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Innovation policy and firm patent value: evidence from China

Aiting Xu[a,b], Caijuan Cheng[a], Keyang Qiu[a], Xiaoxu Wang[c] and Yuhan Zhu[a,b]

[a]School of Statistics and Mathematics, Zhejiang Gongshang University, Hangzhou, China; [b]Collaborative Innovation Center of Statistical Data Engineering, Technology & Application, Zhejiang Gongshang University, Hangzhou, China; [c]School of Statistics and Data Science, Nankai University, Tianjin, China

ABSTRACT

This study aims to contribute to the empirical literature that evaluates the impact of the *Science & Technology (S&T) Outline*, a Chinese innovation policy implemented in 2006, measured by the scale of patent value. We first create a comprehensive patent valuation model (CPVM), derived from the extended patent renewal model and a variety of feature indices, to measure a firm's patent value. From a database with over 700,000 Chinese patents from 1985 to 2013, we find that the patent value increases after the release of the *S&T Outline*, and the scale of patent value after 2006 is about 26.52 times more than that before 2006. Further, we use a quasi-difference in differences (DID) model to estimate the growth effect caused by the innovation policy. The results indicate that the *S&T Outline* had a significant effect on the promotion of patent value, in industries with high patent intensity. Considering the lag effect of the *S&T Outline*, we construct innovation correlation networks to visualise and compare its promotion effect. We find that regional networks have a gathering tendency after policy implementation, while industrial networks have a decentralising tendency.

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1. Introduction

Technological innovation drives firm competitiveness and sustains the growth of an economy (Danguy, 2016; Mai et al., 2019; Yeo, 2019). In the United States (US) and European countries, a primary concern for long-term economic development is the nationwide technical performance (Negassi & Sattin, 2019; Tomasz & Arkadiusz, 2019). In recent years, China has gained a reputation of being the 'world's factory', and has aspired to improve its innovation capacity from 'made in China' to 'created in China'. Since the 1980s, it has initiated several programmes to reform its innovation system (Ma et al., 2009). In 2006, China announced a 15-year 'Medium- to

CONTACT Yuhan Zhu yuhan.zhu@mail.zjgsu.edu.cn

Long-Term Plan for the Development of Science and Technology (2006–2020)' or the *S&T Outline*, which emphasises the strategic role of technological innovation at the national level.

With its shift from the 'processing factory' to the 'innovation base', China has experienced explosive growth in domestic patent applications (Hu & Jefferson, 2009; Li, 2012), surpassing all other economies to become the world's biggest filer of patent applications since 2011 (World Intellectual Property Organization, 2012). The information implicit in the number of patents issued at different times, in different industries, and to different types of inventors also contains essential information that supports techno-economic analysis (Griliches, 1998; Watanabe et al., 2001). However, several studies have pointed out discrepancies in the quantity versus the actual quality of patents in China (Dang & Motohashi, 2015; Ma et al., 2009), given the incentives to produce several low-value patents (Ernst, 2011). The total value added by patent-intensive industries amounted to only 11.6% of China's gross domestic product (GDP) in 2018[1], far below 38.2% of the US' GDP in 2014[2].

The lack of heterogeneity in patents also poses a challenge to technological innovation at the firm level in China (Hu et al., 2020; Schankerman & Pakes, 1986; Zeebroeck, 2011). Some scholars have studied the value of patents as a sophisticated and reliable proxy of firm innovation, a signal of quality (Gambardella, 2013; Ribeiro & Shapira, 2020; Tukoff-Guimares et al., 2021). A patent has no value unless commercialised, and the patent value can remove the 'noise'[3] in patent counts, as an accurate measure of the innovative output of firms (Schankerman & Pakes, 1986). However, given the difficulty of assessing patent value (Hsieh, 2013; Hwang et al., 2021; Layne-Farrar & Lerner, 2011), many studies have considered patent counts as an indicator of innovation (Bronzini & Piselli, 2016; Cappelen et al., 2012). Moreover, few studies have provided empirical evidence on the economic value of these patents. It remains unclear whether innovation policy has resulted in the promotion of the value of Chinese patents.

This study shifts the perspective from the number to the value of patents, which helps evaluate China's efforts in boosting its innovation system and progress. The value of the patent is measured at the firm level and reveals the extent to which policy incentives can stimulate patent value. Since the *S&T Outline* is the most strategic innovation policy in China (Cao et al., 2006), we set 2006 as the baseline for the *S&T Outline* to start exerting its effects.

This study contributes to the literature on innovation in developing countries, such as China, in the post-innovation stage. First, a comprehensive patent valuation model (CPVM) was proposed based on an extended patent renewal model and a variety of feature indices for different patents including three essential procedures, namely, estimating the average patent value, fitting, and predicting the patent renewal pattern, and constructing a feature index for an individual patent. Thereafter, we used CPVM to calculate the economic value of each patent. Second, by matching the patent value of firms with industrial and regional economic data, we empirically demonstrated the effects of the *S&T Outline*, with findings that provide useful policy insights. Third, we constructed innovation correlation networks linking industries and regions to visualise and compare the promotion effect before and after the release of the *S&T Outline*.

The remainder of this paper is as follows. Section 2 presents the literature review, while section 3 provides an extended model of patent valuation, introducing the study's empirical methodology. Section 4 reports the econometric results and section 5 presents the discussion and conclusion.

2. Literature review

2.1. Measurement of firm innovation performance

Public policy focuses on stimulating economic growth while emphasising the advancement of firm innovation (Lee & Trimi, 2018; Skm & Ab, 2020). There is a growing demand to assess firm innovation and technological change to increase our knowledge about innovation drivers (Kleinknecht et al., 2002; Seddighi & Mathew, 2020).

Firm innovation performance can be measured in terms of innovative inputs such as research and development (R&D) expenditures, staff qualifications (Blanco et al., 2020; Forsman, 2011; Nilsson & Ritzen, 2014), and intensity (Chen et al., 2019), or innovation outputs, such as patent applications (De Rassenfosse et al., 2013; Huang et al., 2015; Mairesse & Mohnen, 2004), holdings (Mairesse & Mohnen, 2004), citations (Beneito, 2006; Chen et al., 2012; Lahiri, 2010; Verhoeven et al., 2016), frequency (Ahuja & Katila, 2001), and quantity (Bellamy et al., 2014). Among these, the patent count indicators, such as applications, holdings, and the number of patents, are widely used to measure firms' innovation activity. Patent counts are frequently used to measure innovation performance first, because patents are the most extensively used output indicators of innovation given the easy accessibility of data and representativeness of technological novelty (Hsu et al., 2015), and second, because the number of patents has a significantly positive correlation with new product introduction (Brouwer & Kleinknecht, 1999) and technical capabilities of firms (Hoetker, 2005).

However, the number of patents is not the best indicator of the innovation level of firms. Prior studies have highlighted that simple patent counts are incapable of accurately capturing the value of underlying innovations (Chen et al., 2012; Griliches, 1990) because the technological quality and economic value of patents differ greatly (Griliches, 1990). Thus, patent value is a relatively more accurate measure of innovation performance than patent counts because it involves the quality and economic gains of various patents. Many scholars have attempted to overcome the disadvantages of patent counts to measure a firm's innovation capability by estimating patent value (Gambardella, 2013; Lawryshyn et al., 2017; Park & Park, 2006; Schankerman & Pakes, 1986; Yang et al., 2015). Therefore, we consider that patent value data can reflect the heterogeneity and authenticity of technological creativity, and employ this data to investigate the technological innovation performance of firms.

2.2. Methods of patent valuation

Existing research on estimating patent value can be roughly divided into estimating the value of a single patent from a micro perspective, or the average value of a cohort of patents from a macro perspective. The former methods include the comprehensive evaluation, cost, discounted cash flow, market, and option pricing methods. The latter includes the survey method and patent renewal model. The patent renewal model is widely used by scholars because of its objectivity, reliability, and easy access to basic data (Zhang et al., 2014).

Proposed by Pakes and Schankerman (1984), this model is based on the patentee's expected return maximisation decision theory, and estimates the average value of a cohort of patents based on the discounted value of expected net return by setting the initial return distribution function and expected return decay mode of a cohort of invalid patents. Setting the expected return decay mode is important for the model. Many scholars, such as Bessen (2009) and Danish et al. (2020) used the exponential expected return decay mode proposed by Pakes and Schankerman (1984) and Schankerman and Pakes (1986) to study patent value in the United Kingdom (UK), US, Germany, France, Finland, India, and other countries. Given the uncertainty of successful realisation of a patent's economic value after it is granted, some researchers have improved the expected return decay mode. Pakes (1986), Lanjouw (1998), Deng (2011), Zhang et al. (2014) and other scholars believe that the patentee's learning ability, commercial strategy, and responses when the patent is infringed will have an impact on the expected return of the patent. The random expected return decay mode is then introduced into the model to estimate the patent value.

However, the patent renewal model has some limitations. First, the setting of the expected return decay mode needs improvement. It takes a long time for an invention patent to be authorised, commercialised, and put on the market because of the high complexity of technical knowledge. During this time, imitation, replacement, and the speed of elimination is slow. Paradoxically, the exponential expected return decay mode assumes that the expected return of the invention patent decays rapidly from the beginning. Furthermore, the operation procedure of the random expected return decay mode is complicated and lacks practicality due to various assumptions or parameters, although it considers the uncertainty of return. Second, limiting the application object of the model to expired patents leads to a failure in estimating the value of several unexpired invention patents. Most invention patents are valid, and have a maximum protection period of 20 years. Third, the patent value estimated by the expected net return cannot reveal the real value of the patent. The expected net return is a conceptual return measured according to accounting principles and deviates from the actual return of patents. Thus, this study sets the expected return decay mode according to the actual characteristics of invention patents, establishes the renewal probability prediction model for unexpired patents, and constructs feature indices for different patents based on their characteristics. We also propose an extended model for comprehensively estimating the patent value considering the expected total return as the patent value.

2.3. Effects of innovation policy

Over the past few decades, innovation policy has emerged as a normal instrument to promote the commercial exploitation of new ideas (OECD., 2003). Policymakers and scholars have prioritised the role of innovation policy in economic development.

Studies in expanding numbers evaluate the effectiveness of two main innovation policies, namely tax incentives (indirect support policy) and direct subsidies (direct support policy). Tax incentives mainly refer to R&D tax credits and patent boxes, while R&D subsidies are part of the direct subsidy policy. They aim to encourage firms to enhance investment in the innovation process by reducing costs (Bronzini & Piselli, 2016).

There are three main types of empirical conclusions about the effectiveness of innovation policy. First, the effect of the R&D subsidy or tax credit policy is significantly positive (Czarnitzki et al., 2011; Foremanpeck, 2013; Radicic et al., 2016). Second, the incentive effect of tax incentives is heterogeneous in the industry. Castellacci and Lie (2015) show that the effectiveness of R&D tax credits is, on an average, stronger for firms in the service and low-tech sectors. Third, direct subsidies have a crowding-out effect that negatively influence private investment (Dimos & Pugh, 2016; Montmartin & Herrera, 2015).

Recent attempts have examined the effects of innovation policies on patent activities, but the conclusions are inconsistent. Bronzini and Piselli (2016) used a regression discontinuity design strategy to study the effect of R&D subsidies on the number of patents. They provided evidence of the effectiveness of R&D subsidies in smaller firms. However, Cappelen et al. (2012) and Zanghelini and Andrade (2015) illustrated that R&D tax credits or other tax incentive policies have failed to produce any noticeable effect on firms' patent activities.

Thus, most existing studies have concentrated on the effects of various forms of innovation support policy at the micro level. Few studies have evaluated the impact of major innovation policies in a country or region at a macro level. As countries like China transform from traditional manufacturing countries to innovation hubs, they have launched several innovation incentive policies to promote technology upgradation. It is difficult to accurately reveal the impact of the overall innovation policy environment on innovation activity only by examining the effects of individual innovation policies at the micro level. There may be superposition or crowding-out effects among the various policies. Since the *S&T Outline* guides various innovation policies such as R&D subsidies and patent tax credits in China, this paper analyses the technological innovation effects that it induces.

2.4. Construction of innovation network

Scholars have realised the importance of innovation networks in gaining access to scarce resources, managing complex innovation processes, and enhancing technological capabilities (Pyka, 2002). Gradually, theoretical research on innovation has eliminated traditional innovation ideas, and shifted focus to the interaction and structural differences of individuals in the innovation relationship. This is divided into three aspects, namely, structural characteristics (Fujiwara & Aoyama, 2010; Rahmandad & Sterman, 2008; Schilling & Phelps, 2007), functionality (Asheim et al., 2011; Audretsch et al., 2008; Carlsson et al., 2002) and performance of innovation (Sandstrom & Carlsson, 2008; Straub et al., 2004). With the rapid development of theoretical systems and method tools, and the continuous changes in knowledge and innovative activities, the dynamic evolution process and the motivation of innovation networks are now receiving increased attention (Garcia, 2005; Savin & Egbetokun, 2016).

Of late, patents have been applied to innovation networks. In the extant literature, the links between individuals have been modelled in several ways (Beaudry & Schiffauerova, 2011). Yoon and Park (2004) first proposed the patent network analysis method, constructing a patent network using co-occurring keywords in each patent specification, and researching the prediction of network evolution. Leydesdorff and Vaughan (2006), Sternitzke et al. (2008), and Breschi and Lissoni (2009) constructed a patent cooperation network based on patent counts or citations. Von Wartburg et al. (2005) further used bibliographic literature using bibliographic coupling as a similarity measure. However, they did not perform dynamic network analysis from the innovation network perspective.

Some scholars have begun to research the evolution of patent networks. Inoue et al. (2010) used the names and addresses of organisations and the inventors of patents to create a network, and combined these with the preference connection mechanism and the geographical distance between nodes to propose a network evolution model. Choe and Lee (2017) examined the structure, characteristics, and evolution of a research collaboration network using co-assignee information on joint patents in South Korea. Despite significant efforts to analyse patent networks, most research is still based on simple patent counts or citations, limiting the scope of analysis and the richness of potential information (Yoon & Park, 2004). This is especially true for increasingly complex patent information, where the challenges of patent data use remain.

While there are many limitations to the use of patent information included in patent counts and patent citations (Murray, 2002), we see that patent value is a better indicator of firms' innovation capability. Therefore, this study attempts to construct innovation correlation networks from the perspective of patent value and observe dynamic changes through visualisation.

3. Method and materials

From the patent economic value perspective, we provide a framework based on the CPVM and difference-in-differences (DID) estimation. These establish a link between patents counted by pieces and their economic value, and further examine whether the innovation policy (*S&T Outline*) promotes the accumulation of patent value. Finally, we construct innovation correlation networks linking industries and regions to visualise and compare the promotion effect before and after the release of *the S&T Outline*.

3.1. Method for estimating patent value

Patent value is defined as the total economic return that a patent can generate during its life. Patents can provide their owners with a degree of market power that conveys a stream of profits that exceeds the profits they could earn without patents (Bessen, 2008). These additional profits embody the economic returns yielded by patents for patentees, and can be realised through licensing, sale, or production. Here, the patent value is estimated in terms of economic value and closer to its market value. Accordingly, patent evaluation is executed by estimating the patentee's economic returns.

In our CPVM model, we follow three steps: measuring the average patent value, fitting and predicting the patent renewal pattern, and constructing the feature index for the value of an individual patent.

3.1.1. Average value of patents

Here, we propose an extended patent renewal model to measure the average value of patents at the aggregate level. The patentee must pay an annual renewal fee to maintain patent protection else the patent lapses permanently (Lanjouw, 1998). Thus, a patent renewal model was proposed to estimate the private returns of the patentee based on the rational decision-making mechanism, in which patentees choose an optimal age to stop paying the renewal fee. Let $\{C_{tj}\}$ denote the sequence of renewal fees at different ages of a patent in cohort j, and $\{R_{tj}\}$ denote the sequence of returns generated by a patent during the coming year. The decision problem of the patentee is choosing an optimal lifespan T^* to maximise the discounted value of net returns $\sum_{t=1}^{T^*}\{R_{tj}-C_{tj}\}(1+s)^{-t}$, where s is the discounted rate. The original patent renewal model endowed each cohort patent[4] with an initial return R_{oj}, and assumed $\{R_{tj}\}$ decay with a fixed rate based on R_{oj}. Thus, $R_{tj}=R_{oj}\prod_{a=1}^{t}(1-\delta_{aj})$, where δ_{aj} is the decay rate of patent returns. Since $\{C_{tj}\}$ is non-decreasing at t, $\{R_{tj}\}$ does not increase at t, and the sequence of net returns $\{R_{tj}-C_{tj}\}$ is non-increasing at t. The condition for renewal of the patent at age t is $\{R_{tj}-C_{tj}\}\geq 0$. In other words, there exists a unique optimal lifespan T^* such that for any $t\leq T_j^*$, $\{R_{tj}-C_{tj}\}\geq 0$, and for any $t\leq T_j^*$, $\{R_{tj}-C_{tj}\}<0$. Therefore, the renewal rate RW_{tj} of patents in cohort j at age t can be calculated as follows.

$$RW_{tj}=\int_{z_{tj}} f(R_{oj};\theta_j)dR_{oj}=1-F(z_{tj};\theta_j\Big) \tag{1}$$

where $f\ (R_{oj};\theta_j)$ and $F\ (z_{tj};\theta_j)$ denote the density and distribution functions of initial returns R_{oj}, respectively, and $z_{tj}=C_{tj}\prod_{a=1}^{t}(1-\delta_{aj})^{-1}$. Given the functional form for the distribution of R_{oj}, the parameter $f\ (R_{oj};\theta_j)$ and decay rate δ_{aj} can be estimated based on the proportion of patents calculated by the patent lifespan observed and the proportion of patents predicted by equation (1).

In the uncommercialised application stage, invention patents are eliminated gradually due to the high complexity of technical knowledge. The expected return of invention patents correspondingly decays slowly in the early stages. However, the exponential expected return decay mode of the original model which assumed that $\{R_{tj}\}$ decays rapidly from the beginning, ignores this feature of invention patents. Thus, we measure the value of a patent more precisely using an extended patent renewal model. We assume that the patentee has an expected initial return from the patent in the application stage, and subsequent returns at each age t of the patent decay, based on its initial expected return RE_{oj}. The decay rate here is initially slow or zero. Thereafter, it experiences an increase due to technology upgradation and depreciation of present knowledge. The specific formula is as follows.

$$R_{tj} = RE_{oj}e^{-k_j t^2} \tag{2}$$

where k_j is the variable parameter of the decay rate, estimated using the above-mentioned method. We also refer to pertinent studies and assume the functional form of the initial returns distribution as a log-normal distribution, with $s = 0.1$. Finally, the average value of a patent in cohort j can be calculated using the estimation results of the parameters. The specific calculated formula[5] is as follows.

$$A_j = \sum_{i=1}^{T_j^*} e^{\hat{\mu}_j + \hat{\sigma}_j^2/2 - \hat{k}_j t^2}(1+s)^{-t} \tag{3}$$

where $\hat{\mu}_j$ and $\hat{\sigma}_j{}^2$ denote the mean and variance of the log-normal distribution functions, respectively, and $T_j{}^*$ denotes the average optimal lifespan of patents in cohort j, calculated using the following formula.

$$T_j^* = \sum_{i=1}^{t} pr_{tj}t \tag{4}$$

where pr_{tj} denotes the proportion of patents whose lifespan is t in cohort j.

3.1.2. Patent renewal pattern fitting and prediction

The renewal-based approach relies on the fact that all patents in cohort j have lapsed. Since the *Patent Law of the People's Republic of China* came into force on April 1, 1985, most invention patents have not expired. The patent renewal approach cannot estimate the value of these patents. Thus, we fit the patent renewal pattern of each cohort in which all the patents have lapsed. The results indicate that the renewal pattern of each cohort of patents fits well with the log-normal distribution function. Appendix A shows the detailed results. Therefore, we can use the theoretical distribution function of each cohort of patents whose lifespan cannot be observed so far, to predict their renewal probability at age t. The parameter of the distribution function can be estimated using the value of the parameter of the practical patent renewal distribution. We test the trend of mean and variance of patent renewal distribution from the 1985 to the 1999 cohort, finding a growing trend in the mean of patent renewal distribution, and no significant trend in the variance of distribution. Appendix B shows the detailed results. A tendency forecast helps estimate the mean of patent renewal distribution of each cohort including unexpired patents, and the average value of the variances of the 1985 to 1999 cohorts estimates the variance of the distribution.

Thus, the average value of patents in a particular cohort including unexpired patents can be estimated using the method proposed in section 3.1.

3.1.3. Measuring value of the individual patent

The value of an individual patent can be measured through a feature index constructed based on the lifespan information of each patent. We design three types of feature indices according to the characteristics of several patents, including lapsed patents, unexpired patents, and patents with short lifespans. We first convert the average optimal lifespan of patents from a yearly to a monthly basis,[6] and then construct a feature index for the value of individual patents in each cohort according to the characteristics of each patent. Finally, we calculate the value of each patent based on different feature indices and the corresponding average value information.

Given that the lapsed patents' lifespan information can be observed, the feature index of value for these patients can be constructed using the lifespan information of each patent directly. Let In_{ij} denote the feature index of value for patent i in cohort j, L_{ij} the lifespan of patent i in cohort j, and AL_{ij} the average optimal lifespan of patents in cohort j. The specific calculated formula of the feature index can be defined as follows.

$$In_{ij} = \frac{L_{ij}}{AL_j} \tag{5}$$

The value of each patent in cohort j can be measured as below.

$$V_{ij} = In_{ij}A_j \tag{6}$$

where V_{ij} is the value of patent i in cohort j.

Since the lifespan information of unexpired patents cannot be observed, the construction of the feature index of value for these patents requires additional information, obtained from the *IncoPat Global Patent Database* (IGPD),[7] with over 120 million pieces of patent information from 120 authorities, such as the patent offices of different countries and business vendors. Our patent data include the number of patent claims, simple patent families, extended patent families, international patent documentation families, the patent value degree (PVD) calculated by IGPD's evaluation model, the mechanical stability of patent, the scope of patent (SOP) evaluated by IGPD, and so on. A correlation test examines the relevance between these factors and the lifespan of each lapsed patent. The results prove that PVD and SOP have a forward correlation with the lifespan of patents. Appendix C presents detailed results. We construct the feature index for the value of these patents based on their PVD and SOP information. First, the mean of the PVD and SOP are calculated to convert the data into a dimensionless form. Thereafter, the mean correlation coefficient of PVD, SOP, and lifespan of all patents is used to calculate the weight values of the two factors. Third, based on the weight value of the factors, the summary values of PVD and SOP of each patent are calculated as follows.

$$W_{ij} = w_{ijD}D_{ij} + w_{ijS}S_{ij} \tag{7}$$

where W_{ij} denotes the summary value of PVD and SOP of patent i in cohort j, w_{ij*} denotes the weight value of PVD or SOP of patent i, and D_{ij} and S_{ij} denote the dimensionless value of PVD or SOP of patent i. The feature index for the value of each patent is constructed through W_{ij} and the value of the patents with the most extended life observed till now in cohort j. Since many patents have the same lifespan and there are multiple patents with the most extended lifespan in cohort j, we calculate the mean W_{aj} of the value below the median of W_{mj}[8]. W_{mj} denotes the sum weighted value of PVD and SOP of patents with the most extended lifespan observed in cohort j. The feature index for the value of the unexpired patents is found as follows.

$$V_{ij}^{*} = \frac{W_{ij}}{W_{aj}} V_{aj} \tag{8}$$

where $V_{ij}{}^{*}$ denotes the value of unexpired patents, and V_{aj} denotes the value of patents with the most observable lifespan in cohort j.

Patents with a relatively short lifespan have a relatively low economic value[9]. To compensate for overestimating patent values, we adjust the value based on an additional feature index, illustrating the value of patents with a short lifespan more accurately. First, we calculate the average renewal rate and associated value of patents aged 1–6. Second, the values of patents aged 1–6 are adjusted. Third, we construct a feature index for each patent selected to calculate their value. The specific calculation formula is as follows.

$$V_{ij}^{\circ} = \frac{L_{ij}}{L_{stj}} V_{stj} \tag{9}$$

where $V_{ij}{}^{\circ}$ denotes the value of patents whose lifespan is below six in cohort j, L_{ij} the lifespan of these patents on a monthly basis, L_{stj} the standard lifespan of patents at age t in cohort j on a monthly basis, and V_{stj} the value of patents whose lifespan is L_{stj} on a monthly basis.

3.2. Difference-in-differences estimation

The DID method estimates treatment effects, based on the data obtained from natural experiments, using modelling to effectively control prior differences between the research objects and effectively separate the accurate results of the treatment effects. Given its simplicity and its potential to circumvent endogeneity problems (Bertrand et al., 2004), we employ DID estimation to assess the impact of *S&T Outline* on patent value. Since the *S&T Outline* aims to improve the country's overall innovation capability, we cannot define treatment and control groups with 0 and 1 only. Moreover, this policy affects different industries in varying degrees. F Non-patent-intensive industries are less dependent on patent innovation, and therefore less influenced by the *S&T Outline* (Kou & Liu, 2020). Here, patent intensity of an industry is a grouping variable. The quasi-DID model formula is as follows.

$$\begin{aligned} Patent_{ijt} = \alpha_0 + \alpha_1 intensity_i \cdot Policy06_t + \alpha_2 Policy06_t + \alpha_3 intensity_i \\ + Industry_{i,t-1}\beta + Region_{j,t-1}\gamma + \eta_{it} + \eta_{jt} + \varepsilon_{ijt} \end{aligned} \tag{10}$$

where $Patent_{ijt}$ denotes the patent value of industry i from region j in 2012, $Intensity_i$ the intensity of patent value, and $Policy06_t$ the time dummy variable, if $t \geq 2006$. $Policy06 = 1$, if $t < 2006$, $Policy06 = 0$. $Intensity_i{}^{*}Policy06_t$ is an interactive item for both variables. $Intensity_i$ divides the sample data into treatment (high patent intensity) and control (low patent intensity) groups. α_i is the corresponding regression coefficient, and α_1 is the DID estimator, indicating the net effect of the *S&T Outline*. ε is an error that accounts for the discrepancy between the predicted and observed data.

The DID model contains control variables and fixed effects. $Industry_{i,t\text{-}1,}$ and $Region_{j,t\text{-}1}$ are industrial and regional control variables, η_{it} is the industry-year fixed effect, and η_{jt} is the region-year fixed effect.

To confirm that all effects are caused by the *S&T Outline* implementation, we need to conduct the following robustness test.

1. Parallel trends test. In the absence of the *S&T Outline*, the difference between the treatment and control groups is constant over time. Here, we employ the event study introduced by Jacobson et al. (1993) to conduct the parallel trends assumption. The test formula is as follows.

$$Patent_{ijt} = \alpha_0 + \sum_{K=1990}^{2013} \alpha_k D_{ik} + Industry_{i,t-1}\beta + Region_{j,t-1}\gamma \\ +\eta_{jt} + \eta_t \cdot PV_{ij} + \varepsilon_{ijt} \tag{11}$$

where D_{ik} represents the interaction item between the industry patent intensity and a series of dummy variables of the year, and $\eta_t{\cdot}PV_{ij}$, the interaction item between the annual average patent value and the fixed effect of the year of industry i in region j before the implementation of *S&T Outline*.

1. Placebo test. Even if the treatment and control groups have the same trend before *S&T Outline* is implemented, we need to identify whether other policies affect the simultaneously changing trend. A placebo test makes a regression estimate of the default treatment group or assumed policy time. According to equation (10), the estimated coefficient α_1 is as follows.

$$\frac{\hat{\alpha}_1 = \alpha_1 + \beta \cdot cov\left(intensity_i \cdot Policy06_t, \varepsilon_{ijt} \middle| C\right)}{var\left(intensity_i \cdot Policy06_t \middle| C\right)} \tag{12}$$

where C represents all control variables and fixed effects, and β denotes the influence of unobservable factors on the explained variable. If $\beta = 0$ is supported, the unobservable factors do not affect the estimated results.

The influence factors are extracted from the statistics yearbook and listed in Table 1. The data are from China Statistical Yearbook 1990–2014, China Industry Statistical Yearbook 1990–2014, and China Statistical Yearbook on Science and Technology 1990–2014.

3.3. Innovation correlation networks construction

This study constructs innovation correlation networks to describe the tendency of the policy to impact the patent value and compare the promotion effect before and after the release of the *S&T Outline*. The first step explores the relationship between the patent value of each region and the industry. Presently, different fields employ

Table 1. Influence factors related to patent value.

	Symbols	Indices	Descriptions
Dependent variable	*Y*	Patent value	Total patent value (after logarithm)
Independent variables	*Intensity*	Patent intensity	Patent applications per industrial personnel
	*Policy*06	*S&T Outline* or Not	Year $\geq$ 2006, *Policy*06 = 1; Year <2006, *Policy*06 = 0
	ln*Tasset*	Industrial total asset	Industrial total asset (after logarithm)
	ln*IR&DE*	Industrial R&D funds	Industrial R&D expenditure (after logarithm)
	IR&D_per	Industrial R&D personnel	Scale of industrial R&D personnel
	ln*RGDP*	Regional economy	Regional GDP (after logarithm)
	IndStr	Industry structure	Industrial value-added/regional GDP*100%
	ln*RR&DE*	Regional R&D funds	Regional R&D expenditure (after logarithm)
	RR&D_per	Regional R&D personnel	Scale of Regional R&D personnel

Source: Authors.

distance indicators to describe the relationship (Spelta & Araújo, 2012; Tola et al., 2008). Since the construction methods between regional and industrial innovation-related networks are similar, the formula for regional innovation correlation networks is as below.

$$D_{ij} = \sqrt{2(1 - C_{ij})} \tag{13}$$

where i and j represent different provinces, and C_{ij} represents the correlation coefficients of two time series, $\vec{y}(i)$ and $\vec{y}(j)$ as follows.

$$C_{ij} = \frac{\left|\vec{y}(i)\vec{y}(j)\right| - |\vec{y}(i)||\vec{y}(j)|}{\sqrt{\left(\left|\vec{y}^{2}(i)\right| - \left|\vec{y}(i)\right|^{2}\right)\left(\left|\vec{y}^{2}(j)\right| - \left|\vec{y}(j)\right|^{2}\right)}} \tag{14}$$

Let $patent_{pt}$ represent the patent value of province p in year t and record it as $\overrightarrow{patent}(p) = (patent_{p1}, patent_{p2}, \ldots, patent_{pt})$. The standardised patent value of each province is as follows.

$$\overrightarrow{patent}_{N}(p) = \frac{\overrightarrow{patent}(p) - \left|\overrightarrow{patent}(p)\right|}{\sqrt{t\left(\left|\overrightarrow{patent}^{2}(p)\right| - \left|\overrightarrow{patent}(p)\right|^{2}\right)}} \tag{15}$$

where t represents the number of elements of the vector $\overrightarrow{patent}(p)$, which represents the number of years. p, $q = 1, 2, \ldots, N$ represent the sample provinces. Vectors $\overrightarrow{patent}(p)$ and $\overrightarrow{patent}(q)$ are standardised and substituted in equation (14). We obtain C_{pq}. This is substituted in equation (13), and we obtain the Euclidean distance between provinces p and q as follows.

$$D_{pq} = \sqrt{2(1 - C_{pq})} = \left| \overrightarrow{patent_N}(p) - \overrightarrow{patent_N}(q) \right| \tag{16}$$

The distance matrix $\boldsymbol{D}$ can be constructed based on equation (16). Since the value of C_{pq} is [-1,1], the value range of d_{pq} for each element in the distance matrix is [0,2]. The larger the C_{pq} value, the smaller is the corresponding d_{pq}, indicating that the more consistent the changes in patent values between the two regions, the higher is the degree of correlation. When d_{pq}=0, the patent values of the two places change in the same proportion and direction, and the degree of innovation connection between the two regions can be expressed by the reciprocal of distance (Spelta & Araújo, 2012).

$$Q_{pq} = 1/d_{pq} \tag{17}$$

where Q_{pq} is the innovation correlation strength between provinces p and q. The strength matrix $Q(p,q)=(Q_{pq})_{N\times N}$ comprising Q_{pq} represents the spatial association network matrix of regional innovation. Each element of the network matrix determines the edge of the regional innovation-related network, and each region is the 'point' in the network. Together, these points and edges constitute the spatial association network of regional innovation in China. ForceAtlas2[10] was used for network spatialisation.

4. Results

4.1. Estimation results of patent value

Table 2 presents the final patent value estimates for the six cohorts. The estimates reveal that the distribution of patent values is severely skewed in each cohort. The median value is far below the mean value of firm patents from 1990 to 2013, and the value increases sharply with the quantile. For example, the mean value in 1990 was 102.6 thousand Yuan, approximately four times higher than the median value. This demonstrates a polarisation problem as few patents have a sharp competitive edge. The results indicate that patent counts are inadequate measures of technical creativity at firms because there is considerable heterogeneity among patents. Thus, it is challenging to employ number of patents to examine the causes and consequences of variation across groups while valuing innovation (Lanjouw et al., 1998). Hence, we use patent value as a measure of technical innovation performance to compensate for

Table 2. Patent value distribution of firms, by quantile: 1990-2013.

Quantile	1990	1995	2000	2005	2010	2013
0.25	19.9	39.6	120.2	251.5	355.7	468.2
0.50	29.2	65.1	219.0	466.2	687.8	1,043.5
0.75	314.9	501.3	1,294.9	2,332.6	3,273.0	4,823.0
0.90	939.8	1,399.5	3,445.7	5,902.6	8,315.4	13,255.5
0.95	1,821.7	2,604.3	6,217.9	10,332.7	14,580.6	24,462.5
Mean	102.6	126.2	232.2	272.0	384.4	1,109.2

Note: patent values are in 1998 thousand Yuan.
Source: Authors.

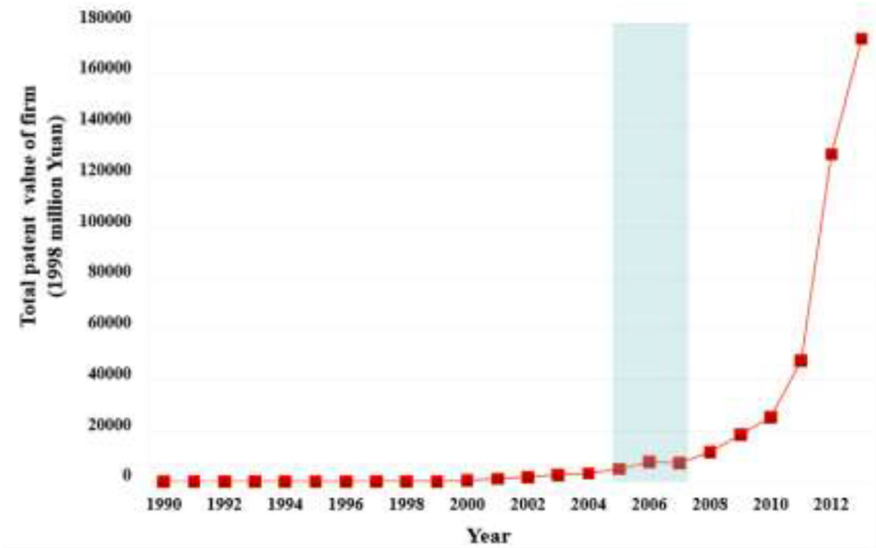


Figure 1. Trend of the scale of patent value for firms over time.
Source: Authors.

the deficiency of patent counts and investigate the trends and structure of patent development more accurately.

The scale of patent value is calculated for each application year to explore the trend of firm patent value at an aggregate level. The amount of patent value has increased and become steeper in recent times (Figure 1). Estimated at 173930.1 million yuan in 2013, the total patent value is 4411.1 times higher than that in 1990. The average growth rate of the scale of patent value during 1990–2006 was 44.73%, and during 2006–2013 was 62.20%, reflecting the rapid progress of technical innovation during later periods. The growth rate of the amount of patent value witnessed a dramatic increase around 2007, a possible result of a one-year lag of stimulation by the 2006 innovative policy.

The industry-level patent value is calculated at an interval of three or four years to investigate their relative importance (Figure 2). The share of Manufacture of Chemical Raw Material and Chemical Products (C26) and Processing of Petroleum, Coking, and Other Fuels (C25) have occupied leading positions during the years, followed by Mining of Ferrous Metal Ores or Non-ferrous Metal Ores (C31/32) and Manufacture of Medicines (C27), experiencing a gradual decrease. Other industries, such as the share of Service of Telecommunications, Radio, Television and Satellite Transmission (I63), Manufacture of Communication, Computer, Other Electronic Equipment (C39), Manufacture of Electrical Machinery and Equipment (C38), Manufacture of General Purpose Machinery (C34) show a continuous uptrend. By 2013, the Manufacture of Communication, Computer, and other Electronic Equipment (C39) became the largest industry with a share of 12.7%, followed by Services of Telecommunications, Radio, Television, and Satellite Transmission (I63) (12.4% share), and Manufacture of Chemical Raw Material and Chemical Products (C26), Manufacture of Electrical Machinery and Equipment (C38), and Manufacture

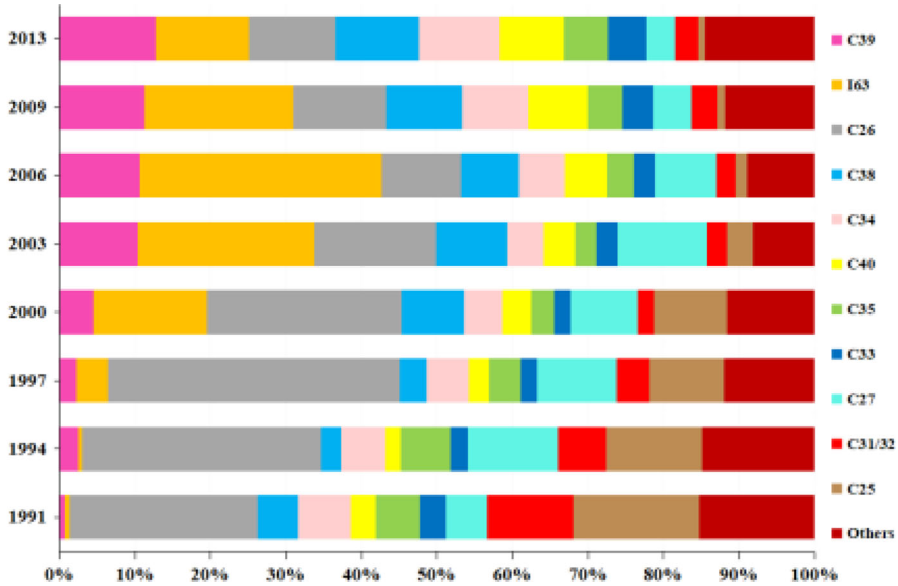


Figure 2. Share of each industry in total patent value of firms (%).
Source: Authors.

of General Purpose Machinery (C34), with shares of 11.4%, 11.1%, and 10.8%, respectively. Although the share of Service of Telecommunications, Radio, Television, and Satellite Transmission (I63) decreases relative to other industries' increase, the scale of patent value in this industry has burgeoned, with a fast-annual growth rate of 50.4% during 2006–2013. These reflect the change in the industrial structure of firms' innovative activities.

From the regional distribution perspective, the scale of the patent value of 31 regions is estimated in Figure 3, displaying a sharp unevenness. There is a dense concentration of the amount of patent value in the eastern coastal strip in 2000, especially in Beijing, Guangdong, Shanghai, Jiangsu, and Shandong, with average shares of 31.8%, 21.5%, 11.2%, 6.4%, and 5.7%, respectively. However, the total share in another region is less than 30%, and in Chongqing, Ningxia, Guizhou, and Qinghai, in the western region, it is less than 0.3%.

Thus, there is a substantial regional disparity in technical innovation capacity in China, and the economically developed provinces display intense patent creativity. This inequality is first, due to resource concentration at the state level, leading to higher patent values in developed areas and second, due to the presence of knowledge-based industries driven by patent resources facilitating demand.

4.2. DID Estimation and robustness analysis

Table 3 summarises the results of the DID analysis for the *S&T Outline* effect. The mean variance inflation factors (VIF) for models 1–4 is all less than 10 (VIF exceeding 10 indicates a high possibility of severe multicollinearity and the necessity of correction and modification). We employ robust standard errors to control heteroscedasticity.

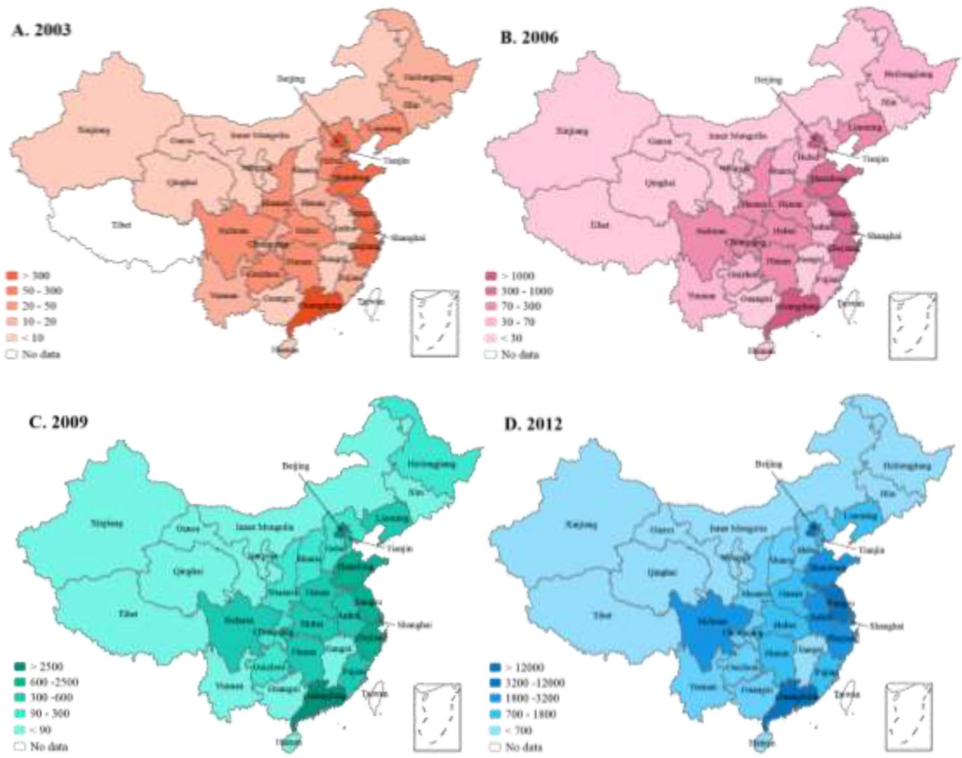


Figure 3. Share of regions in the total patent value of firms (unit: million yuan).
Source: Authors.

In terms of 'DID factors', when the intensity of invention patents in the industry, dummy variable of *S&T Outline*, and the interaction term of the two–representative coefficients evaluate the implementation effect of *S&T Outline*, exerting a significant positive effect. This reflects the enhancement of the patent value of Chinese firms on an average, due to the *S&T Outline*. In Model 1, the two coefficients and their interaction terms obtained statistical significance at a confidence of 10%. However, after controlling for all kinds of industrial and regional variables, the significance of interaction items increases, reaching a 1% significance level in Model 4. This proves that the development of the intensity of invention patents in the industry is due to the implementation of the *S&T Outline*. A series of cases illustrate the promotion effect symbolised by the intensity of invention patents, for example, the average absolute value of growing 1% for the patent value of I63 in 2006 and later is 63173.3 thousand Yuan, while in industries like A02 with lower intensity of invention patents, the average absolute value of growing 1% is only 26.8 thousand yuan[11].

From the industry characteristics perspective, the level of industry assets and the allocation of R&D resources are the key factors that affect patent value in China. Assets provide a simplified view of the economic resources, laying the corporate-level foundation of patent development. R&D resources give companies a simple to measure expenditure and personnel input, and they generally compromise the knowledge basis of patent development. Industries' good assets and strong R&D support play a dominant role in patent value enhancement.

Besides, the regional economic level, structure, and allocation of R&D resources provide insights into patent value in China. The parameter estimation results in Model 4 illustrate that the proportion of industrial added value in a region is significantly higher than that of regional GDP. From a statistical point of view, the catalytic effect of the economic development structure on patent value enhancement is higher than that of overall economic growth because in Model 4, two aggregate indicators weaken the significance of regional GDP to a certain extent at the same time. These are the assets at the industry level and the economy at the regional level. Furthermore, the effect of regional R&D resource allocation on patent value and related mechanisms is like that at the industry level.

Models 1–4 support the above conclusion, verifying the study's robustness.

From Models 1–4 in Table 3, *the S&T Outline* adds more favourable momentum to the promotion of the invention patent value of firms in high patent-intensive industries than in low patent-intensive industries. This may only be because it captures the industry differences that existed before the implementation of this policy. Before 2006, the growth rate of patent applications in high-patent-intensive industries was considerably higher than that in low patent-intensive industries.

The parallel trend test in equation (11) examines the applicability of DID. Using 1990 as the base period for the sample and the patent value as the explained variable, we conduct a regression analysis, and find that the coefficient of α_k before 2006 is not significant at 5% confidence. It only becomes significantly positive post 2006. Further, the coefficient increases year after year, indicating that the parallel trend test passes and that the effect of the *S&T Outline* on innovation promotion in China is increasing.

Further, we cannot control some unobservable and time-variant industrial or regional characteristics in the present model. Thus, the placebo test was carried out as per Li et al. (2016) to indirectly evaluate the existence and effect of omitted variables. Bootstrap sampling is employed to repeat 1000 times, and the figure of kernel density illustrates the 'wrong' estimation coefficient $\hat{\alpha}_1$. As shown in Figure 4, the coefficient obeys the normal distribution, and the mean value is close to 0 (far less than the real value 1.045). Thus, $\beta = 0$ is supported, and the omitted variables of the industry and regions do not affect the conclusions.

4.3. Innovation networks before and after the publication of S&T outline

Here, we measure the innovation output based on the patent value at both the region and industry levels, and the innovation networks from 2001–2005 and 2006–2010 are visualised in view of ForceAtlas2. From 2001–2005, the publication of the *S&T Outline* was still in progress, and from 2006–2010, it had been implemented.

4.3.1. Regional innovation networks

The regional innovation network is divided into four parts (Figure 5, corresponding to different colours), and the overall pattern shows a development trend of 'gathering'.

Table 3. Results of DID analysis for the *S&T Outline* effect.

	Variables	Model 1	Model 2	Model 3	Model 4
DID factors	Intensity*Policy06	1.045* (0.637)	1.675** (0.817)	1.574** (0.750)	1.745*** (0.698)
	Intensity	2.571** (1.236)	2.402*** (0.983)	2.323*** (0.936)	2.582*** (0.954)
	Policy06	1.542* (0.829)	1.759*** (0.674)	1.627*** (0.663)	1.946*** (0.784)
Industrial variables	lnTasset		0.754* (0.397)		0.672* (0.382)
	lnIR&DE		0.843** (0.401)		0.699* (0.376)
	IR&D_per		0.034** (0.015)		0.021* (0.013)
Regional variables	lnRGDP			0.653** (0.573)	0.448* (0.230)
	IndStr			1.552** (0.732)	1.043** (0.497)
	lnRR&DE			0.653* (0.346)	0.468* (0.275)
	RR&D_per			0.015* (0.008)	0.009* (0.003)
Industry-year fixed effect				Yes	
Province-year fixed effect			Yes		
Year fixed effect					Yes
Constant		11.836*** (1.18732)	12.987*** (0.97639)	12.762*** (1.25294)	12.076*** (1.09876)
Observations		17046	17046	17046	17046
R-squared		0.272	0.337	0.346	0.454
Number of years		24	24	24	24

Note: Robust standard errors in parentheses.
Source: Authors.
***$p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

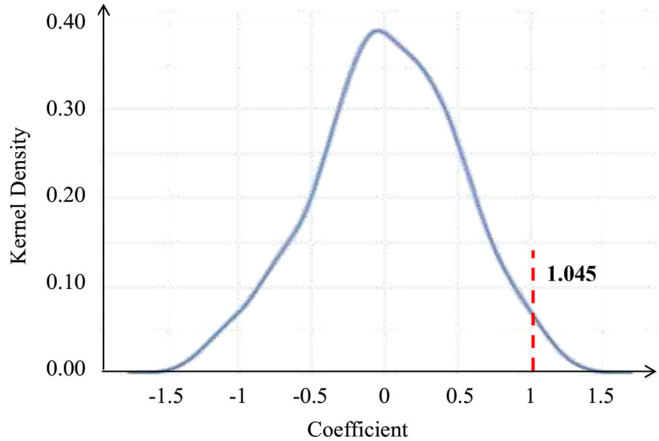
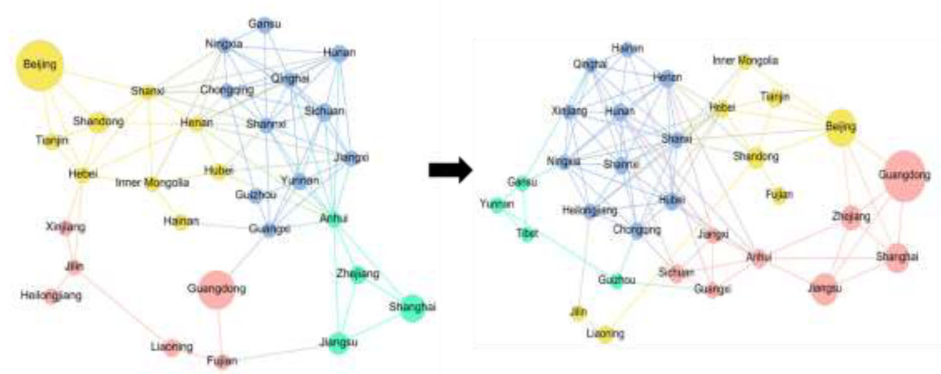


Figure 4. Placebo test for the DID model. It shows the distribution of 'wrong' estimation coefficients after 1000 placebo tests; the vertical dashed line indicates the 'correct' estimation coefficients.
Source: Authors.



2001–2005: before the publication of *S&T Outline*   2006-–2010: after the publication of *S&T Outline*

Figure 5. The regional innovation networks from 2001–2005 and 2006–2010. The circle size indicates the scale of patent value.
2001–2005: before the publication of *S&T Outline*
2006-–2010: after the publication of *S&T Outline*.
Source: Authors.

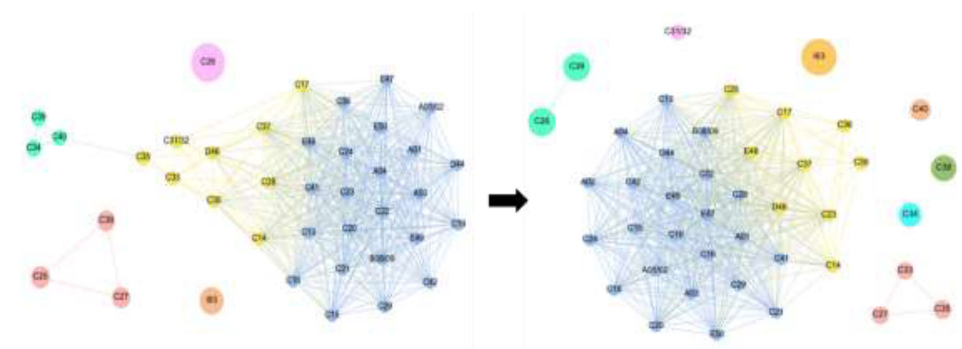
Before the publication of *the S&T Outline*, the patent value of Beijing and Guangdong was superior to other provinces due to landslides, and each promoted the innovation development of neighbouring provinces (Figure 5, left). Beijing, as a representative region of the innovation network, expanded its radiation scope to the west and north of China. As a hub, it facilitates business transactions in Tianjin, Shandong, Shanxi, and other geographically adjacent regions, and connects the innovation network of the western region through Shanxi and the northeast region through Hebei. Similarly, the Guangdong Innovation Center plays a central role in the development of a wide radiation range in the eastern coastal areas of China. Guangdong establishes an innovation network across Fujian, Guangxi, and the delta region along the Pearl River Delta, connecting the network of the Yangtze River Delta.

After the publication of *the S&T Outline*, the patent value of Guangdong and Beijing continue at the forefront nationwide, and the consolidation of the relationship chain with other provinces improves with increased coordination degrees of innovative development (Figure 5, right). Beijing has broken through geographical limits and constructed a new relationship chain integrated with Guangdong, Shanghai, and Zhejiang. Thus, Beijing has expanded its geographical reach from the northern innovation network to the Yangtze River Delta, Pearl River Delta, and other economically developed regions. The patent value of Shanghai, Jiangsu, Zhejiang, and other regions also increases rapidly, and the gap between their patent values and those of Guangdong and Beijing narrows.

Furthermore, the total patent value of Beijing and Guangdong is very high, but their degree centrality is lower than those of Shanxi, Henan, and Shaanxi, with lower patent values from 2001–2005. After the publication of *the S&T Outline*, the degree centrality of provinces with high patent value increases, but with a significant disparity with provinces with low patent value indicating that the *S&T Outline* has effectively promoted innovation levels and the degree of coordination of innovation in each province. However, for provinces with high innovation levels, such as Guangdong and Beijing, the roles and values in the innovation network have not been fully stimulated and released.

4.3.2. Industrial innovation correlation networks

The industrial innovation correlation network is different from the regional one because the overall pattern of the network presents a development trend of 'decentralisation' (Figure 6), possibly due to the guidance of the policy. The *S&T Outline* stipulates that the key areas and priority themes for S&T development in China focus on the information, modern service, and manufacturing industries, all highly patent-intensive. This policy promotes patent value levels in some industries. However, it ignores the innovation development of industries with low patent density,



2001–2005: before the publication of *S&T Outline* 2006–2010: after the publication of *S&T Outline*

Figure 6. Industrial innovation networks from 2001–2005 and 2006-–2010. The circle size indicates the scale of patent value. The detailed explanation of specific industry codes is presented in *Appendix D*.
2001–2005: before the publication of *S&T Outline*
2006–2010: after the publication of *S&T Outline*.
Source: Authors.

Figure 7. Theil indexes and its decomposition-indexes (within-industry and between-industry) from 1990–2013.
Source: Authors.

leading to an ever-widening gap in innovation levels among industries. Before the publication of *S&T Outline*, the two industries, C26 and I63, were independent of the innovation network; C25, C27, and C38 formed innovation correlations by themselves; the remaining industries formed an innovation correlation network. After the publication of the *S&T Outline*, the number of industries independent of the innovation correlation network increased from two to five. These include C31/32, C34, C38, C40, and I63. C27, C35, and C33 formed innovation correlations; C26 and C39 formed a relationship chain; the remaining industries formed an innovation correlation network.

The trend of the Theil index of firm-level patent values from 1990–2013 illustrates that the disparity in innovation level among firms is expanding. The increase in disparity after the publication of the *S&T Outline* shows an upward trend (Figure 7). Before its publication, the annual growth rate of the Theil index was 3.28%, while after, it grew to 5.86%. After the Theil index decomposition, innovation inequality within industry takes the central part, accounting for more than 80% while innovation inequality among industries accounts for less than 20%. We note that innovation inequality among industries has increased significantly since the publication of the *S&T Outline*, and its inequality proportion increased rapidly from 14.27% in 2005 to 18.60% in 2010.

5. Conclusion

This study evaluates the effect of innovation policy in China and innovation catching-up on the technological innovation performance of firms. Unlike most literature, we focus on patent value as a measure of innovation output, instead of patent counts. Based on the IGPD data, the firm-level analysis comprises more than 700,000 patents, from 1985–2013.

After the proposal of CPVM, which is extended by the traditional patent renewal model and several feature indexes, we estimate the economic value of each patent more precisely and find that the value is skewed and distributed among patents. This suggests that the indicator of patent counts alone does not fully explain the uneven distribution of technological innovation output. Besides, the amount of firm patent value is found to multiply, estimated at 173930.1 million yuan in 2013, appropriately 4411 times higher than in 1990. Accordingly, the scale of patent value of high-tech industries experienced significant development, such as I63 and C39, with an average annual growth of 47.4% and 49.2%, respectively. Moreover, there is a wide disparity in regional technological innovation in China. The scale of patent value of Beijing, Guangdong, Shanghai, and Jiangsu, the top four, jointly contribute more than 65% of the total patent value in 2013.

Considering that the *S&T Outline,* promulgated and implemented in 2006, is one of the most critical innovation policies introduced in the past decades, this study uses the quasi-DID model to identify its impact on the patent value of China. The well-designed operation of *S&T Outline* promotion significantly improved the innovation performance of firms concerning patent value and was more conducive to the promotion of patent value in invention-patent-intensive industries. Thus, there were different policy effects for industries with various patent densities. From the patent quality standpoint, the *S&T Outline* does not fully strengthen the country's innovation capacity in industries, especially for industries with low patent intensity. We need to understand and grasp the organic balance between the growth in the quantity of patents and the improvement of the patent quality.

We construct innovation correlation networks to visualise and compare the significant promotion effect before and after the release of the *S&T Outline*. There is a significant disparity in the development trends between regional and industrial networks. Regional networks have a gathering tendency after the operation of the *S&T Outline*, while industrial networks have a decentralising tendency.

At the regional level, Beijing and Guangdong both have high patent values, while their ties with other provinces are less than some areas with low patent value. There is an imbalance between the accumulation of patent value and the coordination of the regions, and the collection of patent quality among regions lacks mutual coordination. Therefore, the maximum use of the cooperation mechanism, the efficient sharing of innovation resources, and the effective implementation of patent activities within and between areas are encouraged.

At the industrial level, the worsening inequality in patent value has been ongoing and becoming more severe after the release of the *S&T Outline*. Industries that are growing substantially have a higher patent value. The patent values of I63, C26, and C39 account for about 47.50% from 2006–2010. Thus, top-level policy design is essential to balance the development of innovation capacity between high and low-patent-intensity industries. Policymakers should provide favourable patent subsidy industries with lower patent values.

Notes

1. Data source: China National Intellectual Property Administration. http://www.sipo.gov.cn/zscqgz/1146679.htm.

2. Data source: *Intellectual Property and U.S. Economy: 2016 Update*. https://www.uspto.gov/sites/default/files/documents/IPandtheUSEconomySept2016.pdf.
3. 'Noise' is defined as the unexplained variation found within the number of patents.
4. We define each application year as a cohort.
5. The principle of derivation is similar to that in Schankerman and Pakes (1986).
6. Since the range of lifespan on a monthly basis is from 12 to 240 and the range of lifespan on a yearly basis is from 1 to 24, using lifespan on a monthly basis to reveal the characteristic of patents can capture their differences more accurately.
7. https://www.incopat.com/login?locale=en.
8. Since renewal-based approach assumes that patents with long lifespan are more valuable than those with short lifespan, we must ensure that the W_{ij} of unexpired patents is greater than lapsed patents.
9. Since the max lifespan of invention patents in China is 20 years, and for most invention patents, it takes a long time to grant, we define the range of short lifespan is from 1 to 6 years.
10. ForceAtlas2 is a force-directed layout close to other algorithms used for network spatialization.
11. Absolute value of growing 1% = The value of base period/100.

Disclosure statement

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ORCID

Yuhan Zhu http://orcid.org/0000-0001-9313-5868

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Appendix A

Table A K-S test of patent renewal pattern fitting effects.

Year	Mean	Variance	P value
1985	2.2144	0.3858	0.9510
1986	2.1185	0.3778	0.6784
1987	2.1150	0.4250	0.3392
1988	2.0923	0.4216	0.2733
1989	2.0711	0.4500	0.2332
1990	2.1054	0.4721	0.3393
1991	2.0624	0.5055	0.3837
1992	2.1736	0.5022	0.5968
1993	2.3006	0.4639	0.7807
1994	2.4033	0.4381	0.6328
1995	2.4181	0.4455	0.5630
1996	2.4657	0.4288	0.4627
1997	2.4948	0.4591	0.3132
1998	2.5038	0.4672	0.2944
1999	2.5190	0.4381	0.3254

Source: Authors.

Appendix B

Table B1. Trend test of patent renewal distribution' mean.

Coefficients	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	1.996147	0.046579	42.855	2.98e-16 ***
t	0.034139	0.004817	7.087	5.45e-06 ***

Note: ***denotes significance at the 1% level.
Source: Authors.

Table B2. Trend test of patent renewal distribution' variance.

Coefficients	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.420373	0.017208	24.429	7.03e-13 ***
t	0.002974	0.00178	1.671	0.117

Source: Authors.

Appendix C

Table C. Pearson's correlation coefficient between lifespan and PVD, SOP of patent.

Year	PVD	SOP
1985	0.7816***	0.7828***
1986	0.4943***	0.8462***
1987	0.5402***	0.8756***
1988	0.7703***	0.7707***
1989	0.5796***	0.8179***
1990	0.6639***	0.9043***
1991	0.5915***	0.8739***
1992	0.6064***	0.8993***
1993	0.6556***	0.8939***
1994	0.6563***	0.8674***
1995	0.6784***	0.8785***
1996	0.6140***	0.8737***
1997	0.6455***	0.8793***
1998	0.6014***	0.8574***
1999	0.5784***	0.8376***

Note: ***denotes significance at the 1% level.
Source: Authors.

Appendix D

Table D1. Provinces in China.

	Provinces		Provinces		Provinces
1	Beijing	2	Tianjin	3	Hebei
4	Shanxi	5	Inner Mongolia	6	Liaoning
7	Jilin	8	Heilongjiang	9	Shanghai
10	Jiangsu	11	Zhejiang	12	Anhui
13	Fujian	14	Jiangxi	15	Shandong
16	Henan	17	Hubei	18	Hunan
19	Guangdong	20	Guangxi	21	Hainan
22	Chongqing	23	Sichuan	24	Guizhou
25	Yunnan	26	Tibet	27	Shannxi
28	Gansu	29	Qinghai	30	Ningxia
31	Xinjiang				

Source: Authors.

Table D2. Industrial Sectors in China.

Code	Industrial Sectors
A01	Farming
A02	Forestry
A03	Animal Husbandry
A04	Fishery
A05	Professional and Support Activities for Agriculture, Forestry, Animal Husbandry and Fishery
B06	Mining and Washing of Coal
B07	Extraction of Petroleum and Natural Gas
B08	Mining and Processing of Ferrous Metal Ores
B09	Mining and Processing of Non-ferrous Metal Ores
B10	Mining and Processing of Non-metal Ores
B11	Professional and Support Activities for Mining
B12	Mining of Other Ores
C13	Processing of Food from Agricultural Products
C14	Manufacture of Foods
C15	Manufacture of Liquor, Beverages and Refined Tea
C16	Manufacture of Tobacco
C17	Manufacture of Textile
C18	Manufacture of Textile, Wearing Apparel and Accessories
C19	Manufacture of Leather, Fur, Feather and Related Products and Footwear
C20	Processing of Timber, Manufacture of Wood, Bamboo, Rattan, Palm and Straw Products
C21	Manufacture of Furniture
C22	Manufacture of Paper and Paper Products
C23	Printing and Reproduction of Recording Media
C24	Manufacture of Articles for Culture, Education, Arts and Crafts, Sport and Entertainment Activities
C25	Processing of Petroleum, Coal and Other Fuels
C26	Manufacture of Raw Chemical Materials and Chemical Products
C27	Manufacture of Medicines
C28	Manufacture of Chemical Fibers
C29	Manufacture of Rubber and Plastics Products
C30	Manufacture of Non-metallic Mineral Products
C31	Smelting and Pressing of Ferrous Metals
C32	Smelting and Pressing of Non-ferrous Metals
C33	Manufacture of Metal Products
C34	Manufacture of General Purpose Machinery
C35	Manufacture of Special Purpose Machinery
C36	Manufacture of Automobiles
C37	Manufacture of Railway, Ship, Aerospace and Other Transport Equipment
C38	Manufacture of Electrical Machinery and Apparatus
C39	Manufacture of Computer, Communication and Other Electronic Equipment
C40	Manufacture of Measuring Instruments and Machinery
C41	Other Manufacture
C42	Utilization of Waste Resources
C43	Repair Service of Metal Products, Machinery and Equipment
D44	Production and Supply of Electric Power and Heat Power
D45	Production and Supply of Gas
D46	Production and Supply of Water
E47	Construction of Buildings
E48	Civil Engineering
E49	Construction Installation
E50	Building Decoration and Other Construction
I63	Service of Telecommunications, Radio and Television and Satellite Transmission

Source: China National Bureau of Statistics.