision to renew reflects the owner's judgement of whether the patent is valuable or not.[11]. Figure 4 plots the 3-years-out renewal rates of both internal (self-developed) and external (purchased) patents granted within 2005 to 2012. The blue-circle line plots the renewal rate of in-house patents (those that are not traded three years after being granted). Their renewal rates are around 80% before 2008, but start to decline from 2008. Overall, it declines by about 10 percentage points within the data sample.

The purchased patents, tracked by the red-square line, exhibit a higher renewal rate than in-house patents. This may come from a selection effect: with a positive transaction cost in the patent market, only good enough patents can overcome a positive transaction cost. But even for these patents, the average renewal rate still decline after 2008. In other words, 2008 appears to be a turning point for the average patent quality.

Our second measure of patent quality is the extent to which subsequent patents cite it. In Figure 5, we plot the average 3-years-out citation count as a function of the year in which the patents are granted. We normalize the citation count in 2004 to be 0. Before 2008, the average citation count barely changes. After 2008, the citation count declines gradually. Hence we find a similar pattern as before: the average patent quality declines after 2008.

As a third measure of patent quality, we estimate the marginal contribution of an additional patent to a firm's productivity by regressing firm-level labor productivity (sales per employee) in a year on the number of newly obtained patents in the previous year, controlling for both industry and year fixed effects as well as firm location and ownership. To distinguish between the elasticity before 2008 and after 2008, we use a post-2008 dummy (inclusive) and interact it with the number of newly obtained patents. The result is reported in column 1 of table 1. We can see a difference in the marginal contribution of the patents to firm productivity. Before 2008, the labor productivity tends to increase by 4.1% following an additional patent. However, after 2008, the marginal contribution not only is smaller but

[11]Using patent renewal as a proxy for patent quality is first explored by Pakes (1986). A large literature follows this idea (such as Cornelli and Schankerman (1999), Lanjouw (1998), and Bessen (2008))

the point estimates suggest a decline by 0.9% (0.050-0.041).

In column 2, we control for firm fixed effects (which subsume the industry, location, and ownership dummies) and find a similar result. In this case, while the marginal contribution of patent ownership to firm productivity is not negative after 2008, it is smaller than before 2008 nonetheless. To summarize, while the quantity of patents has grown faster after 2008, the quality has declined on average.

## 3.2 Bureaucrats can count but cannot differentiate quality

We have access to the detailed evaluation scores made by the bureaucrats on all applicant firms that have received a subsidy in a large city in 2008. We will use the data to evaluate a number of questions. First, can the bureaucrats tell the difference between low and high quality patents? Second, do they care whether the patents are developed in-house by the applicant firms or purchased from other firms? Third, how much do they care about the quantity of patents?

We use two different proxies for patent quality: the 3 -years out citation count and the renewal rate in three years after being granted. To be clear, neither information is available to the bureaucrats at the time of reviewing a firm's application for an InnoCom subsidy. So we are examining if the bureaucrats have the ability to look for and analyze any soft information in the application process that help them to forecast the quality of the patents. If they are able to do that, we would expect their scores on the applicants to be correlated with the subsequent citation count or renewable rate. On the other hand, if bureaucrats are unable to tell the quality of the patents, then their scores would be uncorrelated with the average quality of the patents in an applicant firm's IPRs portfolio.

We regress the points an applicant firm receives on a measure of quality of the IPRs portfolio, controlling for the firm's observed characteristics (sales in 2007, ownership and industry) and means of IPRs count.[12] The regression sample is censored as only those firms that have succeeded in obtaining a subsidy are in it. However, for our purposes, the data censoring may not matter.

[12]Collected by the Municipal Science & Technology Commission of a large city, the data includes the grading information of the four categories, as well as other firm characteristics.

The results are reported in Table 2. The left hand side is the firm's point in the IPRs counts category (out of 30). In column 1, we see that that score tends to rise with more IPRs. However, once the IPRs count reaches six, additional IPRs do not raise the score significantly. (The points assigned to firms with six IPRs and those with more IPRs are the same statistically.) After controlling for the IPRs count, we see that the effect of higher quality patents in terms of a subsequent citation is statistically indifferent from zero.

In column 2, we measure the patent quality by the renewal rates three years after patent being granted and find similar results. That is, bureaucrats do not systematically assign a higher score to those firms with patents that will have a higher renewal rate.

In columns 3 and 4, we use firm's total points (the sum of the points across four categories) as the dependent variable, and re-run regressions similar to columns 1 and 2. Again, there is no evidence that the bureaucrats can tell the quality of the patents as they do not assign more points to those applicants with higher quality IPRs. It will be reasonable for applicant firms to infer that the patent quality would not affect their chance of obtaining a subsidy.

Another interesting regressor is in-house patents as a share of an applicant firm's total IPRs count. As this variable is never significant, this suggests that the bureaucrats do not distinguish between in-house and externally purchased IPRs. This validates our understanding of an InnoCom design feature that counts the IPRs that a firm owns, regardless of where they come from. (The mastermind behind the InnoCom program may reason that it is a good thing if the program can inspire innovation by firms that are not directly applying for an InnoCom subsidy.)

### 3.3 Subsidy-competing enterprises (SCEs) with a low initial IPRs count show a faster growth in patents

Since the likelihood of receiving a subsidy is much higher for an SCE with 6 IPRs than one with fewer IPRs, but does not increase further once it reaches 6 IPRs, the policy may encourage those firms with fewer than six IPRs initially to reach the count of six. Figure 6 confirms this conjecture. The left graph of Figure 6 plots the density of the IPRs of those SCEs in 2007, the year before the policy change. The right graph of Figure 6 plots the density of these firms in 2008. A notch point at six IPRs is clearly observed for 2008, the year when the policy change implemented, but not in the year before.

Is the change in the distribution of IPRs count generated by the InnoCom program, or some other unobserved shocks? Denoting $N_{it}$ as the number of newly acquired IPRs by SCE $i$ in year $t$, we run the following regression:

$$ln(N_{it}) = \alpha_1 D_{it-1} + \alpha_2 D(t \geq 2008) + \alpha_3 D_{it-1} \times D(t \geq 2008) + s_{it-1} + \mu_i + \epsilon_{it} \qquad (1)$$

where $D_{it-1}$ is a dummy which equals to 1 if both the count of IPRs in the prior year $IPR_{it-1} < 6$ and $\text{Invention}_{it-1} = 0$, and 0 otherwise;[13] $D(t \geq 2008)$ is a dummy that equals to one in 2008 and afterwards, and zero otherwise; $s_{it-1} = 1$ if firm $i$ has obtained a subsidy within the previous 3 years, and 0 otherwise; $\mu_i$ is a firm fixed effect that captures time-invariant firm heterogeneity, and $\epsilon_{it}$ is an iid random error.

While $\alpha_1$ captures any general time-invariant difference in the number of IPRs between the two types of SCEs, $\alpha_2$ captures any general increase in the number of IPRs after 2008 caused by factors common to all SCEs. The key coefficient of interest is $\alpha_3$, which measures the difference in the number of newly acquired IPRs between those SCEs with fewer than 6 IPRs initially and other SCEs. If those SCEs with a low IPRs count in the previous year have a stronger motivation to acquire more IPRs than the other SCEs already with 6 or more IPRs, we would expect $\alpha_0 > 0$. Note that the above specification cannot capture the total effect of the InnoCom program on SCEs, but only compares the difference between these two types of SCEs. Those SCEs with a high initial IPRs count are not a control group as they could respond to the policy change by trying to produce more IPRs and sell some of them to those firms with a low initial IPRs count.

Once approved, an InnoCom subsidy is given for three years. This means that those firms that have received a subsidy within three years would not need to apply again during this window. We use $s_{it-1}$ to account for possibly different incentives for such firms to increase IPRs. In the first column of Table 3, $\alpha_3$ is 0.13. This means that the SCEs with fewer than six prior IPRS acquire 0.13% more IPRs than other SCEs. In the second column, we change

[13]In all subsequent analysis, we convert one invention patent to six (other) IPRs.

the dependent variable to the number of newly self-developed patents.[14] We can see that these SCEs with fewer than six prior IPRs develop 0.04% more in-house innovation than other SCEs. As this number is smaller than $\alpha_3$ in the first column, it implies that these SCEs also purchase more IPRs from patent trade market than other SCES.

In the third column, we switch back to IPRs count. With the year fixed effects, all time-varying aggregate shocks that are common to all firms are controlled for. D($t \geq 2008$) is dropped as it is absorbed by the year fixed effects. Importantly, the estimate of $\alpha_3$ becomes even larger: those SCEs with fewer than six initial IPRs increase their IPRs by about 0.22% more than other SCEs.

To check whether the SCEs with exactly six IPRs and those with more than 6 IPRs receive similar scores, we add a regressor $D(IPR_{it-1} = 6) \times D(t \geq 2008)$ in the fourth column of Table 3. $D(IPR_{it-1} = 6)$ is a dummy, which equals to 1 if the firm $i$ has just 6 IPRs in year $t - 1$ and 0 otherwise. The new coefficient compares SCEs with 6 IPRs and those with more than 6 IPRs. As the coefficient on the new regressor is not statistically different from zero and $\alpha_3$ remains the same as before, this confirms the strong incentive for many SCEs to reach 6 IPRs to qualify for an InnoCom subsidy but not beyond.

To check for a possible pre-trend, we estimate separate $\alpha_3$ for each year and plot them in Figure 7. The circle-solid line represents the point estimates when the dependent variable is ln(IPRs count), and capped spikes represent 90% confidence intervals.[15] Before 2008, $\alpha_3$ is around zero, implying that annual addition of IPRs is similar between firms low or high initial count of IPRs. $\alpha_3$ begins to rise significantly above zero since 2008. That is, firms with a low initial IPRs count starts to add more patents than the other group after 2008. This pattern is consistent with column 1 of Table 3. Overall, $\alpha_3$ gradually increases since 2008. This implies that incentives to get more IPRs for SCEs with lower than 6 IPRs become stronger over time. A possible explanation of the gradual increase could be the reaction time. Since firms have a short reaction time in 2008, they may not find enough IPRs to apply for the program. So the increase of IPRs at the beginning may not be as large as the increase

[14]Note that for software, we cannot distinguish in-house innovation and external purchase copyrights.

[15]Note that we control dummies D($t \geq 2008$) and $D(IPR_{it-1} = 6)$. So we lose one year degree of freedom. The graph starts from 2006.

in the later years.

To confirm our conjecture on "time of reaction", we estimate $\alpha_3$ year by year but use ln(total patents) and ln(in-house patents) as the dependent variables, respectively. Figure 8 plot $\alpha_3$ of these two specifications. The circle-solid line represents point estimates when the dependent variable is the total patent count, and the red bar represents point estimates when the dependent variable is in-house patent count. Capped spikes denote the 90% confidence intervals. For the total patent count, the pattern is similar to Figure 7: the new patent count after 2008 is significantly higher for SCEs with low initial IPRs. In comparison, there is no significant difference between the two groups before 2008. This is consistent with our previous result that the 2008 policy change has encouraged firms to strive for six IPRs.

In comparison, the pattern for in-house patents is different. While it is similar between the two groups of SCEs before 2008, the in-house patent count for SCEs with IPRs lower than 6 is lower than SCEs with 6 or more IPRs. Then since 2009, SCEs with IPRs lower than 6 self develop more patents than other SCEs. In other words, consistent with our "reaction time" conjecture, SCEs in 2008 mainly rely on external patents to increase their IPRs to 6. Since 2009, they gradually catch up, and self develop patents as well.

### 3.4 The decline in patent quality after 2008 is more pronounced for those owned by the SCEs with a low pre-2008 IPRs count

As shown in Figure 4, the patent quality declines since 2008. If this decline is driven by the InnoCom policy change, in a similar logic as the previous fact, we would expect to see a more significant decline in the renewal rate of those patents held by the SCEs with low pre-2008 IPRs count.

Let indicator variable $V_{ikt} = 1$ when SCE $i$ chooses to renew patent $k$ in year $t$. If $V_{ikt} = 0$, then that patent is not renewed. We consider the following regression.

$$V_{ikt} = \beta_1 D_{it-1} + \beta_2 D(\mathrm{OY}_{ik} \geq 2008) + \beta_3 D_{it-1} \times D(\mathrm{OY}_{ik} \geq 2008) + s_{it-1} + X_{kt} + \mu_i + \mu_t + \epsilon_{ikt} \quad (2)$$

where $\mathrm{OY}_{ik}$ is the year that firm $i$ obtains the patent $k$. (If the patent is developed in-house, then it is the year of receiving patent approval. If the patent is purchased from outside, it equals to the year of purchase). $D(\mathrm{OY}_{ik} \geq 2008)$ is a dummy, which equals to 1 if the patent $k$ is obtained after 2008. $D_{it-1}$ and $s_{it-1}$ are defined in the same way as in equation (1). $X_{kt}$ is a vector of observed characteristics of patent $k$, including patent's age, industry classification, and type (invention, utility or design). $mu_i$ and $mu_t$ are firm and year fixed effects, respectively. $\beta_1$ and $\beta_2$ measure the differences in the renewal rates between treatment group, those firms with fewer than 6 IPRs in the prior year ($D_{it-1} = 1$), and the control group ($D_{it-1} = 0$), and before and after 2008, respectively.

The key coefficient of interest is $\beta_3$, which measures differential change in the renewal rate of the patents owned by the treatment group of firms after 2008, relative to the control group of firms. If additional IPRs are acquired for the purpose of competing for a subsidy, rather than for their intrinsic productivity-enhancing value, then the new IPRs are likely to be of low quality and would not be worth the renewal cost once the InnoCom review process is over. This would imply $\beta_3 < 0$. On the other hand, if the bureaucrats reviewing the InnoCom applications can identify the true quality of patents and take it into account in deciding which firms to award a subsidy, or if firms acquiring IPRs for their true scientific value for any other reason, then there may not be a relative decline in the quality of the patents. In that case, we may see $\beta_3 = 0$.

In column 1 of Table 5, $\beta_3$= -0.029 and is significantly different from 0. In other words, the patents owned by the firms with a low pre-2008 IPRs count are indeed less likely to be renewed after 2008 relative to those owned by the other group.

Patents of different vintage may have different quality for reasons unrelated to the InnoCom program. To account for this, in column 2, we include additional fixed effects for years of obtaining the patent. In this case, $\beta_3$= -0.045 and is different from zero at the 5 percent level. The quality difference in the patents acquired by different groups of SCEs become bigger. In other words, the reduced form evidence is consistent with the conjecture that those firms with fewer than six prior IPRs tend to acquire low-quality IPRs just to compete for a subsidy from the InnoCom program. Because many of these newly acquired patents do not have a high scientific or commercial value, firms often do not bother to incur an expense to renew them once the InnoCom application process is over.

In Figure 9, we estimate $\beta_3$ separately for each year to see if there is a pre-trend in the observed pattern. The circle-solid line represents the point estimates, and capped spikes represent 90% confidence intervals. Prior to 2008, the patent renewal rate by the SCEs with a low IPRs count is somewhat higher than the SCEs with more IPRs. This may suggest that the patents are more valuable to firms with a small number of IPRs. However, after 2008, we see a reversal: patent renewal rate by the SCEs with a low pre-2008 IPRs count becomes significantly lower than the other group.

## 3.5 The patents sold by NCEs to those SCEs with a low initial IPRs count exhibit the fastest growth in quantity but also the most significant decline in quality.

If purchased patents are not recognized in the InnoCom application process, then those firms that do not satisfy the minimum eligibility conditions for a subsidy (NCEs) would not be affected by the pro-innovation subsidy policy. However, since patent can be traded, and the purchased patents can be used in SCEs' application for an InnoCom subsidy, the pro-innovation industrial policy can generate additional effects beyond a direct effect on the SCEs. Indeed, while the patent trade grew about 40% a year before 2008, the growth rate jumps to 76% a year after 2008.

To see the contribution of patent trade from different seller-buyer types, we separate the trade to 9 groups. Define a trade belongs to group 1 ($g = 1$) if both the buyer and seller are SCEs with fewer than 6 prior IPRs; Define a trade belongs to groups 2 or 3, if both the buyer and seller are SCEs with more than 6 IPRs, or both are NCEs, respectively. We define similarly groups 4 to 9 considering all possible combinations of the seller's and buyer's types.

Table 4 reports the share of patent trade of each group of buyer-seller type in 2006, 2007 and 2012. While the shares in each group are quite similar from 2006 to 2007, the pattern is different in 2012. Specifically, patents sold by either NCEs or SCEs with a high initial IPRs account to SCEs with with a low initial IPRs count grows sharply from 2007 to 2012. At the same time, patent sale by SCEs with an initial IPRs smaller than 6 declines significantly. These findings are consistent with the incentives of the InnoCom program: the policy gives those SCEs initially with fewer than six IPRs a strong incentive to purchase patents externally and discourages them to sell patents. This also means that the NCEs now face a new demand for their patents from the SCEs.

It is informative to also look at the differential quality of traded patents depending on who is selling to whom. We separate all buyers (and sellers) into three groups: those SCEs with a low initial IPRs count, those SCEs with a high initial IPRs count, and the NCEs. This yields 9 seller-buyer types. Note that those patents purchased by SCEs with a low initial IPRs count presumably include many used primarily to qualify for a InnoCom subsidy. As such, their quality migh decline after 2008. In contrast, the patents purchased by NCEs are not used to compete for a subsidy. Their quality is unlikely changed by the InnoCom program.

Table 6 reports the change in the average renewal rate of the patents by seller-buyer type before and after 2008. A striking feature is that the quality decline for the post-2008 patents is pronounced in all patent groups except those that are purchased by NCEs. If the bureaucratic committee reviewing applications for an InnoCom subsidy count the number of patents but do not differentiate the patent quality, than it would not be surprising that many SCEs with a low initial IPRs count would buy many low-quality patents.

Note that the patents invented by NCEs but are not traded could include those produced with a hope to sell to SCEs to quality for a subsidy. In other words, even though patents that are not sold could suffer a quality decline after 2008.

It is useful to emphasize that there can be other factors in the economy that might affect the patent quality across all groups of patents. For example, a change in the quantity or quality of engineering graduates from Chinese colleges or a breakthrough in the world technological frontier that spills over to China. To isolate the effect of the InnoCom policy change in 2008, it is useful to perform comparisons between groups before and after 2008.

# 4 Model

We model the market equilibrium under the InnoCom program by incorporating the salient data patterns documented in the previous section. Each firm in the model first attempts to develop patentable innovations in-house, and patent trade takes place afterwards.[16] The new subsidy policy implemented in 2008, which counts the number of patents but does not adjust for quality, affects the aggregate welfare by altering the decisions on patent production and trade. We lay out a model that aims to capture the salient features of the subsidy program, and calibrate the model to quantify various channels through which the program affects the welfare. The potential benefit of the InnoCom program is to generate more patents, hence more knowledge spillover. In Appendix B, we show that the knowledge spillover is mainly concentrated within the eight InnoCom industries. Hence the model makes assumptions that are consistent with this observation as well. We calibrate the model to match the corresponding moments before the InnoCom program, as well as the change in the relative moments after 2008 between the SCE with low and high initial IPRs count (i.e., a Difference-in-Difference measure.

## 4.1 Environment

There are two industries ("InnoCom targeted industry" and "all other industries") and four types of firms. Subsidy-competing enterprises (SCEs) are the set of the firms in the targeted industry that satisfy minimum R&D expenditure share required by InnoCom. We divide them into two types depending on whether they initially have a patent or not, and denote them as $S_h$ and $S_l$, respectively. Non-subsidy-competing entities (NCEs) include two types as well: Those that are in the targeted industry but do not satisfy the minimum requirement on R&D expenditure share, and those outside the targeted industry. We use subscripts $N_1$ and $N_2$ to denote them respectively.

We assume that an SCE that owns a patent may receive a subsidy from the InnoCom program with probability $\rho$. [17] We normalize the measure of all SCEs to be 1, in which $h$ fraction initially has a patent initially and $1-h$ fraction does not. For the NCEs, we denote by $\beta_1$ and $\beta_2$ the measures of $N_1$ and $N_2$ respectively. While $h$ and $\beta_1$ are exogenously

[16] We focus on patents and leave out other types of IPRs because we do not have the relevant data on their trade. While many sophisticated and commercially valuable softwares receive a patent in the United States, software registration in China is done through a different government agency. We are not able to obtain reliable information on trade in software.

[17] Owning a patent in the model corresponds to owning six IPRs in the data.

given, the measure of those NCEs outside the targeted industries, $\beta_2$, will be endogenously determined.

Patents are heterogeneous in terms of their quality $x$, and firms are heterogeneous in terms of their profits. Specifically, if a firm holds an active patent with quality $x$, its profit without the subsidy is $\pi + x\pi$, where $\pi$ is the firm profit without holding a patent ($x = 0$), and a patent with quality $x$ can increase the firm's profit by a rate $x$. Denote by $\pi_h$, $\pi_l$, $\pi_1$ and $\pi_2$ the values of $\pi$ for four types of firms (the SCEs with an initial patent, the SCES without an initial patent, the NCEs in the targeted industry, and the NCEs outside the targeted industry), respectively. For simplicity, we assume $\pi_h = \pi_l = \pi_S$, where $\pi_S$ is the value of $\pi$ for the SCEs.

For those SCEs which initially have a patent, we assume the initial patent quality is $\bar{x}$. These SCEs may produce a new patent $x$ and own two patents before going to the patent trade market. We assume that the profit (without subsidy) is $\pi_S + x\pi_S + \bar{x}\pi_S$. In other words, we assume no complementarity between the two patents.

There are three stages in the economy. In the first stage, each firm attempts to develop a patentable innovation in-house. We assume that each firm can invent at most 1 patent. It chooses an innovation success probability of $\theta$, and a parameter $\lambda$ that governs the likelihood that the patent is of a high quality. Formally, the patent quality distribution $G(x; \lambda)$ is a Bernoulli: $x = x_H$ with probability $\lambda$; $x = x_L$ with probability $1 - \lambda$; and $x_H > x_L$. The innovation cost $C(\lambda, \theta)$ is increasing and convex in both $\lambda$ and $\theta$, and $C_{\lambda\theta} > 0$. The last inequality means that the marginal cost of increasing $\theta$ is higher for high quality patents. The innovation costs for SCEs and NCEs, denoted by $C_S$ and $C_N$, respectively.[18] In other words, the minimum eligibility requirements of the InnoCom program distinguishes firms' innovation abilities. At the end of the first stage, some firms fail to achieve a patentable invention on their own. While some SCEs with an initial patent may end up with two patents, an initial one with quality $\bar{x}$ and a new one with quality $x$.[19]

In the second stage, a market in patent trade opens. Those SCEs with no patent enter as potential buyers. Those SCEs with more than 1 patent plus both types of NCEs that

[18]The innovation costs for the two NCEs are the same as we lack the data to differentiate them.

[19]Hence firms in the model will have either 0, 1 or 2 patents after the innovation stage.

have succeeded in producing a patent enter the market as sellers.[20] A buyer and a seller will randomly meet with each other. There is a fixed cost $\sigma \geq 0$ in executing a trade. So a trade will only take place if the joint surplus of the trade after the transaction cost is positive. The SCEs with two patents are assumed to want to sell the newly invented patent.[21]

In the last stage, any SCE with a patent will receive a subsidy in the amount of $T\pi_S$ with probability $\rho$. The subsidy is proportional to the gross profit because the subsidy in the InnoCom program takes the form of a reduction in the corporate income tax. All firms then decide whether to renew their patent at cost $c + \varepsilon$, where $c$ is a common component of the renewal cost for all patent holders. $\varepsilon$ is an unobserved individual shock, which follows a normal distribution with mean 0 and standard deviation $\Omega_\varepsilon$. The individual component could reflect additional preparation cost that differs by firms. The individual component can also be negative if the ownership of a patent bring additional benefits not explicitly modeled here[22]

The $\pi$ of a firm within the InnoCom industries (SCEs and $N_1$) equals to $Az$, where $z \in \{z_S, z_1\}$ is the firm-level productivity, and $A$ is the endogenous aggregate productivity of the InnoCom industries. It depends on the total innovation in the sector. However, any individual firm takes $A$ as given. In other words, $A$ captures the positive externality of innovation. We assume $A = A_0 K^\eta$, where $A_0$ is a constant, $K$ is the aggregate knowledge capital which will be explained later. $\eta \geq 0$ is the parameter of the knowledge spillover.

Those NCEs outside the targeted industries do not benefit from a knowledge spillover from innovation in the targeted industries. (This assumption is supported by the empirical findings in Table A6.) If the NCE is a non-firm entity (such as an individual inventor or a university research institute), $\pi_2$ can be interpreted as the utility of holding a patent. The timing of the model is summarized in Figure 10.

---

[20]We assume that NCEs do not buy patents from the SCEs, and the SCEs with an initial patent do not buy additional patents. These simplifying assumptions are motivated the data patterns documented earlier, since these trade shares in the data are small comparing to the sales from either the NCEs or the SCES with a high initial patent count to the SCES with a low patent count.

[21]Since the two types of SCEs have the same productivity, both the sellers and the buyers are different between which patent to buy since the prices of the high and quality patents would adjust.

[22]For example, some firms may be able to use patent ownership to reduce office rent or cost of bank loans.

### 4.1.1 Production

We perform backward induction starting from the last stage. The value of a patent with quality $x$ to a firm with profit $\pi$ is $V(\pi, x) = E_\varepsilon (\pi x - \varepsilon - c)^+$, where $(.)^+$ equals to 0 if the value in the parenthesis is negative. $E_\varepsilon$ is the expectation taken over the random component of renewable cost $\varepsilon$. The above equation implies a cutoff for the patent renewal decision: if the patent quality is bad enough, the firm will not renew the patent and the extra benefit from the patent is 0. Hence the renewal probability is $\Phi(\frac{\pi x - c}{\Omega_\varepsilon})$, where $\Phi$ is the CDF of a standard normal distribution.

For an SCE with no initial patent, its value with no patent (and hence no subsidy) is $\pi_S$. After acquiring a new patent with quality $x$, its value is

$$V(\pi_S, x) + \pi_S + \rho T \pi_S$$

where the last term is the expected subsidy.

For an SCE with an initial patent, if it invents a new patent with quality $x$ and still holds it to the production stage, its value is

$$V(\pi_S, x) + V(\pi_S, \bar{x}) + \pi_S + \rho T \pi_S$$

where the first two terms are the values from two patents, the third term is the firm value without patent, and the last term is the expected subsidy. On the other hand, if it sells the newly invented patent and holds the old patent, its value is

$$V(\pi_S, \bar{x}) + \pi_S + \rho T \pi_S$$

The NCEs in the targeted industry are not eligible to apply for a subsidy. The values are $V(\pi_1, x) + \pi_1$ and $\pi_1$ with and without a patent, respectively. These firms can still benefit from a productivity spillover from the innovations by other firms in the same sector through a higher aggregate productivity $A$.

Finally, for those NCEs outside the targeted industry, the firm value with a patent is $V(\pi_2, x)$, and its value without a patent is $\pi_2$. They do not enjoy a knowledge spillover from targeted industries.

#### 4.1.2 Patent Trade

The measure of the SCEs without a patent before trade is $(1-\theta_l)(1-h)$, where $\theta_l$ is the self-innovation success rate of $S_l$. They are the potential buyers in the patent market. Similarly, the measure of NCEs with a patent is $\beta_1\theta_1+\beta_2\theta_2$, where $\theta_1$ and $\theta_2$ are the innovation success rates of the two types of NCEs and $S_h$ respectively. $h\theta_h$ is the measure of SCEs with an extra patent to sell, where $\theta_h$ is the innovation success rate. They are potential sellers.

In the market for patent trade, a seller and a buyer are randomly matched. The buyer-seller ratio is

$$\delta = \frac{(1-\theta_l)(1-h)}{\beta_1\theta_1+\beta_2\theta_2+h\theta_h} \tag{3}$$

Denote a buyer meets a seller with probability $q_{buyer}(\delta)$ and a seller meets a buyer with probability $q_{seller}(\delta)$, where $q'_{buyer}<0$ and $q'_{seller}>0$. When a buyer meets a seller with patent quality $x$ and profit $\pi \in \{\pi_S, \pi_1, \pi_2\}$, the trade surplus is

$$S(\pi_S,\pi,x) = V(\pi_S,x) + \rho T\pi_S - V(\pi,x) - \sigma \tag{4}$$

where $\sigma$ is the random transaction cost, which is drawn from an exponential distribution with mean $\phi$. We denote the CDF of $\sigma$ as $F(\sigma)$. The trade will happen if $S(\pi_S,\pi,x)\geq 0$. An efficient trade is defined as one that can improve the value of the patent even without the subsidy, i.e., $V(\pi_S,x)-V(\pi,x)>\sigma$. When $\rho>0$ (i.e., with Innocom subsidy), some inefficient trade will happen.

The expected joint surplus is denoted by

$$S^+(\pi_S,\pi,x) = \int \left[V(\pi_S,x)+\rho T\pi_S - V(\pi,x)-\sigma\right]^+ dF(\sigma)$$

where $(.)^+$ indicates that the trade will happen iff $S(\pi_S,\pi,x)\geq 0$.

We assume that the surplus from a successful trade $S^+(\pi_S,\pi,x)$ is split equally between the buyer and the seller. Hence upon their meeting, the expected value of buyer and seller would both increase by $\frac{1}{2}S^+(\pi_S,\pi,x)$.

### 4.1.3 Innovation stage

Firms are assumed to try to develop a patentable innovation in house before deciding on whether to go to the patent exchange market. A representative SCE without an initial patent chooses the innovation quality parameter $\lambda_l$ and the probability of innovation success $\theta_l$ to maximize its expected value $w_l$,[23]

$$w_l = \max_{\lambda_l, \theta_l} \theta_l \int V(\pi_S, x)\, dG(x; \lambda_l) + \theta_l \rho T \pi_S + (1 - \theta_l) TV_S + \pi_S - C_S(\lambda_l, \theta_l) \tag{5}$$

where $TV_S$ is the value of purchasing patents for SCEs.

$$\begin{aligned} TV_S \quad = \quad & q_{buyer} \frac{\beta_1 \theta_1}{\beta_1 \theta_1 + \beta_2 \theta_2 + h\theta_h} \int \frac{1}{2} S^+ (\pi_S, \pi_1, x)\, dG(x; \lambda_1) + \\ & q_{buyer} \frac{\beta_2 \theta_2}{\beta_1 \theta_1 + \beta_2 \theta_2 + h\theta_h} \int \frac{1}{2} S^+ (\pi_S, \pi_2, x)\, dG(x; \lambda_2) + \\ & q_{buyer} \frac{h \theta_h}{\beta_1 \theta_1 + \beta_2 \theta_2 + h\theta_h} \int \frac{1}{2} S^+ (\pi_S, \pi_S, x)\, dG(x; \lambda_h) \end{aligned}$$

The first four terms of equation (5) are the value of producing/acquiring a patent. With probability $\theta_l$, the SCE obtains a patent by itself, with the patent quality drawn from distribution $G(x; \lambda_l)$. So the expected firm production value is $\int S^+ (\pi_S, \pi_N, x)\, dG(x; \lambda_l)$ (the first term). In addition, with probability $\rho$, the firm will receive an Innocom subsidy of $T\pi_S$ (the second term). The third term describes the value of purchasing a patent: $1 - \theta_l$ is the probability that the SCE needs to purchase a patent. With probability $q_{buyer} \frac{\beta_1 \theta_1}{\beta_1 \theta_1 + \beta_2 \theta_2 + h\theta_h}$, it will meet an NCE $N_1$, with patent quality $x$ drawn from distribution $G(x; \lambda_1)$. With probability $q_{buyer} \frac{\beta_2 \theta_2}{\beta_1 \theta_1 + \beta_2 \theta_2 + h\theta_h}$, it will meet an NCE $N_2$, with patent quality follows a distribution $G(x; \lambda_2)$. With probability $q_{buyer} \frac{h \theta_h}{\beta_1 \theta_1 + \beta_2 \theta_2 + h\theta_h}$, it will meet an SCE with more than one patent, $S_h$, whose patent quality follows a distribution $G(x; \lambda_h)$. The fourth term is the SCE's profit $\pi_S$ from other sources not affected by the patent renewal decision. The last term, $C_S$, is the innovation cost.

A representative SCE with an initial patent chooses quality of innovation $\lambda_h$ and probability of success $\theta_h$ to maximize the following expected value $w_h$.

[23] Although $x$ follows a Bernoulli distribution, we abuse the notation slightly and use integration over density $G(x; \lambda)$ when we define values.

$$
\begin{aligned}
w_h &= \max_{\lambda_h,\theta_{S(h)}} \theta_h \left[ \int V(\pi_S, x)\, dG(x;\lambda_h) + q_{seller} \int \frac{1}{2} S^+(\pi_S, \pi_S, x)\, dG(x;\lambda_h) \right] \\
&\quad + \pi_S + V(\pi_S, \bar{x}) + \rho T \pi_S - C_S(\lambda_h, \theta_h) \qquad (6)
\end{aligned}
$$

With probability $\theta_h$, the SCE can produce a second patent, whose value equals to the production value plus the value from patent trade.

A representative NCE in the targeted industries chooses quality of innovation $\lambda_1$ and probability of success $\theta_1$ to maximize its expected value $w_1$.

$$
\begin{aligned}
w_1 &= \max_{\lambda_1,\theta_1} \theta_1 \left[ \int V(\pi_1, x)\, dG(x;\lambda_1) + q_{seller} \int \frac{1}{2} S^+(\pi_S, \pi_1, x)\, dG(x;\lambda_1) \right] \\
&\quad + \pi_1 - C_N(\lambda_1, \theta_1) \qquad (7)
\end{aligned}
$$

With probability $\theta_1$, the NCE produces a patent and can guarantee to achieve at least $\int V(\pi_1, x)\, dG(x;\lambda_1)$. Moreover, with probability $q_{seller}$, it meets an SCE in the patent trade market and receives an extra value from trade in the amount of $\int \frac{1}{2} S^+(\pi_S, \pi_1, x)\, dG(x;\lambda_1)$.[24] The third term is NCE's profit without a patent and the last term is its innovation cost. Note that the difference from the above $S_h$ problem is that an NCE cannot obtain an InnoCom subsidy.

For an NCE outside the targeted industry, $N_2$, its problem is similar with equation (7) except that its value would be zero without a patent.

$$
\begin{aligned}
w_2 &= \max_{\lambda_2,\theta_2} \theta_2 \left[ \int V(\pi_2, x)\, dG(x;\lambda_2) + q_{seller} \int \frac{1}{2} S^+(\pi_S, \pi_2, x)\, dG(x;\lambda_2) \right] \\
&\quad + \pi_2 - C_N(\lambda_2, \theta_2) \qquad (8)
\end{aligned}
$$

[24] Hence we assume that if an NCE wants to sell a patent, it needs to produce a new patent first. In the data, we find that over 80% purchased patents are generated within three years. In the calibration, we match moments using traded patents that are younger than three years. The results are similar.

### 4.2 The Equilibrium

We first define some aggregate variables. In the last stage (i.e., after the patent trade), the measure of $S_l$ owning a patent with quality $x$ is

$$\begin{aligned} p_l(x) \;=\; & (1-h)\,\theta_l g(x;\lambda_l) + (1-h)(1-\theta_l)\, q_{buyer} \frac{\beta_1\theta_1}{\beta_1\theta_1+\beta_2\theta_2+h\theta_h} \times \\ & g(x;\lambda_1)\, F\left(V(\pi_S,x)+\rho T\pi_S - V(\pi_1,x)\right) \\ & + (1-h)(1-\theta_l)\, q_{buyer} \frac{\beta_2\theta_2}{\beta_1\theta_1+\beta_2\theta_2+h\theta_h} g(x;\lambda_2)\, F\left(V(\pi_S,x)+\rho T\pi_S - V(\pi_2),x)\right) \\ & + (1-h)(1-\theta_l)\, q_{buyer} \frac{h\theta_h}{\beta_1\theta_1+\beta_2\theta_2+h\theta_h} g(x;\lambda_h)\, F(\rho T\pi_S) \end{aligned} \tag{9}$$

where $g$ is the density function of the quality distribution $G$. The first term is the measure of firms with in-house invention of quality $x$. The next three terms collectively give the measure of the firms with a purchased patent of quality $x$. With probability $q_{buyer}\frac{\beta_1\theta_1}{\beta_1\theta_1+\beta_2\theta_2+h\theta_h}$(or $q_{buyer}\frac{\beta_2\theta_2}{\beta_1\theta_1+\beta_2\theta_2+h\theta_h}$), an SCE without a patent meets an $N_1$(or $N_2$ and $S_h$) with patent quality $x$. Depending on the realization of the transaction cost, patent trade happens with probability $F(V(\pi_S,x)+\rho T\pi_S - V(\pi_1,x))$ (or $F(V(\pi_S,x)+\rho T\pi_S - V(\pi_2,x))$ and $F(V(\rho T\pi_S)))$.

The measure of the NCEs in the targeted industry owning a patent of quality $x$ after the paten trade is

$$p_1(x) = \beta_1\theta_1 g(x;\lambda_1)\left[1 - q_{seller} F\left(V(\pi_S,x)+\rho T\pi_S - V(\pi_1,x)\right)\right] \tag{10}$$

where the term before the bracket is the measure of $NCE_1$ which have obtained a patent with quality $x$, and the entire term in the bracket is the probability that patent $x$ is not sold because either the seller does not meet a buyer or the transaction cost is too high.

Similarly, the measure of the NCEs outside the targeted industry is

$$p_2(x) = \beta_2\theta_2 g(x;\lambda_2)\left[1 - q_{seller} F\left(V(\pi_S,x)+\rho T\pi_S - V(\pi_2,x)\right)\right] \tag{11}$$

To allow for knowledge spillover, we define the aggregate knowledge capital as

$$K = \int x\left((1-h)\,\theta_l g(x;\lambda_l) + h\theta_h g(x;\lambda_h) + \beta_1\theta_1 g(x;\lambda_1)\right) dx + h\bar{x} \tag{12}$$

Equation (12) suggests that high quality patents contribute more in the aggregate knowledge capital. The last term is the contribution from the SCEs with no initial patent. As the data suggests, innovations from non-InnoCom industries do not contribute to the aggregate productivity of the InnoCom industries.

To close the model, we assume free entry outside the targeted industry:

$$w_2 = \kappa \tag{13}$$

where $\kappa$ is the entry cost.[25]

Given the InnoCom policy $\rho$ and $T$, and the distribution of the SCEs and their patents before the policy shock $h$ and $\bar{x}$, an equilibrium is defined as $\lambda_l$, $\theta_l$, $\lambda_h$, $\theta_h$, $\lambda_1$, $\theta_{N(f)}$, $\lambda_2$, $\theta_{N_2}$, $K$, $\beta_2$ and $\delta$ such that (i) The NCE and SCE's problems (5) to (8) are solved. (ii) Equations (3), (12) and (13) are solved.

### 4.3 Welfare Decomposition

We define the welfare as the sum of all firm values net of the social cost of the subsidy. With free entry outside the targeted industry, the net value of these NCEs ($N_2$) is zero. The welfare can thus be written as follows:

$$Welfare = (1-h)\, w_l + h w_h + \beta_1 w_1 - (1+\tau)\, TS \tag{14}$$

The total subsidy $TS = \rho T \pi_S (\int p_l\,(x)\, dx + h)$, where $\int p_l\,(x)\, dx + h$ is the number of SCEs with at least a patent. $\tau \geq 0$ denote the marginal cost of collecting one unit of tax. Without distortions in tax collection, $\tau = 0$. But in general, it may cost the society more than one dollar for every dollar of subsidy given out by the government.

It is convenient to rearrange the terms in the aggregate welfare expression so that Part of it is linked to patent trade, denoted by $W^T$, and the remainder not related to patent trade, denoted as $W^{NT}$.

$$Welfare = W^T + W^{NT} \tag{15}$$

[25] In the data, most new entrants after 2008 come from out the targeted industries.

The InnoCom induced patent trade alters the welfare through two channels. The first channel is a change in the patent quality and quantity by those firms that wish to sell their patents to those SCEs that need an extra patent to compete for a subsidy. The potential sellers include the SCEs with a initial patent ($S_h$), and the NCEs both in and outside the targeted industry. We label the corresponding component related to these potential sellers by $W^T_{SCE_h}$ and $W^T_{NCE}$ respectively.

The second channel is possible mis-allocation of patents from the highest-value users who are not eligible for an InnoCom subsidy to a lower-value user who happens to be eligible for a subsidy. This component of welfare is labeled by $W^T_{reassignment}$.

Patent trade expands the set of the SCEs that are eligible for a subsidy and may therefore raise the fiscal cost of the subsidy program. Denote $TS^T$ as the subsidy received by SCEs holding external patents. Thus $TS^T = TS - \rho T \pi_S[(1-h)\theta_l + h]$, where $\rho T \pi_S[(1-h)\theta_l + h]$ is the subsidy received by the SCEs holding in-house patents.

The contribution of patent trade to the aggregate welfare can be written as

$$W^T = W^T_{SCE_h} + W^T_{NCE} + W^T_{reassignment} - \tau TS^T \tag{16}$$

where the first three components are defined as

$$W^T_{SCE_h} = h\left[\theta_h \int V(\pi_S, x)\, dG(x;\lambda_h) - C_S(\lambda_h, \theta_h)\right]$$

$$\begin{aligned} W^T_{NCE} &= \beta_1 \left[\underbrace{\theta_1 \int V(\pi_1, x)\, dG(x;\lambda_1) - C_N(\lambda_1, \theta_1)}_{\text{value from innovation of } N_1}\right] + \\ &\quad \underbrace{\beta_2 \left[\theta_2 \int V(\pi_2, x)\, dG(x;\lambda_2) - C_N(\lambda_2, \theta_2) - \kappa\right]}_{\text{value from innovation of } N_2} \end{aligned}$$

$$W^T_{reassignment} = \underbrace{2(1-h)(1-\theta_l)\, TV_S}_{\text{surplus from trade}} - \underbrace{TS^T}_{\text{subsidy to SCEs holding external patents}}$$

In the $W^T_{reassignment}$, the first component is the surplus from trade. $(1-h)(1-\theta_l)$ is the measure of the potential buyers. Each buyer's expected gain, $TV_S$, is half of the surplus. However, the trade surplus includes the value from subsidy. So after removing $TS^T$ in the second component, $W^T_{reassignment}$ captures the net value from patent reassignment. For notational convenience, we will group together the innovations of potential patent sellers, and define $W^T_{seller} = W^T_{SCE_h} + W^T_{NCE} - \tau TS^T$.

The part of the aggregate welfare that is not linked to patent trade, $W^{NT}$ in the equation (15), consists of two components. First, both the SCEs with an initial patent and some of the other SCEs that succeed in producing a patent will have a chance to receive a subsidy without buying additional patent from patent trade. These SCEs' expected subsidy is $\rho T\pi_S[(1-h)\theta_l + h]$. As the InnoCom applicant review does not differentiate patent quality, some of the SCEs with no initial patent may respond by producing more low-quality patents. We denote this part by $W^{NT}_{SCE}$, which equals to the value SCEs' in-house patents minus the social cost of the subsidy that they receive.

$$W^{NT}_{SCE} = (1-h)\left[\theta_l \int V(\pi_S, x)\, dG(x;\lambda_l) - C_S(\lambda_l,\theta_l)\right] + hV(\pi_S,\bar{x}) - \tau\rho T\pi_S[(1-h)\theta_l + h]$$

where the second term is the value of $S_h$'s initial patent, which does not relate to trade.

Second, if the subsidy program leads to more patents in the targeted industry, the values of the firms in the targeted industry may go up due to an increase in aggregate productivity $A$ (knowledge spillover). We denote this part as $W^{NT}_{\text{productivity}}$:

$$W^{NT}_{\text{baseline profit}} = \pi_S + \beta_1\pi_1$$

where $\pi_S$ is the total baseline profit of all SCEs (whose collective measure is 1), and $\beta_1\pi_1$ is the total baseline profit of the NCEs in the targeted industry. Then $W^{NT} = W^{NT}_{SCE} + W^{NT}_{\text{baseline profit}}$.

To summarize, the InnoCom program alters the aggregate welfare both directly and indirectly. The direct effect induces subsidy-eligible firms (SCEs) to alter the quality and quantity of the patents that they produce. On the one hand, the incentive from the subsidy program induces the SCEs to lower the average quality of their patents so as to raise their chance of receiving a subsidy. On the other hand, all firms in the target industry may enjoy a productivity boost from an increase in the total patent count in the industry. The net effect depends on model parameters.

Patent trade enables several indirect effects. This includes additional resource waste as those firms not eligible for a subsidy are also incentivized to produce low-quality patents with the hope of selling them to subsidy eligible firms that lack a patent. By enlarging the set of SCEs with a patent, this could increase the fiscal cost of the subsidy program. The indirect effect also includes a trade-enabled misallocation that allows a low-efficiency but subsidy-eligible firm to own a patent even if the same patent would have generated more firm value if it were owned by a high-efficiency but subsidy-ineligible firm. As more subsidy-ineligible firms now produce low-quality patents and enter the patent trade market, this makes it easier for a potential buyer to find a seller. In other words, both the number of inefficient trade and the number of total trade may have increased. As these channels take on different signs, We are interested in their relative importance. We are also interested in potentially better ways to implement the subsidy.

## 4.4 Calibration

To calibrate the model, we impose some parametric assumptions. We assume that the innovation cost has the form

$$C_S(\lambda, \theta) = \frac{v_{0S}}{2}(\lambda_S \theta)^2 + \frac{v_{1S}}{2}\theta^2, \quad C_N(\lambda, \theta) = \frac{v_{0N}}{2}(\lambda_N \theta_N)^2 + \frac{v_{1N}}{2}\theta_N^2$$

$v_{0S}, v_{1S}$, $v_{0N}$ and $v_{1N}$ are parameters that are different between SCEs and NCEs. In the above cost functions, the innovation cost is increasing and convex in $\theta$ and $\lambda$. Meanwhile, when $\lambda$ increases, the marginal cost of increasing $\theta$ is higher.

The matching functions are assumed to take the following forms:

$$q_{buyer} = \frac{1 - \exp(-b\delta)}{\delta}, \;\; q_{seller} = 1 - \exp(-b\delta)$$

where $b$ is a parameter that measures the matching efficiency.[26]

[26]This matching function is widely used in the search literature, such as Petrongolo and Pissarides (2001).

**Pre-determined parameters**

We assume that the low quality patent contributes nothing to the profit of the patent holder, i.e., $x_L = 0$. As the SCEs account for approximately 1/3 of the firms in the InnoCom targeted industries, we set the measure of the NCEs in the targeted industry, $\beta_1 = 2$, since the measure of the SCEs is normalized to 1. We set the fraction of the SCEs with a patent to $h = 0.22$ to match the observed fraction of the firms with six or more IPRs in the InnoCom targeted industries before 2008.

For the SCEs and the NCEs in Innocom targeted industries, we see their firm-level profits. We normalize $z_S = 1$ and calibrate $z_1 = 0.9$ to match the average relative profit between these two groups. Since many innovators outside the InnoCom targeted industries are individuals or research institutes, we do not directly observe their benefits of holding patents. We calibrate $z_2$ internally.

As approximately 60% of the SCEs receive an InnoCom subsidy in the data, we set $\rho = 0.6$. As the InnoCom subsidy takes the form of a reduction in the corporate income tax by 10 percentage points, we set $T = 0.1$. We calibrate $\eta = 0.01$ to match the elasticity reported in column 2 of Table A6.[27] Finally, Chen et al. (2021) estimates the cost of the InnoCom program budget with $\tau = 0.2$.[28] Ming (2009) estimates the $\tau$ in a reduced form way, and find $\tau$ is between 0.2 to 0.4. We set $\tau = 0.2$ in our baseline analysis. We explore the robustness of $\eta$ and $\tau$ later.

**Internally-calibrated parameters**

To solve the model, we need to know 13 parameters additionally, which can be grouped into eight categories: (1) 4 innovation cost parameters $v_{0S}, v_{1S}, v_{0N}$ and $v_{1N}$; (2) Patents quality of SCEs with initial high IPRs $\bar{x}$; (3) 2 parameters for trade market, the matching efficiency $b$ and the average patent transaction cost $\phi$; (4) The entry cost $\kappa$; (5) The aggregate

[27]Notice that $K$ is defined as the patent count weighted by $x$ In the model. While in Table A6, $K$ is defined as patent counts weighted by renewal rates. In principle, if we have several periods in the model, we can compute the knowledge capital as Table A6, and regress $\ln A$ on it. We then can choose $\eta$ to make the regression coefficient from the model be 0.01. However, since we only calibrate two periods in the model, we cannot do this exercise but simply impose $\eta = 0.01$. We will explore the robustness in Figure 11.

[28]They get this estimate by assuming the utility from public spending is the same between China and US. Using the average tax rate in China to infer the public spending, $\tau$ can be estimated.

productivity of targeted industry $A_0$; (6) Other NCEs' productivity $z_2$; (7) The mean and standard deviation of renewal cost $c$ and $\Omega_\varepsilon$; and (8) Good patent quality $x_H$.we calibrate them to match the corresponding moments in the data.[29]

Since many factors other than the InnoCom program may have changed in the economic environment after 2008, we calibrate our model to match the data moments shortly before the 2008 policy change. We pay special attention to the difference between the SCEs with a low initial IPRs count and those with a high initial IPRs after the InnoCom program. While both groups of firms are affected by the InnoCom program, they are affected differently. For example, those with a low initial IPRs count are incentivized to buy patent from the market, and those with a high initial IPRs count may wish to sell their patents. The relative changes in patents quantity and quality between these two groups, as identified in Table 3 (column 3) and Table 5 (column 2), capture the most significant effect of the 2008 policy in the InnoCom program. [30]

We start by explaining the intuition in the identification of the innovation cost parameters ($v_{0S}$, $v_{1S}$, $v_{0N}$, $v_{1N}$), which directly determine patent quality and quantity. We calibrate them to match the counts and renewal rates of the self-developed patents by the SCEs and the NCEs, respectively.

Similarly, $\bar{x}$, which measures the patents quality of SCEs with initial patents, is calibrated to match the renewal rates of the SCEs with six or more initial IPRs.

Parameters $b$ and $\phi$ determine the frictions in the patent trade market. We calibrate $b$ to match the number of purchased patents by the SCEs as it directly changes the number of trade. Meanwhile, since $\phi > 0$, it generates a selection effect that high quality patents are more likely to be traded. So we calibrate $\phi$ to match the renewal rates of externally purchased patents owned by the SCEs, which reflect the quality of the traded patents.

For parameters in categories 4 to 6, we calibrate them as follows. The entry cost, $\kappa$, is calibrated to match the number of other NCEs before 2008. $A_0$ and $z_2$ can be considered as sector productivity shocks of the InnoCom targeted industries and other industries, respec-

[29]The numerical details are provided in Appendix C.

[30]We will also perform a robustness check later that would allow the 2008 policy shock to also alter some of the fundamental parameters.

tively. We calibrate them to match the average before-tax profits of the Innocom industries and the renewal rate of other NCEs before/after the policy shock. (As we cannot directly observe the profits of other NCEs outside the Innocom industries, we use the renewal rates to infer $z_2$).

Lastly, for the remaining three parameters, $\Omega_\varepsilon$, the standard deviation of the renewal cost shock, is calibrated to match the dispersion of the renewal rate before and after the 2008 policy shock. $x_H$ and $c$ are calibrated to match the profit difference between the SCEs with and without a patent before and after 2008. Intuitively, when $c$ increases, more patents will not be renewed. Hence the profit difference between the firms with and without a patent would decrease.

The parameters and the model fit are shown in Table 7. The model fits the data well. A unit value in the model is 10,000 RMB. First, as $x_H = 0.17$, a high quality patent can increase the firm's profit by 17%. Second, the renewal cost $c$ is about 0.77 with standard deviation of 7.23. The annual renewal cost per patent paid to the patent bureau is about 1,000RMB (0.1 in model value). However, the the cost of renewal to a firm may include additional costs such as the fees paid to a law firm. In any case, our estimate of $c$ is much greater than 1,000 RMB.

From Table 7, we can see that the SCEs have smaller innovation costs than the NCEs in both quality and quantity dimensions ($v_0$ and $v_1$). As the SCEs are selected based on ther RD expenditure, this difference may reflect the fact that the SECs are selected to have a comparative advantage in innovation.

### Model Validation

We perform a number of validation tests. First, we compare model-predicted increases in patent trade with those in the data. After de-trending the patent trade using the average growth rate before 2008, we find that the purchases by the SCEs with a low initial IPRs count from the NCEs exhibit an increase in growth rate by 5% and that from the SCEs with a high initial IPRs count exhibit an increase in the growth rate by 2%. The first two rows of Panel B in Table 7 report the increases predicted by our model, which are close to the data. The faster increase in trade from the NCEs to the SCEs is partly due to an increase in the number of NCEs after the InnoCom policy shock.

Second, we compare model-predicted increases in patent by firm type with those in the data. In our model, an SCE with an initial patent would attempt to produce more patents since the value to sell patents increases under the policy shock. The first row of Panel B in Table 7 compares the increase of patent count before and after the policy shock in the model with that in the data. Our model predicts that the SCE with a high initial IPRs raises patent production by 1%, while in the data the increase is about 7%.[31] This may suggest that additional factors outside the InnoCom program have also induced firms to do more innovation.

The innovation by the NCEs after the policy shock is another untargeted moment. Our model predicts that the NCEs would increase their patents by 2% after the policy shock since they can now sell patents to subsidy eligible firms. In comparison, the data shows a slightly larger increase in the NCEs' in-house innovations.

# 5 Welfare and Policy Analysis

To understand the effect of the pro-innovation subsidy program, we compare the model economy with and without the subsidy program, and report the results in Table 8. In the first column, we use the parameters in Table 7 and assume the subsidy does not exist ($\rho = 0$, i.e., a "laissez faire" economy). In the second column, we consider an economy with the InnoCom program (as in the real world). In the third column, we report the difference between the two cases. In both cases, we report the total welfare and decompose it into several sources as section 4.3. The first row is the total subsidy, which is about 3.4 billion RMBs per year after 2008.[32] The second row is the average patent quality $x$. Without the subsidy, the average $x$ is about 4.37%. With the subsidy program, it declines to 2.01%. This reflects the incentive created by the InnoCom program that induces the firms to focus on patent count rather than quality.

[31] The average growth rate of the patents during 2005-2007 is used to detrend the patent counts in the years after 2008.

[32] The annual total InnoCom subsidy for this city in our sample is about 3.4 billion RMBs. In our model, we scale up the measure of SCEs to match the total subsidy in the data.

In the next few rows, we report the aggregate welfare as well as its components based on the decomposition discussion in section 4.3. Row (a) report the net value of the patents developed by patent sellers, $W^T_{seller}$, which consists of $W^T_{seller} = W^T_{SCE_h} + W^T_{NCE} - \tau TS^T$. This value declines by 0.46 billion RMBs because both the NCEs and the SCEs with an initial patent waste resources to produce low quality patents for sale to subsidy-competing firms.

In Row (b), we report the mis-allocation effect: there is the change in firm value from assigning patents from inventors to SEC users ($W^T_{reassignment}$). This number declines by 0.27 billion RMB, suggesting that inefficient trade has taken place in response to the subsidy.

In Row (c), $W^{NT}_{SCE}$ is the value of SCEs' in-house patents net of the social cost of the subsidy. This is a direct welfare effect of the InnoCom program. Since the SCEs waste resources to produce low quality patents, $W^{NT}_{SCE}$ declines by 1.28 billion RMBs.

Row (d) presents the welfare component not related to patent trade $W^{NT}_{\text{baseline profit}}$. Since the increase in the quantity of patents is dominated by low-quality ones, with some decline in the number of high-quality ones, the aggregate (quality weighted) knowledge capital declines slightly, and correspondingly its contribution to the aggregate productivity decreases. As a result, the total profit not linked to patents decreases by 0.01 billion RMBs.

Overall, the aggregate welfare declines by 2.02 billion RMBs. Importantly, patent trade induced by the subsidy creates additional loss (row (a)+(b)), raising the welfare loss by more than 50% ((0.27+0.46)/1.29).

**Robustness**

The aggregate welfare depends on two key parameters: the externality $\eta$ and the shadow value of the fiscal budget $\tau$. We then explore another robustness check: what is the combination of $\eta$ and $\tau$ that makes the InnoCom program welfare neutral (that is the welfare level with subsidy (column 2 of Table 8) equals to the welfare without subsidy (column 1 of Table 8)). Figure 11 shows the "welfare break-even" value of $\tau$ for any given $\eta$, holding all other parameters the same as Table 7). When $\eta$ increases, the knowledge externality increases, so we can tolerate a higher level of social cost of funding $\tau$ that makes the subsidy welfare neutral. If $\tau$ is above/below the solid line in Figure 11, the InnoCom program generates a welfare loss/gain. In the baseline case ($\eta = 0.01$), the InnoCom program always generates a welfare loss for any value of $\tau \geq 0$ (It would only be welfare enhanced if $\tau \leq -0.37$. That is, it costs the society only 63 cents for every dollar of government subsidy, which is impossible). Lucking et al. (2019) estimates that the knowledge spillover is bounded above by 0.2. Even in this case, the welfare break-even $\tau$ is still negative. Chen et al. (2021) and Ming (2009) estimate the social cost of funding $\tau$ in China to be between 0.2 to 0.4. This means that the InnoCom program can generate a welfare gain only if $\eta$ is greater than 0.3, which is implausible.

In sum, we find that the InnoCom program is likely to have hurt the aggregate welfare, and the patent trade has played a quantitatively important role in augmenting the welfare loss. As the existing literature on patent trade focuses exclusively on its beneficial role, our analysis points to the possibility that the effect of patent trade can be turned on its head when there are subsidy-induced distortions in the economy.

**Alternative subsidy policies**

We simulate alternative policies. In Table 9, we consider two different subsidization rules while maintaining the same values of all other parameter as in Table 7. Since the welfare loss enabled by patent trade is significant, in our first policy experiment, we modify the InnoCom program design to count only self-developed patents. The subsidy probability is maintained at $\rho = 0.6$ for firms with a patent. While the patent trade market still opens, no SCE buys a patent only to enhance its chance to receive an InnoCom subsidy. The results are reported in the first two columns of Table 9. Compared to the actual subsidy program described in column 2 of Table 8), we see that the total subsidy declines to 2.75 billion, and the patent quality increases to 3.45%. Since purchased patents are no longer recognized for the subsidy application purpose, the trade enabled losses (parts c and d in the InnoCom case) have nearly disappeared. Overall, the aggregate welfare level is better than the current InnoCom program, although it is still lower than the laisse faire case (in column 1 of Table 9). After all, the in-house patents of the subsidy competing firms still suffer from a quality decline.

In the second experiment reported in columns 3 and 4, the hypothetical policy change is to maintain a fixed total subsidy budget (at 3.4 billion RMBs) plus to exclude purchased patents from the subsidy consideration. This implies that the probability of obtaining a subsidy per eligible firm $\rho$ is increased somewhat.

Relative to the InnoCom program, the new policy delivers a higher welfare (by 0.72 billion RMBs). This comes primarily from saving money from subsidizing the production of low-quality patents by firms outside the targeted industry. However, the new policy is not better than simply not recognizing purchased patents for the subsidy application purpose (in Column 1 of Table 9).

In sum, some modifications of the subsidy program can improve upon the InnoCom program, especially those that eliminate trade-enabled losses. The key is to reduce or eliminate the incentive to produce low-quality patents by firms not eligible to compete for a subsidy. However, none of the program modifications manages to generate a result better than laissez faire (no InnoCom at all).

**Optimal subsidy policies**

Taking all the model parameters as given except the probability of awarding a subsidy to an SEC, $\rho$, we search for the optimal value of $\rho$ that would maximize the welfare. We find that the optimal $\rho$ is 0.001, a very small number. The consequences of having the subsidy probability are reported in the first column of Table 10. By design, the welfare level under optimal $\rho$ is higher than under either the actual InnoCom program (in Column 2 of Table 8) or any of the four alternative policies considered in Table 9. Since the optimal $\rho$ is not far from zero, it is not surprising that the welfare level in this case is not far from that under laissez faire either. In other words, not having any subsidy program (given the constraint of other program design features) is close to be the socially optimal thing to do.

Fundamentally, because the bureaucrats are not able to distinguish patent quality, a subsidy program that is contingent upon applicant firms achieving a certain number of patents tends to induce firms to devote resources to produce low-quality patents. If the subsidy program also recognizes purchased patents by applicant firms as the current InnoCom program does, rather than inspiring more genuine innovation outside subsidy competing firms, as the program designer wishes, it may augment the welfare loss of the whole program by inducing more resource waste in producing low-quality patents by firms not otherwise competing for a subsidy.

To see this point clearly, consider a different counterfactual experiment in which the bureaucrats not only distinguish patent quality but assign different probabilities of granting a subsidy depending on the patent quality. Let $\rho_H$ and $\rho_L$ be the probabilities for an SEC to receive a subsidy when the patent quality is $x_H$ and $x_L$, respectively. We then search for the optimal values of $\rho_H$ and $\rho_L$ that would maximize the welfare, holding all other model parameters as given. We find that when $\rho_H = 0.62$ and $\rho_L = 0$, the welfare is maximized. In other words, the optimal program design would not subsidize firms with a low-quality patent, but would subsidize those with a high-quality patent with a probability that is higher than that observed in the actual InnoCom program.

The results under such a program design are reported in the third and fourth columns of Table 10. The welfare level under such a program is higher than not only the actual InnoCom program in Column 2 of Table 8 but also the laissez faire case in Column 1 of Table 8. Of course this experiment would require the bureaucrats to be able to differentiate high- versus low-quality patents, which seems unlikely.

# 6 Conclusion

We study how the largest pro-innovation subsidy policy in China, the InnoCom program, changes the aggregate welfare. We pay special attention to the role of patent trade. By counting purchased patents by applicant firms in competing for a subsidy, the architect of InnoCom may hope to use patent trade to inspire more innovations even by firms not directly competing for a subsidy. (This feature is shared by the patent box policy in the European Union, Canada, Australia, and other countries, in which the subsidy is granted to firms holding a patent regardless of who invented the patent in the first place.) We show that in the Innocom context, because the bureaucrats do not distinguish patent quality, the welfare change enabled by patent trade is negative. In other words, this program feature induces more resource waste in producing low-quality patents by firms not otherwise competing for a subsidy.

Given that realistically estimated spillover effect is not strong, even the optimally designed subsidy program in the Chinese context is unlikely to generate a welfare gain. However, if the program design can overcome the quality differentiation challenge, then a pro-innovation subsidy program can improve the social welfare.

A patent box policy that ties a subsidy to value added linked to a patent can be interpreted as an attempt to subsidize only high quality innovation. Since the mapping between any particular piece of value added to a patent is often ambiguous, it will be interesting for future research to zoom on this issue as a reassessment of the welfare effect of other pro-innovation subsidy programs.

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# Tables and Figures

Table 1: Labor Productivity and Patent

| | $\ln(\text{labor prod}_{it})$ | $\ln(\text{labor prod}_{it})$ |
|---|---|---|
| $(\text{New patent}_{it-1}) \times (t \geq 2008)$ | -0.060*** | -0.037* |
| | (0.021) | (0.022) |
| $\text{New patent}_{it-1}$ | 0.041*** | 0.043** |
| | (0.013) | (0.025) |
| Year FEs | Y | Y |
| Firm FEs | | Y |
| Obs. | 31,332 | 10,995 |
| Adj. R2 | 0.42 | 0.77 |

Notes: This table shows the marginal change of firm labor productivity when the patent count increases.

Table 2: Correlation between Evaluation Points and IPRs Quality

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | PT in IPRs count | | Tot. PT | |
| | Ave. citation | Ave. renewal rate | Ave. citation | Ave. renewal rate |
| Quality proxy | 0.030 | 0.015 | 0.085 | -3.916 |
| | (0.025) | -0.051 | (0.061) | (2.516) |
| $\ln(Sales)$ | 0.079*** | 0.067** | 0.776** | 0.801*** |
| | (0.027) | -0.038 | (0.312) | (0.355) |
| In-house IPRs sh. | 0.001 | -0.002 | -0.087 | 0.885 |
| | (0.003) | -0.003 | (0.047) | (0.591) |
| (IPRs=1-2) | 0.000 | 0.000 | 0.03 | 0.03 |
| | (0.000) | (0.000) | (0.02) | (0.02) |
| (IPRs=3) | 0.805 | 0.241 | 1.185 | 0.985 |
| | (0.784) | (0.471) | (1.318) | (1.018) |
| (IPRs=4) | 1.092** | 2.479*** | 2.992** | 2.122** |
| | (0.338) | (0.702) | (1.338) | (1.088) |
| (IPRs=5) | 3.096*** | 6.207*** | 5.001*** | 5.771** |
| | (0.427) | (0.661) | (2.072) | (2.220) |
| (IPRs=6) | 6.665*** | 10.018*** | 8.561*** | 10.111*** |
| | (0.274) | (0.523) | (2.470) | (3.709) |
| (IPRs$>$ 6) | 6.813*** | 10.163*** | 8.999*** | 10.195*** |
| | (0.321) | (0.492) | (3.021) | (3.712) |
| Industry/ownership | Y | Y | Y | Y |
| Obs. | 2,470 | 2,470 | 2,470 | 2,470 |
| Adj. R2 | 0.62 | 0.62 | 0.16 | 0.18 |

Notes: This table shows the correlation between 2008 subsidized firms' patents quality and their evaluation grades by the bureaucrat. The dependent variables are points in IPRs count (column 1 and 2) and total points (column 3 and 4) in the InnoCom evaluation. Quality proxy is the average citation (column 1 and 3) or renewal rates (column 2 and 4) of patents owned by a firm. In-house IPRs share is the share of self-developed IPRs. In each regression, we control ownership and industry.

Table 3: Number of New IPRs in Relation to the Timing of InnoCom Policy

| | (1) ln(IPRs) | (2) ln(Self-dev.patent) | (3) ln(IPRs) | (4) ln(IPRs) |
|---|---|---|---|---|
| $D_{it-1} \times D(t \geq 2008)$ | 0.129** | 0.043* | 0.217*** | 0.213*** |
| | (0.043) | (0.024) | (0.027) | (0.047) |
| $D(IPR_{it-1} = 6) \times D(t \geq 2008)$ | | | | -0.046 |
| | | | | (0.053) |
| $D(t \geq 2008)$ | Y | Y | | Y |
| $D_{it-1}$, $s_{it-1}$ | Y | Y | Y | Y |
| Firm FEs | Y | Y | Y | Y |
| Year FEs | | | Y | Y |
| Obs. | 10,477 | 10,407 | 10,477 | 10,477 |
| Adj. R2 | 0.75 | 0.78 | 0.77 | 0.77 |

Notes: This table presents the estimation results of the equation (1) of SCEs. The observation is at firm-year level. $N_{it}$ is the new obtained IPRs of firm $i$ in year $t$. $D_{it} = 1$ if $IPR_{it} < 6$ and invention$_{it} = 0$. $s_{it} = 1$ if the firm is subsidized within three years. Standard errors are reported in the parentheses and clustered at the firm-year level. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Patent Trade Shares

| Seller \ Buyer | SCEs IPRs<6 | SCEs IPRs≥6 | NCEs |
|---|---|---|---|
| | | 2006 | |
| SCEs IPRs<6 | 0.075 | 0.003 | 0.021 |
| SCEs IPRs≥6 | 0.068 | 0.011 | 0.075 |
| NCEs | 0.198 | 0.031 | 0.518 |
| | | 2007 | |
| SCEs IPRs<6 | 0.081 | 0.001 | 0.016 |
| SCEs IPRs≥6 | 0.045 | 0.012 | 0.068 |
| NCEs | 0.154 | 0.020 | 0.603 |
| | | 2012 | |
| SCEs IPRs<6 | 0.006 | 0.001 | 0.005 |
| SCEs IPRs≥6 | 0.136 | 0.029 | 0.056 |
| NCEs | 0.328 | 0.083 | 0.356 |

Notes: This table shows the share of patent trade from 9 categories based on buyers' and sellers' characteristics. The sum of all 9 cells within one year equals to 1.

Table 5: The Renewal Rates of New Obtained Patents in Relation to the Timing of InnoCom Policy

| | (1) | (2) |
|---|---|---|
| | $V_{ikt}$ | $V_{ikt}$ |
| $D_{it-1} \times (\text{OY}_{\cdot ik} \geq 2008)$ | -0.029** | -0.045** |
| | (0.015) | (0.022) |
| $(\text{OY}_{\cdot ik} \geq 2008)$ | Y | |
| $D_{it-1}$, $s_{it-1}$ | Y | Y |
| Patent char/Firm FEs/Year FEs | Y | Y |
| OY. FE | | Y |
| Obs. | 159,510 | 159,510 |
| Adj. R2 | 0.42 | 0.51 |

Notes: The observation is at firm-patent-year level. $V_{ikt} = 1$ if the firm $i$ renews patent $k$ in year $t$, and 0 otherwise. $\text{OY}_{\cdot ik}$ is the year of obtaining patent $k$. $D_{it} = 1$ if $IPR_{it} < 6$ and $\text{invention}_{it} = 0$. $s_{it} = 1$ if the firm is subsidized within three years. Patent characteristics include patent age, industry classification and type (invention, utility or design). Standard errors are reported in the parentheses and clustered at the firm-patent-year level. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: 3yrs Renewal Rate of Traded Patents

| Seller \ Buyer | SCEs IPRs<6 | SCEs IPRs≥6 | NCEs |
|---|---|---|---|
| | Traded in 2006-2007 | | |
| SCEs IPRs<6 | 0.973 | 0.981 | 0.982 |
| SCEs IPRs≥6 | 0.951 | 0.972 | 0.962 |
| NCEs | 0.960 | 0.971 | 0.954 |
| | Traded in 2008-2012 | | |
| SCEs IPRs<6 | 0.951 | 0.941 | 0.972 |
| SCEs IPRs≥6 | 0.873 | 0.972 | 0.941 |
| NCEs | 0.710 | 0.943 | 0.891 |

Notes: This table decomposes the 3yrs renewal rate of traded patents based on buyers' and sellers' characteristics.

Table 7: Parameters and Model Fit

| Param. | Value | Moments | Data | Model |
|---|---|---|---|---|
| | | Panel A: Parameters and targeted moments | | |
| Before policy | | | | |
| $v_{1N}$ | 41.22 | NCE self-developed patents | 2.56 | 2.56 |
| $v_{0N}$ | 73.21 | Renewal rate of NCE patents | 0.77 | 0.77 |
| $v_{1S}$ | 37.14 | SCE with IPRs<6 self-developed patents | 0.99 | 0.99 |
| $v_{0S}$ | 70.09 | Renewal rate of SCE with IPRs<6 self-developed patents | 0.91 | 0.91 |
| $\bar{x}$ | 0.19 | Renewal rate of SCE with IPRs≥6 self-developed patents | 0.92 | 0.92 |
| $b$ | 4.07 | External patents per SCE | 0.88 | 0.88 |
| $\phi$ | 0.14 | Renewal rate of SCE with IPRs<6 external patents | 0.99 | 0.99 |
| $\kappa$ | 48.19 | NCE/SCE | 6.86 | 6.86 |
| $A_0$ | 2.01 | InnoCom industry profit | 4.85* | 4.85 |
| $z_2$ | 6.77 | Renewal rates of other NCEs | 0.72 | 0.72 |
| $\Omega_\epsilon$ | 7.23 | Sd of renewal rates | 0.15 | 0.15 |
| After policy | | | | |
| $x_H$ | 0.17 | Dif-Dif: ln(patents) of SCEs with IPRs$<6/\geq 6$ | 0.23 | 0.24 |
| $c$ | 0.77 | Dif-Dif: renewal rate of SCEs with IPRs$<6/\geq 6$ | -0.04 | -0.05 |
| | | Panel B: Untargeted moments | | |
| | | $\Delta$ ln(Trade) from NCE to SCEs with IPRs$<6$ | 0.05** | 0.04 |
| | | $\Delta$ ln(Trade) from SCEs with IPRs$\geq 6$ to SCEs with IPRs$<6$ | 0.02** | 0.02 |
| | | $\Delta$ ln(patents) of SCEs with IPRs$\geq 6$ | 0.07** | 0.01 |
| | | $\Delta$ ln(patents) of NCEs | 0.03** | 0.02 |

Notes: This table reports the parameters and model fit by comparing the moments in the model and the data. The moments before and after the subsidy are computed using data from 2005-2007 and 2008-2012 respectively. The model value is 10,000RMB.

* We use the average profit per worker of the InnoCom industries.

** These four numbers are computed by detrending the patent counts after 2008 using average growth rates of patent counts before 2008.

Table 8: Welfare Decomposition

| | (1) Laissez Faire $\rho = 0$ | (2) InnoCom $\rho = 0.6$ | (2)-(1) Difference |
|---|---|---|---|
| Subsidy | 0 | 3.40 | 3.40 |
| Ave. quality $x$ | 4.37% | 2.01% | -2.32% |
| (a) $W^T_{seller}$ ((a.1)+(a.2)): | 2.36 | 1.90 | -0.46 |
| (a.1) $W^T_{SCE_h} + W^T_{NCE}$ | 2.36 | 2.24 | -0.12 |
| (a.2) Fiscal social cost $-\tau TS^T$ | 0.00 | -0.34 | -0.34 |
| (b) $W^T_{reassignment}$ | 0.01 | -0.26 | -0.27 |
| (c) $W^{NT}_{SCE}$ | 0.88 | -0.40 | -1.28 |
| (d) $W^{NT}_{baselineprofit}$: | 364.31 | 364.30 | -0.01 |
| Welfare ((a)+(b)+(c)+(d)) | 367.56 | 365.54 | -2.02 |

Notes: This table reports the economy in two scenarios: the economy without InnoCom program (column 1), and the economy with InnoCom program (column 2). $W^T_{seller}$, $W^T_{reassignment}$ and $W^{NT}_{SCE}$ are defined as section 4.3. All numbers are in billion RMB, except the average $x$ has not unit.

Table 9: Alternative Subsidy Policies

| | Only Inhouse patents, $\rho = 0.6$ | | Only Inhouse patents with a fixed budget | |
|---|---|---|---|---|
| Subsidy | 2.75 | | 3.40 | |
| Ave. $x$ | 3.45% | | 3.53% | |
| Welfare relative to | Laissez-Faire | InnoCom | Laissez-Faire | InnoCom |
| (a) $W^T_{seller}$ ((a.1)+(a.2)): | -0.01 | 0.45 | -0.01 | 0.45 |
| (a.1) $W^T_{SCE_h} + W^T_{NCE}$ | -0.01 | 0.11 | -0.01 | 0.11 |
| (a.2) Fiscal social cost $-\tau TS^T$ | 0.00 | 0.34 | 0.00 | 0.34 |
| (b) $W^T_{reassignment}$ | 0.00 | 0.27 | 0.00 | 0.27 |
| (c) $W^{NT}_{SCE}$ | -1.37 | -0.09 | -1.77 | -0.49 |
| (d) $W^{NT}_{baselineprofit}$: | -0.21 | -0.20 | 1.43 | 1.44 |
| Welfare ((a)+(b)+(c)+(d)) | -1.59 | 0.43 | -1.30 | 0.72 |

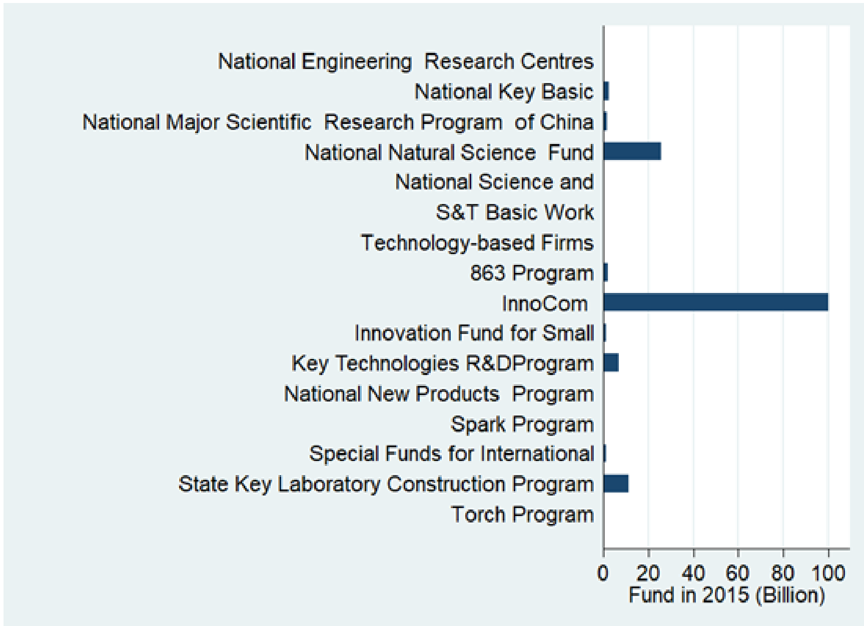
Notes: This table reports the economy in two different policies: only subsidizing in-house patents with $\rho = 0.6$ (column 1 and 2), and only subsidizing in-house patents with a fixed fiscal budget (column 3 and 4). $W^T_{seller}$, $W^T_{reassignment}$ and $W^{NT}_{SCE}$ are defined as section 4.3. All numbers are in billion RMB, except the average $x$ has not unit.

Table 10: Optimal Subsidy Policies

| | Optimal sub. wo. SEP. patents quality $\rho = 0.001$ | | Optimal sub. if only SEP. in-house patents quality $\rho_H = 0.62$, $\rho_L = 0$ | |
|---|---|---|---|---|
| Subsidy | 0.00 | | 0.90 | |
| Ave. $x$ | 4.30% | | 5.20% | |
| Welfare relative to | Laissez-Faire | InnoCom | Laissez-Faire | InnoCom |
| (a) $W^T_{seller}$ ((a.1)+(a.2)) | -0.01 | 0.45 | -0.02 | 0.44 |
| (a.1) $W^T_{SCE_h} + W^T_{NCE}$ | -0.01 | 0.11 | -0.01 | 0.11 |
| (a.2) Fiscal social cost $-\tau TS^T$ | 0.00 | 0.34 | -0.01 | 0.33 |
| (b) $W^T_{reassignment}$ | 0.00 | 0.27 | 0.00 | 0.27 |
| (c) $W^{NT}_{SCE}$ | -0.01 | 1.27 | -0.33 | 0.95 |
| (d) $W^{NT}_{baselineprofit}$: | 0.03 | 0.02 | 1.09 | 1.10 |
| Welfare ((a)+(b)+(c)+(d)) | 0.01 | 2.01 | 0.74 | 2.76 |

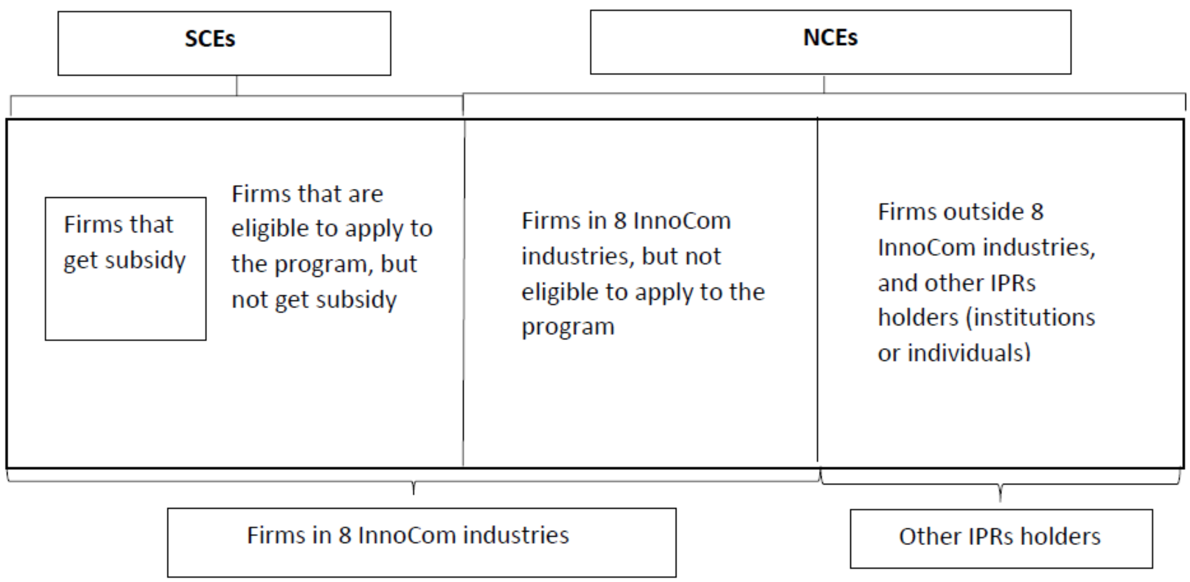
Notes: This table reports the economy in two different policies. Column 1 assumes that the bureaucrat cannot tell patents quality, and search $\rho$ to maximize welfare. Column 2 assumes that the bureaucrat can tell patents quality but does not count purchased patents for subsidy, then search subsidy intensity for high and low quality in-house patents. $W^T_{seller}$, $W^T_{reassignment}$ and $W^{NT}_{SCE}$ are defined as section 4.3. All numbers are in billion RMB, except the average $x$ has not unit.

Figure 1: The Subsidies of Various Pro-innovation Policies by Chinese Central Government



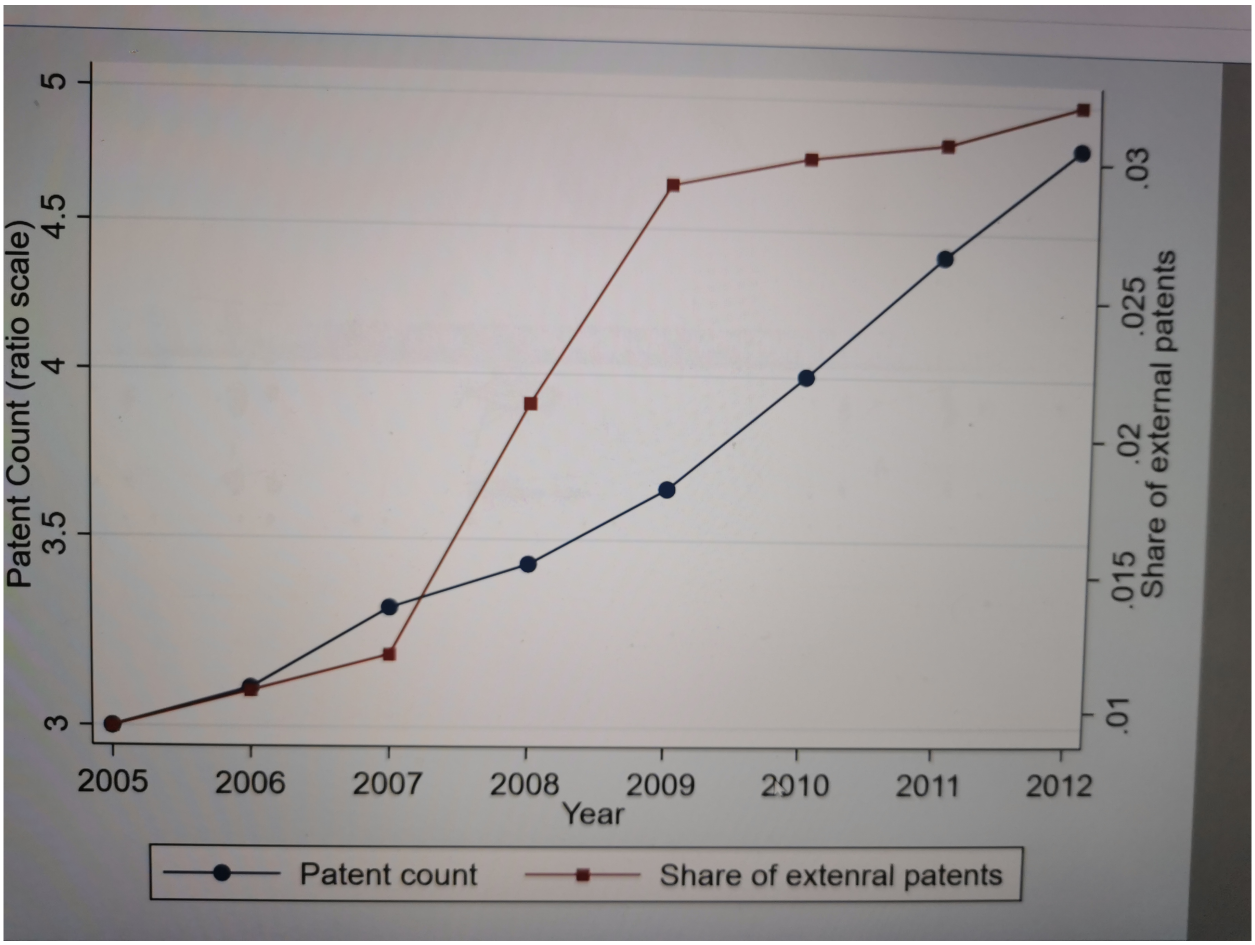

Notes: This figure shows subsidies of various major pro-innovation policies supported by by Chinese Central Government. Source: China Yearbook of Science and Technology 2015.

Figure 2: The Data Structure



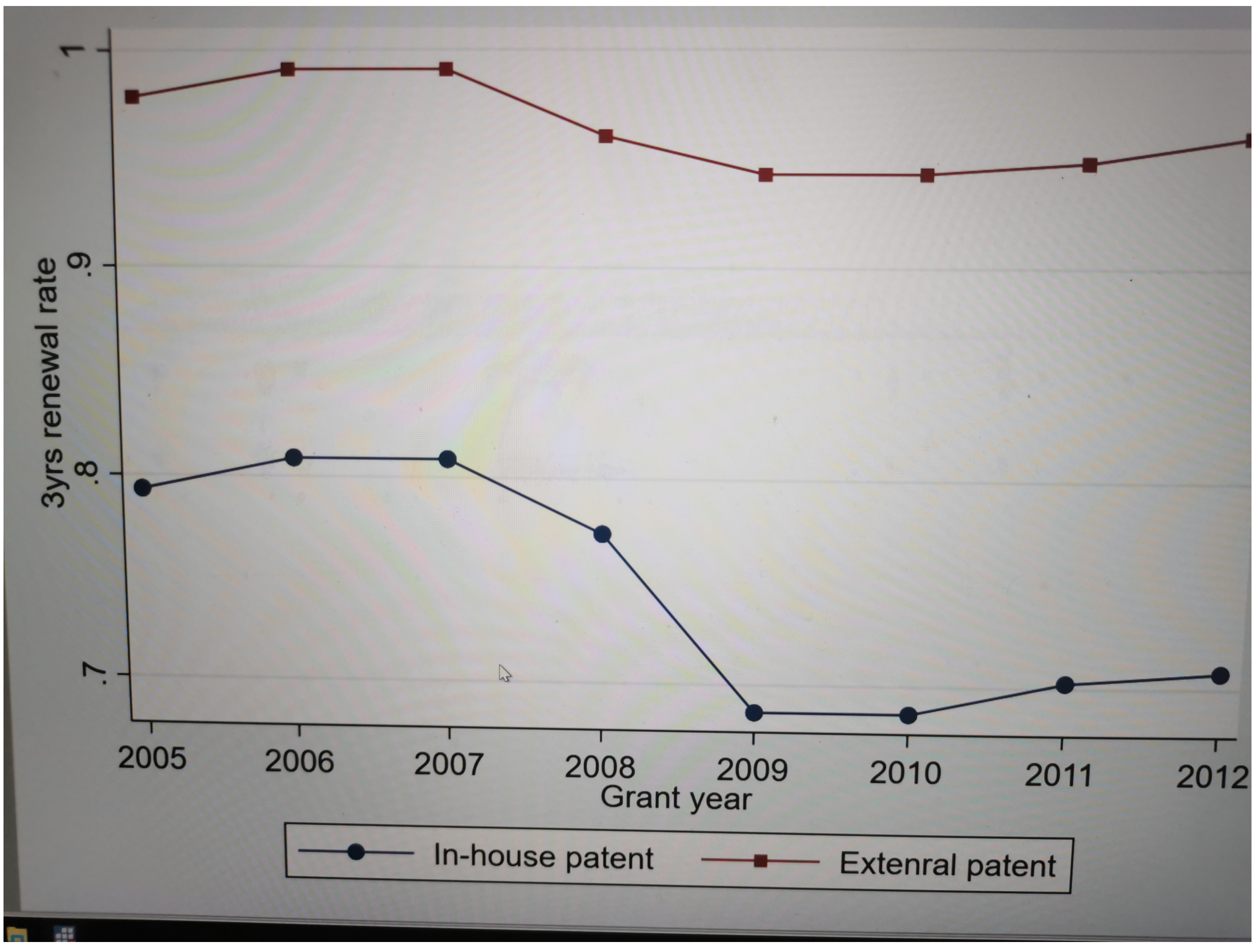

Notes: This figure shows the data structure of the sample.

Figure 3: Granted Patents and Traded Patents per firm from 2005-2012



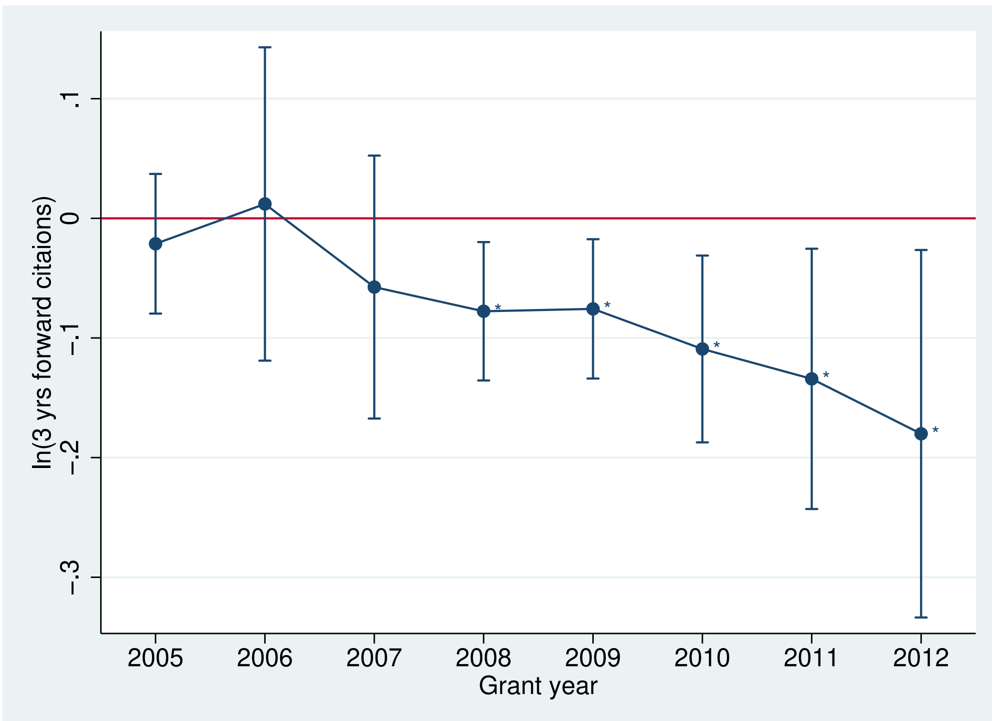

Notes: This figure shows the number of new obtained patents and share of external patents per firm from 2005-2012.

Figure 4: 3Yrs Renewal Rates of Internal and External Patents from 2005-2012



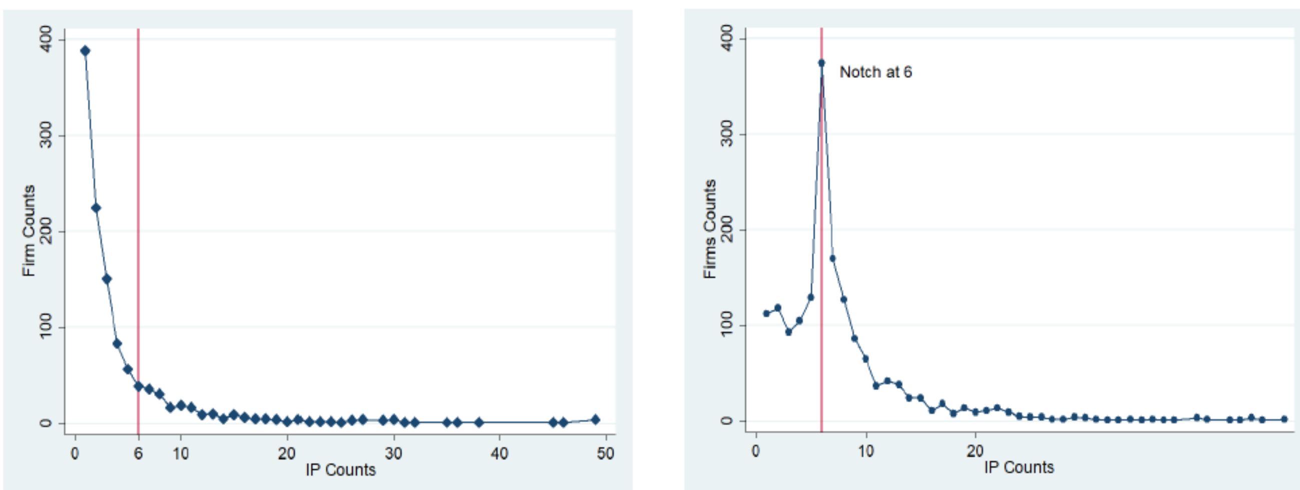

Notes: This figure shows the average 3-years renewal rates of internal and external patents granted within 2005-2012. External(internal) patent is defined as a patent that has (not)been traded within 3 years after granted.

Figure 5: 3 Years Forward Citations of Patents




Notes: This figure shows the average ln(3 years forward citations) of patents granted from 2005 to 2012. The citation in 2004 is normalized to 0. Capped spikes represent 90% confidence intervals.

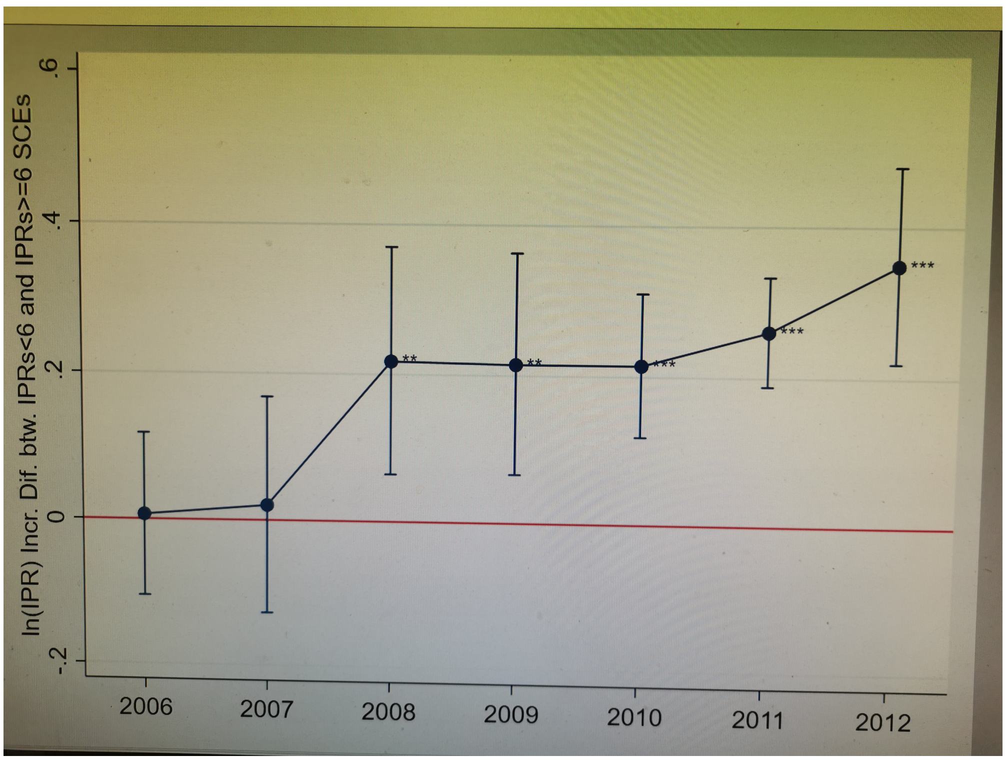
Figure 6: The IPRs Holding Distribution




Year 2007 Year 2008

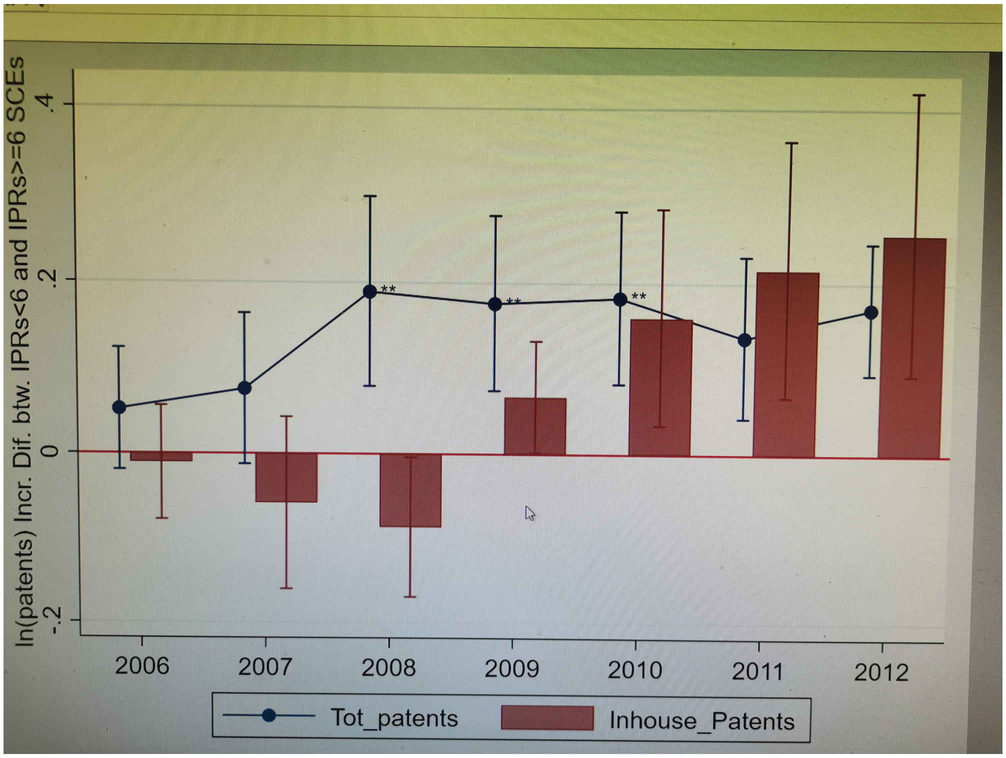
Notes: This figure shows the IPRs (patents and software copyrights) holding distributions of the subsidized firms in Beijing in year 2007 and 2008.

Figure 7: New IPRs of SCEs with IPRs<6 over Years



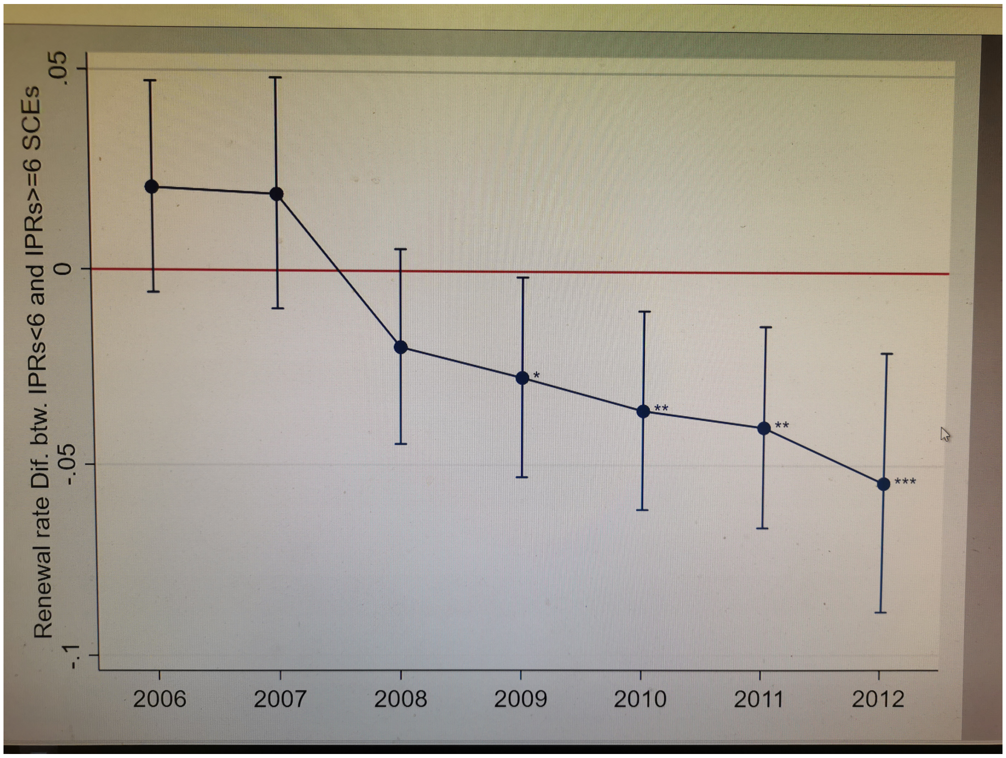

Notes: This figure shows estimates of $\alpha_3$ in equation (1) by years. The circles indicate point estimates of $\alpha_3$. New IPRs of SCEs with IPRs$\geq$6 is normalized to 0 in each year. Capped spikes represent 90% confidence intervals.

Figure 8: New (in-house) Patents of SCEs with IPRs<6 over Years




Notes: This figure shows estimates of $\alpha_3$ in equation (1) by years using $ln(patents)$ (circle) and $ln$(in-house patents) (red bar) as dependent variables. New patents of SCEs with IPRs≥6 is normalized to 0 in each year. Capped spikes represent 90% confidence intervals.

Figure 9: 3Yrs Renewal Rates of SCEs with IPRs<6 over Years




Notes: This figure shows estimates of $\beta_3$ in equation (2) by years. Renewal rates of SCEs with IPRs$\geq$6 is normalized to 0 in each year. Capped spikes represent 90% confidence intervals.

Figure 10: Timing

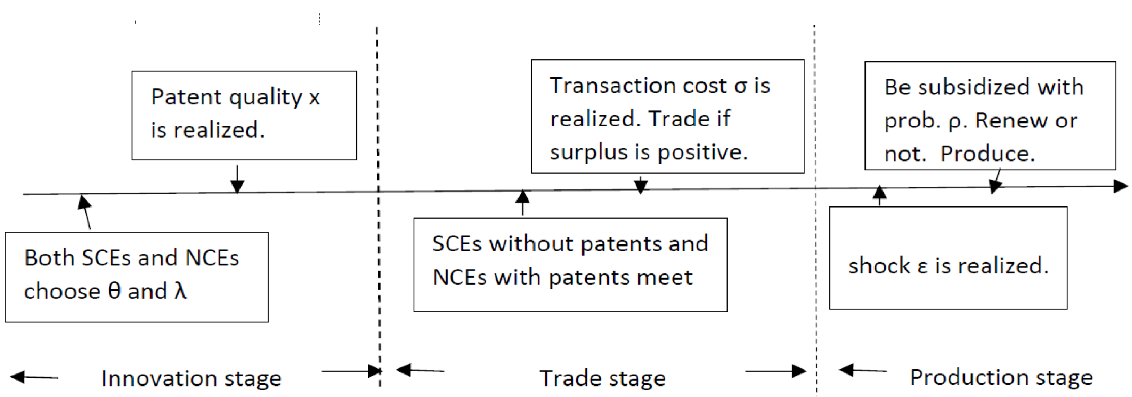
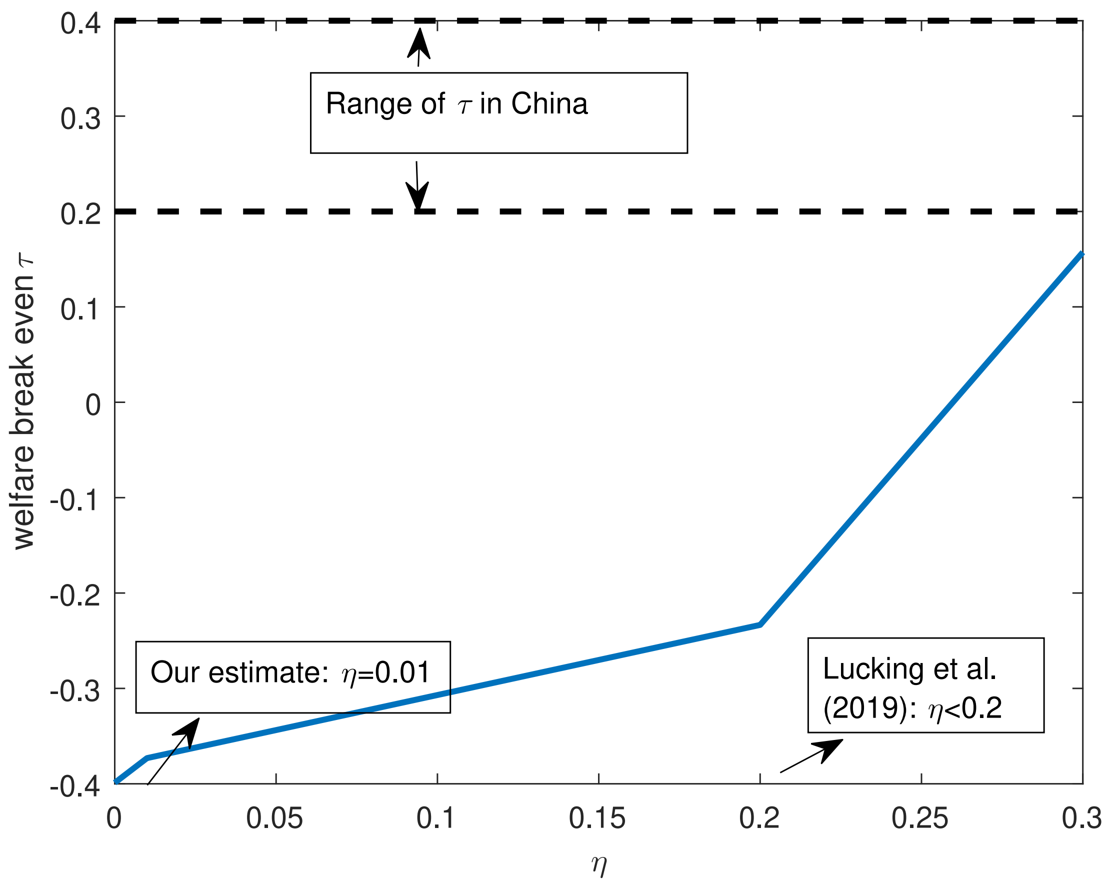


Figure 11: Combinations of social cost of public funding $\eta$ and technological spillover parameter $\tau$ that make InnoCom Program Welfare Neutral




Notes: This figure shows the combinations of knowledge externality parameter $\eta$ and shadow value of public funding $\tau$ that makes the policy welfare neutral (the welfare with and without the policy after 2008 are the same).

# Online Appendix (not for publication in print)

## A Details of the InnoCom Program

This section has two parts. In the first part, we explains the details on how the InnoCom program evaluates firms. In the second part, we compares the program with other innovation subsidy programs in China.

Table A1 lists the conditions that the firm must satisfy in order to apply for the Innocom program. As we can see, the pre-requirements are based on the R&D-to-sales ratio, the sales of high-tech products, the share of R&D workers, and the number of IP rights (IPRs).

After the application, the local government evaluates the firms based on four parts:the intellectual property rights, the ability to manage R&D, S&T commercialization, and the firm growth. The full marks in the 4 parts are 30, 30, 20, 20 respectively.

We explain the grading criteria of holding intellectual property rights in the first column of Table A2. A noteworthy point is the grading scheme of the IPRs. The firm gets an "A" if they have 6 or more IPRs. Here we emphasize two important points. First, the subsidy program only counts the number of IPRs but does not take into account the quality of the IPRs. Second, the firms do not get any extra points if they have more than 6 IPRs.

We explain the grading criteria of the last three categories in Table A3. We can see that for each category, it has 6 levels (A to F). Different levels represent different points the firm can get in that category. The total points of the three categories are 70.

Moreover, when the program was first introduced in 2008, the program recognized two ways of holding an IPRs: the firm can either be the owner of the IPRs (either innovate in-house or purchase from outside) or can hold the IPRs under an exclusive license. In other words, for those patents which the firm borrow from others, the program still count them.

The InnoCom program is the largest pro-innovation program in China. Table A4 list budgets of various pro-innovation programs in China. As we can see, InnoCom program's budget significantly dominates other programs.

Table A5 shows the coverage of the InnoCom program in our data set. On average, the program each year provides a subsidy to more than 5,800 firms, about 68% of all SCEs, or

21% of all firms in the eight industries. The subsidy (tax reduction) is about 0.62 million RMB per firm per year, or 1.86 million RMB over three years.

Table A1: Necessary Requirements of the Innocom Program

| | |
|---|---|
| R&D Intensity | 6% if sales < 50 millions of RMB<br>4% if sales > 50 & sales < 200 millions of RMB<br>3% if sales > 200 millions of RMB |
| Sales of High Tech Products | 60% of total sales |
| Workers with College Degree | 30% of workforce |
| R&D Workers | 10% of workforce |
| IP right | Necessary |

Table A2: Grading Scheme of the IPRs Counts

| Letter Grade | Points | Criteria |
|---|---|---|
| A. | 30-24 | 6 or more IPRs (or at least 1 invention) |
| B. | 24-18 | 5 IPRs |
| C. | 18-12 | 4 IPRs |
| D. | 12-6 | 3 IPRs |
| E. | 6-0 | 1-2 IPRs |
| Notes: Both purchased and self-developed IPRs are counted. | | |

Notes: This table explains the grading scheme of the IPRs counts in the InnoCom program.

Table A3: The Grading Scheme of the Innocom Program

| Category | Grading Criteria |
|---|---|
| Ability to transform research projects to business (30 points) | A. Above 4 items (30-24 points)<br>B. 3-4 items (30-24 points)<br>C. 2-3 items (18-12 points)<br>D. 1-2 items (12-6 points)<br>E. 1 item (0-6 points)<br>F. 0 item (0 point) |
| Research management ability (20 points) | (1) Make research proposals<br>(2) Have R&D expenditure accounting system<br>(3) Co-operate with research institutions<br>(4) Have independent research departments<br>(5) R&D workers' performance evaluation system<br><br>A. 5 items (16-20 points)<br>B. 4 items (12-16 points)<br>C. 3 items (8-12 points)<br>D. 2 items (4-8 points)<br>E. 1 item (0-4 points)<br>F. 0 item (0 point) |
| Firm growth (20 points) | Asset growth (10 points)<br>A. $\geq$35% (8-10 points)<br>B. $\geq$25% (6-8 points)<br>C. $\geq$15% (4-6 points)<br>D. $\geq$5% (2-4 points)<br>E. $<$ 5% (0-2 points)<br>F. $\leq$ 0 (0 points)<br><br>Sales growth (10 points)<br>A. $\geq$35% (8-10 points)<br>B. $\geq$25% (6-8 points<br>C. $\geq$15% (4-6 points)<br>D. $\geq$5% (2-4 points)<br>E. $<$5% (0-2 points)<br>F. $\leq$ 0 (0 points) |

Table A4: Budgets of Various Pro-Innovation Policies in China

| Programs | Program names in Chinese | Fund in 2015 (Billion) |
|---|---|---|
| InnoCom | 高新科技企业认定 | 100 |
| National Natural Science Fund | 国家自然科学基金 | 25.8 |
| State Key Laboratory Construction Program | 国家重点实验室 | 11.5 |
| Key Technologies R&D Program | 科技支撑计划 | 7.0 |
| National Key Basic Research Program of China | 国家重点基础研究发展计划（973计划） | 2.7 |
| 863 Program | 863计划 | 2.0 |
| National Major Scientific Research Program of China | 国家重大科学研究计划 | 1.7 |
| Special Funds for International Technology Cooperation | 国际科技合作与交流专项经费 | 1.4 |
| Innovation Fund for Small Technology-based Firms | 科技型中小企业技术创新基金 | 1.1 |
| National Science and Technology Infrastructure Program | 科技基础条件平台专项 | 0.3 |
| S&T Basic Work | 科技基础性工作专项 | 0.2 |
| Torch Program | 火炬计划 | 0.2 |
| Spark Program | 星火计划 | 0.2 |
| National Engineering Research Centres | 国家工程技术 | 0.1 |

Table A5: Coverage of InnoCom Program

| Year | No. of new Innocom firms | %. in SCEs | % in 8 Innocom Ind. | Sub. per firm-year |
|---|---|---|---|---|
| 2008 | 2,470 | 52% | 5% | - |
| 2009 | 5,167 | 59% | 16% | 0.58 |
| 2010 | 6,401 | 67% | 20% | 0.53 |
| 2011 | 7,204 | 72% | 33% | 0.74 |
| Average | 5,860 | 68% | 21% | 0.62 |

Notes: This table shows the number of new InnoCom firms from 2008-2011, and the share of subsidized firms in all SCEs and 8 high-tech industries in our data set. The last column shows the annual subsidy (tax return) per InnoCom firm, which is computed using the State Administration Tax Data. The tax information of InnoCom firms in 2008 is missing.

# B Knowledge spillover is positive but modest

The main motivation of the InnoCom program is to encourage more innovations, hence may increase the aggregate productivity through the knowledge externality. To gauge the welfare effect of the InnoCom program, we need to know to what extent the knowledge externality depends on the quality and quantity of patents. We estimate the knowledge externality as follows.

Let $i$ and $j$ denote two industries. Denote $N_{it}$ as the total patents (cumulative) in industry $i$ up to year $t$, and $r_{it}$ as the average renewal rate (survival rate of patents three years after granted) of the industry $i$. Define $K_{it}$ as the measure of total patents with which industry $i$ interacts in the aggregate productivity. We call $K_{it}$ as the "knowledge capital" facing by $i$. Specifically, we distinguish the knowledge capital from the same sector $K_{it}^{within}$, and from other sectors $K_{it}^{other}$,

$$K_{it}^{within} = d_{ii} N_{it} r_{it}, \; K_{it}^{other} = \sum_{j \neq i} d_{ij} N_{jt} r_{jt} \tag{17}$$

where $d_{ij}$ is the knowledge distance between industry $i$ and $j$, which is measured as the share of patent citations between industry $i$ and $j$ within all patent citations. The above functions imply that high quality patents (high renewal rates) contribute more to the knowledge capital. Meanwhile, the knowledge externality is greater between two industries that cite each other more frequently.

Consider a firm $f$ in industry $i_f$. We then estimate the following equation

$$\ln \pi_{ft} = \eta_1 \ln K_{i_f,t}^{within} + \eta_2 \ln K_{i_f,t}^{other} + \mu_f + \mu_t + error \tag{18}$$

where $\pi_{ft}$ is firm $f$'s labor productivity (profit/workers),$K_{i_f,t}^{within}$ and $K_{i_f,t}^{other}$ are the knowledge capital facing by firm $f$, and $\mu_f$ and $\mu_t$ are the firm and time fixed effects. $\eta_1$ and $\eta_2$ measure the knowledge externality from the same sector and other sectors.

Firm $f$'s own innovation may change $K$. So we only focus on firms without any patents. To exclude the impact of InnoCom program, we focus on 2000-2007, a sample one year before the InnoCom program.[33]

[33]We use Annual Survey of Chinese Manufacture Enterprises dataset since this data covers firms financial

Some unobserved shocks may affect $\pi_{ft}$ and industry level innovations at the same time. So we instrument $K_{i_f,t}^{within}$ and $K_{i_f,t}^{other}$ as

$$IV_{it}^{within} = d_{ii}\frac{Patent_{i0}}{TotPatent_0}S_t,\ IV_{it}^{other} = \sum_{j\neq i} d_{ij}\frac{Patent_{j0}}{TotPatent_0}S_t \tag{19}$$

where $Patent_{i0}$ is the patent counts of industry $i$ in 1998, and $TotPatent_0$ is the total patent counts in 1998. $S_t$ is the total subsidy to innovations from Chinese central government. The assumption is that the total innovation subsidy changes patent counts in different industries proportional to the initial patent share across industries. Meanwhile, the total subsidy does not directly change the productivity of firms without any patents.

Table A6 reports the estimation results of $\eta$. In the first column, the OLS estimates suggest that when the industry's total patents increase by 1%, the labor productivity of a firm without patents increases by 0.052%. However, if other industry's patents increase by 1%, the firm's labor productivity drops by 0.102%. In the second column, we instrument $K$ and find that $\eta_1$ decreases to 0.01, which means that the knowledge externality within the same sector is very small. Meanwhile, the knowledge externality across sectors is slightly negative (-0.012), although not significantly away from 0.[34]

In the third column, we change the definitions of $K$ by simply counting patent numbers without adjusted by renewal rates. Comparing to column 2, both $\eta_1$ and $\eta_2$ decrease, and the knowledge externality within the sector becomes not significant. This result suggests that the productivity benefits more from other firms' high quality patents.

Are the knowledge externality in InnoCom industries different from other industries? This question is important when we discuss the welfare of the InnoCom program. In the fourth column, we allow $\eta$ to be different for InnoCom industries, by introducing a dummy $D$ which indicates whether the industry is targeted by the InnoCom program. The coefficient before $K^{within} \times D_{InnoCom}$ and $K^{other} \times D_{InnoCom}$ reflect the difference of $\eta_1$ and $\eta_2$ between InnoCom industries and other industries. As we see, we do not detect any significant difference.

Since the patent quality declines after the InnoCom program was implemented, will $\eta$

information up to 2009. However, in the tax records administrative data, the observation starts from 2007.

[34] In the first stage, we find the F statistics is over 2,000.

of InnoCom industries decrease after 2008? We then restrict the sample to 2008-2009, and estimate a similar equation as column 4. The result is shown in column 5 of Table A6. Comparing with column 4, in terms of non-InnoCom industries, the knowledge externality within the sector is barely unchanged (0.015), and the knowledge externality across sectors decreases but still not significant away from 0. However, the knowledge externality of InnoCom industries decrease both for $\ln K^{within}$ and $\ln K^{others}$, although they are not significant. One reason for any insignificant decline may be that we adjust patent count by renewal rates, which may have captured patents quality decline.

So we conjecture that if $K$ is not adjusted by renewal rates, the externality of InnoCom industries would drop significantly after 2008. In column 6 and 7, we estimate equations similar as column 4 and 5, but do not adjust $K$ by renewal rates. (The sample is before 2008 in column 6, and after 2008 in column 7.) First, comparing column 6 to 4, $\eta_1$ slightly declines, which may suggest that high quality patents contribute more to the within sector knowledge externality. Second, we again do not detect a significant difference in $\eta$ between InnoCom industries and other industries before the InnoCom subsidy. After 2008, the externality of other sectors are barely not changed (comparing column 7 and 6), but the within sector externality of InnoCom industries significantly decreases. Overall, column 7 suggests that if the patent count increases by 1% in the InnoCom industry after 2008, the labor productivity of other firms in the same industry without patents would decline by 0.004% (0.011-0.015). This result confirms our conjecture: InnoCom program pushes down the patents quality, hence more patents (without adjusting the quality ) do not contribute too much to other firms' productivity.

To sum up, a small but positive knowledge externality exists within the sector, but we do not find any significant knowledge externality across sectors. With US data, Lucking et al. (2019) use R&D expenditure to measure $K$ and find that $\eta$ from 0 to 0.2. Our estimates are significant smaller than theirs. These may be either because the knowledge externality within China is smaller or because we measure $K$ by patent counts. After an innovation is patented, the knowledge spillover would decrease due to the patent protection.

Table A6: Knowledge Externality of Patents

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | OLS | IV | IV | IV | IV | IV | IV |
| | | | raw K | InnoCom Ind. | InnoCom Ind. | InnoCom Ind. | InnoCom Ind. |
| | | | | | Post-2008 | raw K | raw K / Post-2008 |
| $\ln K^{within}$ | 0.052*** | 0.010* | 0.009 | 0.011* | 0.015* | 0.01 | 0.011 |
| | -0.012 | -0.006 | -0.008 | -0.007 | -0.008 | -0.008 | -0.013 |
| $\ln K^{other}$ | -0.102*** | -0.012 | -0.013 | -0.011 | -0.024 | -0.013 | -0.009 |
| | -0.025 | -0.016 | -0.017 | -0.019 | -0.017 | -0.019 | -0.026 |
| $\ln K^{within} \times D_{InnoCom}$ | | | | -0.005 | -0.013 | -0.004 | -0.015* |
| | | | | -0.008 | -0.009 | -0.008 | -0.009 |
| $\ln K^{other} \times D_{InnoCom}$ | | | | 0.008 | 0.003 | 0.007 | 0.004 |
| | | | | -0.009 | -0.009 | -0.009 | -0.009 |
| Firm FE | Y | Y | Y | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y | Y | Y | Y |
| IV | | Y | Y | Y | Y | Y | Y |
| K: Renewal rate adj. | Y | Y | | Y | Y | | |
| Sample after 2008 | | | | | Y | | Y |
| KP Wald F stat | | 2175.7 | 3017.11 | 5929.45 | 1500 | 4594.17 | 1400.04 |
| Obs. | 1,120,443 | 1,120,443 | 1,120,443 | 1,120,443 | 373,074 | 1,120,443 | 373,074 |
| Adj. R2 | 0.65 | 0.65 | 0.65 | 0.65 | 0.67 | 0.65 | 0.67 |

Notes: This table reports the estimates of knowledge spillover within and across sectors (equation (18)). The dependent variable is the log of labor productivity (profit/worker) of a firm without patent. The $D_{InnoCom} = 1$ if the firm is in an InnoCom industry and 0 otherwise. In column (3), $K$ is not adjusted by the renewal rate. The IV of column (2) to (7) is defined in equation (19). "KP Wald F stat" refers to Kleibergen-Paap Wald F-statistic in the first stage estimation. Standard errors are reported in the parentheses and clustered at the firm-year level. *** p<0.01, ** p<0.05, * p<0.1.

# C Numerical Details

We assume that $x$ follows a Bernoulli distribution: $x = x_H$ with probability $\lambda$ and $x = x_L$ with probability $1-\lambda$. And $x_H > x_L$. Furthermore we assume that $C = \frac{v_0}{2}(\lambda\theta)^2 + \frac{v_1}{2}\theta^2$. Then the optimization of the SCE is

$$\begin{aligned} w_S \quad = & \max_{0\leq\lambda_l(z)\leq 1, 0\leq\theta_S(z)\leq 1} \Delta\left(z\right)\lambda_l\left(z\right)\theta_l\left(z\right) + B\left(q_S,\lambda_N\right)\theta_l\left(z\right) + \frac{q_S}{2}[\lambda_N S^+\left(z,x_H,\rho\right) + \\ & \left(1-\lambda_N\right)S^+\left(z,x_L,\rho\right)] - \frac{v_{0S}}{2}(\lambda_l\left(z\right)\theta_l\left(z\right))^2 - \frac{v_{1S}}{2}\theta_l^2\left(z\right) \end{aligned}$$

where $\Delta\left(z\right) = V\left(z,x_H\right) - V\left(z,x_L\right)$ and $B\left(q_S,\lambda_N\right) = V^S\left(z,x_L\right) + \rho T\left(z\right) - \frac{q_S}{2}\left[\lambda_N S^+\left(z,x_H,\rho\right) + \left(1-\lambda_N\right)S^+\left(z,x_L,\rho\right)\right.$.

The optimal conditions yield that

$$\theta_l\left(z\right) = \max(\min(\frac{B\left(q_S,\lambda_N\right)}{v_{1S}},1),0)$$

$$\lambda_l\left(z\right) = \max(\min(\frac{\Delta\left(z\right)}{v_{0S}\theta_l\left(z\right)},1),0) \text{ if } \theta_l > 0\text{; otherwise } \lambda_l = 0$$

Similarly, the optimization of the NCE is

$$w_N = \max_{0\leq\lambda_N\leq 1, 0\leq\theta_N\leq 1} D\left(q_N,\theta_l\right)\lambda_N\theta_N + E\left(q_N,\theta_S\right)\theta_N - \frac{v_{0N}}{2}(\lambda_N\left(z\right)\theta_N\left(z\right))^2 - \frac{v_{1N}}{2}\theta_N^2\left(z\right)$$

where $D\left(q_N,\theta_l\right) = V\left(z_N,x_H\right) - V\left(z_N,x_L\right) + \frac{q_N}{2}\sum_z \alpha\left(z\right)\left[S^+\left(z,x_H,\rho\right) - S^+\left(z,x_L,\rho\right)\right]$, and $E\left(q_N,\theta_l\right) = V\left(z_N,x_L\right) + \frac{q_N}{2}\sum_z \alpha\left(z\right)S^+\left(z,x_L,\rho\right)$. And $\alpha\left(z\right) = \frac{(1-\theta_l(z))p(z)}{\sum_z(1-\theta_l(z))p(z)}$ is the share of SCEs with productivity $z$ that are buyers.

Then the optimal conditions of NCE yield

$$\theta_N = \max\left(\min\left(\frac{E\left(q_N,\theta_l\right)}{v_{1N}},1\right),0\right)$$

$$\lambda_N = \max\left(\min\left(\frac{D\left(q_N,\theta_l\right)}{v_{0N}\theta_N},1\right),0\right) \text{ if } \theta_N > 0\text{; otherwise } \lambda_N = 0$$

The free entry condition of NCE can be written as

$$D(q_N, \theta_l)\,\lambda_N\theta_N + E(q_N, \theta_l)\,\theta_N = C_N(\lambda_N, \theta_N) + \kappa \tag{20}$$

We can see that an increase of $\rho$ will increase $B$ and $E$. So $\theta_S(z), \theta_N$ would increase, and $\lambda_l(z)$ will decrease. The change of $\lambda_N$ depends on $D$. Generally, when $\rho$ increases, $D$ may decrease. So $\lambda_N$ would decrease.

We can solve the model as follows. For each period, guess $\delta$. Then solve $q_S$ and $q_N$. Then guess $\lambda_N$, solve $\lambda_S(z)$ and $\theta_S(z)$. Then we can solve $E$ and $D$, and we can update the guess $\lambda_N$ from NCE's optimality policy. Then we can check the NCE's free entry condition to pin down $\delta$. In the end, we need verify the guess of the aggregate productivity.

# D More tables

Table A7: Decomposition of the Annual Patent Trade Growth

| Seller \ Buyer | SCEs IPRs<6 | SCEs IPRs≥6 | NCEs |
|---|---|---|---|
| | 2006-2007 | | |
| SCEs IPRs<6 | 0.080 | -0.667 | -0.238 |
| SCEs IPRs≥6 | -0.338 | 0.091 | -0.093 |
| NCEs | -0.222 | -0.355 | 0.164 |
| | 2007-2012 | | |
| SCEs IPRs<6 | 0.108 | -0.002 | -0.017 |
| SCEs IPRs≥6 | 0.055 | 0.016 | 0.091 |
| NCEs | 0.151 | -0.001 | 0.331 |

Notes: This table decomposes the annual patent trade growth into 9 categories based on buyers' and sellers' characteristics.

Table A8: Summary Statistics of the SCEs and NCEs before and after 2008

| | 2005-2007 | | | 2008-2012 | | |
|---|---|---|---|---|---|---|
| | SCEs IPRs$<6$ | SCEs IPRs $\geq 6$ | NCEs | SCEs IPRs$<6$ | SCEs IPRs $\geq 6$ | NCEs |
| Per-firm: | | | | | | |
| Internal patents | 0.99 | 5.26 | 2.56 | 3.21 | 6.83 | 2.79 |
| External patents | 0.69 | 1.40 | 0.03 | 1.37 | 1.42 | 0.02 |
| 3Yrs renewal rate of: | | | | | | |
| In-house. patents | 0.91 | 0.92 | 0.77 | 0.83 | 0.88 | 0.64 |
| External patents | 0.99 | 0.95 | 0.96 | 0.97 | 0.91 | 0.89 |
| $\frac{ln(\text{labor prod})}{\text{patents}}$ | 0.07 | 0.04 | 0.02 | -0.05 | 0.002 | -0.01 |

Notes: This table shows the summary statistics of SCEs and NCEs before and after 2008 (balanced panel).

Table A9: Effects of InnoCom on Quality of Patents Produced by NCEs

| | (1) $Renew_{it}$ | (2) $Renew_{it}$ | (3) $Renew_{it}$ |
|---|---|---|---|
| $Psale^{SCE}_{it-1} \times (t \geq 2008)$ | -0.066*** | -0.071 | -0.070*** |
| | -0.018 | -0.041 | -0.02 |
| $Psale^{NCE}_{it-1} \times (t \geq 2008)$ | -0.019 | -0.02 | -0.027 |
| | -0.013 | -0.013 | -0.023 |
| $Psale^{SCE,IPRs<6}_{it-1} \times (t \geq 2008)$ | | -0.075** | |
| | | -0.026 | |
| $Psale^{SCE}_{it-1}, Psale^{NCE}_{it-1}$ | Y | Y | Y |
| $Psale^{SCE,IPRs<6}_{it-1}$ | | Y | |
| Firm/Year FEs | Y | Y | Y |
| Individual NCEs | | | Y |
| Obs. | 22,486 | 22,486 | 12,987 |
| Adj. R2 | 0.35 | 0.35 | 0.34 |

Notes: This table presents the estimation results of renewal rates of new patents (equation (**??**)) of NCEs. $PSale^{SCE}_{it-1}$, $PSale^{NCE}_{it-1}$ and $PSale^{SCE,IPRs<6}_{it-1}$ are the number of patents sold to SCEs, NCEs and SCEs with IPRs fewer than 6, respectively. Standard errors are reported in the parentheses and clustered at the firm-year level. *** p<0.01, ** p<0.05, * p<0.1.