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Article

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Independent technical directors and their effect on corporate innovation in China[☆]

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ABSTRACT

As outside advisors, independent directors serve as both consultants and monitors. Based on empirical studies of corporate innovation and independent directors, we used data from listed firms in China from 2007 to 2017 to examine the effect of hiring independent technical directors on the board of directors. This study focused on a firm's innovation performance and the extent to which this performance is influenced by the relevance of a director's expertise to the activities of the firm. The results show that when the technical expertise of an independent director is relevant to the operational field of the firm, the firm should perform better in terms of innovation. This result is still significant when applying the two-stage instrumental variable method, showing a higher significance when using the exogenous event of the 2014 Wenfeng.plc case. Moreover, independent technical directors influence innovation primarily by encouraging firms to deepen their current field of research rather than expanding to other fields. Our findings can guide corporations to hire more relevant independent technical directors and can help the government design more accurate policies that promote innovation and entrepreneurship.

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1. Introduction

With China facing an economic slowdown after decades of rapid growth, Premier Keqiang Li stated that the key to further development was to strengthen cooperation between industries and research institutions. This has sparked increased interest in combining theoretical studies with practical applications. Increasingly, independent directors, a natural bridge between universities and businesses, have emerged from universities.

Since 2001, the Securities and Exchange Commission has requested that at least one third of the boards of listed firms in China be independent directors. According to Ferris et al. (2003), independent directors play two roles: supervisors and consultants. As supervisors, they monitor and evaluate the performance of managers and influence their compensation. As consultants, they give professional advice on business operations and strengthen firms' research capabilities.

In their supervisory role, independent directors are less likely to conspire with managers (Fama & Jensen, 1983) because they are put on the board through a nomination process (Cavaco et al., 2017). They also tend to be more sensitive to the opinions of outsiders about the company (Laux, 2008). Thus, independent directors can effectively monitor business operations. Agrawal and Chadha (2005) found that when an audit committee includes independent directors with a CPA or CFA qualification, the firm will have better earnings management. However, their study focused only on independent directors with a financial background and did not examine all independent technical directors. Moreover, if the cost of information is relatively high in a firm, a higher number of independent directors can have a negative effect on corporate performance (Duchin et al., 2010; Cavaco et al., 2017).

In their role as consultants, independent directors can support a corporation by providing external communication channels and reducing information costs (Bazerman & Schoorman, 1983). They can also make valuable suggestions that insiders cannot (Dalton et al., 1999). Fich and White (2005) found that when an external CEO is appointed to the board, the firm's potential can be better realized, especially when the CEO belongs to the same industry and has relevant business knowledge. However, they examined all board members and did not specifically study independent directors.

Specific industry knowledge is crucial for a corporation (Coles et al., 2008; Linck et al., 2008). Audretsch and Lehmann (2010) found that technology companies tend to recruit academics as independent directors to compensate for the board's lack of professional knowledge. Similarly, White et al. (2014) showed that large, rapidly growing corporations tend to appoint academics as independent directors. Masulis and Zhang (2018) provided evidence that if independent directors are distracted, the company's firm-specific knowledge will decrease and board commitment will decrease. In this respect, independent directors mainly fulfill their consulting role through low-cost knowledge transfer (McCabe & Nowak, 2008). This is a natural process for both the firm and independent directors. However, the literature has highlighted the tendency of certain types of corporations to hire academics as independent directors but has not explained it. In this study, we supplement the literature by examining the effect of having more independent academic directors with relevant backgrounds on a firm's innovation performance. Our research also investigated the mechanisms used to influence a corporation.

The literature on the relationship between independent technical directors and corporate innovation performance is still limited. On the one hand, independent technical directors can use their expertise to help companies improve their innovation performance. On the other hand, as a company knows its main activities, employing a specialist can have a lesser effect than hiring a generalist. In addition, as independent directors have no real control over a company, it is difficult to judge the real effect of an independent director on a firm's innovation performance. The relationship between independent technical directors and corporate innovation performance requires further analysis and evaluation.

Using panel data from listed firms on the Shanghai Stock Exchange (SSE) and the Shenzhen Stock Exchange (SZSE) in China from 2007 to 2017, this study explored whether matching the expertise of independent directors and the activities of their companies affects the number of applications and authorizations for innovation patents. In China, there are three types of patents: technical invention patents, utility model patents, and design patents. Design and utility model patents indicate changes in the appearance or functions of existing products. Technical invention patents refer to the creation of a new product. This study used the

number of technical invention patents as a measure of real innovation and considers the other two types of patents as strategic innovations.

The technical invention patent application rate was used to measure the quantity of innovation, and the authorization rate was used to measure the quality of innovation. Using empirical analysis, we found that when the expertise of independent directors is relevant to the firm's activities, the technical invention patent application rate increases and the number of applications for design patents decreases, while the number of utility patents is not statistically significant. Thus, in terms of innovation quantity, corporate innovation performance improves as the company allocates more resources to technical invention patents, which are of higher quality than the other two types.

Similar results are obtained for the authorization rate, also indicating an improvement in innovation performance. Based on these results, we can conclude that independent technical directors can use their expertise and knowledge to help listed companies achieve technological innovation and provide technical guidance. Therefore, if companies hire independent directors with relevant business expertise, the industry should perform better in terms of innovation and have healthier economic growth.

We tested our results using the two-stage instrumental variable (IV) approach, and the results are still significant, which helps us eliminate selection bias. We also introduced an exogenous event, the 2014 Wenfeng.plc shock. Wenfeng.plc did not disclose important information regarding the transfer of shares in its annual report, but the independent directors signed the statements. This case was deemed a major problem by the Chinese Securities and Exchange Commission. We used this case to help solve the endogeneity problem, and the results for all observations after 2014 are much more significant. Furthermore, we studied how independent technical directors fulfill their role as consultants within the firm and found that they prefer to use their knowledge to help companies explore their current research field rather than expanding to other fields. If firms want to introduce cutting-edge breakthroughs and gain a competitive advantage in their industry, this is of great practical importance. Using the mechanism test, we show that independent technical directors improve corporate innovation performance mainly by encouraging firms to spend more on R&D and enabling them to obtain more government subsidies.

This study makes three main contributions. First, previous studies only focused on the academic major of independent directors, and few studies examined their research expertise. In contrast, we examined theories about the characteristics of independent directors. Using manual data collection and processing, this study explored how the correlation between the expertise of a director and the main activities of the firm influences innovation performance.

Second, we contribute to the literature on the advisory function of a board. To date, no study has specifically shown whether the consulting role of independent directors can improve the innovation performance of firms. From the perspective of corporate governance in listed companies, we focused on the consulting role of independent directors in terms of corporate innovation. We showed how a system of independent directors can play a role in corporate governance and decision-making.

Third, compared with most other countries in which corporations prefer to hire technical experts with experience in their fields, the recent guidelines of the government have incentivized Chinese corporations to hire academics from universities. As our study focused on the Chinese context, we were able to analyze whether technical professionals can contribute to corporate innovation and, therefore, to the development of the industry, further stimulating economic growth.

Fourth, our findings provide advice to both corporations and governments to improve innovation capabilities. The idea of combining industry operations and academic research has been promoted for decades, and the Chinese government has adopted relevant policies. However, corporations may mistakenly focus on strategic innovation rather than technical innovation. In addition, if firms hire more independent directors with expertise relevant to their activities, the application and authorization rates for design patents may decrease.

The rest of this paper is organized as follows. [Section 2](#) reviews the literature and develops our research hypotheses. [Section 3](#) presents the descriptive statistics. [Sections 4–6](#) report and analyze the results of our empirical tests. [Section 7](#) summarizes the conclusions and suggests policy implications.

2. Literature review and hypothesis development

This paper is based on two streams of literature. The first explores the relationship between the characteristics of independent directors as outsiders and firm decisions. The second is related to the factors that stimulate innovation in a corporation.

2.1. Characteristics of independent directors and corporate decisions

Numerous studies have concluded that independent directors with little or no connection to a company can significantly influence corporate performance, both positively and negatively. For instance, independent directors can limit managerial discretion because they can punish managers after undesirable outcomes (Fama & Jensen, 1983). Ahmed and Duellman (2007) found that firms with a high proportion of independent directors recognize losses more quickly, suggesting that they have high earnings quality. Ferreira et al. (2011) found a positive relationship between the proportion of independent directors and earnings informativeness. Other studies have shown a positive correlation between the presence of independent directors and firm performance (e.g., Rosenstein & Wyatt, 1990; Ferris et al., 2003; Swan and Honeine, 2010; Armstrong et al., 2014; Al-Dhamari and Ismail, 2013). In contrast, Yermack (1996) showed that a smaller proportion of independent directors on the board results in better corporate performance, consistent with the results of several other studies (e.g., Bhagat & Black, 2002; Anderson et al., 2004; Boone et al., 2007).

Many studies have focused on the different characteristics of independent directors and how they affect the way companies operate. Using a sample of U.S. firms, Adams and Ferreira (2009) found that female directors have a significant effect on board inputs and firm outcomes. Masulis and Mobbs (2014) argued that when firms with independent directors experience an exogenous increase in the relative ranking of directors, their performance will improve. Other characteristics studied include the background of independent directors (Gang et al., 2007), gender (Shukeri et al., 2012; Ferreira et al., 2018), reputation (Brochet & Srinivasan, 2014; Fos et al., 2017), and tenure (Bonini et al., 2017).

Recent studies have examined the mechanisms by which the characteristics of independent directors influence corporate innovation. As mentioned earlier, in general, independent directors play two roles: monitors and consultants (Ferris et al., 2003). Monitoring can be seen as an intrinsic requirement of the board member position, while consulting allows them more freedom. As monitors, outside board members increase the oversight of business operations by the board (Balsmeier et al., 2017). They can terminate managers for poor performance (Weisbach, 1988), incentivizing them to perform better (Sitglitz & Weiss, 1983). Innovation is part of daily operations, so it can be enhanced by increased board control.

As consultants, independent directors can help companies find solutions at a lower cost than hiring outside consulting services. Jiraporn et al. (2017) investigated the effect of independent directors on corporate innovation by using R&D investments to quantify innovation performance. They concluded that board governance has a significant effect on innovation productivity. Similar studies have found a significant correlation between the characteristics of independent board members and innovation, but these studies have mainly focused on the proportion of independent directors on monitoring committees (Faleye et al., 2011) or on the transition to an independent board of directors (Balsmeier et al., 2017).

However, there has been little research on the relevance of the expertise of an outside board member for the main area of innovation of the company. In addition, unlike monitoring, consulting relies mainly on the expertise of independent directors.

2.2. Corporate innovation performance

The second stream of literature explores the factors that contribute to improving corporate innovation performance. Over the past decade, the number of studies on corporate innovation has increased considerably. Innovation is vital for national economic growth and can help a corporation develop its long-term competitive advantage (Porter, 1992). Some studies have argued that firm characteristics can increase corporate innovation. For instance, firms embedded in alliance networks with both high clustering and high reach have more innovative outputs than those without these characteristics (Schilling & Phelps, 2007). In addition, firms with

independent boards are expected to have more innovation activities (Balsmeier et al., 2017). However, Bazrafshan et al. (2016) showed that there is an optimal level of firm disclosure and that once this level is reached, firm performance decreases.

2.3. Hypothesis development

The presence of independent directors can have opposite effects on corporations, depending on their role. As consultants, independent directors can provide the management team with different opinions and expertise (Balsmeier et al., 2017), especially if they are university professors or experts in their field. Their suggestions and experiences can inspire the management team to increase a firm's innovation activities by developing new ideas and putting them into practice. As monitors, independent directors can exercise stronger control over the management team (Sitglitz & Weiss, 1983). Therefore, managers are pressured to produce decent results in a short period. These managers tend to pursue fewer exploratory projects to improve overall performance (Manso, 2011). R&D investments are typically long-term projects that can possibly hurt short-term financial outcomes. Therefore, managers may be incentivized to reduce investment in R&D. A board may also avoid exploring new areas if it finds that the short-term stock market cannot properly reflect the investment made in innovation (Cohen et al., 2013). As a result, corporate investment in real innovation may decrease.

However, these studies may not be relevant to China's unique setting. Independent directors can have different effects on Chinese firms. China's patent law divides patents into three categories—design patents, utility model patents, and technical invention patents—and research in China must recognize these categories. Innovation activities should be divided into high-quality and low-quality innovations. High-quality innovations help improve technology and competitive advantages, while low-quality innovations benefit from government subsidies or are introduced to comply with laws and regulations. Only high-quality innovations contribute to business development. Therefore, we propose Hypothesis 1.

H1. Firms with independent directors whose expertise is relevant to their operational field will have more high-quality innovations.

As mentioned earlier, independent directors can serve as monitors or consultants. Faleye et al. (2011) argued that the quality of monitoring improves when independent directors are given more oversight duties, but intense monitoring can interfere with the process of sharing strategic information between CEOs and directors (Holmstrom, 2005). If the jobs of technical directors are related to the activities of the firm, they will naturally transfer their knowledge to the management team in their role as consultants (McCabe & Nowak, 2008). This helps the corporation develop a firm-specific competitive advantage (Osterloh & Frey, 2006). For the firm, hiring an independent director with expertise relevant to its activities is a way to transfer knowledge at a lower cost. Thus, independent technical directors are more likely to provide expertise to the management team (Rosenstein & Wyatt, 1990) and to impose less control over management (Byrd & Hickman, 1992), allowing them and other types of independent directors to fulfill their own duties.

In addition, Williamson (1975) described an internal market mechanism in a multidivisional firm in which internal groups compete for limited resources. Resources are defined as a firm's physical, human, and organizational assets (Wernerfelt, 1984). As R&D resources involve these three types of assets, they can be subject to a similar competitive mechanism. According to Mathews' (1997) resource leverage view, because R&D resources are limited, innovation projects must compete to obtain resources. We expect firms to offer incentives to focus on high-quality innovations, thereby reducing the physical and human resources allocated to low-quality innovations.

Thus, the reallocation of innovative resources and the redeployment of human capital contribute to refocusing the scope of innovation (Alon et al., 2016). Moreover, when independent directors act as consultants, they can provide resources to conduct important research in the operational field of the company. When a firm has access to appropriate resources, it will choose to conduct high-quality research rather than low-quality research. Therefore, we propose Hypothesis 2.

H2. Firms with independent directors whose expertise is relevant to their operational field will have fewer low-quality innovations.

3. Empirical design

3.1. Sample selection

Data from Chinese firms listed on the SSE and the SZSE from 2007 to 2017 were collected and used in this study. We excluded the following firms: firms receiving special treatment due to poor performance, firms with negative equity or a negative fixed asset ratio, firms without directors, and firms with an abnormal debt to asset ratio, i.e., less than or >1 . We winsorized the tails of the distribution at the 1% and 99% levels. In total, 721 corporations and 5123 observations were used in the analyses. All data on patents, independent directors, and operational fields were collected from the China Stock Market & Accounting Research (CSMAR) database. Table 1 presents the raw data and the processed data classified by industry type. The proportion in each industry did not change significantly after removing noise from the raw data.

3.2. Measurement of key variables

As innovation is abstract and subjective for companies, several recent studies have used patent data to quantify it (e.g., Amore et al., 2013; Brav et al., 2018; Donges et al., 2019). Some studies have used R&D investment as a measure of innovation (e.g., Faleye et al., 2011; Manso, 2011; De Simone et al., 2017; Chircop et al., 2018), but this measure cannot distinguish between high-quality and low-quality innovations. Other researchers have used raw patent counts and the number of citations received by a patent to measure the financial and technical value of an innovation (Harhoff et al., 1999; Hall et al., 2005; Cerqueiro et al., 2016). Some research has even looked at technology classes (González-Urbe and Groen-Xu, 2017). When researchers study innovation in China, they generally assume that design patents are more likely to be low-quality innovations because they do not make significant technological changes. In contrast, technical invention patents are more likely to be considered high-quality innovations.

In this study, we measured the innovation capability of companies using the number of patent applications filed and the number of patents authorized. We divided patents into three categories according to the degree of innovation: technical invention patents, utility model patents, and design patents. Given the high degree of skewness in the absolute value of the number of patents, which cannot reflect the relative relationship of the three patent types, we measured the dependent variables by their proportion. The more technical the invention patents filed by a firm, the greater its technological achievements, and the stronger its innovation capability. For the quantity of corporate innovation, we used the proportion of technical invention patent applications (*Invent-apply*), the proportion of utility model patent applications (*Utility-apply*), and the proportion of design patent applications (*Design-apply*) to the total number of innovations. For the quality of corporate innovation, we used the proportion of authorized technical invention patents (*Invent-grant*), the proportion of authorized utility model patents (*Utility-grant*), and the proportion of authorized design patents (*Design-grant*) to the total number of innovations. In other words, we measured the motivation for corporate innovation and the strategies used from two aspects, quantity and quality.

In terms of key independent variables, 867 independent technical directors specializing in law and accounting were eliminated from the 721 corporations. To determine whether the professional background and research fields of independent directors correspond to the operational field of their companies, we used various sources, including their resumes, firms' annual reports, and official company websites. We then created a key independent variable, *Specialist*, which is equal to 1 if the expertise of an independent director corresponds to the operational field of the firm, and 0 otherwise.

Following Balsmeier et al. (2017), we defined control variables as those that can interfere in the relationship between the expertise of an independent director and corporate innovation in terms of patent applications and authorizations. We found that there are significant differences in the proportion of R&D expenditure to total assets (*R&D*) and in company size, measured by total assets (*Size*), among the companies in our sample. These two variables have significant positive correlations with innovation activities. Tobin's *Q* is often used as an important indicator to measure the performance or growth of a company. Therefore, we used *Tobin's Q* to control the effect of a company's future growth potential on its innovation activities. As replacement costs

Table 1

Variable allocation for the manufacturing industries. This table represents the raw data that we collected from the CSMAR database and the processed data without noise classified by industry. We specifically chose companies in the manufacturing industries, i.e., category C in the database, and calculated the frequency, percentage, and cumulative percentage of each industry.

Industry	Raw Data			Processed Data		
	Frequency	Percentage	Cumulative Percentage	Frequency	Percentage	Cumulative Percentage
Manufacturing Industry						
Special equipment manufacturer	1311	7.80	7.80	232	8.52	8.52
Instrument manufacturer	269	1.60	9.40	37	1.36	9.88
Other manufacturer	136	0.81	10.21	8	0.29	10.17
Agricultural and sideline food processor	358	2.13	12.34	71	2.61	12.78
Chemical manufacturer	1682	10.00	22.34	246	9.03	21.81
Chemical fiber manufacturer	205	1.22	23.56	20	0.73	22.54
Pharmaceutical manufacturer	1741	10.36	33.91	313	11.49	34.03
Printing and reproduction of recorded media	61	0.36	34.28			
Furniture manufacturer	70	0.42	34.69	12	0.44	34.47
Waste resources recycling	57	0.34	35.03			
Education, recreation, and sports supplies manufacturer	80	0.48	35.51	11	0.40	34.88
Non-ferrous metal smelting and rolling	741	4.41	39.92	132	4.85	39.72
Wood, bamboo, rattan, palm, grass products manufacturer	86	0.51	40.43	3	0.11	39.83
Rubber and plastic products manufacturers	480	2.85	43.28	85	3.12	42.95
Car manufacturer	804	4.78	48.06	103	3.78	46.73
Electrical machinery and equipment manufacturer	1562	9.29	57.35	309	11.34	58.08
Leather, fur, and feather products manufacturer	32	0.19	57.54	1	0.04	58.11
Petroleum processor, coking, and nuclear fuel processor	195	1.16	58.70	27	0.99	59.10
Textile industry	438	2.61	61.31	80	2.94	62.04
Clothing industry	231	1.37	62.68	42	1.54	63.58
Computers, and other electronic equipment manufacturer	2275	13.53	76.21	419	15.38	78.96
General equipment manufacturer	1016	6.04	82.26	167	6.13	85.10
Paper products manufacturer	234	1.39	83.65	33	1.21	86.31
Wine, beverage, and refined tea manufacturer	435	2.59	86.24	69	2.53	88.84
Metal products manufacturer	405	2.41	88.65	53	1.95	90.79
Transporting equipment manufacturer	468	2.78	91.43	71	2.61	93.39
Non-metallic mineral products manufacturer	701	4.17	95.60	97	3.56	96.95
Food industry	249	1.48	97.08	48	1.76	98.72
Ferrous metals industry	491	2.92	100.00	35	1.28	100.0
Total	16,813	100.00		2724	100.00	

are difficult to obtain, we used the ending balance of total assets. In addition, we controlled for the logarithm of age (*Ln_Age*), the liability-to-asset ratio (*Leverage*), the fixed capital ratio (*Tangibility*), the size of the board (*Boardsize*), the proportion of independent directors on the board (*Indepboard*), institutional ownership (*Inst*), the internal control index (*Intercontrol_index*), the logarithm of analyst coverage (*Ln_coverage*), and the revenue growth rate (*Growth_rev*). To reduce the skewness of the numerical values, we used the logarithms of these values. See Appendix A for the definitions of the variables.

Table 2 presents the descriptive statistics of the main variables. The mean of the key independent variable, *Specialist*, is 0.615, indicating that 61.5% of the companies in manufacturing industries employed independent technical directors during the study period. From the perspective of R&D expenditure, the maximum value of R&D expenditure of listed companies in China is 21.9% and the minimum value is 0.0%. The standard deviation of the sample is 0.0112, which indicates that the ratio of R&D expenditure to total assets in Chinese companies is significant.

On average, the proportion of technical invention patent applications is higher than the proportion of other patent applications. The proportions of technical invention patent applications and utility model patent applications to the total number of patent applications are approximately 0.4, while the proportion of design patent applications to the total number of patent applications is only 0.097. On average, the number of authorized technical invention patents is significantly lower than the number of technical invention patent applications. In comparison, the proportion of authorized utility model patents and that of authorized design patents are much higher. In addition, the average number of years of listing of the companies in the sample is 5.36 years. The average number of board members is 8.969. The average number of independent directors is 3.293, and the ratio of R&D expenditure to total assets is 0.33%.

Table 2

Descriptive statistics of the variables. The sample consisted of 721 firms with financial and patent data available from the CSMAR database. Patents are divided into three categories according to the degree of innovation, i.e., technical invention patents, utility model patents, and design patents. We calculated the proportion of each category in the patent data, distinguishing between authorizations and applications and defining them as *Invent-apply*, *Utility-apply*, *Design-apply*, *Invent-grant*, *Utility-grant*, and *Design-grant*. *Specialist* is the key dummy variable. If the expertise of independent directors hired by the company in a given year corresponds to its operational field, *Specialist* = 1; otherwise, *Specialist* = 0. *Ln_Size* is computed as the logarithm of total assets. *Ln_Age* is computed as the logarithm of the company's trading years since the IPO. *Leverage* is computed as total liabilities divided by total assets. *Tangibility* is computed as the carrying value of fixed assets divided by total assets. *Tobin's Q* is computed as market capitalization divided by asset replacement cost. *R&D* is computed as R&D expenditure divided by total assets. *Boardsize* is computed as the number of directors. *Indepboard* is computed as the number of independent directors. The control variables are winsorized at the 1st and 99th percentiles.

Variable	Sample size	Mean	Std dev	Min	Median	Max
<i>Invent-apply</i>	2043	0.473	0.348	0.000	1.000	1.000
<i>Utility-apply</i>	2043	0.430	0.337	0.000	0.400	1.000
<i>Design-apply</i>	2043	0.097	0.228	0.000	0.500	1.000
<i>Invent-grant</i>	2021	0.351	0.386	0.000	0.000	1.000
<i>Utility-grant</i>	2021	0.537	0.395	0.000	0.167	1.000
<i>Design-grant</i>	2021	0.112	0.252	0.000	0.667	1.000
<i>Specialist</i>	5123	0.615	0.487	0.000	0.000	1.000
<i>Ln_Size</i>	5123	21.970	1.267	19.170	21.719	28.000
<i>Ln_Age</i>	3971	1.551	0.763	0.000	2.944	2.833
<i>Tangibility</i>	5105	0.182	0.143	0.000	0.171	0.852
<i>Tobin's Q</i>	4993	2.584	2.155	0.113	1.775	24.940
<i>R&D</i>	3147	0.003	0.011	0.000	0.000	0.219
<i>Boardsize</i>	5106	8.969	1.811	3.000	9.000	18.000
<i>Indepboard</i>	5107	3.293	0.632	1.000	3.000	8.000
<i>Leverage</i>	2021	0.401	0.198	0.024	0.394	0.946
<i>Inst</i>	2043	0.188	0.201	0.000	0.125	1.487
<i>Intercontrol_index</i>	2043	660.314	133.001	0.000	676.590	999.750
<i>Ln_coverage</i>	2043	1.388	1.135	0.000	1.946	4.174
<i>Growth_rev</i>	2043	1.211	0.515	0.263	1.1024	5.429

3.3. Construction of the empirical model

When creating the model, we first verified the relationship between the relevance of the expertise of an independent director and the firm's technical invention patent application rate, which is illustrated in the line chart in Fig. 1. The horizontal axis indicates the year and the vertical axis indicates the average number of technical invention patent applications. As shown in Fig. 1, when the expertise of the independent director is relevant to the operational field of the company ($Specialist = 1$), the average number of technical invention patent applications is significantly higher than when $Specialist$ is equal to 0. This indicates that the relationship between the expertise of independent directors and the operational field of their companies has a positive effect on the number of patent applications.

Fig. 2 shows the relationship between the relevance of the expertise of independent directors and the number of technical invention patent authorizations in companies. The horizontal axis indicates the year and the vertical axis indicates the average number of invention patents granted. As the graph shows, when the expertise of the independent director corresponds to the main activities of the company ($Specialist = 1$), the average number of invention patents granted is significantly higher than when $Specialist$ is equal to 0. This indicates that the relationship between the expertise of independent directors and the operational field of their companies has a positive effect on the authorization of technical invention patents.

To explain how the relationship between the relevance of the expertise of independent technical directors and the operational field of their companies influences corporate innovation, we followed Balsmeier et al. (2017) and constructed the following model using the ordinary least squares (OLS) method:

$$Patent_{i,t+1} = \beta_0 + \beta_1 Specialist_{i,t} + \gamma_t + \mu_i + X_{it} + \varepsilon_{it} \quad (1)$$

There are six indicators that measure how patents work in terms of quantity and quality. As innovation activities are delayed to some extent, following Atanassov (2013), we used patent data lagged by one year ($t + 1$) to measure the effect of hiring independent technical directors in year t . The key explanatory variable, $Specialist_{i,t}$, measures whether the expertise of the independent directors hired in year t corresponds to the main operational field of their companies. As fixed effects can eliminate the influence of unobserved variables that are constant over time, we adopted a two-way fixed effects model. The subscripts i and t represent the i^{th} firm and the t^{th} year, respectively ($t = 2007, \dots, 2017$), γ_t represents time fixed effects, μ_i represents firm fixed effects, X_{it} represents other control variables, and ε_{it} is the residual term. We used heteroskedasticity-robust standard errors.

4. Empirical results of the baseline model

The regression results of Model (1) are presented in Table 3. The dependent variables in Columns 1 to 3 are the three types of patent applications: the proportion of technical invention patent applications, the propor-

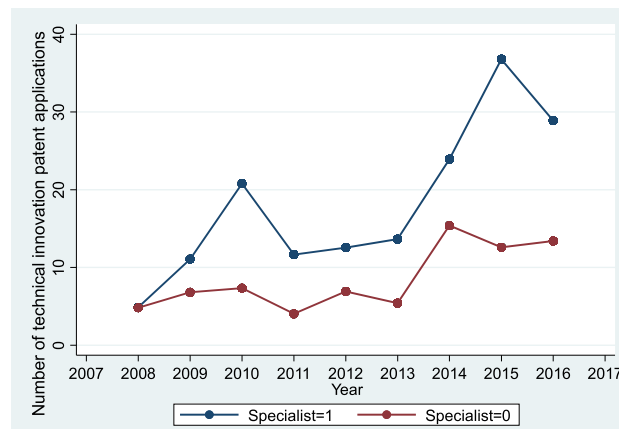


Fig. 1. Relevance of the expertise of independent directors and patent applications.

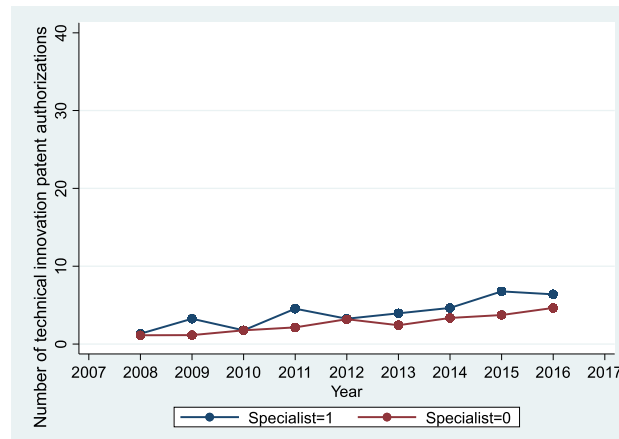


Fig. 2. Relevance of the expertise of independent directors and patent authorizations.

tion of utility model patent applications, and the proportion of design patent applications, respectively. The results show that having independent technical directors with expertise in the operational field of their companies significantly increases the proportion of technical invention patent applications, with a coefficient of 0.07, significant at the 1% level. However, the proportion of utility model patent applications is not significantly affected, and there is a negative effect on the proportion of design patent applications, with a coefficient of -0.05 , which is significant at the 1% level. These results indicate that the participation of independent technical directors encourages firms to focus on high-quality technical invention patents rather than blindly increasing the number of patents. Therefore, the involvement of independent technical directors improves firms' innovation capability.

The dependent variables in Columns 4–6 are the proportion of the three types of authorized patents: technical invention patents, utility model patents, and design patents. The coefficient of authorized technical invention patents is 0.05, and that of authorized design patents is -0.05 , both of which are significant at the 1% level. These results indicate that independent technical directors with expertise in the operational field of their companies not only motivate companies to increase their innovation activities but also improve the quality of their invention patents.

As independent directors can have a long-term effect on innovation performance, we further studied how hiring relevant independent technical directors affects the number of patent applications over the following three years. The assumption is that the proportion of patent applications is a better indicator of a firm's initiative than the proportion of authorized patents. Table 4 shows that by employing independent technical directors, corporations experience an increase in the proportion of technical invention patent applications and a decrease in the proportion of design patents in subsequent years, and this positive effect increases over time. This implies that independent technical directors contribute more as consultants when they stay on the board for a longer period.

5. The endogeneity problem and robustness tests

We examined the robustness of the causal relationship between independent technical directors and corporate innovation from two aspects. First, we used propensity score matching (PSM) to test the robustness of the benchmark model, and we found that the test results are essentially consistent with Table 3. Second, we used a placebo test to confirm that the significance we found was indeed due to the presence of independent directors.

5.1. PSM test: exclusion of inter-group heterogeneity

To reduce the endogeneity problem caused by sample selection bias and the influence of confounding variables, we used the PSM method and the variable *Specialist* to perform a logit regression on the control

Table 3

Independent technical directors and corporate innovation: Baseline results. This table presents the panel regression estimates of Model (1) for the number of patents classified by degree of innovation from 2007 to 2017 as a function of *Specialist*. We used the patent data in year $t + 1$ to measure the effect of hiring independent technical directors in year t . *Specialist* measures whether the expertise of the independent directors hired in year t corresponds to the operational field of their companies. We adopted the firm and year fixed effects model for analysis. The t-statistics are reported in brackets. ***, **, and * indicate that the parameter estimates are significantly different from 0 at the 1%, 5%, and 10% levels, respectively.

	(1) <i>Invent-apply</i>	(2) <i>Utility-apply</i>	(3) <i>Design-apply</i>	(4) <i>Invent-grant</i>	(5) <i>Utility-grant</i>	(6) <i>Design-grant</i>
<i>Specialist</i>	0.07*** (2.72)	-0.01 (-0.65)	-0.05*** (-3.38)	0.05** (2.10)	-0.00 (-0.18)	-0.05*** (-3.00)
<i>Tangibility</i>	-0.03 (-0.38)	0.07 (0.88)	-0.04 (-0.78)	-0.16* (-1.77)	0.22** (2.51)	-0.05 (-0.94)
<i>Ln_Age</i>	0.05 (1.03)	-0.08* (-1.80)	0.03 (0.90)	0.10** (2.03)	-0.13*** (-2.77)	0.03 (1.03)
<i>Ln_Size</i>	-0.00 (-0.05)	-0.01 (-0.38)	0.01 (0.61)	0.01 (0.44)	0.01 (0.59)	-0.02 (-1.43)
<i>Leverage</i>	0.02 (0.28)	-0.02 (-0.34)	0.00 (0.06)	0.03 (0.38)	-0.10 (-1.13)	0.06 (1.13)
<i>R&D</i>	0.03 (0.06)	0.28 (0.61)	-0.31 (-0.90)	0.47 (1.07)	-0.32 (-0.67)	-0.16 (-0.44)
<i>Tobin's Q</i>	0.00 (0.18)	-0.01 (-0.95)	0.00 (0.85)	0.01 (1.29)	-0.01 (-0.64)	-0.01 (-1.15)
<i>Indepboard</i>	-0.25 (-1.14)	0.02 (0.10)	0.23 (1.38)	-0.21 (-0.88)	-0.06 (-0.22)	0.27 (1.36)
<i>Boardsize</i>	-0.01 (-0.90)	0.01 (0.91)	-0.00 (-0.15)	-0.01 (-0.76)	0.01 (0.59)	0.00 (0.11)
<i>Inst</i>	0.07 (1.01)	-0.06 (-1.04)	-0.01 (-0.23)	-0.04 (-0.61)	0.09 (1.38)	-0.05 (-0.96)
<i>Intercontrol_index</i>	0.00 (1.60)	-0.00 (-0.76)	-0.00 (-0.82)	0.00 (1.04)	-0.00 (-0.31)	-0.00 (-0.85)
<i>Ln_coverage</i>	0.01 (1.09)	-0.01 (-0.65)	-0.01 (-0.83)	-0.01 (-0.85)	0.01 (0.74)	0.00 (0.22)
<i>Growth_rev</i>	-0.03 (-1.23)	-0.00 (-0.22)	0.03 (1.45)	-0.01 (-0.48)	-0.01 (-0.43)	0.02 (1.44)
Constant	0.36 (1.01)	0.80*** (2.64)	-0.16 (-0.70)	-0.04 (-0.10)	0.70** (2.11)	0.34 (1.37)
Firm and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2043	2043	2043	2021	2021	2021
F-value	1.72	0.92	1.83	1.63	1.73	1.74
Adj. R^2	0.23	0.27	0.22	0.23	0.29	0.21

variables to obtain propensity scores. The regression results show that the liability-to-asset ratio, the proportion of R&D expenditure, and the fixed capital ratio all affect the choice of a company to hire an independent director. Therefore, it was necessary to match the companies using the PSM method. We estimated a propensity score model and calculated the propensity score for each listed company. In addition, nearest neighbor matching was applied to the one-to-one matching of each listed company. To ensure the effectiveness of the PSM method, we carried out a balance test of the samples, with satisfactory results. The estimation results are presented in Table 5.

5.2. Falsifiability test: assuming false key explanatory variables

To ensure that the significance of the main results was not simply due to random or accidental factors, we conducted a placebo test. We assumed that the relationship of the expertise of an independent director and the operational field of the company did not occur in the same year as the innovation performance of the company, but one to three years before the change. To this end, we created three false variables, *Specialist_{t-1}*, *Specialist_{t-2}*, and *Specialist_{t-3}*. We then used these variables in turn to replace the key explanatory variable

Table 4

Independent technical directors and corporate innovation: Long-term effect. This table presents the regression estimates of the number of patents classified by degree of innovation from 2007 to 2017 as a function of *Specialist* in the long term. We used the patent data to measure the effect of hiring independent technical directors in year $t + 2$, $t + 3$, and $t + 4$. *Specialist* measures whether the expertise of the independent directors hired in year t corresponds to the operational field of their companies. We controlled for firm and year fixed effects. Unless otherwise indicated, the figures in brackets are t-statistics, clustered at the firm level. ***, **, and * indicate that the parameter estimates are significantly different from 0 at the 1%, 5%, and 10% levels, respectively.

	(1) <i>Invent-apply</i> _{$t+2$}	(2) <i>Design-apply</i> _{$t+2$}	(1) <i>Invent-apply</i> _{$t+3$}	(2) <i>Design-apply</i> _{$t+3$}	(1) <i>Invent-apply</i> _{$t+4$}	(2) <i>Design-apply</i> _{$t+4$}
<i>Specialist</i>	0.10** (2.42)	-0.07*** (-3.03)	0.13*** (3.01)	-0.08*** (-2.83)	0.14*** (2.65)	-0.08** (-2.05)
<i>Tangibility</i>	0.05 (0.50)	0.03 (0.78)	-0.09 (-0.74)	0.05 (0.72)	0.04 (0.20)	0.11 (1.34)
<i>Ln_Age</i>	0.13** (2.30)	0.03 (1.19)	0.13* (1.79)	0.03 (0.91)	0.20** (2.16)	0.02 (0.44)
<i>Ln_Size</i>	0.04** (2.33)	-0.01 (-1.34)	0.05** (2.52)	-0.01 (-1.48)	0.04 (1.48)	-0.02 (-1.21)
<i>Leverage</i>	0.09 (0.92)	-0.01 (-0.23)	0.13 (1.17)	-0.00 (-0.04)	-0.11 (-0.65)	0.08 (0.87)
<i>R&D</i>	-0.31 (-0.55)	-0.09 (-0.36)	-0.86 (-1.21)	-0.29 (-1.56)	-0.23 (-0.31)	-0.18 (-0.59)
<i>Tobin's Q</i>	0.01 (0.83)	-0.01 (-1.30)	0.02 (1.12)	-0.01* (-1.89)	-0.02 (-0.99)	-0.00 (-0.60)
<i>Indepboard</i>	-0.26 (-0.85)	0.31 (1.49)	0.19 (0.50)	-0.14 (-0.48)	0.06 (0.10)	-0.20 (-0.64)
<i>Boardsize</i>	-0.03** (-2.41)	0.00 (0.44)	-0.02 (-1.24)	-0.01 (-1.14)	-0.02 (-1.28)	-0.01 (-1.05)
Constant	-0.57 (-1.34)	0.15 (0.67)	-1.02** (-2.01)	0.50* (1.82)	-0.81 (-1.22)	0.55 (1.48)
Firm and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	885	885	575	575	339	339
F-value	4.05	2.77	3.59	2.33	2.34	1.13
Adj. R^2	0.28	0.18	0.24	0.20	0.31	0.35

Table 5

Independent technical directors and corporate innovation: PSM results. This table presents the PSM regression estimates of the number of patents classified by degree of innovation from 2007 to 2017 as a function of *Specialist*. We used the patent data in year $t + 1$ to measure the effect of hiring independent technical directors in year t . *Specialist* was used to conduct a logit regression on the control variables to obtain propensity scores. We estimated the propensity score model and calculated the propensity score for each listed company. Nearest neighbor matching was applied to the one-to-one matching of each listed company, and 990 valid observations were obtained, representing 327 listed companies. We controlled for firm and year fixed effects. The t-statistics are reported in brackets. ***, **, and * indicate that the parameter estimates are significantly different from 0 at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	<i>Invent-Apply</i>	<i>Utility-apply</i>	<i>Design-apply</i>	<i>Invent-grant</i>	<i>Utility-grant</i>	<i>Design-grant</i>
<i>Specialist</i>	0.11*** (3.20)	-0.02 (-0.54)	-0.09*** (-3.30)	0.10** (2.59)	-0.01 (-0.22)	-0.09*** (-3.08)
<i>Tangibility</i>	-0.02 (-0.25)	0.05 (0.52)	-0.02 (-0.34)	-0.16 (-1.42)	0.24** (2.25)	-0.08 (-1.25)
<i>Ln_Age</i>	0.06 (1.21)	-0.07 (-1.56)	0.01 (0.27)	0.10* (1.83)	-0.10* (-1.80)	-0.00 (-0.04)
<i>Ln_Size</i>	0.04** (1.99)	-0.03** (-2.27)	-0.00 (-0.26)	0.01 (0.69)	0.01 (0.94)	-0.03** (-2.34)
<i>Leverage</i>	-0.01 (-0.08)	-0.06 (-0.80)	0.07 (1.17)	0.06 (0.51)	-0.08 (-0.75)	0.02 (0.35)
<i>R&D</i>	-0.20 (-0.29)	0.62 (1.01)	-0.43 (-1.15)	0.86 (1.55)	-0.38 (-0.59)	-0.48 (-1.03)
<i>Tobin's Q</i>	0.01 (1.63)	-0.01* (-1.80)	-0.00 (-0.07)	0.01 (1.33)	-0.00 (-0.19)	-0.01** (-1.99)
<i>Indepboard</i>	-0.61** (-2.29)	0.22 (0.84)	0.40** (2.22)	-0.08 (-0.26)	-0.46 (-1.61)	0.54** (2.37)
<i>Boardsize</i>	-0.02** (-2.39)	0.02** (2.52)	-0.00 (-0.08)	-0.01 (-0.54)	-0.01 (-0.91)	0.02** (2.18)
Constant	-0.14 (-0.36)	1.12*** (3.34)	0.02 (0.09)	-0.21 (-0.53)	0.75** (1.97)	0.46* (1.68)
Firm and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	837	837	837	799	799	799
F-value	3.28	1.79	3.11	2.51	1.24	3.04
Adj. R ²	0.27	0.31	0.15	0.26	0.31	0.19

Specialist and regressed the baseline model again to examine whether the number of patent applications and authorizations of a company still increased. The placebo results are reported in detail in Table 6. The results indicate that there is no significant change in the results after changing the timing, so the main results are robust.

5.3. Placebo test: 500 sampling regressions

To determine whether the two relationships discussed above still exist if the independent directors are of any profession, not just relevant technical fields, we conducted another placebo test to ensure that when the variable *Specialist* is randomly selected, it has no processing effect on the number of technical invention patent applications. To do so, we first disordered the variable *Specialist* and randomly assigned each value of *Specialist* to each observation to generate a simulated explanatory variable *Random_Specialist*. We repeated the process 500 times and recorded the estimated coefficient of β_1 and its t-value for each sample.

We first regressed the number of technical invention patent applications on *Random_Specialist* and recorded the results. As shown in the upper left panel of Fig. 3, the t-statistic of the *Random_Specialist* coefficient of 500 repeated samples is an inverted U-shape around 0. This result suggests that there is no correlation between the number of technical invention patent applications and *Random_Specialist*. We then regressed the other explanatory variables on *Random_Specialist*, including the number of design patent applications, the number of technical invention patent authorizations, and the number of design patent authorizations. The results are similar.

Table 6

Independent technical directors and corporate innovation: Placebo test. This table presents the regression estimates of the placebo test for the number of patents classified by degree of innovation from 2007 to 2017 as a function of *Specialist* during the previous period. We used the patent data in year t to measure the effect of hiring independent technical directors in year t . *Specialist t-1* assumes that the expertise of the independent directors hired in year $t-1$ corresponds to the operational field of their companies. *Specialist t-2* assumes that the expertise of the independent directors hired in year $t-2$ corresponds to the operational field of their companies. *Specialist t-3* assumes that the expertise of the independent directors hired in year $t-3$ corresponds to the operational field of their companies. We controlled for firm and year fixed effects. The t-statistics are reported in brackets. * indicates that the parameter estimates are significantly different from 0 at the 10% level.

	(1) <i>Invent-apply</i>	(2) <i>Utility-apply</i>	(3) <i>Design-apply</i>	(4) <i>Invent-grant</i>	(5) <i>Utility-grant</i>	(6) <i>Design-grant</i>
<i>Specialist t-1</i>	0.02 (0.46)	-0.00 (-0.01)	-0.02 (-0.43)	0.04 (0.69)	0.03 (0.61)	-0.07 (-1.26)
<i>Specialist t-2</i>	-0.04 (-0.71)	-0.03 (-0.30)	0.07 (1.16)	-0.13* (-1.69)	0.12* (1.81)	0.01 (0.17)
<i>Specialist t-3</i>	-0.10 (-1.38)	0.11 (1.19)	-0.01 (-0.11)	0.02 (0.14)	0.08 (0.91)	-0.10 (-0.87)
Control variables	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Firm and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

In Table 7, we calculated the average coefficient for each explanatory variable and conducted additional t-tests, rejecting the original hypothesis at the 1% and 5% significance levels. As shown in Table 7, the average coefficients of the explanatory variables are 0.000 for technical invention patent applications, 0.000 for design patent applications, 0.002 for technical invention patent authorizations, and 0.000 for design patent authorizations, respectively. Furthermore, the probabilities of positive and negative β coefficients is similar. In summary, the placebo test shows that the virtual processing effect performed does not exist, which means that the appointment of independent technical directors is the variable that promotes corporate innovation performance.

5.4. Two-stage instrumental variable approach

We adopted the two-stage IV approach. Table 8 presents the results of the following two-stage IV specification:

$$\text{First stage: } \widehat{Specialist}_{i,t} = b_0 + b_1 AveSpecialist_{i,t} + Specialist_{i,t} + controlledvariables + e_{i,t}$$

$$\text{Second stage: } Patent_{i,t+1} = \beta_0 + \beta_1 \widehat{Specialist}_{i,t} + controlled\ variables + \varepsilon_{i,t}$$

The $AveSpecialist_{i,t}$ is the first-stage IV for firm i in year t , which refers to the average of the $Specialist_{i,t}$ in the manufacturing industry except for the treatment firm, and $\widehat{Specialist}_{i,t}$ is the projected value of $Specialist_{i,t}$ obtained from the first-stage regression. Controlled variables stack a list of control variables, as before. The instruments are the degree of proximity between the presence of independent directors and corporate innovation performance. We also controlled for firm and year fixed effects and clustered standard errors at the firm level in all the regressions.

According to the regression results of Stage 2, the coefficients for the numbers of technical invention patents filed and granted are 0.22 and 0.19, respectively. Both coefficients are positive and significant at the 1% level. In addition, the coefficients for the numbers of design patents filed and authorized are -0.19 and -0.20, respectively, both of which are significant at the 1% level, which addresses the problem of selection bias.

5.5. Exogenous shock: the Wenfeng.plc shock

In addition to the 2SLS model above, we introduced an exogenous event. We followed the approach of Black and Kim (2012), who used the Korean law of 1999 as an exogenous shock to evaluate the influence of outside board members, and chose the case of Wenfeng.plc in the context of China. In this case, Wenfeng.-

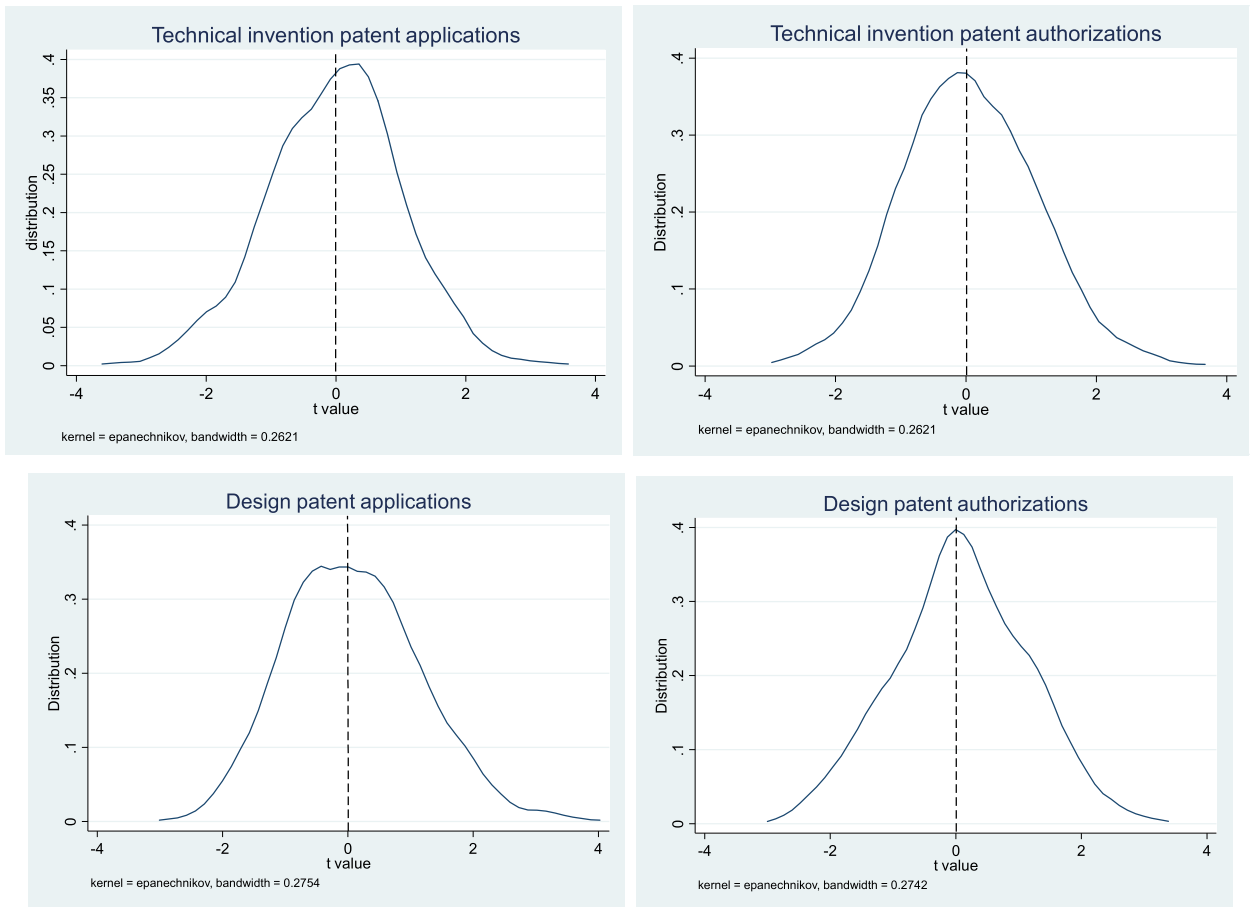


Fig. 3. Kernel density estimate. Figure shows the kernel density estimates of the t-statistics. We regressed the explanatory variable *Random_Specialist* on the dependent variables, including the number of technical invention patent applications, the number of technical invention patent authorizations, the number of design patent applications, and the number of design patent authorizations. The process was repeated 500 times, and the t-statistic of the *Random_Specialist* coefficient for the 500 repeated samples is recorded for each sample. In this figure, the horizontal axis represents the t-statistic and the vertical axis represents the distribution.

Table 7

Placebo test (500 repeated samples). This table presents the regression estimates of Model (1) using the 500 repeated samples for the number of patents classified by degree of innovation from 2007 to 2017 as a function of *Specialist*. The key explanatory variable, *Specialist*, in the sample was randomly assigned to each observation based on a retractable (repeatable) sampling method. For each sample, the estimated coefficient of β_1 and its t-value are recorded. In Table 7, Mean β_1 for *Random_Specialist* reports the descriptive statistics of the estimated coefficient β_1 for the simulated explanatory variables (the names of the columns are the explanatory variables). In square brackets, the probabilities that the estimated coefficient β_1 is significantly positive [$\beta > 0$ & $\alpha < 5\%$] or significantly negative [$\beta < 0$ & $\alpha < 5\%$] at the 5% level are reported. In the regression, we clustered the data by firm according to the stock codes and used robust regression to deal with heteroskedasticity. *** indicates that the parameter estimates are significantly different from 0 at the 1% level.

Variable	<i>Invent-apply</i>	<i>Design-apply</i>	<i>Invent-grant</i>	<i>Design-grant</i>
β_1	0.07***	-0.05***	0.05***	-0.05**
t-test	$p = 0.000$ ***	$p = 0.000$ ***	$p = 0.000$ ***	$p = 0.000$ ***
Mean β_1 for <i>Random_Specialist</i>	0.000	0.000	0.002	0.000
[$\beta > 0$ & $\alpha \leq 5\%$; $\beta < 0$ & $\alpha \leq 5\%$]	[2.2%; 3.2%]	[4.6%; 1.4%]	[3.4%; 2%]	[3.8%; 3%]
[$\beta > 0$ & $\alpha \leq 1\%$; $\beta < 0$ & $\alpha \leq 1\%$]	[0.6%; 0.4%]	[1.6%; 0.2%]	[0.8%; 0.4%]	[0.8%; 0.2%]

Table 8

Two-stage instrumental variable approach. This table presents the two-stage instrumental variable regression estimates for the number of patent applications and authorizations from 2007 to 2017 as a function of *Specialist*. The $AveSpecialist_{i,t}$ is the first-stage IV for firm i in year t , which refers to the average of the $Specialist_{i,t}$ in the manufacturing industry except for the treatment firm, and $\widehat{Specialist}_{i,t}$ is the projected value of *Specialist* obtained from the first-stage regression. Controlled variables stack a list of control variables. We controlled for firm and year fixed effects. The t-statistics are reported in brackets. ***, **, and * indicate that the parameter estimates are significantly different from 0 at the 1%, 5%, and 10% levels, respectively.

	Stage 1		Stage 2				
	<i>Specialist</i> (1)	<i>Invent- apply</i> (2)	<i>Utility- apply</i> (3)	<i>Design- apply</i> (4)	<i>Invent- grant</i> (5)	<i>Utility- grant</i> (6)	<i>Design- grant</i> (7)
<i>Specialist</i>		0.22*** (5.41)	-0.03 (-0.68)	-0.19*** (-5.44)	0.19*** (4.21)	0.01 (0.30)	-0.20*** (-4.90)
<i>Tangibility</i>	2.05*** (5.53)	0.09 (1.53)	-0.11* (-1.90)	0.02 (0.54)	-0.05 (-0.68)	0.04 (0.62)	0.00 (0.09)
<i>Ln_Age</i>	-0.19 (-0.99)	0.08*** (2.70)	-0.14*** (-4.85)	0.06*** (2.85)	0.14*** (4.07)	-0.22*** (-6.35)	0.08*** (3.60)
<i>Ln_Size</i>	0.09* (1.75)	0.01 (0.97)	-0.01 (-1.36)	0.00 (0.48)	0.00 (-0.43)	0.02** (2.31)	-0.02*** (-2.78)
<i>Leverage</i>	-0.77** (-2.50)	-0.09* (-1.80)	0.15*** (3.00)	-0.06 (-1.52)	-0.07 (-1.24)	0.07 (1.25)	0.00 (-0.06)
<i>R&D</i>	13.99** (2.28)	0.59 (0.79)	-0.52 (-0.75)	-0.07 (-0.30)	1.04 (1.64)	-1.31** (-1.98)	0.27 (0.85)
<i>Tobin's Q</i>	0.07** (2.07)	0.01 (1.32)	-0.02*** (-3.51)	0.01*** (2.67)	0.01** (1.98)	-0.02*** (-2.84)	0.01 (1.34)
<i>Indepboard</i>	-0.43 (-0.43)	-0.33** (-2.17)	-0.09 (-0.58)	0.43*** (3.89)	-0.18 (-1.08)	-0.24 (-1.37)	0.42*** (3.40)
<i>Boardsize</i>	0.03 (1.01)	-0.01 (-1.13)	0.00 (-0.49)	0.01** (2.19)	0.00 (-0.51)	-0.01 (-1.56)	0.01*** (2.63)
<i>AveSpecialist</i>	5.11*** (16.17)						
Constant	-4.49*** (-3.39)	0.1 (0.47)	1.15*** (5.85)	-0.25* (-1.82)	0.03 (0.13)	0.83*** (3.50)	0.14 (0.94)
Observations	2,227	2,064	2,064	2,064	2,043	2,043	2,043
Adj. R^2		0.00	0.03	-0.02	0.01	0.04	-0.01
Weak IV F-statistic		368.5***	368.5***	368.503***	362.14***	362.14***	362.14***

plc transferred 15% of its shares to Lu Yongmin, who held the shares of the Wenfeng Group on behalf of other investors. In fiscal year 2014, Wenfeng.plc did not disclose this information in its annual report. However, independent directors Fan and Jiang signed written confirmation opinions on the report. This case was classified as a significant problem by the China Securities Regulatory Commission in 2014, greatly affecting the conduct of listed companies. Based on this event, we can reasonably infer that other listed companies may act differently before and after 2014.

We divided our sample into two groups: before and after 2014. The first group included all observations before or during 2014, and the second group included all observations after 2014. We ran the baseline regressions again group by group, and the results are presented in Table 9.

In the regression results before 2014, the coefficient for the number of technical invention patents is positive but not significant. However, after 2014, this coefficient is 0.11, which is significant at the 1% level. In addition, the coefficient for the number of authorized technical invention patents is 0.07, which is significant at the 5% level. Regarding the number of design patents, the coefficients of applications and authorizations are negative before 2014 and significant at the 1% and 10% levels, respectively, and the number of authorized design patents decreases more significantly after 2014, significant at the 5% level.

Table 9

Exogenous shock: The Wenfeng.plc shock. The two tables below present the regression results of the baseline model after dividing the sample into two groups, i.e., before and after 2014. Panel A presents the results for all observations before or during 2014, and Panel B presents the results for all observations after 2014. The dependent variables are the proportion of technical invention patents filed, the proportion of utility patents filed, and the proportion of design patents filed to the total number of patents filed in year $t + 1$. *Specialist* measures whether the expertise of the independent directors hired in year t corresponds to the operational field of their companies. We controlled for firm and year fixed effects. The t-statistics are reported in brackets. ***, **, and * indicate that the parameter estimates are significantly different from 0 at the 1%, 5%, and 10% levels, respectively.

Panel A: Subsample before or during 2014

	(1)	(2)	(3)	(4)	(5)	(6)
	<i>Invent-apply</i>	<i>Utility- apply</i>	<i>Design- apply</i>	<i>Invent-grant</i>	<i>Utility-grant</i>	<i>Design-grant</i>
<i>Specialist</i>	0.04 (1.21)	0.03 (0.92)	-0.06*** (-3.50)	0.03 (0.90)	0.00 (0.12)	-0.03* (-1.93)
<i>Tangibility</i>	-0.03 (-0.35)	0.02 (0.24)	0.01 (0.25)	-0.23** (-1.97)	0.19* (1.76)	0.05 (0.77)
<i>Ln_Age</i>	0.05 (0.98)	-0.07 (-1.45)	0.02 (0.65)	0.08 (1.27)	-0.12** (-2.13)	0.05 (1.50)
<i>Ln_Size</i>	0.02 (1.42)	-0.01 (-0.87)	-0.01 (-1.06)	-0.00 (-0.01)	0.02 (1.11)	-0.02* (-1.79)
<i>Leverage</i>	-0.05 (-0.55)	0.07 (0.82)	-0.02 (-0.45)	0.01 (0.06)	-0.05 (-0.48)	0.05 (0.87)
<i>R&D</i>	0.29 (0.43)	0.03 (0.06)	-0.32 (-0.90)	0.51 (0.90)	-0.66 (-1.10)	0.15 (0.47)
<i>Tobin's Q</i>	0.00 (0.06)	0.01 (0.76)	-0.01 (-1.29)	0.01 (1.28)	-0.01 (-0.65)	-0.01 (-1.38)
<i>Indepboard</i>	-0.14 (-0.41)	-0.37 (-1.23)	0.51** (2.27)	0.13 (0.39)	-0.61* (-1.70)	0.48** (2.09)
<i>Boardsize</i>	-0.00 (-0.33)	-0.00 (-0.02)	0.00 (0.40)	0.00 (0.14)	-0.01 (-0.79)	0.01 (0.99)
Constant	-0.04 (-0.12)	0.99*** (2.87)	0.05 (0.24)	0.06 (0.14)	0.80* (1.85)	0.14 (0.60)
Firm and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1067	1067	1067	1075	1075	1075
F-value	0.68	0.93	2.62	1.36	1.52	1.85
Adj. R^2	0.22	0.24	0.26	0.23	0.29	0.24

Panel B: Subsample after 2014

	(1)	(2)	(3)	(4)	(5)	(6)
	<i>Invent-apply</i>	<i>Utility- apply</i>	<i>Design- apply</i>	<i>Invent-grant</i>	<i>Utility-grant</i>	<i>Design-grant</i>
<i>Specialist</i>	0.11*** (3.20)	-0.07** (-2.19)	-0.04 (-1.41)	0.07** (2.33)	-0.01 (-0.36)	-0.06** (-2.41)
<i>Tangibility</i>	-0.01 (-0.09)	0.09 (0.86)	-0.08 (-1.11)	-0.16 (-1.38)	0.25** (2.12)	-0.09 (-1.06)
<i>Ln_Age</i>	0.04 (0.57)	-0.08 (-1.21)	0.04 (0.75)	0.06 (0.95)	-0.09 (-1.23)	0.03 (0.49)
<i>Ln_Size</i>	0.00 (0.15)	-0.00 (-0.25)	0.00 (0.10)	0.01 (0.66)	0.01 (0.30)	-0.02 (-1.24)
<i>Leverage</i>	-0.03 (-0.36)	-0.03 (-0.31)	0.06 (0.78)	-0.04 (-0.38)	-0.08 (-0.78)	0.12 (1.40)
<i>R&D</i>	0.24 (0.26)	0.12 (0.15)	-0.35 (-0.63)	0.89 (0.93)	-0.31 (-0.39)	-0.58 (-0.92)
<i>Tobin's Q</i>	0.00 (0.13)	-0.01 (-1.07)	0.01 (1.23)	-0.00 (-0.18)	0.00 (0.12)	0.00 (0.10)
<i>Indepboard</i>	-0.31 (-1.23)	0.30 (1.19)	0.01 (0.05)	-0.28 (-1.04)	0.25 (0.78)	0.03 (0.13)
<i>Boardsize</i>	-0.01 (-0.67)	0.01 (1.17)	-0.00 (-0.68)	-0.00 (-0.41)	0.01 (1.09)	-0.01 (-0.80)
Constant	0.40 (0.89)	0.60 (1.52)	-0.01 (-0.02)	0.04 (0.08)	0.41 (0.92)	0.55 (1.63)

(continued on next page)

Table 9 (continued)

	(1)	(2)	(3)	(4)	(5)	(6)
	<i>Invent-apply</i>	<i>Utility-apply</i>	<i>Design-apply</i>	<i>Invent-grant</i>	<i>Utility-grant</i>	<i>Design-grant</i>
Firm and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	995	995	995	965	965	965
F-value	1.56	1.27	1.13	1.45	1.00	1.15
Adj. R^2	0.26	0.33	0.19	0.25	0.30	0.22

5.6. Exogenous event: CEO retirement

To address the endogeneity problem, we used the retirement of independent directors as a criterion to create a subsample. Theoretically, independent directors change after the CEO retires, and this period of change is not outside the company's pursuit of independent technical directors, such as for a new technology project.

Table 10

Exogenous event: CEO retirement. This table presents the panel regression estimates of the number of patents classified by degree of innovation from 2007 to 2017 as a function of *Specialist*, using the subsample of years after the CEO's retirement. We used the patent data in year $t + 1$ to measure the effect of hiring independent technical directors in year t . *Specialist* measures whether the expertise of the independent directors hired in year t corresponds to the operational field of their companies. We controlled for firm and year fixed effects. The t-statistics are reported in brackets. ***, **, and * indicate that the parameter estimates are significantly different from 0 at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	<i>Invent-apply</i>	<i>Utility-apply</i>	<i>Design-apply</i>	<i>Invent-grant</i>	<i>Utility-grant</i>	<i>Design-grant</i>
<i>Specialist</i>	0.24*** (3.28)	-0.05 (-0.87)	-0.19** (-2.48)	0.25*** (2.84)	-0.06 (-0.58)	-0.19*** (-3.23)
<i>Tangibility</i>	-0.00 (-0.00)	0.07 (0.39)	-0.07 (-0.70)	0.10 (0.35)	0.12 (0.38)	-0.22 (-1.31)
<i>Ln_Age</i>	0.21 (1.07)	-0.40** (-2.46)	0.19 (1.36)	0.30 (1.33)	-0.23 (-0.75)	-0.07 (-0.49)
<i>Ln_Size</i>	-0.08 (-1.54)	0.06 (1.64)	0.01 (0.31)	-0.09 (-1.44)	0.03 (0.39)	0.06 (1.60)
<i>Leverage</i>	0.66*** (2.73)	-0.32 (-1.52)	-0.34 (-1.28)	0.50 (1.42)	-0.35 (-0.87)	-0.15 (-0.75)
<i>R&D</i>	1.95 (0.82)	-0.86 (-0.50)	-1.09 (-0.79)	6.28** (2.66)	-5.76** (-2.48)	-0.52 (-0.29)
<i>Tobin's Q</i>	0.02 (0.95)	-0.01 (-0.58)	-0.01 (-0.69)	0.02 (0.76)	-0.02 (-0.46)	-0.01 (-0.34)
<i>Indepboard</i>	-0.11 (-0.19)	0.01 (0.02)	0.10 (0.19)	0.25 (0.43)	0.26 (0.35)	-0.51 (-1.25)
<i>Boardsize</i>	-0.02 (-0.76)	0.00 (0.19)	0.02 (0.83)	-0.02 (-0.64)	0.03 (0.61)	-0.01 (-0.30)
<i>Inst</i>	-0.39* (-1.76)	0.23 (1.53)	0.16 (0.94)	-0.72*** (-3.42)	0.88*** (2.91)	-0.16 (-1.14)
<i>Intercontrol_index</i>	-0.00 (-0.78)	0.00*** (2.83)	-0.00 (-1.36)	0.00 (0.57)	0.00 (1.42)	-0.00* (-1.78)
<i>Ln_coverage</i>	0.09*** (2.77)	-0.12*** (-4.71)	0.03 (1.04)	0.06 (1.02)	-0.15*** (-2.98)	0.10** (2.56)
<i>Growth_rev</i>	0.02 (0.50)	-0.09** (-2.27)	0.07** (2.29)	-0.09 (-1.60)	-0.05 (-0.76)	0.14*** (3.67)
Constant	1.44 (1.18)	0.20 (0.19)	-0.64 (-0.65)	1.16 (0.76)	0.21 (0.12)	-0.38 (-0.50)
Firm and year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	125	125	125	122	122	122
F-value	17.40	6.61	5.51	5.91	4.75	3.84
Adj. R^2	0.77	0.81	0.86	0.58	0.63	0.79

The endogeneity problem can thus be addressed. Specifically, we used data on the age of CEOs and kept an observation if the CEO was over 60, the legal retirement age in China. Then we constructed a new dummy variable, *Post*, equal to 1 if the year is after the CEO's retirement, and 0 otherwise. We only kept observations with *Post* = 1, which means that the company has already gone through the CEO's retirement. We used the new subsample and ran the main regression. The results are reported in Table 10.

Based on the criterion for *Post*, the number of observations is significantly smaller. However, the regression results are essentially the same as those of the baseline model. The coefficients for the numbers of technical patents filed and authorized are 0.24 and 0.25, respectively, both of which are significant at the 1% level. The coefficients for the numbers of design patents filed and granted are -0.19 and -0.19, which are significant at the 5% and 1% levels, respectively. Therefore, after excluding the endogeneity problem, the results are still significant and consistent with the results of the main regression model.

6. Further analysis

6.1. Mechanism test: the role of R&D expenditure

Next, we investigated the mechanism by which independent directors affect corporate innovation. As more R&D expenditure can promote innovation performance, we examined whether the appointment of independent technical directors stimulates R&D expenditure. To this end, we constructed the following model:

Table 11

Independent technical directors and corporate innovation: Mechanism test. This table presents the panel regression estimates of Model (2) for the number of patent applications from 2007 to 2017 as a function of *Specialist* and *R&D*. The dependent variables are the proportion of technical invention patents filed, the proportion of utility patents filed, and the proportion of design patents filed to the total number of patents filed in year $t + 1$. *R&D* refers to the proportion of R&D expenditure to total assets in a company. *Specialist* measures whether the expertise of the independent directors hired in year t corresponds to the operational field of their companies. The key explanatory variable is the interaction term of *R&D* and *Specialist*. We controlled for firm and year fixed effects. The t-statistics are reported in brackets. ***, **, and * indicate that the parameter estimates are significantly different from 0 at the 1%, 5%, and 10% levels, respectively.

	(1) <i>Invent-apply</i>	(2) <i>Utility-apply</i>	(3) <i>Design-apply</i>
<i>R&D*Specialist</i>	3.81* (1.79)	-2.12 (-0.80)	-1.69 (-0.57)
<i>Specialist</i>	0.08** (2.21)	-0.00 (-0.12)	-0.07*** (-2.78)
<i>R&D</i>	-3.79* (-1.88)	2.40 (0.94)	1.38 (0.47)
<i>Tangibility</i>	-0.00 (-0.02)	0.03 (0.42)	-0.03 (-0.61)
<i>Ln_Age</i>	0.06 (1.17)	-0.05 (-1.13)	-0.01 (-0.24)
<i>Ln_Size</i>	0.03** (1.97)	-0.03** (-1.99)	-0.01 (-0.60)
<i>Leverage</i>	0.00 (0.01)	-0.05 (-0.71)	0.05 (0.90)
<i>Tobin's Q</i>	0.02** (1.97)	-0.01 (-1.59)	-0.00 (-0.83)
<i>Indepboard</i>	-0.58** (-2.24)	0.15 (0.59)	0.43** (2.51)
<i>Boardsize</i>	-0.02* (-1.89)	0.02* (1.91)	0.00 (0.17)
Constant	-0.13 (-0.34)	1.00*** (3.16)	0.12 (0.53)
Firm and year fixed effects	Yes	Yes	Yes
Observations	939	939	939
F-value	3.63	1.23	2.80
Adj. R^2	0.29	0.34	0.17

$$Patent_{i,t+1} = \beta_0 + \beta_1 Specialist_{i,t} + \beta_2 R\&D + \beta_3 Specialist_{i,t} \times R\&D + \alpha X_{it} + \gamma_t + \mu_i + \varepsilon_{it} \quad (2)$$

The dependent variables are the proportion of technical invention patent applications, the proportion of utility patent applications, and the proportion of design patent applications to the total number of patent applications in firms. The key explanatory variable is the product of *R&D* and *Specialist*. The *R&D* variable is the proportion of R&D expenditure to total assets in a company. A larger *R&D* indicates that the company attaches greater importance to innovation activities. The other control variables remain unchanged. Table 11 shows the regression results of Model (2).

In Table 11, the product of *R&D* and *Specialist* is important. It represents the net effect of the expertise of independent directors and its relevance to corporate innovation performance. The coefficient before *Invent-apply* is 3.81, which is significant at the 10% level. This indicates that independent technical directors encourage corporations to spend more on R&D. However, the coefficients before *Utility-apply* and *Design-apply* are both negative and not statistically significant. This implies that the appointment of independent technical directors steers the R&D and innovation activities of companies, which supports our mechanism test.

6.2. Mechanism test: the role of R&D expenditure and R&D subsidies

We conducted two other tests with different dependent variables. The new dependent variables are *R&D expenditure* and *R&D subsidy*. *R&D expenditure* refers to R&D expenditure for the firm's next fiscal year,

Table 12

Mechanism test: The role of R&D expenditure and R&D subsidies. This table presents the regression estimates of *R&D expenditure* and *R&D subsidy* in year $t + 1$ as a function of *Specialist*. *R&D expenditure* refers to R&D expenditure in the next fiscal year of the firm, and *R&D subsidy* refers to R&D subsidies granted by the government in the next period. We controlled for firm and year fixed effects. The t-statistics are reported in brackets. ***, **, and * indicate that the parameter estimates are significantly different from 0 at the 1%, 5%, and 10% levels, respectively.

	(1) <i>R&D expenditure</i>	(2) <i>R&D subsidy</i>
<i>Specialist</i>	0.01** (2.58)	0.01** (2.44)
<i>Tangibility</i>	-0.01 (-1.16)	0.02 (1.13)
<i>Ln_Age</i>	-0.02*** (-2.81)	-0.00 (-0.31)
<i>Ln_Size</i>	-0.00 (-0.98)	-0.00 (-1.26)
<i>Leverage</i>	-0.02 (-1.43)	-0.02 (-1.31)
<i>R&D</i>	1.06*** (7.29)	0.04 (0.19)
<i>Tobin's Q</i>	0.00* (1.66)	0.00 (1.14)
<i>Indepboard</i>	0.05* (1.84)	-0.02 (-0.54)
<i>Boardsize</i>	-0.00 (-0.57)	0.00 (0.63)
<i>Constant</i>	0.12*** (2.92)	0.09* (1.69)
Firm and year fixed effects	Yes	Yes
Observations	1,282	1,395
F-value	11.82	2.25
Adj. R^2	0.36	0.08

and *R&D subsidy* refers to R&D subsidies granted by the government in the next period. The regression results are presented in Table 12.

The results show that the regression coefficients of *Specialist* on *R&D expenditure* and *R&D subsidy* are 0.01 and 0.01, both of which are significant at the 5% level. This indicates that the appointment of relevant independent technical directors in a given fiscal year encourages companies to spend more on R&D while obtaining more government subsidies for their R&D activities in the next period. In addition, R&D expenditure and R&D subsidies are necessary for further innovation activities. In this sense, independent directors with relevant expertise promote corporate innovation by improving R&D expenditure and government subsidies in their companies.

6.3. R&D quality and the appointment of independent directors

To measure the reliability of our indicators, we further analyzed the relationship between the appointment of independent technical directors and the patent citation rate, which indicates recognition of innovation. We followed Balsmeier et al. (2017) and Lanjouw and Schankerman (2004) and used several patent indicators to describe the quality of innovation, in addition to the number of patent applications and authorizations. We changed the independent variables in Model (1) to *Patent Citation* and *Self-Citation*.

Patent Citation measures the position of a patent in the distribution of citations compared with other patents granted in the same patent category and in the same year. Based on the frequency of patent citations, the degree of innovation recognition can be divided into the top 1% of patents, the top 2–10% of patents, patents that are not in the top 10% but have been cited at least once, and patents that have never been cited. If a patent is in the top 1% or the top 2–10%, it is in the highest percentile of the citation distribution among patents in the same patent category in the same year. To further measure whether independent technical directors can improve the quality of corporate innovation, we selected the top 1% and the top 2–10% of patents as indicators.

Self-Citation measures the number of times a company cites other patents from the same corporation. Following Faleye et al. (2011), more self-citations indicate that a corporation is deepening its current research field, while fewer self-citations suggest that a corporation is expanding its research scope or exploring new fields.

Table 13 presents the number of patents with citations in the top 1%, the top 2–10%, and self-citations. As the results show, the coefficient for patents with citations in the top 1% is 0.05, which is significant at the 10% level. The coefficient for patents with citations in the top 2–10% is 0.11, which is significant at the 5% level. We can therefore conclude that the appointment of independent technical directors promotes high-quality innovations in companies. Moreover, the *Self-Citation* coefficient is 0.24, which is statistically significant, suggesting that corporations mainly delve into their current research field rather than expanding the scope of their research. In short, independent technical directors further promote innovation in the operational field of their companies.

In addition, we introduced the variable *Newpatent* as our new dependent variable, which refers to new patents granted in a new field for firms, as patents in a new field can better represent the innovation capability of a company. Thus, we used this new dependent variable to rerun the regression with the control variables and the fixed effects.

Based on the regression results, the effect of *Specialist* is positive in terms of new patents granted. We can thus infer that the appointment of independent technical directors can improve corporate innovation by improving the number of new patents granted in a new field for companies.

7. Conclusions

We studied all A-share companies listed on the SSE and the SZSE in China from 2007 to 2017 and found that independent technical directors can use their expertise to help public companies with technical innovation, contributing to industrial and economic growth in general. The results are still significant when applying the two-stage IV model, which helps us deal with selection bias. In addition, we used the Wenfeng.plc shock in 2014 as an exogenous event to address the endogeneity problem, and we found that the results for

Table 13

Independent technical directors and corporate innovation: R&D quality. This table presents the regression estimates of the number of patent citations, self-citations, and new patents granted to the company in a new field from 2007 to 2017 as a function of *Specialist*. *Top1* represents the position of the patent in the top 1% of the distribution of citations compared with other granted patents in the same patent category and in the same year. *Top2_10* represents the position of the patent in the top 2–10% in the distribution of citations compared with other granted patents in the same patent category and in the same year. *Self-Citation* represents the number of times a company cites other patents from the same corporation. *Newpatent* represents the number of new patents granted to a firm in a new field. We used the patent data in year $t + 1$ to measure the effect of hiring independent technical directors in year t . *Specialist* measures whether the expertise of the independent directors hired in year t corresponds to the operational field of their companies. We controlled for firm and year fixed effects. The t-statistics are reported in brackets. ***, **, and * indicate that the parameter estimates are significantly different from 0 at the 1%, 5%, and 10% levels, respectively.

	(1) <i>Top1</i>	(2) <i>Top2_10</i>	(3) <i>Self-Citation</i>	(4) <i>Newpatent</i>
<i>Specialist</i>	0.05* (1.71)	0.11** (2.14)	0.24** (2.21)	0.82** (2.08)
<i>Tangibility</i>	0.08 (0.62)	−0.00 (−0.01)	−0.05 (−0.12)	−0.37 (−0.30)
<i>Ln_Age</i>	−0.00 (−0.64)	0.00 (0.77)	0.00 (0.15)	0.89 (1.22)
<i>Ln_Size</i>	0.08** (2.33)	0.08*** (2.72)	0.22*** (3.36)	1.62** (2.34)
<i>Leverage</i>	−0.00 (−0.02)	−0.08 (−0.63)	0.09 (0.32)	−2.78* (−1.70)
<i>R&D</i>	3.05 (1.46)	1.84 (1.18)	9.15** (2.00)	−14.24 (−1.06)
<i>Tobin's Q</i>	0.02 (1.57)	0.01 (1.14)	0.03 (1.34)	0.17 (1.06)
<i>Indepboard</i>	0.17 (0.57)	0.85** (2.17)	1.76 (1.63)	−0.94 (−0.27)
<i>Boardsize</i>	−0.01 (−1.40)	0.00 (0.13)	0.08 (1.64)	0.24 (1.59)
Constant	−1.76** (−2.09)	−1.91*** (−2.93)	−5.70*** (−3.87)	−0.21 (−0.13)
Firm and year fixed effects	Yes	Yes	Yes	Yes
Observations	831	831	831	−0.00
F-value	1.5666	2.3197	3.5099	(−0.49)
Adj. R^2	0.3022	0.4030	0.3281	0.07

invention patents after 2014 are much more significant. Moreover, specialists can successfully play the role of consultants when their field of expertise is relevant to the operational field of their companies. We also took a closer look at the mechanism by which independent directors increase corporate innovation. We found that independent technical directors increase R&D in the company's current research field rather than expanding to other fields. Furthermore, independent technical directors increase corporate innovation by encouraging firms to spend more on R&D and by enabling them to obtain more government subsidies for R&D.

This study provides empirical evidence to encourage companies to hire academics with relevant backgrounds as independent directors. In addition, we not only enrich and develop the capital market literature but also offer a new perspective for research on the consulting role of independent directors. If corporations adopt a differentiation strategy and want to expand to other fields, they should consider hiring independent technical directors.

This study can guide policymaking and the development of practical applications in the following ways. First, the government is encouraged to conduct research before publishing policy changes that evaluate the difficulty of corporate innovation, based on the relevance of the expertise of technical specialists and the operational field of companies. Second, firms should make full use of independent directors who genuinely participate in corporate governance and innovation and foster industrial transformation. Third, when hiring university professors as independent technical directors, companies should give priority to hiring individuals

whose expertise is consistent with their main activities, which will promote innovation and sustainable and healthy economic development.

Declaration of Competing Interest

The authors declared that there is no conflict of interest.

Appendix A. Variable definitions

This table presents the definitions of the variables used in our models, including the dependent variables, the independent variables, and the control variables.

Variable	Abbreviation	Definition and measurement
Dependent variables	<i>Invent-apply</i>	Number of technical invention patent applications out of the total number of patents filed
	<i>Utility-apply</i>	Number of utility model patent applications out of the total number of patents filed
	<i>Design-apply</i>	Number of design patent applications out of the total number of patents filed
	<i>Invent-grant</i>	Number of technical invention patents authorized out of the total number of patents authorized
	<i>Utility-grant</i>	Number of utility model patents authorized out of the total number of patents authorized
	<i>Design-grant</i>	Number of design patents authorized out of the total number of patents authorized
Independent variables	<i>Specialist</i>	Dummy variable: if the expertise of an independent director corresponds to the operational field of the company, <i>Specialist</i> = 1; otherwise, <i>Specialist</i> = 0
Control variables	<i>Ln_Size</i>	Logarithm of total assets
	<i>Ln_Age</i>	Logarithm of the company's trading years since the IPO
	<i>Leverage</i>	Total liabilities divided by total assets
	<i>Tangibility</i>	Carrying value of fixed assets divided by total assets
	<i>Tobin's Q</i>	Tobin's Q = market capitalization divided by asset replacement cost
	<i>R&D</i>	R&D expenditure divided by total assets
	<i>Boardsize</i>	Logarithm of the number of directors
	<i>Indepboard</i>	Number of independent directors out of the total number of directors
	<i>Inst</i>	Whether the company is controlled by large institutional investors
	<i>Intercontrol_index</i>	The internal control condition of the company
	<i>Ln_coverage</i>	Analyst monitoring and coverage on the company
<i>Growth_rev</i>	Revenue growth rate	

Appendix B. Expertise of independent directors and corporate innovation

Fig. 1 shows the relationship between the relevance of the expertise of independent directors and the number of technical invention patent applications in companies. The x-axis represents the year and the y-axis represents the number of technical innovation patent applications. The blue line indicates when the expertise of independent directors is relevant to the operational field of their companies. The red line indicates the opposite. Fig. 2 shows the relationship between the relevance of the expertise of independent directors and the number of technical invention patent authorizations in companies. The x-axis represents the year and the y-axis represents the number of technical innovation patents authorized. The blue line indicates when the expertise

of independent directors is relevant to the operational field of their companies. The red line indicates the opposite.

References

- Adams, R.B., Ferreira, D., 2009. Women in the boardroom and their impact on governance and performance. *J. Financ. Econ.* 94 (2), 291–309. <https://doi.org/10.2139/ssrn.1107721>.
- Agrawal, A., Chadha, S., 2005. Corporate governance and accounting scandals. *J. Law Econ.* 48 (2), 371–406. <https://doi.org/10.1086/430808>.
- Ahmed, A.S., Duellman, S., 2007. Accounting conservatism and board of director characteristics: an empirical analysis. *J. Account. Econ.* 43 (2–3), 411–437. <https://doi.org/10.1016/j.jacceco.2007.01.005>.
- Al-Dhamari, R.A., Ismail, K.N.I.K., 2013. Governance structure, ownership structure and earnings predictability: Malaysian evidence. *Asian Acad. Manage. J. Account. Finance* 9 (1), 1–23. <https://doi.org/10.6084/m9.figshare.4732957.v3>.
- Amore, M.D., Schneider, C., Zaldokas, A., 2013. Credit supply and corporate innovation. *J. Financ. Econ.* 109 (3), 835–855. <https://doi.org/10.1016/j.jfineco.2013.04.006>.
- Anderson, R.C., Mansi, S.A., Reeb, D.M., 2004. Board characteristics, accounting report integrity, and the cost of debt. *J. Account. Econ.* 37 (3), 315–342. <https://doi.org/10.1016/j.jacceco.2004.01.004>.
- Armstrong, C.S., Core, J.E., Guay, W.R., 2014. Do independent directors cause improvements in firm transparency? *J. Financ. Econ.* 113 (3), 383–403. <https://doi.org/10.2139/ssrn.2031801>.
- Audretsch, D. B., & Lehmann, E., 2010. Entrepreneurial access and absorption of knowledge spillovers: Strategic board and managerial composition for competitive advantage. Available at SSRN 873859. doi:10.1111/j.1540-627X.2006.00161.x.
- Atanassov, J., 2013. Do hostile takeovers stifle innovation? Evidence from antitakeover legislation and corporate patenting. *The Journal of Finance* 68 (3), 1097–1131. <https://doi.org/10.1111/jofi.12019>.
- Balsmeier, B., Fleming, L., Manso, G., 2017. Independent boards and innovation. *J. Financ. Econ.* 123 (3), 536–557. <https://doi.org/10.1016/j.jfineco.2016.12.005>.
- Bazerman, M.H., Schoorman, F.D., 1983. A limited rationality model of interlocking directorates. *Acad. Manag. Rev.* 8 (2), 206–217. <https://doi.org/10.5465/amr.1983.4284723>.
- Bazrafshan, E., Kandelousi, A.S., Hooy, C.W., 2016. The impact of earnings management on the extent of disclosure and true financial performance: Evidence from listed firms in Hong Kong. *The British Accounting Review* 48 (2), 206–219. <https://doi.org/10.1016/j.bar.2015.09.001>.
- Bhagat, S., Black, B., 2002. The non-correlation between board independence and long-term firm performance. *J. Corporat. Law* 27 (2), 231–273. <https://doi.org/10.2139/ssrn.133808>.
- Black, B.S., Kim, W., 2012. The effect of board structure on firm value: a multiple identification strategies approach using Korean data. *J. Financ. Econ.* 104 (1), 203–226. <https://doi.org/10.1016/j.jfineco.2011.08.001>.
- Bonini, S., Deng, J., Ferrari, M., & John, K., 2017. On long-tenured independent directors. Available at SSRN 2965588. doi: Bonini, 10.2139/ssrn.2965588.
- Boone, A.L., Field, L.C., Karpoff, J.M., Raheja, C.G., 2007. The determinants of corporate board size and composition: an empirical analysis. *J. Financ. Econ.* 85 (1), 66–101. <https://doi.org/10.1016/j.jfineco.2006.05.004>.
- Brav, A., Jiang, W., Ma, S., Tian, X., 2018. How does hedge fund activism reshape corporate innovation? *J. Financ. Econ.* 130 (2), 237–264. <https://doi.org/10.1016/j.jfineco.2018.06.012>.
- Brochet, F., Srinivasan, S., 2014. Accountability of independent directors: evidence from firms' subject to securities litigation. *J. Financ. Econ.* 111 (2), 430–449. <https://doi.org/10.1016/j.jfineco.2013.10.013>.
- Byrd, J.W., Hickman, K.A., 1992. Do outside directors monitor managers: evidence from tender offer bids. *J. Financ. Econ.* 32 (2), 195–221. [https://doi.org/10.1016/0304-405X\(92\)90018-S](https://doi.org/10.1016/0304-405X(92)90018-S).
- Cavaco, S., Crifo, P., Rebérioux, A., 2017. Independent directors: Less informed but better selected than affiliated board members? *J. Corporate Finance* 43, 106–121. <https://doi.org/10.1016/j.jcorpfin.2017.01.004>.
- Cerqueiro, G., Hegde, D., Penas, M.F., Seamans, R.C., 2016. Debtor rights, credit supply, and innovation. *Manage. Sci.* 63 (10), 3311–3327. <https://doi.org/10.1287/mnsc.2016.2509>.
- Chircop, J., Collins, D.W., Hass, L.H., 2018. Accounting comparability and corporate innovative efficiency. Available at SSRN 2810448. <https://doi.org/10.2308/accr-52609>.
- Cohen, L., Diether, K., Malloy, C., 2013. Misvaluing innovation. *Rev. Financ. Stud.* 26 (3), 635–666. <https://doi.org/10.1093/rfs/hhs183>.
- Coles, J.L., Daniel, N.D., Naveen, L., 2008. Boards: does one size fit all? *J. Financ. Econ.* 87 (2), 329–356. <https://doi.org/10.1016/j.jfineco.2006.08.008>.
- Dalton, D.R., Daily, C.M., Johnson, J.L., Ellstrand, A.E., 1999. Number of directors and financial performance: a meta-analysis. *Acad. Manag. J.* 42 (6), 674–686. <https://doi.org/10.5465/256988>.
- De Simone, L., Huang, J., Krull, L.K., 2017. R&D and the rising foreign profitability of US multinational corporations. Available at SSRN 3050016. <https://doi.org/10.2308/accr-52620>.
- Donges, A., Meier, J.M.A., & Silva, R., 2019. The impact of institutions on innovation. Available at SSRN 2815541. <https://doi.org/10.2139/ssrn.2815541>.
- Duchin, R., Matsusaka, J.G., Ozbas, O., 2010. When are outside directors effective? *J. Financ. Econ.* 96 (2), 195–214. <https://doi.org/10.1016/j.jfineco.2009.12.004>.

- Faleye, O., Hoitash, R., Hoitash, U., 2011. The costs of intense board monitoring. *J. Financ. Econ.* 101 (1), 160–181. <https://doi.org/10.1016/j.jfineco.2011.02.010>.
- Fama, E.F., Jensen, M.C., 1983. Separation of ownership and control. *J. Law Econ.* 26 (2), 301–325. <https://doi.org/10.1086/467037>.
- Ferreira, D., Ferreira, M.A., Raposo, C.C., 2011. Board structure and price informativeness. *J. Financ. Econ.* 99 (3), 523–545. <https://doi.org/10.2139/ssrn.983524>.
- Ferreira, D., Ginglinger, E., Laguna, M.A., Skalli, Y., 2018. Board quotas and director-firm matching. Available at SSRN 2992213. <https://doi.org/10.2139/ssrn.2992213>.
- Ferris, S.P., Jagannathan, M., Pritchard, A.C., 2003. Too busy to mind the business. Monitoring by directors with multiple board appointments. *J. Finance* 58 (3), 1087–1111. <https://doi.org/10.2307/3094573>.
- Fich, E.M., White, L.J., 2005. Why do CEOs reciprocally sit on each other's boards? *J. Corporate Finance* 11 (1–2). <https://doi.org/10.2139/ssrn.249975>.
- Fos, V., Li, K., Tsoutsoura, M., 2017. Do director elections matter? *Rev. Financ. Stud.* 31 (4), 1499–1531. <https://doi.org/10.2139/ssrn.2609815>.
- Gang, W., Zezhong, X., Travlos, N., Hong, Z., 2007. Background of Independent Directors and Corporate Performance. *Economic Research Journal* 3. https://doi.org/10.1007/978-3-642-27711-5_39.
- González-Urbe, J., Groen-Xu, M., 2017. CEO contract horizon and innovation. Available at SSRN 2633763. <https://doi.org/10.2139/ssrn.2633763>.
- Hall, B.H., Jaffe, A., Trajtenberg, M., 2005. Market value and patent citations. *Rand Journal of Economics* 16–38. <https://doi.org/10.3386/w7741>.
- Harhoff, D., Narin, F., Scherer, F.M., Vopel, K., 1999. Citation frequency and the value of patented inventions. *Review of Economics and Statistics* 81 (3), 511–515. <https://doi.org/10.1162/003465399558265>.
- Holmstrom, B., 2005. Pay without performance and the managerial power hypothesis: a comment. *J. Corporate Law* 30, 703–713. <https://doi.org/10.2139/ssrn.899096>.
- Jiraporn, P., Lee, S.M., Park, K.J., Song, H.J., 2017. How do independent directors influence innovation productivity? A quasi-natural experiment. *Appl. Econ. Lett.* 1–7. <https://doi.org/10.1080/13504851.2017.1329927>.
- Lanjouw, J.O., Schankerman, M., 2004. Patent quality and research productivity: Measuring innovation with multiple indicators. *The Economic Journal* 114 (495), 441–465. <https://doi.org/10.1111/j.1468-0297.2004.00216.x>.
- Laux, V., 2008. Board independence and CEO turnover. *J. Account. Res.* 46 (1), 137–171. <https://doi.org/10.1111/j.1475-679X.2008.00269.x>.
- Linck, J.S., Netter, J.M., Yang, T., 2008. The determinants of board structure. *J. Financ. Econ.* 87 (2), 308–328. <https://doi.org/10.1016/j.jfineco.2007.03.004>.
- Manso, G., 2011. Motivating innovation. *J. Finance* 66 (5), 1823–1860. <https://doi.org/10.1111/j.1540-6261.2011.01688.x>.
- Masulis, R.W., Mobbs, S., 2014. Independent director incentives: where do talented directors spend their limited time and energy? *J. Financ. Econ.* 111 (2), 406–429. <https://doi.org/10.1016/j.jfineco.2013.10.011>.
- Masulis, R.W., Zhang, E.J., 2018. How valuable are independent directors? Evidence from external distractions. *J. Financ. Econ.* 132 (3), 226–256. <https://doi.org/10.1016/j.jfineco.2018.02.014>.
- McCabe, M., Nowak, M., 2008. The independent director on the board of company directors. *Manager. Audit. J.* 23 (6), 545–566. <https://doi.org/10.1108/02686900810882101>.
- Osterloh, M., Frey, B.S., 2006. Shareholders should welcome knowledge workers as directors. *J. Manage. Governance* 10 (3), 325–345. <https://doi.org/10.1007/s10997-006-9003-4>.
- Porter, M.E., 1992. Capital disadvantage: America's failing capital investment system. *Harvard Bus. Rev.* 70 (5), 65–82. <https://doi.org/10.1108/eb022838>.
- Rosenstein, S., Wyatt, J.G., 1990. Outside directors, board independence, and shareholder wealth. *J. Financ. Econ.* 26 (2), 175–191. [https://doi.org/10.1016/0304-405X\(90\)90002-H](https://doi.org/10.1016/0304-405X(90)90002-H).
- Schilling, M.A., Phelps, C.C., 2007. Interfirm collaboration networks: the impact of large-scale network structure on firm innovation. *Manage. Sci.* 53 (7), 1113–1126. <https://doi.org/10.1287/mnsc.1060.0624>.
- Shukeri, S.N., Shin, O.W., Shaari, M.S., 2012. Does board of director's characteristics affect firm performance? Evidence from Malaysian public listed companies. *Int. Bus. Res.* 5 (9), 120–127. <https://doi.org/10.5539/ibr.v5n9p120>.
- Stiglitz, J.E., Weiss, A., 1983. Incentive effects of terminations: Applications to the credit and labor markets. *The American Economic Review* 73 (5), 912–927. <https://doi.org/10.7916/D80K2KJV>.
- Swan, P.L., Honeine, S., 2010. Is company performance dependent on outside director “skin in the game”? Available at SSRN 1746536. <https://doi.org/10.2139/ssrn.1746536>.
- Weisbach, M.S., 1988. Outside directors and CEO turnover. *J. Financ. Econ.* 20 (88), 431–460. [https://doi.org/10.1016/0304-405X\(88\)90053-0](https://doi.org/10.1016/0304-405X(88)90053-0).
- Wernerfelt, B., 1984. A resource-based view of the firm. *Strateg. Manag. J.* 5 (2), 171–180. https://doi.org/10.1007/11538059_98v.
- White, J.T., Woidtke, T., Black, H.A., Schweitzer, R.L., 2014. Appointments of academic directors. *J. Corporate Finance* 28, 135–151. <https://doi.org/10.1016/j.jcorpfin.2013.12.007>.
- Yermack, D., 1996. Higher market valuation of companies with a small board of directors. *J. Financ. Econ.* 40 (2), 185–211. [https://doi.org/10.1016/0304-405X\(95\)00844-5](https://doi.org/10.1016/0304-405X(95)00844-5).