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The Impact of U.S. Entity List on Enterprise Innovation in China

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Abstract

We examine the impact of the U.S. export control policies, particularly the Entity List, on the innovation behavior of Chinese enterprises. The Entity List is a crucial tool for the U.S. to restrict the export of high-tech products to certain Chinese companies. Using a staggered Difference-in-Differences (DID) model and data from A-share listed companies in China from 2017 to 2022, we find that being added to the Entity List significantly boosts patent applications and R&D input among targeted Chinese firms. This positive effect is concentrated in firms facing more intense market competition and higher production factor costs, suggesting that the export control policy could stimulate innovation by raising competition and costs.

Keywords: Innovation; Export Control Policy; Difference-in-Differences; Entity List

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Introduction

Export control policies, particularly those implemented by the U.S. through its Entity List, have gained significant attention in recent years due to their potential impact on global technology transfer and enterprise innovation (Houser, 2020). They serve as crucial tools for the U.S. to restrict the export of high-tech products. With the escalating China-U.S. trade tensions, Chinese enterprises have increasingly become targets of this policy, raising concerns about its potential consequences on their innovation.[1]

Entity List is one important tool of export control regulation. In 2018, the U.S. government unilaterally announced additional tariffs on Chinese goods, provoking a trade conflict with China. On August 1st of the same year, the Bureau of Industry and Security (BIS) of the U.S. Department of Commerce listed 44 Chinese companies on the export control Entity List on the grounds of activities that violate U.S. national security or foreign policy interests. On August 26th, 24 more Chinese companies were added to the list on the grounds of helping the Chinese military build artificial islands in the South China Sea. Since then, the U.S. Entity List has been updated frequently, involving many Chinese companies and scientific research institutions whose industries mainly focus on high-tech fields such as information technology, aerospace, and biological medicine. As shown in Figure 1, the Entity List has been expanding since 2018, and by the end of 2023, 713 Chinese entities had been included in the scope of sanctions[2] (see Research Methodology section for Figure 1). The restricted industries on the Entity List almost cover all the ten key sectors emphasized in the Made in China 2025 Strategy.[3]

The Entity List is a blocklist of trade entities in the Export Administration Regulations (EAR) issued by the BIS. Enterprises included in the Entity List will not be able to import goods, technologies or software in the U.S., nor will they be able to import any items transiting from the U.S. unless they apply for special permission from the U.S. Department of Commerce. When purchasing products from China or third-country companies, if the proportion of U.S. controlled items in the value of the product exceeds 25%, or the product is directly produced using U.S.-origin technology or software, the Entity List companies will also be unable to purchase the product. Therefore, once a company is included in the Entity List, it will not only be unable to trade with U.S. companies but product transactions with third countries or even domestic companies may also be interrupted due to the involvement of U.S. goods or technologies in the value chain.

As China's production and innovation in the field of high-tech are still highly dependent on key products and core technologies imported from developed countries, the Entity List policy raises a deep concern about the high-tech innovation in China. Given the strategic importance of innovation to spur economic growth and competitiveness, understanding how external policies such as the Entity List affect domestic enterprises' innovation efforts is paramount.

We investigate the impact of the U.S. export control policies on the innovation behavior of Chinese enterprises. Specifically, we study whether the Entity List policy stimulates or

[1] https://www.reuters.com/world/china/china-slams-us-adding-firms-export-control-list-vows-action-2024-08-25/
[2] The statistical data comes from the official website of the Bureau of Industry and Security of the US Department of Commerce, https://www.bis.gov.
[3] The "ten key sectors" are: new information technology; high-end numerically controlled machine tools and robots; aerospace equipment; ocean engineering equipment and high-end vessels; high-end rail transportation equipment; energy-saving cars and new energy cars; electrical equipment; farming machines; new material; bio-medicine and high-end medical equipment.

stifles innovation among targeted Chinese enterprises. We employ a staggered Difference-in-Differences (DID) model using A-share listed companies in China spanning 2017 to 2022. This methodology allows us to identify the effect of being added to the Entity List on enterprises' innovation activities. Using the patent application as the proxy for firm innovation, we document evidence that the Entity List policy significantly boosts the patent application among target firms. We document similar results using Research and Development (R&D) input as the alternative proxy for innovation activity.

Furthermore, we explore the underlying mechanisms through which this policy may influence innovation, focusing on two potential channels: intensified market competition and increased production factor costs. We find that the increase in patent applications is mainly in firms facing more fierce competition and higher factor costs. These results prove that the Entity List policy increases firm innovation by raising product competition and input costs.

Our paper contributes to three strands of literature. First, our study is related to the literature on the effect of trade friction on firm innovation. Generally, international trade facilitates knowledge spillover and innovation (Bustos, 2011; Coelli et al., 2022). However, some other researchers argue that the results could be mixed because of the heterogeneity of firms (Bombardini et al., 2017). Benguria et al. (2022) document a decrease in the R&D of Chinese firms after the trade war between China and the U.S. Our paper focuses on Entity List policy, one important regulation belonging to trade friction, and documents positive effects. Besides the financial constraint and subsidy channel found by prior literature (Shen et al., 2024), we document that competition and factor costs are the additional channels through which Entity List policy can boost innovation.

Second, our paper is related to the literature on competition and innovation. The prior studies have not reached a consensus. Shu and Steinwender (2019) state, "overwhelmingly positive evidence for such in developing economies, largely positive evidence for such in Europe, and mixed evidence for such in Northern America." In the case of China, Liu et al. (2021) show that import competition reduces firm innovation. Our paper investigates the inclusion of the Entity List policy, which reduces the competition of target firms (Shen et al., 2024). Akcigit et al. (2024) suggest that firms in sectors with a smaller technological gap from the U.S. experienced a less pronounced decline in patent output than those in other sectors. We find more patent applications after the shock, consistent with the results of Kang et al. (2025), who studied the impact of the U.S. Export Control Reform Act enacted in 2018.

Third, our paper relates to the literature on factor price and innovation. Boler et al. (2015) document international sourcing, which reduces R&D costs and improves R&D investment and firm performance. Liu and Qiu (2016) find that input tariff cuts result in less innovation by Chinese firms. They argue that input tariff reduction has two opposite effects on a firm's decisions on innovation: it may promote innovation from the reduction in innovation costs, but it may also reduce innovation because foreign technologies become cheaper. Therefore, in their study, the factor price channel is dominated. Our results show the existence of the factor price channel and document positive effect of Entity List is mainly achieved through higher factor prices.

The remainder of the paper is organized as follows. Section 2 provides the literature review and hypothesis development. Section 3 describes the methodology and data. The main empirical results are reported in Section 4, followed by a discussion of the potential mechanism in Section 5. Section 6 concludes with policy implications.

Literature Review and Hypothesis Development

The consequence of U.S.-China export control regulations (ECRs).

The U.S. Entity List is a prominent example of ECRs, which have had profound impacts on the operations of Chinese firms. These impacts can be analyzed through three primary channels, as documented in prior literature:

First, ECRs can cause disruptions in the supply chain. The export control policies between the U.S. and China have caused global supply chain disruptions. Many Chinese firms rely on components and raw materials imported from the U.S. or other countries affected by the trade policy. Trade restrictions can lead to delays in supply, increased costs, and even the need to find alternative suppliers (Han et al., 2024). This can disrupt production schedules and increase uncertainty for Chinese firms (Liu & Ma, 2020). Some studies have found that Chinese manufacturers have faced significant challenges in sourcing components and raw materials due to trade restrictions, leading to production delays and declines in market value (Huang et al., 2023).

Second, ECRs can reduce the competition for imports from foreign firms. When ECRs limit the ability of foreign firms to export their products to China, domestic firms face less competition in the market. This can allow Chinese firms to gain market share and expand their operations (Shen et al., 2024). Moreover, the withdrawal of foreign firms can create a vacuum that Chinese firms can fill with their own products and services, further enhancing their market position. Consistent with this idea, Autor et al. (2020) show that increased import competition from China led to significant declines in patenting activities by U.S. firms, particularly those that were less profitable and less capital intensive, highlighting how trade exposure can suppress innovation among foreign competitors. Similarly, ECRs might provide Chinese firms with more opportunities to innovate by restricting foreign competition.

Third, ECRs can inhibit the knowledge spillover of imports. Free trade can facilitate the flow of advanced technology and expertise into the importing country, while the ECRs impede such spillover (Bloom et al., 2016; Brandt & Lim, 2024; Buera & Oberfield, 2020; Fosfuri et al., 2001). As a result, Chinese firms may miss opportunities for learning, absorbing, and adapting advanced technologies and know-how, thereby stifling innovation and technological progress.

Hypothesis development

To further explore how the Entity List may influence innovation, we examine two channels: market competition and input costs.

Based on the economic consequences of ECRs outlined above, we argue ECRs can affect the innovation of Chinese firms in both positive and negative ways. On the positive side, ECRs can reduce Chinese firms' reliance on foreign technology, motivating them to pursue independent innovation. Additionally, ECRs can reduce import competition from U.S. firms, providing Chinese firms opportunities to gain market share and innovate to meet market demand. However, on the negative side, ECRs can hinder the knowledge spillover from imports, limiting Chinese firms' ability to learn from foreign counterparts and reducing their innovation. These mechanisms present competing effects, making the overall impact of the Entity List policy on Chinese firm’s innovation theoretically ambiguous.

Therefore, the question of how the Entity List policy affects Chinese enterprises' innovation is an empirical one. We form the null hypothesis as follows:

Hypothesis 1: The Entity List policy does not affect Chinese enterprises' innovation.

Market competition is a potential channel through which the Entity List affects innovation. The link between market competition and enterprise innovation is not straightforward. Aghion et al. (2005) analyze data from British enterprises and find a relationship between product market competition and innovation that follows an inverted U-shape. They proposed a theoretical model that believes that when the technological levels of enterprises in the market are similar, innovation can enable enterprises to escape the pressure of competition by relying on differentiated products. Therefore, market competition will promote enterprise innovation, which is called the "Escape competition effect." Conversely, if the technological levels of enterprises are very different, the profit growth that less-advanced enterprises can obtain through innovation is small. Therefore, the more intense the competition, the more it will hinder innovation, which is called the "Schumpeterian effect" (Schumpeter, 1942). Hashmi (2013) uses data from publicly listed U.S. manufacturing companies and identifies a slight negative correlation between market competition and enterprise innovation in the highly competitive U.S. market.

China has made significant progress in the level of marketization, but compared with developed countries, there is still room for improvement. This situation is more suitable for the "escape competition effect" under a low level of competition. Using Chinese public companies data, He et al. (2015) find that product market competition can promote enterprise R&D investment, where the finding is consistent with the escape competition effect. Before implementing the Entity List policy, companies on the list gained monopoly power over other companies in the same industry through products and technologies imported from the U.S. However, after being sanctioned by the Entity List, listed companies no longer have these monopoly advantages. Therefore, the Entity List has increased the competition in the Chinese market. The "escape competition effect" will encourage companies to conduct more R&D and innovation activities. Although the relationship between competition and innovation is not always linear, as excessive competition may discourage innovation by reducing potential returns, in China, where competition is still relatively moderate, the escape competition effect is more likely to dominate.

We propose Hypothesis 2 based on the above analysis:

Hypothesis 2: The Entity List policy has promoted Chinese enterprises' innovation activities by improving market competition.

The theory of factor prices and innovation, proposed by Hicks (1963), suggests that changes in the relative price of production factors could stimulate innovation to reduce reliance on expensive factors. Prior studies find evidence consistent with this argument (Boler et al., 2015). The Entity List policy hinders the procurement channels of enterprises' original production factors and forces them to find alternative solutions. While looking for substitutes, enterprises incur additional procurement and transportation costs and may pay higher prices for raw materials. These marginal costs are ultimately reflected in the increase in the rising cost of production inputs. Therefore, the Entity List increases the cost of production factors of enterprises. It will encourage enterprises to carry out more R&D and innovation activities.

While rising input costs can create short-term financial pressure, prior studies suggest that such cost shocks can also act as a catalyst for firms to seek cost-reducing innovations (e.g., Boler et al., 2015; Hicks, 1963). Given the persistent and structural disruptions caused by the Entity List, which have led to a sustained increase in input costs, the incentive to innovate as a strategic response is likely to dominate.

We propose Hypothesis 3 based on the above analysis:

Hypothesis 3: The Entity List policy has promoted the innovation activities of Chinese enterprises by increasing the cost of input factors.

Research Methodology

Regression model

The inclusion of Chinese firms in the U.S. Entity List is exogenous. Firms can hardly predict whether it will be subject to export control. Therefore, we construct a multi-period DID model to study the impact of the U.S. Entity List on China's corporate innovation,

The regression model is specified as follows:

$$Patent_{i.t} = \beta_0 + \beta_1 DID_{it} + \sum_j \beta_j Control_{it}^j + \mu_i + \tau_t + \varepsilon_{it} \quad (1)$$

The primary dependent variable is enterprise innovation. We use the annual number of patent applications filed by enterprises as a proxy variable for enterprise innovation. The rationale behind using the number of patent applications rather than the number of patents obtained is that the application situation can more quickly reflect the changes in the innovation trend of enterprises after policy shocks. In the robustness test, we use the number of invention patents applied ($Invention$) and the R&D expense scaled by operating income (RD_Incm) as alternative dependent variables.

In the equation (1), the dependent variable $Ln\ (Patent_{i,t})$ is defined as the natural logarithm of the number of patents the enterprise i applied for in year t plus 1.

The core independent variable, DID_{it}, is a dummy variable. It equals one if enterprise i is included in the Entity List in year t and keeps equaling one thereafter, and zero otherwise.

$Control_{i,t}^j$ is a series of control variables that may affect enterprise innovation. Existing literature has demonstrated that the following factors of an enterprise may influence its innovation performance: enterprise size (Yin & Zuscovitch, 1998), asset allocation (Zhang et al., 2020), profitability (Zhou et al., 2014), age and cash flow (Brown et al., 2009), equity concentration (Czarnitzki & Kraft, 2009), and internationalization level (Madsen, 2007). Based on this literature, we control for a series of key factors that may affect the innovation ability of enterprises. Specifically, they include: enterprise age (Age); fixed asset ratio ($FixedAstR$); intangible asset ratio ($IntgAstR$); enterprise size ($LnAst$), measured by the logarithm of total assets; debt-to-asset ratio (Lev); liquidity status ($CashRatio$), measured by cash ratio; profitability (Roa), measured by return on assets; operating revenue growth rate ($RevGth$); holding concentration ($Hldcr$), measured by top five shareholders holding concentration; and internationalization level ($Oversea$), measured by overseas operating income.

We adopt a two-way fixed effect model, where μ_t and τ_t control for the individual fixed effect and the time fixed effect, respectively. ε_{it} is the error term.

Parallel trend test model

The parallel trend assumption is essential for establishing the staggered DID model. We use a dynamic event-study framework to validate the parallel trend assumption. The model incorporates time-to-event indicators to trace policy effects across pre- and post-treatment periods. The model for the parallel trend test is:

$$Patent_{i.t} = \beta_0 + \sum_{a=-4}^{-2} \beta_a Before_{i,t,a} + \beta_b Current_{i,t,b} + \sum_{c=1}^{3} \beta_c After_{i,t,c} + \sum_j \beta_j Control_{it}^j + \mu_i + \tau_t + \varepsilon_{it} \quad (2)$$

Here, $Before$, $Current$, and $After$indicate years relative to the policy shock when enterprises are affected by the policy. For instance, if enterprise i was listed on the Entity List in 2020, then in the year of 2019, $Before_{i,2019,-1} = 1$, and in other years, $Before_{i,2019,-1} = 0$. For enterprises that have never been on the Entity List, $Before$, $Current$, and $After$ are all 0 in all years.

Mechanism model

To further investigate the potential mechanism, we construct two variables. First, we use the Herfindahl-Hirschman Index (HHI) to measure market competition. It is obtained with the formula $HHI = \sum\left({x_i}/{x}\right)^2$: where x_i is the operating revenue of enterprise i and x is the sum of the operating revenue of all enterprises in the industry. HHI quantifies market competition within an industry based on market share concentration. The more evenly distributed the market share among firms in the industry, the lower the HHI and the greater the level of market competition. The greater the industry monopoly, the higher the HHI and the lower the level of market competition. We add the interaction term of HHI and the dummy variable DID, $HHI \times DID$, into the regression and identify how the Entity List policy affects corporate innovation through market competition through the coefficient of the interaction term. The regression model of the market competition mechanism is:

$$Patent_{i.t} = \beta_0 + \beta_1 DID_{it} + \beta_2 HHI_{it} \times DID_{it} + \sum_j \beta_j Control_{it}^j + \mu_i + \tau_t + \varepsilon_{it} \tag{3}$$

Second, we use operating costs scaled by assets as a proxy variable for enterprises' production cost factors. Operating costs include not only the capital, raw materials, and labor costs of enterprises but also the procurement, transportation, marketing, and other expenses incurred in the production process. Therefore, it can comprehensively measure the impact of the Entity List on the cost of production factors of enterprises. Similarly, we add the interaction term of scaled operating cost and the dummy variable, $Cost\_Ast \times DID$, into the regression and use the interaction term coefficient to identify how the Entity List policy affects enterprise innovation through factor costs. The regression model of the factor costs mechanism is:

$$Patent_{i.t} = \beta_0 + \beta_1 DID_{it} + \beta_2 \operatorname{Cos} t\_Ast_{it} \times DID_{it} + \sum_j \beta_j Control_{it}^j + \mu_i + \tau_t + \varepsilon_{it} \tag{4}$$

Sample selection and data sources

Considering research feasibility and data availability, we select A-share listed companies as the research sample and focus on the period from 2017 to 2022. The number of patent applications of enterprises is the sum of the number of independent and joint applications from the Chinese Research Data Services Platform (CNRDS). The financial information of enterprises comes from the China Stock Market & Accounting Research Database (CSMAR). The sample screening is processed as follows: (1) Companies in the financial industry are eliminated; (2) Special Treatment (ST), Delisting Warning (*ST), and Particular Transfer (PT) listed companies are eliminated[4]; (3) Observations with missing variables used in our regression are eliminated, and all continuous variables are winsorized at the 1st and 99th percentile.

[4] ST and *ST indicate consecutive losses. PT firms face trading suspension. Excluded due to abnormal finances which bias policy impact analysis.

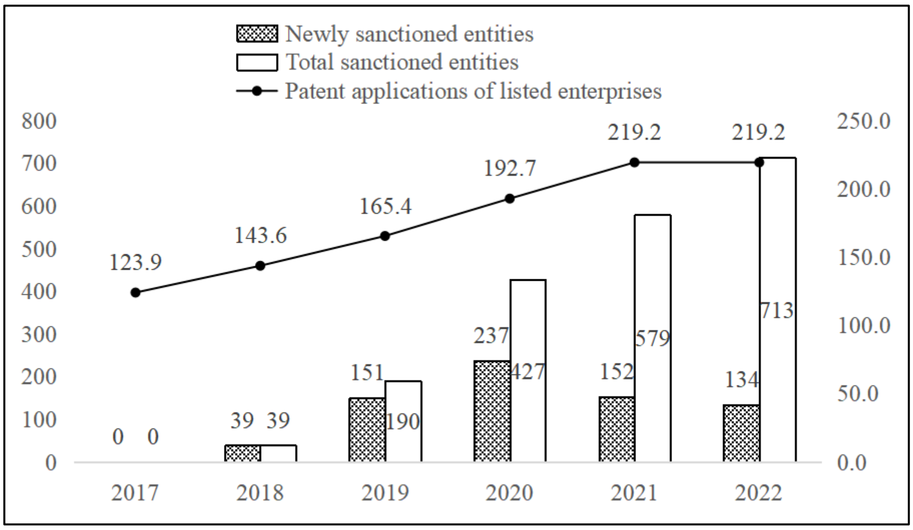

Figure 1: Number of Sanctioned Chinese Entities and Patent Applications
This figure illustrates the number of Chinese entities on the Entity List from 2017 to 2022. The shaded bar chart represents the number of newly sanctioned entities, and the chart represents the total number of sanctioned entities. The data comes from the official website of the Bureau of Industry and Security of the U.S. The line chart represents the total number of patent applications of all listed enterprises, and the data comes from the Chinese Research Data Services Platform.

We obtain the export control Entity List from the official website of the BIS of the U.S. Department of Commerce and sort out the names and years of Chinese-listed companies to construct the core independent variables. Figure 2 shows the distribution of enterprises in the treatment and control groups. After excluding the missing data, we obtain 79 treatment group data from 30 companies. From the distribution of their years, it can be seen that the number of Chinese listed companies on the U.S. Entity List has been increasing year by year from 2018 to 2021.

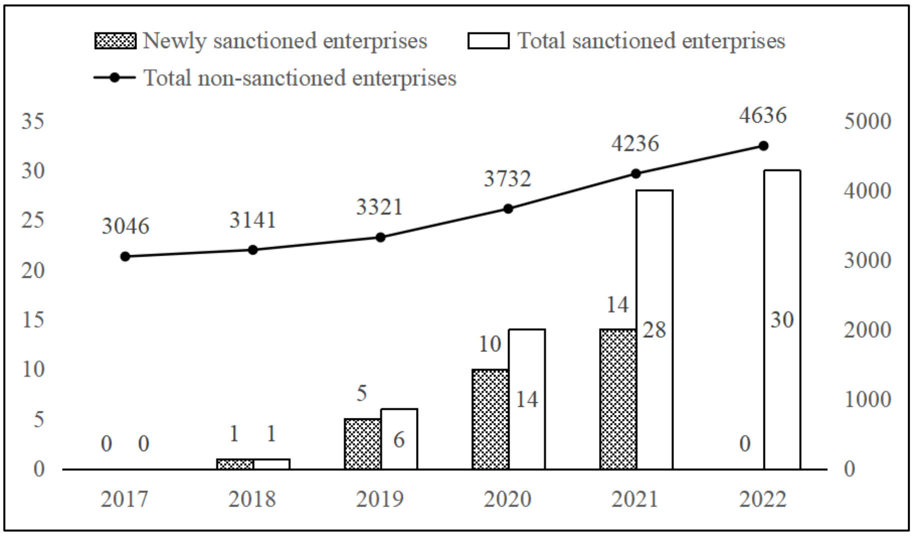

Figure 2: Distribution of Enterprises in Treatment and Control Groups
This figure illustrates the distribution of the treatment group and the control group in the sample. The shaded bar chart represents the number of newly sanctioned enterprises. The blank bar chart represents the total number of sanctioned enterprises (i.e., treatment group enterprises), and the line chart represents the total number of non-sanctioned enterprises (i.e., control group enterprises).

In addition, the construction of the HHI indicator requires the enterprise's industry classification information. The paper uses the third-level industry code of the Shenwan Industry Classification 2021 to match the sample enterprise industry. The data comes from CSMAR. Table 1 presents the statistical results of the HHI of the industries included in the Entity List. The first column lists the specific classifications of the 16 sanctioned industries. The second column reports the average HHI values of each industry from 2017 to 2022, with lower values indicating more intense market competition. The third column shows the percentile ranking of the average HHI of each industry among all 225 industries. A lower percentile value indicates a higher ranking of the industry's competition level in the overall sample. The results show that the average HHI percentile values of the industries covered by the Entity List are generally low, indicating that the market structure of these industries is generally competitive. Specifically, the HHI values of service industries (such as IT services and communication support services) are significantly lower than those of equipment manufacturing industries (such as photovoltaic equipment and communication transmission equipment), suggesting that the service industry is relatively more competitive, while the manufacturing industry is more concentrated.

Table 1: Statistical Results of HHI of the Industries Included in the Entity List

Industries included in the Entity List	Average HHI	Percentile of average HHI
Other special-purpose machinery	0.0916	7.6%
IT services	0.1018	9.8%
Aerospace equipment	0.1192	14.7%
Communication support services	0.1481	23.6%
Road and bridge construction	0.1493	24.0%
Terminal equipment	0.1547	25.3%
Ground armament	0.1574	26.2%
Integrated circuit	0.1600	28.0%
Computer equipment	0.1613	29.8%
Aerospace equipment	0.1647	31.6%
Other electronics	0.1650	32.9%
Software development	0.1757	35.6%
Photovoltaic equipment	0.1801	37.8%
Communication transmission equipment	0.2299	57.3%
Non-metallic new materials	0.2703	65.8%
Electronic system assembly	0.2807	68.4%

This table presents the statistical results of the Herfindahl-Hirschman Index (HHI) of the industries included in the Entity List. The first column lists the specific classifications of the 16 sanctioned industries. The second column reports the average HHI values of each industry from 2017 to 2022. The third column shows the percentile ranking of the average HHI of each industry among all 225 industries.

The descriptive statistical results of all variables are shown in Table 2. Among the core variables, the mean of patent application ($Patent$) is 45.498, with a standard deviation of 329.081, a maximum value of 14,131, and a minimum value of 0. This indicates significant differences in innovation activities among different enterprises, and the data shows a right-skewed distribution. The alternative dependent variables, such as the number of invention patents ($Invention$), research and development expenses (RD), and the ratio of research and development expenses to operating income (RD_Incm), also exhibit a right-skewed distribution. Additionally, the mean of the HHI (HHI) is 0.189, with a minimum value of 0.031 and a maximum value of 0.739, indicating significant differences in industry competition levels, with some industries approaching perfect competition while others showing a high degree of concentration. The mean of the ratio of operating costs scaled by total assets ($Cost\_Ast$) is 57.14%, with a standard deviation of 39.702, suggesting significant differences in cost management efficiency among different enterprises.

In addition, we compare the differences in key variables between the pre-sanction treatment group and the control group through T-tests, and the results are shown in Table 3. The results show that the mean of the logarithm of patent application volume ($LN(Patent)$) for the treatment group is 3.161, significantly higher than that of the control group at 1.999, indicating that the treatment group enterprises have a stronger innovation tendency. This phenomenon is closely related to the policy objective of the Entity List. Given that the U.S. Entity List aims to restrict technology exports, its screening criteria tend to target enterprises in high-tech fields, which typically have a higher innovation intensity. Table 3 reveals that the treatment group enterprises are younger (17.137 vs. 20.576), have a significantly higher debt-to-asset ratio (46.403% vs. 40.646%), and have significantly lower proportions of fixed assets (0.13 vs. 0.195) and cash ratios (0.73 vs. 1.294). Additionally, Table 3 shows that the treatment group enterprises have a larger total asset scale (22.838 vs. 22.254) and higher overseas business revenue (0.002 vs. 0.001).

Because of such difference, it is crucial to introduce these control variables in the main model and conduct the parallel trend tests and placebo tests (See Section 4.2) to identify the net effect of the Entity List policy accurately.

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Table 2: Descriptive Statistics of Variables

Variables	Observations	Mean	SD	Min	Max
Ln(Patent)	22191	2.01	1.73	0	9.577
Patent	22191	45.498	329.081	0	14431
DID	22191	0.36%	5.96%	0	1
Age	22191	20.558	6.115	3	67
FixedAstR	22191	0.194	0.148	0.002	0.661
IntgAstR	22191	0.044	0.049	0	0.325
LnAst	22191	22.259	1.307	18.702	26.162
Ast (100 million CNY)	22191	143.895	376.771	4.618	2846.5
Lev	22191	40.69	20.095	6.107	91.074
CashRatio	22191	1.291	1.822	0.055	10.873
Roa	22191	4.155	7.347	-27.191	33.128
RevGth	22191	14.867	33.996	-54.234	202.084
Hldcr	22191	54.03	15.311	21.04	98.43
Oversea	22191	0.001	0.004	0	0.027
Ln(Invention)	22191	1.443	1.481	0	9.042
Invention	22191	23.848	208.942	0	8448
RD	20186	22.047	49.237	0.105	336.647
RD_Incm	20186	5.549	5.662	0.029	56.6
HHI	22191	0.189	0.14	0.031	0.739
Cost_Ast	22191	57.14	39.702	8.14	255.253
Cost (100 million CNY)	22191	78.145	205.614	1.41	1517.254

The sample consists of 22,191 firm-year observations from 2017 to 2022. We winsorize all continuous variables at 1% and 99%. Because of missing data, some variables used in mechanism tests and control variables in robustness tests have fewer observations.

Table 3: Subgroup Descriptive Statistics and t-test Results

Variables	Pre-sanction treatment group			Control group			T-test
	Observations	Mean	SD	Observations	Mean	SD	
Ln(Patent)	73	3.161	1.659	22039	1.999	1.724	1.162***
DID	73	0	0	22039	0	0	0
Age	73	17.137	4.538	22039	20.576	6.118	-3.439***
FixedAstR	73	0.13	0.124	22039	0.195	0.148	-0.065***
IntgAstR	73	0.041	0.041	22039	0.044	0.049	-0.003
LnAst	73	22.838	1.453	22039	22.254	1.305	0.584***
Ast	73	269.153	569.435	22039	142.774	374.827	126.379***
Lev	73	46.403	16.752	22039	40.646	20.109	5.757**
CashRatio	73	0.73	1.318	22039	1.294	1.824	-0.564***
Roa	73	4.266	8.325	22039	4.155	7.335	0.111
RevGth	73	19.47	33.815	22039	14.84	33.966	4.63
Hldcr	73	52.961	16.396	22039	54.054	15.303	-1.092
Oversea	73	0.002	0.006	22039	0.001	0.003	0.001***

*The first three columns present the sample data of the enterprises in the treatment group before they are included in the Entity List, including observations, means, and standard deviations. The following three columns present the sample data of the control group, including observations, mean values, and standard deviations. The last column presents the t-test results for examining whether there is a significant difference between the means of the two groups of samples. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.*

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Empirical Analysis

Main results

Table 4 reports the regression results of the impact of the Entity List policy shock on the number of patents. Column (1) reports the regression results containing only the core independent variable, which is significantly positive at 1% with a coefficient of 0.88. Column (2) reports the regression results with additional control variables but without fixed effects. DID has a coefficient of 0.81, statistically significant at 1%. The results in column (3) show that when both control variables and time-fixed effects are added, the main variable has a coefficient of 0.76 and is significant at 1%. We add individual fixed effects in column (4) to control the impact of individual characteristic differences further. The result shows a coefficient of 0.66 at 1% significance. The above results show that, compared with enterprises not subject to the Entity List, the number of patents affected by the policy has increased significantly. Therefore, Hypothesis 1 is supported. In addition, the results also have significant economic implications. After controlling for individual and time differences, the Entity List increased the number of patents of affected enterprises by about 66.44%.

Robustness tests

Using heterogeneous robust DID estimators.

Recent studies have shown that if the treatment effects are heterogeneous among different times or cohorts, traditional DID methods may produce biased estimators(Athey & Imbens, 2022). Referring to previous studies (Zhao et al., 2024), we construct two heterogeneous robust DID estimators: the event study interaction estimator (Sun & Abraham, 2021) and the stacked DID estimator (Cengiz et al., 2019). The event study interaction estimator calculates the weighted average effect of each relative time through the interaction weighting method, thereby estimating the dynamic treatment effect more accurately. The stacked DID method splits the treatment group into multiple sub-sample datasets according to the treatment time, and uses the stacked datasets of the sub-samples for DID estimation.

Table 5 presents the regression results of two alternative models. Columns (1) and (2) show the results of the event study interaction model, where the coefficient of the core variable DID is 0.80 in column (1) without control variables included. The coefficient is significantly positive at the 1% level. After adding control variables, the coefficient slightly drops to 0.76 in column (2) but remains highly significant. Columns (3) and (4) present the results of the stacked difference-indifferences model. Without control variables, the DID coefficient is 0.78, and with control variables, it is 0.74, both significant at the 1% level. This means that the heterogeneous treatment effects did not affect the results of the benchmark regression.

Table 4. Benchmark Regression Results

Variables	(1)	(2)	(3)	(4)
	Ln(Patent)			
DID	0.8824***	0.8051***	0.7575***	0.6644***
	(5.6091)	(5.1016)	(4.8572)	(3.9907)
Age		-0.0036	-0.0293***	0.0208***
		(-1.0863)	(-7.5101)	(3.7205)
FixedAstR		-0.0670	-0.0251	-0.0607
		(-0.5894)	(-0.2221)	(-0.4206)
IntgAstR		-0.6759**	-0.7089**	-0.3373
		(-2.2680)	(-2.3999)	(-0.9548)
LnAst		0.1999***	0.1820***	0.1910***
		(9.1088)	(8.4161)	(5.2713)
Lev		-0.0036***	-0.0040***	-0.0033***
		(-4.0376)	(-4.5248)	(-3.3367)
CashRatio		-0.0231***	-0.0351***	-0.0138*
		(-3.3706)	(-5.0998)	(-1.7620)
Roa		0.0022*	0.0027**	0.0003
		(1.9374)	(2.4270)	(0.2725)
RevGth		-0.0005***	-0.0004**	-0.0003*
		(-2.7831)	(-2.0727)	(-1.7717)
Hldcr		-0.0017	-0.0006	-0.0001
		(-1.3335)	(-0.4414)	(-0.0420)
Oversea		32.3356***	33.2418***	16.5692**
		(4.4945)	(4.6111)	(2.0444)
Constant	1.9614***	-2.1069***	-1.4178***	-2.5271***
	(83.5410)	(-4.4006)	(-3.0075)	(-3.2008)
Observations	22,191	22,191	22,191	22,191
R-squared				0.0199
Year FE	NO	NO	YES	YES
Firm FE	NO	NO	NO	YES

*The dependent variable is the natural logarithm of the number of patent applications. The sample consists of 22,191 firm-year observations from 2017 to 2022. Robust t-statistics are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.*

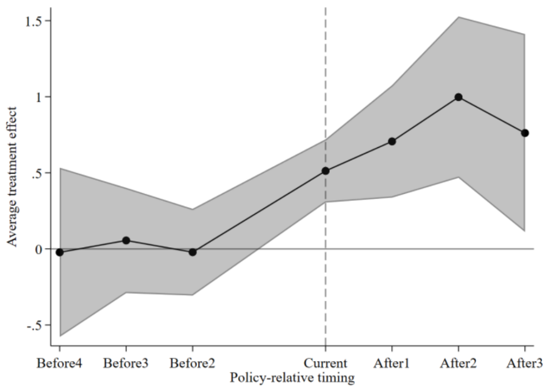
Table 5: Benchmark Regression Results

Variables	Event Study Interact		Stacked DID	
	(1)	(2)	(3)	(4)
	Ln(Patent)			
DID	0.8020***	0.7614***	0.7830***	0.7440***
	(4.03)	(3.76)	(4.18)	(3.417)
Controls	NO	YES	NO	YES
Observations	21,785	21,785	86,690	86,690
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

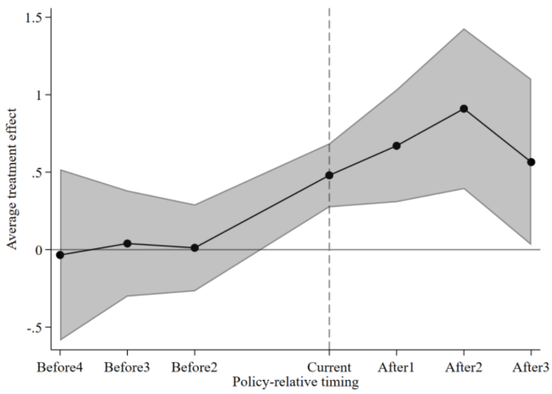
*The dependent variable is the natural logarithm of the number of patent applications. Columns (1) and (2) report the regression results of the event study interact model, and columns (3) and (4) report the regression results of the stacked DID model. Robust t-statistics are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.*

Parallel Trend Test

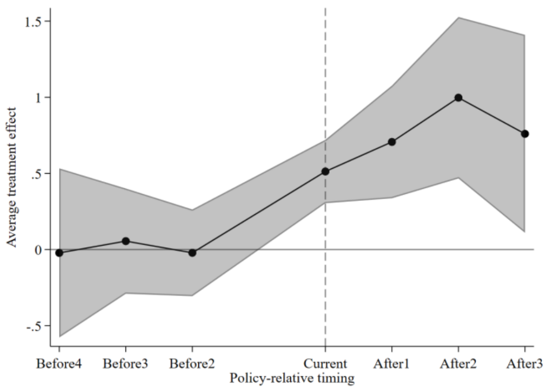
The parallel trend assumption is the key to establishing the staggered DID model. No significant difference between the treatment and control groups should exist before the treatment. To this end, it is necessary to test whether there exists a significant difference in the innovation ability of listed and non-listed enterprises before the policy shock. We set the year before the policy shock as the base period and observe the changes in the number of patents year by year.



Panel A



Panel B



Panel C

Figure 3: Parallel Trend Test Results

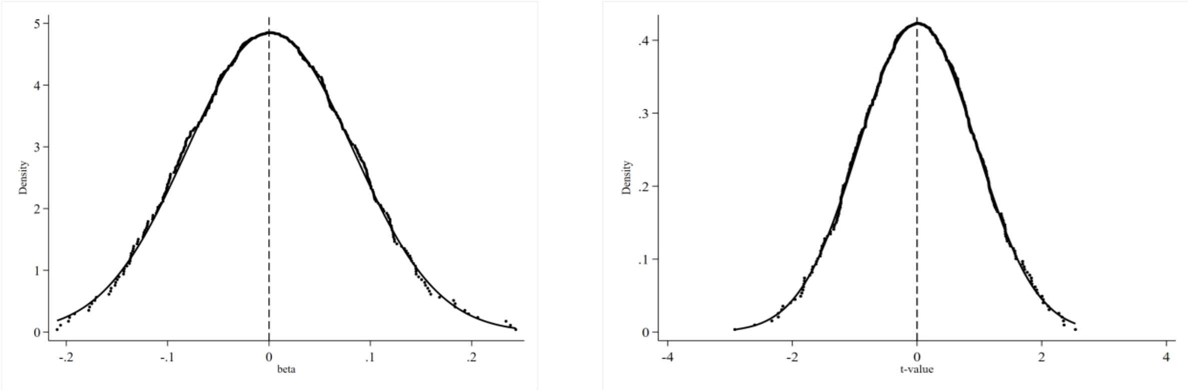
This figure illustrates the dynamic impact of the inclusion of the Entity List on corporate innovation in the years before and after the launch of the shock. Estimated coefficients are plotted at the 95% level. Panel A presents the results based on the benchmark regression model. Panels B and C present the results based on the event study interaction model and the stacked DID model.

Figure 3 shows the parallel trend test results of the regression, where the horizontal axis represents the time distance from the year of the policy shock, the solid points represent the regression estimation coefficients of the dummy variables in each year, and the grey area represent the confidence intervals of each coefficient at the 95% level. Panel A presents the results of the parallel trend test based on the regression model (2). The results show that: (1) before the enterprise is included in the Entity List, the regression coefficients from Before1 to Before3 are not significant, which meets the parallel trend hypothesis of the double difference model; (2) in the current year when the enterprise is included in the Entity List, the regression coefficient is significantly positive at the 95% level, indicating that the policy impact of the Entity List is immediate and has a rapid impact on the enterprise's innovation ability; (3) within three years after being included in the Entity List, the regression coefficients from After1 to After3 are always significantly positive, indicating that the impact of the Entity List on the enterprise's innovation ability is long-term; (4) the regression coefficient from Current to After2 increases year by year, and the regression coefficient of After3 decreases, indicating that the Entity List's promotion of innovation ability is time-sensitive, reaching a peak in the third year after the impact and then weakening.

In addition, Panels B and C present the parallel trend test results based on the event study interaction model and the stacked DID model, respectively. The results show no significant difference between the treatment group and the control group before the event, and the average treatment effect after the event is significantly positive at the 5% level, with a trend similar to that in Panel A. This result further enhances the robustness of the findings in this paper.

Placebo test

We use a placebo test to enhance the robustness of the results. The placebo test uses a pseudo-treatment group method to randomly divide the sample into a treatment group and a control group, randomly set the treatment year for each sample in the treatment group, and then use the pseudo-sample for benchmark regression. The process was repeated 500 times, and the regression coefficient and t-value distribution of the core independent variable DID were plotted, respectively. The results are shown in Figure 4. Panel A of Figure 4 shows the probability density distribution of the estimated coefficient. The results show that the DID coefficient obtained based on the pseudo-treatment group list regression is clustered around zero and normally distributed, much smaller than the true estimated coefficient of 0.66. Panel B shows that the t-value is also clustered around 0, which is much smaller than the true t-value of 4.04. The above results further exclude the possibility that some unobservable factors disturb the research results and enhance the robustness of the results in the main regression.



Panel A **Panel B**

Figure 4: Placebo Tests

This figure illustrates the regression coefficient and t-value distribution of the core independent variable, respectively, based on the 500 bootstrap simulations of the baseline model. Panel A reports the coefficient distribution, and Panel B reports the distribution of the t-value. The placebo test uses a pseudo-treatment group method to randomly divide the sample into a treatment group and a control group and randomly set the treatment year for each sample in the treatment group, and then use the pseudo sample for benchmark regression.

Replacing the dependent variable

According to Patent Law in China, patents are categorized into three types: invention, utility model, and design. Invention patents require novel technical solutions for products, methods or improvements, which are more technical and creative than the other two types of patents and can reflect the core innovation capabilities of enterprises. In addition, enterprise innovation can also be measured from the perspective of innovation input. The total R&D expenses of an enterprise include expensed and capitalized expenditures, which measure the total investment of the enterprise in the research and invention direction. Therefore, we use the number of invention patents and R&D expenses scaled by operating income as dependent variables and conduct a DID model regression to test the robustness of the results.

Table 6 reports the results of the estimated coefficients of the core independent variables for the regression of R&D investment. Column (1) reports the regression results of invention patents, and the coefficient is significantly positive at 1%. Column (2) shows the regression results of scaled R&D expenses, and the coefficient is significantly positive at 5%. The above results show that after replacing the dependent variable, the results of this study are still robust.

Table 6: Replacing the Dependent Variable Regression Results

Variables	(1) Ln(Invention)	(2) RD_Incm
DID	0.6564***	0.0266**
	(3.6036)	(2.1868)
Age	0.0143***	0.0016***
	(3.0421)	(8.5575)
FixedAstR	0.0188	0.0106**
	(0.1449)	(2.4752)
IntgAstR	-0.0914	0.0655***
	(-0.3085)	(3.7616)
LnAst	0.1812***	0.0003
	(6.2279)	(0.2799)
Lev	-0.0021**	-0.0002***
	(-2.4414)	(-5.1328)
CashRatio	-0.0067	-0.0009**
	(-0.9632)	(-2.1043)
Roa	0.0010	-0.0008***
	(0.9595)	(-12.5372)
RevGth	-0.0003**	-0.0001***
	(-2.0069)	(-11.1461)
Hldcr	0.0006	0.0000
	(0.3731)	(0.8552)
Oversea	15.4893**	-0.4562***
	(2.0876)	(-2.9155)
Constant	-2.8644***	0.0254
	(-4.5422)	(1.0741)
Observations	22,191	20,183
R-squared	0.0187	0.1478
Year FE	YES	YES
Firm FE	YES	YES

*The dependent variable is the number of invention patents applied by enterprises (Invention) in column (1) and the R&D expense scaled by operating income (RD_Incm) in column (2). It covers the period 2017-2022. Robust t-statistics are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.*

Mechanism Analysis

We now investigate the mechanisms through which the Entity List sanction positively affects Chinese firms' innovation.

Analysis of market competition mechanism

We use the Herfindahl-Hirschman Index (HHI) to measure market competition. This indicator measures the intensity of market competition by the degree of monopoly in market share. The smaller the HHI value, the lower the degree of monopoly and the more intense the market competition. The escape from competition mechanism believes that the greater the intensity of market competition, the more motivated companies are to improve their innovation capabilities to escape competition and obtain monopoly benefits. The interaction term $HHI \times DID$ is added into the regression and identifies how the Entity List policy affects corporate innovation through market competition through the coefficient of the interaction term.

Table 7: Market Competition Mechanism Test Results

Variables	(1)	(2)	(3)	(4)
	Ln(Patent)			
DID	1.0245***	0.9256***	1.0170***	0.9297***
	(4.2120)	(3.4799)	(4.1854)	(3.4900)
HHI×DID	-1.6822**	-1.9385**	-1.6401**	-1.9687**
	(-2.1750)	(-2.3128)	(-2.1199)	(-2.3455)
HHI			-0.1794	0.1878
			(-1.3066)	(0.8920)
Controls	YES	YES	YES	YES
Observations	22,191	22,191	22,191	22,191
R-squared		0.0191		0.0192
Firm FE	NO	YES	NO	YES
Year FE	NO	YES	NO	YES

*The dependent variable is the natural logarithm of the number of patent applications. The sample consists of 22,191 firm-year observations from 2017 to 2022. We add the interaction term HHI×DID. Robust t-statistics are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.*

Table 8: Subsample Tests Based on Market Competition Level

Variables	HHI > median (HHI)		HHI < median (HHI)	
	(1)	(2)	(3)	(4)
	Ln(Patent)			
DID	0.6837***	0.4978***	0.9133***	0.7550***
	(3.4697)	(2.5851)	(4.1398)	(3.1326)
Controls	YES	YES	YES	YES
Observations	11,078	11,078	11,113	11,113
R-squared		0.0227		0.0160
Firm FE	NO	YES	NO	YES
Year FE	NO	YES	NO	YES

*The dependent variable is the natural logarithm of the number of patent applications. The sample consists of 22,191 firm-year observations from 2017 to 2022. We partition the whole sample into two subsamples based on the median market completion level (HHI). Robust t-statistics are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.*

Table 7 reports the results of the market competition mechanism test. After adding the interaction term, the regression coefficient of the core independent variable, DID , is significantly positive at 1%, indicating that, after considering the cross-product effect of the market competition level, whether a company is included in the Entity List or not still significantly affects the company's innovation ability. Column (1) reports the regression results with only the control variables, and the coefficient of the interaction term is significantly negative at 5%. After adding the fixed effect in column (2), the cross-product coefficient is negative and significant at 5%. In addition, to avoid the impact of the HHI index itself on the regression results, we add the HHI index as an independent control variable to the regression equation, and the results are shown in columns (3) and (4). The interaction term coefficients are still significantly negative at 5% under the fixed effect and non-fixed models. The above results show that the more intense the market competition, the more obvious the Entity List's role in promoting corporate innovation, supporting Hypothesis 2.

To demonstrate more intuitively that escaping competition is a potential mechanism for the Entity List policy to promote the improvement of corporate innovation capabilities, we divide the samples into two groups, higher competition and lower competition, using the median of HHI as the dividing line, and conduct benchmark regression. Table 8 reports the test results. The regression results of columns (1) and (3) show that when control variables are added, and no fixed effects are controlled, the regression coefficients of both groups are significantly positive at 1%, and the regression coefficient of the intense-competition group (0.91) is greater than that of the poor-competition group (0.68). After adding individual and time-fixed effects, the results of columns (2) and (4) show that the regression coefficients decrease a bit but are still significantly non-zero at 1%, and the regression coefficient of the intense-competition group (0.76) is also greater than that of the poor-competition group (0.50). The above results further support Hypothesis 2.

Analysis of the factor costs mechanism

We use operating cost scaled by assets as the proxy variable for production factors costs. According to Hypothesis 3, the higher the cost of production factors, the more incentive enterprises have to conduct R&D activities to reduce cost pressure. Similarly, $Cost\_Ast \times DID$ is added into the regression and uses the interaction term coefficient to identify how the Entity List policy affects enterprise innovation through factor costs.

Table 9 reports the results of the factor costs mechanism test. Column (1) reports the regression results without fixed effects. The DID coefficient and the interaction term coefficient are significantly positive at 1%. After controlling for the fixed effects, column (2) shows that the DID coefficient slightly decreased but was still significantly positive at 5%, and the interaction term coefficient was significantly positive at 5%. In addition, $Cost\_Ast$ is added to the regression as an independent control variable. The results in columns (3) and (4) show that both the DID coefficient and the cross-multiplication term coefficient are significantly positive at least at 5%. The results indicate that the higher the operating cost, the more impact the Entity List has on enterprise innovation, supporting Hypothesis 3.

Table 9: Factor Costs Mechanism Test Results

Variables	(1)	(2)	(3)	(4)
	Ln(Patent)			
DID	0.4745***	0.4259**	0.4754***	0.4344**
	(2.7359)	(2.2680)	(2.7324)	(2.3065)
Cost_Ast×DID	0.0055***	0.0039**	0.0055***	0.0038**
	(3.1353)	(2.1575)	(3.0646)	(2.0191)
Cost_Ast			0.0000	0.0002
			(0.0459)	(0.4071)
Controls	YES	YES	YES	YES
Observations	22,191	22,191	22,191	22,191
R-squared		0.0200		0.0200
Firm FE	NO	YES	NO	YES
Year FE	NO	YES	NO	YES

*The dependent variable is the natural logarithm of the number of patent applications. The sample consists of 22,191 firm-year observations from 2017 to 2022. We add the interaction term Cost_Ast×DID. Robust t-statistics are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.*

Table 10: Subsample Test Results Based on Costs

Variables	Cost_Ast > median(Cost_Ast)		Cost_Ast ≤ median(Cost_Ast)	
	(1)	(2)	(3)	(4)
	Ln(Patent)			
DID	1.0672***	0.8191**	0.6487***	0.5178***
	(3.2463)	(2.2525)	(4.7860)	(3.8881)
Controls	YES	YES	YES	YES
Observations	11,095	11,095	11,096	11,096
R-squared		0.0259		0.0212
Firm FE	NO	YES	NO	YES
Year FE	NO	YES	NO	YES

*The dependent variable is the natural logarithm of the number of patent applications. The sample consists of 22,191 firm-year observations from 2017 to 2022. We partition the whole sample into two subsamples based on the median of the scaled operation cost level (Cost_Ast). Robust t-statistics are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.*

To illustrate more intuitively that deteriorating factor costs serve as a potential mechanism through which the Entity List policy promotes corporate innovation, we divide the samples into high-cost and low-cost groups based on the median of cost and conduct the benchmark regression for each group. Table 10 reports the test results. Columns (1) and (3) without fixed effects show that the regression coefficients of both groups are significantly positive at 1%. The coefficient of the high-cost group (1.07) is greater than that of the low-cost group (0.65). Columns (2) and (4) report the results with fixed effects. The regression coefficient is significantly non-zero at least 5%, and the regression coefficient of the high-cost group (0.82) is also greater than that of the low-cost group (0.52). The above results further support Hypothesis 3.

Conclusion and Discussion

The Entity List policy is an important export control measure for the U.S. to restrict the export of high-tech products and prevent technology spillover. Since the China-U.S. trade friction, Chinese enterprises have become an important target of the Entity List. We construct a staggered DID model to study the impact of the U.S. Entity List on the innovation of Chinese enterprises, using A-share listed companies from 2017 to 2022 as samples. The study finds that the number of patent applications of Chinese enterprises sanctioned by the Entity List showed a significant increase, indicating that the Entity List policy has significantly promoted the innovation behavior of Chinese enterprises. Further mechanism analysis reveals how this policy promotes enterprise innovation through two channels: intensifying market competition and increasing production factor costs. Intensified market competition forces enterprises to seek differentiated advantages through innovation, while increased production factor costs prompt enterprises to seek innovation to reduce cost pressure.

The findings of this paper hold significant policy implications. First, the study demonstrates that export restriction policies did not impede the development of enterprises in importing countries but enhanced their innovation vitality. Consequently, both the governments imposing these policies and those affected by them should conduct a comprehensive assessment of the consequences of export restriction policies on firm operations. The Chinese government can provide timely policy support to enterprises to enhance the nation's indigenous innovation capacity. The U.S. government, however, must weigh the risks of short-term technological restrictions against the long-term consequences of stimulating its competitors' innovation. Secondly, the paper finds that market competition is a potential mechanism for the Entity List policy to promote corporate innovation. In industries with more intense competition, corporate innovation behavior is more active. Therefore, the affected governments should create a fair and transparent market environment to promote healthy competition among enterprises, especially when facing export regulations from restriction-imposing countries.

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Appendix

Table A1: Variable Definition

Variables	Definition
LN(Patent)	The logarithm of the number of patents the enterprise *i* applied for in year *t* plus 1, i.e., Ln(1+#Patent)
Patent	The number of patents
DID	It equals one if the enterprise *i* is included in the Entity List in year *t*; otherwise, it is zero.
Age	Age of enterprises
FixedAstR	Fixed assets ratio
IntgAstR	Intangible assets ratio
LnAst	Ln (Asset). The asset is in the unit of 100 million CNY.
Ast	Asset in the unit of 100 million CNY.
Lev	Debt-to-asset ratio
CashRatio	Cash ratio, i.e., (Cash at bank +Financial assets held for trading+Notes receivable)/Current liabilities
Roa	Return on assets, i.e., Net income attributable to shareholders /Average annual assets
RevGth	Operating revenue growth rate
Hldcr	Top five shareholders holding concentration
Oversea	Overseas operating income
Ln(Invention)	The logarithm of the number of invention patents the enterprise *i* applied for in year *t* plus 1, i.e., Ln(1+# invention patent)
Invention	The number of invention patents
RD	R&D expenses in the unit of 100 million CNY
RD_Incm	R&D expenses /Operating income
HHI	Herfindahl-hirschman index of sales. $HHI = \sum\left({x_i}/{x}\right)^2$: where x_i is the operating revenue of enterprise i and x is the sum of the operating revenue of all enterprises in the industry.
Cost_Ast	Operating costs /Asset
Cost	Operating costs in the unit of 100 million CNY