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Examining export trade and corporate innovation: A multiphase difference-in-differences method

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ABSTRACT

Using a multiphase difference-in-differences model, this study investigates the relationship between export trade and the corporate technological innovation of listed companies. It reveals that engaging in export trade increases corporate innovation input and output. In terms of patent output, export trade greatly promotes the output of invention patents and utility model patents with a high technological content. These conclusions remain valid after a series of robustness and endogeneity tests. Regarding the mechanisms of the observed relationships, export trade stimulates corporate technological innovation mainly by realizing economies of scale and increasing risk-taking. The positive correlation between export trade and corporate technological innovation is strongest among state-owned enterprises, non-high-tech enterprises, enterprises based in central and eastern China, enterprises engaged in general trade, and enterprises exporting to developed economies. Given the growing trade frictions ongoing at the time of writing, the conclusions of this study provide vital practical guidance and empirical evidence for a national strategy of innovation-driven development.

1. Introduction

According to the 2017 Statistics Report[1] released by IP5, a coalition of the world's five largest patent offices, the number of patent applications filed by China in 2017 reached 1.381 million, which is 3% higher than in 2016. As shown in Fig. 1, of the five countries and regions with the most patent filings (which also

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[1] www.fiveipoffices.org/statistics.html.

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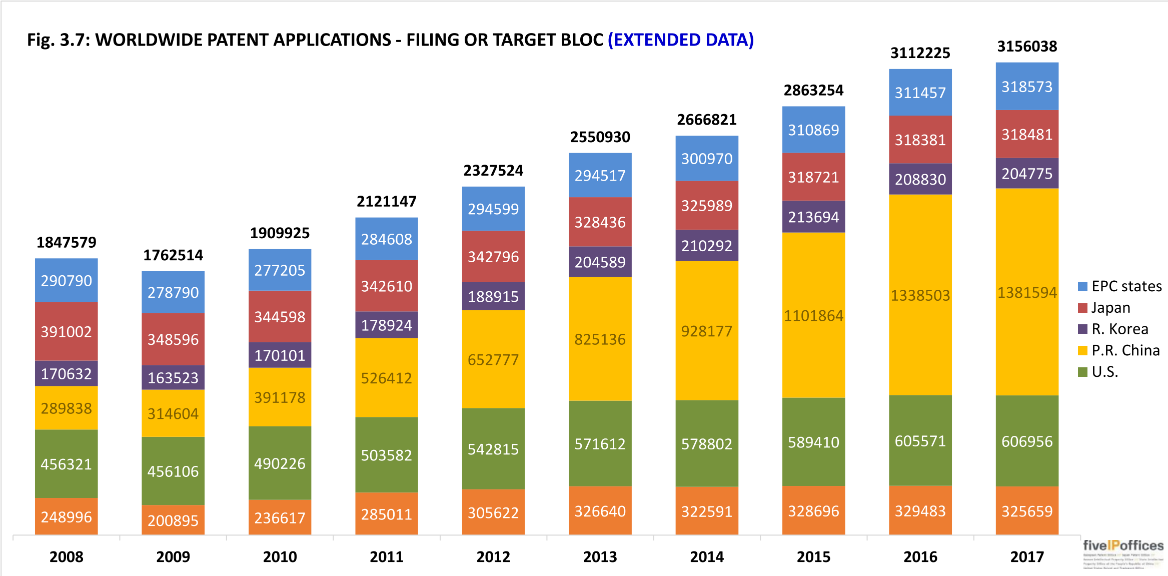
1755-3091/



Filing bloc	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
EPC states	283030	284595	287014	296238	290790	278790	277205	284608	294599	294517	300970	310869	311457	318573
Japan	423081	427078	408674	396291	391002	348596	344598	342610	342796	328436	325989	318721	318381	318481
R. Korea	140115	160921	166189	172469	170632	163523	170101	178924	188915	204589	210292	213694	208830	204775
P.R. China	130384	173327	210501	245161	289838	314604	391178	526412	652777	825136	928177	1101864	1338503	1381594
U.S.	356943	390733	425967	456154	456321	456106	490226	503582	542815	571612	578802	589410	605571	606956
Others	173904	190721	227270	184518	248996	200895	236617	285011	305622	326640	322591	328696	329483	325659
Total	1507457	1627375	1725615	1750831	1847579	1762514	1909925	2121147	2327524	2550930	2666821	2863254	3112225	3156038

Fig. 1. Patent applications of the five countries and regions with the most patent filings from 2013 to 2017, The related data are available at https://www.fiveipoffices.org/wcm/connect/fiveipoffices/8c519416-173d-4b32-99ed-5387045c46a2/IP5+Statistics+Report+2018_2012 2019_full.pdf?MOD=AJPERES&CVID= (p. 40 Fig. 3.7).

include the European Union, the U.S., Japan, and South Korea), China accounts for the largest proportion of the total number of patent applications worldwide, and its share is increasing.

However, lacking core technologies and proprietary brands, most locally operating Chinese enterprises are still merely processors of medium- and low-end products in the global value chain (Tao et al., 2020). Facing growing Sino–U.S. trade frictions and the increasingly stringent restrictions on technology transfer imposed by the U.S. government, Chinese enterprises, which generally lack high-end core technologies, are suffering under constraints imposed by Europe, the U.S., and other countries and regions producing technology spillover effects (Zhang et al., 2018). To overcome its technological dependence on U.S.-led developed countries in the West, China must improve its technological innovation. At the New Economy Forum held in Beijing on November 22, 2019, China's General Secretary Xi Jinping stated: "Innovation is a great challenge of our time. The world is undergoing major and unprecedented changes this century, and a new round of technological change and industrial revolution is in the ascendant."[2] According to Keller (2010), the technological innovation of most countries is attributable to technology spillovers produced by trade. Therefore, whether export trade can effectively promote corporate innovation is an issue of great practical significance.

Most studies of corporate innovation have focused on the roles of national policies, corporate governance, and other non-trade factors. Relevant national policies include juridical protection (Pan et al., 2015), industrial policies (Li and Zheng, 2016; Yu et al., 2016a; 2016b; Howell, 2017), government subsidies (Yang et al., 2015; Mao and Xu, 2015; Guo, 2018), and tax reforms (Lin et al., 2013; Li and Wang, 2017; Sun, 2017). Relevant corporate governance factors comprise mainly ownership structure (La Porta et al., 1999; Li and Yu,

[2] http://www.xinhuanet.com/politics/leaders/2019–11/22/c_1125264342.htm.

2015; Chen et al., 2019), employee motivation (Meng et al., 2019; Zhou et al., 2019), business assessment (Yu et al., 2016a; 2016b; Li et al., 2018), and executive characteristics (Yu et al., 2018a; 2018b; He et al., 2019).

Since the start of its economic reforms and liberalization, China has experienced rapid economic growth and strengthened its trade connections with other countries, becoming a trading power with global influence (He et al., 2020). The rapid growth of export trade greatly increases innovation activities (Li et al., 2016). When enterprises start exporting, they encounter more intense competition in a broader market, which encourages them to innovate. For example, technology spillovers from the advanced products of developed countries have enabled Chinese enterprises to learn from and absorb new technologies (Li and Zhu, 2006; Tao et al., 2020). Increased trade demands also generate more profits for enterprises, thus enhancing their culture of and capacity for innovation. In this sense, export trade is an important factor influencing corporate innovation. Unfortunately, however, the relationship between export trade and corporate innovation has rarely been explored.

In terms of input, enterprises engage in export trade naturally increase their input of production factors because the demand for their products is increasing overseas. In addition, the increased output scale in a broader market lowers average production costs and realizes economies of scale. From the perspective of technology spillovers, exporting enterprises greatly increase their risk-taking by learning from advanced production technologies, technological processes, and organizational management (Xu et al., 2015). Economies of scale and risk-taking and can foster corporate innovation (Lileeva and Trefler, 2010; Zhou et al., 2019). This study seeks to answer the following two questions. How do economies of scale influence the relationship between export trade and corporate innovation? How does the level of risk-taking influence the relationship between export trade and corporate innovation?

To answer these questions, we empirically examine the relationship between export trade and the corporate innovation of listed companies. We find that engaging in export trade promotes corporate innovation in terms of both input and output. Our conclusions remain valid following a series of tests for robustness and endogeneity. Export trade stimulates corporate technological innovation mainly through economies of scale and increased levels of risk-taking. The stimulating effects of export trade are observed mainly in state-owned enterprises, non-high-tech enterprises, enterprises based in central and eastern China, and enterprises that engage in general trade and export to developed countries.

This study makes two contributions to the field. First, related studies have rarely examined listed companies; most have used data on small and medium-sized enterprises (SMEs) from the China Industry Business Performance Database to explore the relationship between export trade and corporate technological innovation (Li et al., 2016). According to the Schumpeterian hypothesis, larger enterprises usually have a stronger and more independent capacity for innovation (Schumpeter, 1942). SMEs generally engage in superficial, application-oriented innovation activities, such as the pure imitation or refinement of existing technologies. In contrast, listed companies have a fundamental and radical potential for technological innovation, such as revolutionizing existing technologies or pioneering explorations of unknown fields (Chi, 2002). They generally engage in high-end innovation activities that erect long-lasting technological barriers and accurately reflect their country's level of technological innovation. Thus, by examining the relationship between listed companies' export trade and corporate innovation, this study serves as an important supplement to the literature in this field. The second contribution made by this study is to clarify the mechanism by which export trade influences corporate innovation from the perspectives of risk-taking and economies of scale. In light of the Sino–U.S. trade frictions ongoing at the time of writing, this study offers vital practical guidance for Chinese enterprises on maintaining their export trade, improving their innovation ability, abandoning their heavy dependence on U.S. science and technology, and contributing to China's transformation into an innovation-driven nation.

Part II of this paper presents the literature review and hypotheses. Part III describes the design of the study. Part IV discusses the empirical results. Part V presents the conclusions and offers recommendations to Chinese enterprises to improve their innovation capacity under the background of Sino–U.S. trade frictions.

2. Literature review and hypotheses

2.1. Literature review

In the field of international trade, two key hypotheses have been proposed regarding the relationship between export trade and corporate technological innovation. The first relates to "self-selection" effects and the second concerns "learning by exporting" effects. The first hypothesis states that export barriers (specifically the costs of transportation, distribution and marketing, and adapting products to meet foreign standards) allow only enterprises with high productivity to overcome the impact of sunk costs and enter the export market. Hence, according to this hypothesis, corporate technological innovation affects exports. In contrast, the hypothesis regarding learning by exporting effects states that exporting enterprises can acquire new technological knowledge from competitors, partners, and customers. Hence, the hypothesis suggests that export trade affects corporate technological innovation (De Loecker, 2007; Zhao and Li, 2007; Qian et al., 2011; Li et al., 2016; Zhang et al., 2016).

2.1.1. Self-selection effects

The concept of self-selection effects is first proposed by Clerides et al. (1998), who state that innovation increases enterprises' productivity and affects their export decisions. In a study of U.S. enterprises, Bernard and Jensen (1999; 2004b) find that even new entrants into the export market are more productive than non-exporting enterprises are. Examining manufacturing data from South Korea, Aw et al. (2000) discover self-selection effects among newly exporting enterprises. Using a trade model with heterogeneous enterprises, Melitz (2003) explains the relationship between enterprise differences and export behaviors and shows that trade openness increases the productivity of an entire industry through the self-selection effects produced by enterprises' exporting behaviors. Studies in this field have also discovered self-selection effects among British enterprises (Girma et al., 2004), German enterprises (Wagner, 2002; Arnold and Hussinger, 2005), and Chinese enterprises (Qian et al., 2011; Yi and Fu, 2011; Qiu et al., 2012). However, other scholars note that the productivity of exporting Chinese enterprises is lower than that of non-exporting enterprises, i.e., the "productivity paradox." They argue that the large number of processing trade enterprises in China has dragged down the average productivity of exporting enterprises, thereby negating self-selection effects (Li, 2010; Lu et al., 2010).

2.1.2. Learning by exporting effects

According to the learning by exporting hypothesis, exporting enterprises in a broad and competitive market learn advanced production technologies that further strengthen their ability to learn (Xiang and Ma, 2013). Long a hotspot issue in the field of international trade, learning by exporting effects have been extensively studied by scholars both in China and abroad, but no unanimous conclusions have been reached. As indicated by the levels of economic development in exporting countries, learning by exporting effects do not arise in the majority of developed countries (Bernard and Jensen, 2004a; Wagner, 2002; Greenaway and Yu, 2004). However, such effects have been observed in newly industrializing economies and developing countries (Clerides et al., 1998; Aw et al., 2000; Alvarez and Lopez, 2005). By taking part in international competition, newly industrializing economies and developing countries are able to learn from and absorb advanced technologies from developed countries, thus improving their independent innovation ability (Aw et al., 2000; De Loecker, 2007; Alvarez and Lopez, 2005). However, from the perspective of industry characteristics, learning by exporting effects are diminished or negated in industries with large numbers of foreign-funded enterprises (Greenaway and Kneller, 2007).

In recent years, extensive efforts have been made to explore learning by exporting effects in samples of Chinese enterprises. Focusing on modes of trade, Zhang et al. (2008), Li and Zhao (2010), Fan and Feng (2013), and Bao et al. (2014) find few or no long-term learning by exporting effects among Chinese enterprises. They conclude that significant learning by exporting effects exist among general trade enterprises but not processing trade enterprises, which account for the majority of Chinese enterprises. Studies show that processing trade enterprises are locked into labor-intensive links with low technological content (Bao et al., 2014). Such enterprises are reliant on low-end manufacturing, exogenous export trade intermediaries, and sufficiently cheap labor, and lack the pressure and motivation to increase their efficiency (Jing et al., 2012). Unlike general trade enterprises, processing trade enterprises enter the international market by joining the global value chains of multinational corporations. They neither directly compete with other enterprises nor enter into direct contact with the ultimate purchasers in the international market, so they do not experience the learning by exporting effects observed among general trade enterprises (Lv et al., 2016). However, some scholars take the opposite view. Using microdata from China, Dai and Yu (2012) find that enterprises exporting for the first time see a productivity increase of 2% in their first year of exporting, but no significant increases in the following years. Examining survey data released by the World Bank, Wang et al. (2011) observe learning by exporting effects among Chinese enterprises. Using the propensity score matching (PSM) difference-in-differences (DID) (PSM-DID) method, Qiu et al. (2012) perform a two-sided test of the causality between the export behaviors and productivity of Chinese manufacturing enterprises. They conclude that significant learning by exporting effects exist among Chinese manufacturing enterprises and that these effects gradually increase over time. Exploring the relationship between enterprises' engagement in export trade and independent innovation, Li et al. (2016) report that the effects of exportation on corporate technological innovation show an inverted "U" shape, with an initial increase followed by a decrease.

2.2. Theoretical analysis and hypotheses

Export trade can promote the technological innovation of a country (Wagner, 2007). When an enterprise begins to export, it must conduct technological innovation to stay competitive in the international arena by meeting the demands of new customers and markets. Compared with non-exporting enterprises, exporting enterprises are more productive (Melitz, 2003; Wagner, 2007) and more competitive (Mao and Sheng, 2014). In pursuit of development, exporting enterprises tend to seek business expansion in the international market after meeting domestic demands (Mao and Wang, 2006). However, an expanded market brings more intense competition, and to earn a place in the highly competitive international market, exporting enterprises must either provide better products or charge lower prices. Both options require technological innovation, either to upgrade product quality (Faruq, 2010) or to reduce costs, leading to lower prices (Chen, 2002).

According to the learning by exporting hypothesis, export trade offers developing countries an important means of acquiring technology spillovers from developed countries and accessing advanced technological knowledge. Within an industry, technology spillovers from new foreign customers and competitors help enterprises to strengthen their technological innovation. Across industries, export trade promotes mutual integration, exchange, and cooperation through the global division of labor. Technology spillovers also facilitate the sharing of innovation-related resources, thus promoting technological innovation among exporting enterprises. Moreover, export trade leads to "induced innovation", as exporting enterprises can improve their technological innovation by "learning during exporting"[3] (Li et al., 2016). By competing in the broader international market, enterprises can strengthen their ability to solve new problems using their existing resources, enhance their technological innovation through the knowledge they have gained from abroad, draw inspiration from different markets and cultures, and improve their ability to innovate (Salomon and Shaver, 2005).

Beyond encouraging enterprises to engage in technological innovation and innovative learning, competition and technology spillovers offer crucial mature conditions and resources that enable enterprises to raise their level of innovation. For exporting enterprises, the domestic market is no longer the sole concern; a broader international export market is bound to create more demand. By meeting both international and domestic demand, exporting enterprises are able to gain more trade profits and engage in more innovative activities (Li, 2002). Considering the effects of export demand, we propose our first hypothesis, as follows.

H1: Other conditions being equal, export trade promotes corporate technological innovation.

Domestic market fragmentation, high credit costs, the absence of intellectual property protection, and other distortions in the institutional environment prevent local Chinese enterprises from using their domestic

[3] Li et al. (2016) suggest that exporting enterprises can improve their technological innovation by "learning during exporting", i.e., "induced innovation" (p. 76).

market capacity to realize economies of scale and achieve rapid growth. Instead, export trade becomes an important means by which Chinese enterprises can realize economies of scale (Zhang et al., 2009). As mentioned above, a broader international market creates more demand, which drives exporting enterprises to expand the scale of their production, increase their input of the factors of production, launch mass production, and realize economies of scale. These outcomes in turn play vital roles in stimulating corporate innovation (Lileeva and Trefler, 2010). The theory of Marshallian externalities stresses the importance of economies of scale and various externalities in promoting innovation (Han and Ke, 2012). When manufacturing a product earns a company increasing returns to scale, the company obtains a cost advantage due to the expanded scale of production and reduced cost per unit product (Krugman, 1980). In addition, economies of scale promote industrial expansion and strengthen industrial competitiveness, which further motivate continuous innovation (Florida, 1994). Therefore, realizing economies of scale helps exporting enterprises to reduce their production costs, increase their profits, and lower their innovation risks while motivating them to engage in technological innovation. Considering the effects of economies of scale, we propose our second hypothesis, as follows.

H2: Other conditions being equal, engaging in export trade motivates enterprises to engage in technological innovation by increasing their economies of scale.

Enterprise innovation is key to gaining a competitive advantage (Teece et al., 1997; Baer, 2012), improving corporate performance, and increasing shareholder wealth. However, innovation also requires investments of time, energy, and resources (such as expenditure on R&D and management of innovation) that have very uncertain returns (Wu et al., 2005; Ling et al., 2008). Enterprises that take more risks usually have a higher tolerance of innovation-related risks and uncertainties, as well as greater confidence in innovation projects with high levels of risk and uncertainty (Faccio et al., 2011). In turn, these firms' higher levels of tolerance and confidence increase their innovation performance.

Exporting enterprises that seek to compete in the international market must guarantee product quality. To meet consumers' demands, newly exporting enterprises must improve their technological processes and standards, upgrade their machinery and equipment, and organize training for their employees to lay a solid foundation for increased risk-taking (Gereffi et al., 2005). Due to learning by exporting effects, enterprises with better production methods, capital equipment, product design, and organizational management are better able to capitalize on risky investment opportunities (Grossman and Helpman, 1990). Moreover, enterprises that enjoy lower average production costs and higher productivity from increased outputs are more motivated and better able to engage in promising and profitable investment activities. This in turn promotes their risk-taking (Xu et al., 2015) and innovation. Considering the importance of technological innovation to risk-taking, we propose our third hypothesis, as follows.

H3: Other conditions being equal, export trade motivates enterprises to conduct technological innovation by increasing their risk-taking.

3. Research design

3.1. Sample selection and data source

As the China customs database currently only contains export trade data on Chinese enterprises for the period 2000–2015, our sample period is 2000–2015. Most related studies have used industrial data on SMEs to study the effect of export trade on innovation. However, unlike listed companies, SMEs engage mainly in imitative and low-end innovation activities (Chi, 2002), which do not fully reflect China's strengths in innovation. Hence, we take companies listed on the Shanghai and Shenzhen A-share stock markets as our sample.

We obtain data on the financial and other characteristics of the enterprises from the China Stock Market and Accounting Research Database, which collects all of the relevant financial indicators of listed companies. We eliminate companies that met any of the following criteria. (1) Contained "ST" (indicating special treatment firms) or "PT" (indicating particular transfer firms) in their abbreviations. The financial data of such listed companies are processed before release and cannot reflect their financial statuses truthfully. (2) Asset–liability ratios above 1. The business conditions of these listed companies are abnormal and have no referential value. (3) Classified as financial or insurance companies. Such firms adopt differential financial accounting systems, which may compromise data consistency. (4) Appeared no more than three times during the sample period. Each sampled company is required to have at least two years of observed values before and after starting to export, so that the continuous effects of export trade on corporate innovation could be seen more clearly. (5) Listed or delisted in the same year as beginning to export. (6) Missing substantial amounts of data. To better study the effects of export trade on corporate innovation, we classified the sampled companies into three categories: non-exporting (non-export) enterprises, existing exporting enterprises, and newly exporting (new-export) enterprises (Dai and Yu, 2012; Qiu et al., 2012; Li et al., 2016).[4] After eliminating existing exporting enterprises, we obtain data on 1507 listed companies and 13,666 company-year observed values (4960 for new-export enterprises and 8706 for non-export enterprises). To avoid the effects of extreme values, we winsorize the main variables at the upper and lower 1%.

3.2. Model design and variable definitions

To explore the effects of engaging in export trade on the technological innovation of our sampled listed companies, we introduce a multi-stage difference-in-differences (multi-DID) model for testing. Following studies of export trade (De Loecker, 2007; Qiu et al., 2012; Li et al., 2016; Zhang et al., 2016) and corporate technological innovation (Li et al., 2016; Zhou et al., 2019), we control for corporate financial variables and corporate governance variables, as well as the corporate fixed effect (*Firm*) and the annual fixed effect (*Year*):

$$Innovi,t = \alpha 0 + \alpha 1 Treati \times Postt + \sum Controls + \sum Firm + \sum Year + \varepsilon i,t \tag{1}$$

where corporate innovation ($Innov_{i,\ t}$) is the explained variable, measured in terms of innovation input and innovation output. Innovation input is measured by corporate R&D intensity, which is defined as the ratio of total R&D inputs to total assets. Listed companies may transfer their innovation activities to their subsidiaries or affiliated companies (Yu et al., 2016a; 2016b). In the above model, innovation output is measured by the natural logarithms of total number of patent applications (*Total*), number of invention patent applications (*Invent*), number of utility model patent applications (*Utility*), and number of appearance design patent applications (*Design*) after adding 1 to them. These variables cover the innovation activities of a listed company and its subsidiaries, associated companies, and joint venture partners. $Treat_i$ is a dummy variable introduced to distinguish the treatment group from the control group, set to 1 for new-export enterprises and 0 for non-export enterprises. $Post_t$ is a dummy variable for enterprise export time, set to 1 for the first and subsequent years of exporting but to 0 for the previous years. $Treat_i \times Post_t$ is a core explanatory variable set to 1 for the first and subsequent years of exporting but to 0 for the previous years. Calculated by the DID method, the coefficient of this variable measures the effects of export trade on the technological innovations of the listed companies, i.e., the average change in the level of corporate innovation of new-export enterprises relative to non-export enterprises.

To test the heterogeneity of the listed companies, we also introduce a series of firm characteristic variables, such as ownership nature (*Soe*), technological level (*Tech*), district (*District*), export destination country type (*Country*), and mode of export trade (*Tradetype*). If a listed company is state-owned, *Soe* is set to 1; otherwise, it is set to 0. Following Gu et al. (2018), we classify the listed companies as high-tech enterprises or non-high-tech enterprises. If a listed company is a high-tech enterprise, *Tech* is set to 1; otherwise, it is set to 0. In terms of regional distribution, if a company is located in western China, *District* is set to 0, but for central and eastern China, it is set to 1. Following Nielsen (2013) and the Human Development Index[5], we classify the export destination country types of the listed companies as developed or developing. If a listed company predominantly exports to developed countries, *Country* is set as 1; otherwise, it is set to 0. Finally, following Li et al. (2016), we classify the modes of export trade of the listed companies as either general trade or processing and mixed trade. If the volume of the processing trade of a listed company account for less than 25% of its total export trade volume, the listed company is deemed as mainly engaged in general trade, so *Tradetype*

[4] A non-export enterprise is defined as an enterprise that do not export during the sample period. An existing exporting enterprise is defined as an enterprise that export throughout the sample period. A new-export enterprise is defined as an enterprise that begin exporting a year after having been listed during the sample period.

[5] Human Development Index is available at http://hdr.undp.org/sites/default/files/hdr2019.pdf. (p. 300–311).

Table 1
Definitions of variables.

Variables	Name	Sign	Definition
Dependent Variables	R&D intensity	*RD*	R&D expenditure/total assets
	Total number of patent applications	*Total*	ln(total number of patent applications + 1)
	Number of invention patent applications	*Invent*	ln(number of invention patent applications + 1)
	Number of utility model patent applications	*Utility*	ln(number of utility model patent applications + 1)
	Number of appearance design patent applications	*Design*	ln(number of appearance design patent applications + 1)
Independent Variables	Export type dummy variable	$Treat_i$	1 for new-export enterprises, 0 for non-export enterprises
	Export time dummy variable	$Post_t$	1 for export year and after, otherwise 0
	Export dummy variable	$Treat_i \times Post_t$	Interaction term of $Treat_i$ and $Post_t$
Moderating Variables	Nature of ownership	*Soe*	1 for state-owned enterprises, otherwise 0
	Technology level	*Tech*	1 for high-tech enterprises, 0 for non-high-tech enterprises
	Location	*District*	1 for enterprises in central and eastern China, 0 for enterprises in western China
	Export destination country type	*Country*	1 for enterprises with developed export destination countries, 0 for enterprises with developing export destination countries
	Export trade type	*Tradetype*	1 for general trade, otherwise 0
Control Variables	Total factor productivity	*Tfp*	Productivity, measured by Levinsohn- Petrin (2003) method
	Company size	*Size*	ln(total assets)
	Financial leverage ratio	*Lev*	Total liabilities/total assets
	Return on assets	*Roa*	Net profits/total assets
	Company growth	*Growth*	(current operating income - last operating income)/last operating income
	Capital stock per capita	*Ak*	Fixed assets/number of employees at the end of the period
	Tangible asset ratio	*Tangibility*	Tangible assets/total assets
	Cash level	*Cash*	Cash and cash equivalents/total assets
	Company listed age	*Age*	ln(company listed age + 1)
	Financial constraints	*KZ*	KZ index. The larger the KZ index, the greater the financial constraints of a listed company
	Board size	*Board*	ln(number of board members)
	Independent director ratio	*Indep*	Number of independent directors/number of board members
	Management shareholding ratio	*Share*	Number of shares held by management/total number of shares in the company
	Chairperson–CEO duality	*Dual*	1 for chairperson–CEO duality, otherwise 0

is assigned a value of 1. Otherwise, the company is deemed as mainly engaged in processing and mixed trade, so *Tradetype* is assigned a value of 0.

The control variables (*Controls*) are as follows: total factor productivity (*Tfp*), company size (*Size*), financial leverage ratio (*Lev*), return on assets (*Roa*), company growth (*Growth*), capital stock per capita (*Ak*), tangible asset ratio (*Tangibility*), cash level (*Cash*), company listing age (*Age*), financial constraints (*KZ*), board size (*Board*), independent director ratio (*Indep*), management shareholding ratio (*Share*), and chairperson–CEO duality (*Dual*). Further, to control for the ownership, industry, and regional characteristics of the enterprise, we add nature of ownership (*Soe*), technology level (*Tech*), and location (*District*) to the model.[6] Specific variable definitions can be found in Table 1.

4. Empirical results

4.1. Summary statistics

Table 2 reports the summary statistics for the main variables. Column (1) presents the statistical characteristics of the full sample; columns (2) and (3) present the mean performance for the main variables of

[6] We thank an anonymous referee for several valuable comments on the control variables that helped to greatly improve the paper.

Table 2
Summary statistics for the variables.

Variables	(1)					(2)	(3)	(4)
	Full sample					*New-export*	*Non-export*	*T-test of (2)-(3)*
	Mean	*Std. Dev.*	*Min*	*Median*	*Max*	*Mean*	*Mean*	
RD	0.0068	0.0161	0.0000	0.0000	0.3272	0.0115	0.0069	0.0046***
Total	1.3925	1.6371	0.0000	0.6931	6.2710	2.2612	1.2466	1.0147***
Invent	0.8880	1.2996	0.0000	0.0000	5.3327	1.5186	0.8001	0.7185***
Utility	0.9379	1.3785	0.0000	0.0000	5.5491	1.6017	0.8113	0.7905***
Design	0.3607	0.8246	0.0000	0.0000	3.8067	0.5723	0.3176	0.2547***
Tfp	14.8667	1.1028	12.2938	14.8104	17.7377	15.1231	14.9649	0.1582***
Size	21.8455	1.2258	19.6026	21.6692	25.4099	21.9490	22.0341	−0.0851***
Lev	0.4748	0.1937	0.0599	0.4865	0.8676	0.4891	0.4747	0.0144***
Roa	0.0354	0.0557	−0.1735	0.0329	0.1982	0.0345	0.0382	−0.0037***
Growth	0.1926	0.4496	−0.5930	0.1212	2.8698	0.1748	0.1912	−0.0164*
Ak	12.5642	1.1882	9.7451	12.4656	15.8661	12.5143	12.6358	−0.1215***
Tangibility	0.9467	0.0700	0.6258	0.9697	1.0000	0.9503	0.9386	0.0117***
Cash	0.1650	0.1193	0.0097	0.1345	0.5990	0.1655	0.1694	−0.0039
Age	2.1620	0.5745	1.0986	2.1972	3.0910	2.2406	2.2619	−0.0212*
KZ	0.2211	1.5458	−4.6660	0.4145	3.6985	0.2856	0.1971	0.0884***
Board	2.2021	0.2220	1.6094	2.1972	2.7081	2.1784	2.2026	−0.0242***
Indep	0.3301	0.1080	0.0000	0.3333	0.5556	0.3611	0.3586	0.0025*
Share	0.0482	0.1360	0.0000	0.0001	0.6300	0.0594	0.0567	0.0027
Dual	0.1634	0.3697	0.0000	0.0000	1.0000	0.1691	0.1579	0.0112
Soe	0.6466	0.4781	0.0000	1.0000	1.0000	0.5992	0.6120	−0.0128
Tech	0.2405	0.4274	0.0000	0.0000	1.0000	0.3445	0.1915	0.1530***
Distract	0.7634	0.4250	0.0000	1.0000	1.0000	0.8085	0.7577	0.0508***

Note: ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

new-export enterprises and non-export enterprises, respectively; and column (4) shows the results of univariate comparisons of firm characteristics between new-export enterprises and non-export enterprises. As shown in the full sample statistics in column (1), the mean and standard deviation of R&D intensity (*RD*) of the listed companies are 0.0068 and 0.0161 respectively; the minimum, median, and maximum values are 0, 0, and 0.3272, respectively; the mean and standard deviation of the logarithms of the total number of patent applications (*Total*) of the listed companies are 1.3925 and 1.6371, respectively; and the minimum, median, and maximum values are 0, 0.6931, and 6.2710, respectively. These results indicate that the overall levels of innovation input and output of listed companies in China are low, and require further improvement. In terms of the three types of patents, the average logarithms of invention patents (*Invent*), utility model patents (*Utility*), and appearance design patents (*Design*) are 0.8880, 0.9379, and 0.3607, respectively. This indicates that the main types of patent applications filed by listed companies in China are invention and utility model patent applications. The results of the inter-group mean test in columns (2)-(4) reveal significant differences between the new-export enterprises and non-export enterprises. In particular, compared with the non-export enterprises, the new-export enterprises have a significantly higher innovation level. We can initially conclude that export trade promotes the technological innovation of Chinese listed companies. Finally, from the perspective of enterprise characteristics, the productivity, asset–liability ratio, tangible asset ratio, and financial constraints of the new-export enterprises are significantly higher than those of the non-export enterprises. In addition, significantly more of the new-export enterprises than the non-export enterprises are high-tech enterprises. Most of the new-export enterprises are located in central or eastern China.

4.2. Baseline regression results

Using a multi-DID model, we empirically examine the relationship between export trade and the technological innovation of listed companies. The regression results are shown in Table 3. Column (1) shows the regression results for the export dummy variable ($Treat_i \times Post_t$) and R&D intensity (*RD*), and columns

Table 3
Export trade and corporate innovation.

Variables	(1) $RD_{i,t}$	(2) $Total_{i,t}$	(3) $Invent_{i,t}$	(4) $Utility_{i,t}$	(5) $Design_{i,t}$
$Treat_i \times Post_t$	0.0047***	0.4178***	0.4539***	0.3166***	0.0288
	(3.763)	(4.248)	(4.930)	(3.713)	(0.536)
Tfp	0.0010**	0.1098**	0.0444	0.1090**	−0.0071
	(2.051)	(2.141)	(1.008)	(2.387)	(−0.276)
Size	−0.0015***	0.2694***	0.2354***	0.2182***	0.1047***
	(−3.077)	(4.408)	(4.281)	(4.136)	(3.577)
Lev	−0.0043**	−0.2388	−0.2168	−0.3705**	0.0061
	(−2.363)	(−1.350)	(−1.377)	(−2.413)	(0.062)
Roa	0.0159***	−0.3223	−0.1347	−0.6807**	0.1705
	(2.944)	(−0.943)	(−0.457)	(−2.320)	(0.789)
Growth	0.0000	−0.0895***	−0.0667***	−0.0683***	0.0025
	(0.048)	(−3.215)	(−2.892)	(−2.755)	(0.156)
Ak	−0.0006	0.0242	0.0280	0.0303	−0.0317***
	(−0.977)	(0.901)	(1.285)	(1.297)	(−2.643)
Tangibility	0.0086**	−0.5971*	−0.3378	−0.3366	−0.0426
	(2.551)	(−1.770)	(−1.096)	(−1.187)	(−0.233)
Cash	−0.0069*	−0.3067	−0.3885**	−0.3434**	−0.0833
	(−1.734)	(−1.570)	(−2.267)	(−2.001)	(−0.708)
Age	0.0024	0.5588***	0.3243***	0.4761***	0.1985**
	(1.332)	(4.253)	(2.754)	(4.045)	(2.491)
KZ	0.0002	0.0032	−0.0061	−0.0085	−0.0015
	(0.781)	(0.260)	(−0.570)	(−0.785)	(−0.194)
Board	−0.0005	0.1864	0.1392	0.1806	−0.0052
	(−0.221)	(1.332)	(1.228)	(1.484)	(−0.068)
Indep	−0.0057	0.3333	0.0275	0.4079	0.0207
	(−1.579)	(0.816)	(0.077)	(1.123)	(0.106)
Share	−0.0001	0.4720	0.0650	0.3585	−0.1278
	(−0.012)	(1.424)	(0.203)	(1.176)	(−0.585)
Dual	−0.0012**	−0.0209	0.0032	−0.0207	−0.0219
	(−2.131)	(−0.340)	(0.060)	(−0.358)	(−0.593)
Soe	0.0015*	−0.0112	−0.0625	0.0270	0.0303
	(1.875)	(−0.103)	(−0.695)	(0.339)	(0.613)
Tech	0.0027**	0.1661	0.1030	0.0881	0.0550
	(2.321)	(1.470)	(0.976)	(1.011)	(0.929)
Distract	−0.0023	−0.0669	−0.1018	−0.0610	0.0070
	(−1.395)	(−0.234)	(−0.543)	(−0.270)	(0.057)
Constant	0.0209*	−7.0631***	−5.5281***	−6.3667***	−1.7879***
	(1.899)	(−5.495)	(−4.805)	(−5.596)	(−2.678)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
N	9827	9827	9827	9827	9827
Adj R^2	0.136	0.271	0.264	0.246	0.027

Note: T-statistics based on robust standard errors clustered at the firm level are reported in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

(2)-(5) show the results of regressing the export dummy variable ($Treat_i \times Post_t$) on the total number of patent applications (Total) and the number of each of three types of patent applications: invention (*Invent*), utility model (*Utility*), and appearance design (*Design*). First, as shown in column (1) and column (2), the coefficients of $Treat_i \times Post_t$ are 0.0047 and 0.4178 respectively, and both are significantly positive at the 1% level. This indicates that export trade increases not only the innovation input but also the innovation output of Chinese listed companies, significantly promoting their technological innovation. The results in columns (3)-(5) show that export trade has a significant positive impact on invention and utility model patents with high technical content, but has no significant impact on design patents. This is basically consistent with the conclusions of the literature (Li et al., 2016).

4.3. Parallel-trend tests

The most important premise of the DID model is that the parallel-trend assumption must be satisfied; that is, the treatment group and the control group must have the same trend before the policy shock. In the field of international trade, studies provide considerable evidence that enterprises with stronger innovation capabilities and higher productivity are more likely to enter the export market (Bernard and Jensen,1999). Therefore, the innovation trend of new-export enterprises may be different from that of non-export enterprises before they engage in export behavior. If so, the results of this paper may be biased. To test whether the sampled new-export enterprises and non-export enterprises satisfied the parallel-trend hypothesis before engagement in export trade, we construct the following regression model:

$$\text{Innovi}, t = \beta 0 + \sum_{n=-4}^{4} [\beta n * (I_{i,t}^{n} \times \mathit{Treati})] + \sum \text{Controls} + \sum \mathit{Firm} + \sum \mathit{Year} + \varepsilon i, t \tag{2}$$

In model (2), I is a dummy variable. If the gap between the year of observations and the year of the export shock is n, I equals 1; otherwise, it equals 0. $n = -1$ denotes the one-year period before the export shock; $n = 1$ denotes the one-year period after the export shock. The range of n is [−15,15]. To ensure that the number of enterprises is balanced across years, the range of n is merged into [−4,4]. As mentioned above, $Treat_i$ is an indicator variable used to identify the treatment group and the control group, taking a value of 1 if firm i is a new-export enterprise and 0 if firm i is a non-export enterprise.

We take the one-year period before the export shock (*D_1*) as the benchmark group, enabling us to observe the differences in innovation between new-export enterprises and non-export enterprises compared with the benchmark group. The regression results are shown in Table 4, in which column (1) reports the results of the parallel-trend test for R&D intensity (*RD*) and columns (2)-(5) show the results of parallel-trend tests for the total number of patent applications (*Total*) and the number of each of the three types of patent applications: invention (*Invent*), utility model (*Utility*), and appearance design (*Design*). According to the regression results in Table 4, the coefficient estimates for the two-year period (*D_2*), three-year period (*D_3*), and four-year period (*D_4*) before export trade are not significant, indicating that new-export listed companies and

Table 4
Parallel-trend tests and long-term effects of exporting.

Variables	(1) $RD_{i,t}$	(2) $Total_{i,t}$	(3) $Invent_{i,t}$	(4) $Utility_{i,t}$	(5) $Design_{i,t}$
D_4	0.0012	−0.0884	−0.0245	−0.1405	−0.0707
	(0.711)	(−0.580)	(−0.176)	(−0.978)	(−0.555)
D_3	−0.0000	−0.0286	−0.0387	−0.0999	−0.0573
	(−0.026)	(−0.215)	(−0.308)	(−0.913)	(−0.552)
D_2	0.0017	−0.0822	0.0205	−0.1116	−0.0592
	(1.317)	(−0.764)	(0.202)	(−1.069)	(−0.822)
Current	0.0040***	0.2818***	0.3287***	0.1008	0.0068
	(3.054)	(3.035)	(3.348)	(1.287)	(0.123)
D1	0.0046***	0.2708**	0.3474***	0.1346	−0.0159
	(3.419)	(2.574)	(3.389)	(1.459)	(−0.277)
D2	0.0044***	0.4127***	0.4507***	0.3259***	−0.0107
	(3.190)	(3.611)	(4.235)	(3.327)	(−0.169)
D3	0.0044***	0.4146***	0.5086***	0.3107***	0.0203
	(3.008)	(3.369)	(4.447)	(2.944)	(0.307)
D4	0.0086***	0.6413***	0.7172***	0.5807***	0.0147
	(5.545)	(5.037)	(6.116)	(5.258)	(0.220)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
N	9827	9827	9827	9827	9827
Adj R^2	0.142	0.275	0.271	0.255	0.027

Note: (1) Control variables are included in all of the above models; (2) T-statistics based on robust standard errors clustered at the firm level are reported in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

non-export listed companies show the same trends in innovation input and innovation output before engaging in export trade. In addition, the coefficient estimates for the current year and the first, second, third, and fourth years of a firm's export behavior (*Current*, *D1*, *D2*, *D3*, and *D4*, respectively) for R&D intensity, the total number of patent applications, and the number of invention patent applications (but not the number of design patent applications) are significantly positive. The coefficient estimates for the second and following years for utility model patent applications are also significantly positive. These results indicate that export trade significantly promotes the technological innovation of listed companies in the long term.

4.4. Robustness tests

4.4.1. Innovation measured at years $t+1$ to $t+3$

According to Holmstrom (1989), enterprise innovation is a complex, long-term, and multi-stage process. Therefore, we use the innovation input and innovation output variables measured at years $t+1$ to $t+3$ as proxies for enterprise innovation, to further explore the relationship between export trade and the technological innovation of the sampled listed companies. Table 5 reports the estimation results. First, Panel A and

Table 5
Robustness tests: Innovation measured at years $t+1$ to $t+3$.

Panel A: R&D intensity			
	$RD_{i,t+1}$	$RD_{i,t+2}$	$RD_{i,t+3}$
$Treat_i \times Post_t$	0.0033***	0.0026**	0.0024**
	(2.819)	(2.277)	(1.988)
N	8,412	7,101	5,856
$Adj\ R^2$	0.125	0.122	0.138
Panel B: Total number of patent applications			
	$Total_{i,t+1}$	$Total_{i,t+2}$	$Total_{i,t+3}$
$Treat_i \times Post_t$	0.3174***	0.2887***	0.2002**
	(3.174)	(3.056)	(2.130)
N	8412	7101	5856
$Adj\ R^2$	0.249	0.225	0.196
Panel C: Number of invention patent applications			
	$Invent_{i,t+1}$	$Invent_{i,t+2}$	$Invent_{i,t+3}$
$Treat_i \times Post_t$	0.3597***	0.3004***	0.3009***
	(3.923)	(3.705)	(3.608)
N	8,412	7,101	5,856
$Adj\ R^2$	0.245	0.226	0.201
Panel D: Number of utility model patent applications			
	$Utility_{i,t+1}$	$Utility_{i,t+2}$	$Utility_{i,t+3}$
$Treat_i \times Post_t$	0.3062***	0.3324***	0.2124**
	(3.479)	(3.926)	(2.536)
N	8412	7101	5,856
$Adj\ R^2$	0.228	0.207	0.174
Panel E: Number of appearance design patent applications			
	$Design_{i,t+1}$	$Design_{i,t+2}$	$Design_{i,t+3}$
$Treat_i \times Post_t$	−0.0129	0.0095	−0.0429
	(−0.241)	(0.163)	(−0.653)
N	8,412	7,101	5,856
$Adj\ R^2$	0.020	0.012	0.010

Note: (1) Control variables are included in all of the above models; firm fixed effects and year fixed effects are controlled for. (2) T-statistics based on robust standard errors clustered at the firm level are reported in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel B show that the coefficient estimates of $Treat_i \times Post_t$ are significantly positive at the 1%, 5%, or 10% level, indicating that export trade promotes the technological innovation of listed companies and this effect occurs in the long term. Second, Panel C to Panel E of Table 5 show that export trade has no significant positive effect on design patent applications but significantly promotes invention patent and utility model patent applications. Therefore, compared with the baseline regression results, the results are unchanged and the research conclusions above are robust.

4.4.2. Remeasurement of innovation variables

In addition to using R&D investment scaled by firm assets and the logarithm of patent applications to proxy for innovation input and innovation output, we use R&D investment scaled by sales and the number of patents obtained by listed companies as alternative proxy variables for enterprise innovation. Specifically, we take the ratio of R&D investment to sales, the total number of patents, the number of invention patents, the number of utility model patents, and the number of appearance design patents obtained by the listed companies plus 1 and then use their natural logarithms to measure enterprise innovation. In addition, to increase the robustness of our results, we use the proxy variables at year $t+1$. The regression results in Table 6 again indicate that export trade promotes the technological innovation of listed companies.

4.4.3. Redefining the treatment group and control group

We define a new-export enterprise as a listed company for which the first year of exporting is later than the year in which the company first appear in the sample period. However, some enterprises withdraw from the export market after exporting (Li et al., 2016) and the failure to maintain exports may bias measurements of the impact of export trade (Zhang et al., 2009). Therefore, following Li et al. (2016), we exclude listed companies that exported but then withdrew from the export market as a robustness test. The regression results are shown in Table 7. The results show that export trade promotes the technological innovation of listed companies. Further, our results remain unchanged after using the proxy variables of innovation measured at years $t+1$ to $t+3$, indicating that the regression results reported in this paper are relatively robust.

Table 6
Robustness tests: Remeasurement of innovation variables.

Panel A: Innovation measured at year t					
Variables	(1)	(2)	(3)	(4)	(5)
	$RD_{i,t}$	$Total_{i,t}$	$Invent_{i,t}$	$Utility_{i,t}$	$Design_{i,t}$
$Treat_i \times Post_t$	0.0085***	0.5179***	0.4349***	0.4482***	0.1192**
	(4.089)	(5.313)	(5.192)	(4.570)	(2.118)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
N	9827	9,827	9,827	9,827	9,827
Adj R^2	0.082	0.301	0.245	0.271	0.043
Panel B: Innovation measured at year t + 1					
Variables	(1)	(2)	(3)	(4)	(5)
	$RD_{i,t+1}$	$Total_{i,t+1}$	$Invent_{i,t+1}$	$Utility_{i,t+1}$	$Design_{i,t+1}$
$Treat_i \times Post_t$	0.0047**	0.4123***	0.3829***	0.3556***	0.0673
	(2.176)	(4.024)	(4.264)	(3.643)	(0.981)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
N	8412	8412	8412	8412	8412
Adj R^2	0.072	0.294	0.247	0.262	0.037

Note: (1) Control variables are included in all of the above models. (2) T-statistics based on robust standard errors clustered at the firm level are reported in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7
. Robustness tests: Redefining the treatment group and control group.

Panel A: R&D intensity			
	$RD_{i,t+1}$	$RD_{i,t+2}$	$RD_{i,t+3}$
$Treat_i \times Post_t$	0.0067**	0.0077***	0.0075***
	(2.467)	(2.995)	(3.007)
N	6051	5072	4170
$Adj\ R^2$	0.089	0.086	0.107
Panel B: Total number of patent applications			
	$Total_{i,t+1}$	$Total_{i,t+2}$	$Total_{i,t+3}$
$Treat_i \times Post_t$	0.4243**	0.4754***	0.3640***
	(2.480)	(3.547)	(2.783)
N	6051	5072	4170
$Adj\ R^2$	0.226	0.205	0.185
Panel C: Number of invention patent applications			
	$Invent_{i,t+1}$	$Invent_{i,t+2}$	$Invent_{i,t+3}$
$Treat_i \times Post_t$	0.5503***	0.6201***	0.6441***
	(3.222)	(4.510)	(4.398)
N	6051	5072	4170
$Adj\ R^2$	0.218	0.203	0.185
Panel D: Number of utility model patent applications			
	$Utility_{i,t+1}$	$Utility_{i,t+2}$	$Utility_{i,t+3}$
$Treat_i \times Post_t$	0.4745***	0.5879***	0.2964**
	(2.800)	(4.247)	(2.412)
N	6051	5072	4170
$Adj\ R^2$	0.198	0.180	0.158
Panel E: Number of appearance design patent applications			
	$Design_{i,t+1}$	$Design_{i,t+2}$	$Design_{i,t+3}$
$Treat_i \times Post_t$	−0.0531	−0.0212	−0.0408
	(−0.563)	(−0.183)	(−0.298)
N	6051	5072	4170
$Adj\ R^2$	0.024	0.017	0.019

Note: (1) Control variables are included in all of the above models; (2) T-statistics based on robust standard errors clustered at the firm level are reported in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

4.4.4. Discussion of endogenous problems

Using the multivariate DID model with appropriate control variables and conducting a series of alternative tests yielded regression results that confirm the positive correlation between export trade and enterprise innovation. However, it remains unclear whether the results are affected by problems of endogeneity that may lead to estimation bias, such as sample self-selection, two-way causality, and the non-randomness (endogeneity) of export policy. To increase the reliability of the conclusions of this paper, we discuss the endogeneity problem of causal identification in this section. Due to limitations on space and consideration of importance, in this section and the following content we focus on the relationship between export trade ($Treat_i \times Post_t$.) and R&D intensity (*RD*), the total number of patent applications (*Total*), and the number of invention patent applications (*Invent*).

(1) Endogeneity problems caused by sample self-selection

Many scholars in China and abroad have identified a self-selection effect among new-export enterprises (Aw et al., 2000; Melitz, 2003; Qian et al., 2011; Yi and Fu, 2011; Qiu et al., 2012). Therefore, although the baseline regression results indicate that export trade promotes the technological innovation of listed enterprises, the issue of inherent selection bias cannot be ignored. To increase the robustness of the results above, we further use the PSM method to explore the relationship between export trade and the technological innovation of listed companies. Specifically, we first estimate a logit regression to predict the export probability of the listed companies with all of the control variables mentioned above. Next, we select samples of non-export enterprises that are similar to those of new-export enterprises by one-to-five nearest neighbor PSM to eliminate significant differences between the treatment group and the control group before the export shock. This reduces the bias caused by the self-selection effect of listed companies before and after exporting. Finally, we re-estimate the multi-DID model using the matched sample to explore the net average impact of export trade on the technological innovation of listed companies. The estimation results are shown in Table 8. The coefficient estimates of $Treat_i \times Post_t$ are all significantly positive at the 1% level for R&D intensity (*RD*), the total number of patent applications (*Total*), and the number of invention patent applications (*Invent*), indicating that export trade promotes the technological innovation of listed companies. Our estimation results are consistent with the baseline results.

(2) Endogeneity problems caused by two-way causality and non-random policies

Although the DID method is an appropriate tool to evaluate the effect of export trade policy, its effectiveness depends on the randomness (exogeneity) of the policy variables. If an enterprise's export behavior is related to its innovation capabilities, the explanatory variable of exporting is endogenous. To solve the problems of two-way causality and policy endogeneity in the model, we implement two main measures. One is to add the lag term of the explained variable to the regression model to control factors that vary between enterprises and across time to eliminate the impact of enterprise innovation on export trade. The second is to find an exogenous instrumental variable (IV).

(1) Adding the lag term of the explained variable to the model

As indicated above, we address potential endogeneity problems in the model by adding the lag term of the explained variables to the model. However, this brings new endogeneity problems due to dynamic panel deviation. To solve the latter problems, we follow Zhang and Zheng (2013) and Feng and Liu (2017) in using the two-stage system generalized method of moments (GMM) method for the regression and adding year dummy variables to the model to control the time trend.

The regression results are shown in Table 9. Columns (1)-(3) report the estimation results of our dynamic panel models for the R&D intensity (*RD*), total number of patent applications (*Total*), and number of

Table 8
Treatment of endogeneity problems: propensity score matching test.

Variables	(1) $RD_{i,t}$	(2) $Total_{i,t}$	(3) $Invent_{i,t}$
$Treat_i \times Post_t$	0.0042***	0.4033***	0.4318***
	(3.303)	(3.456)	(3.956)
Constant	0.0340**	−6.3203***	−5.2824***
	(2.407)	(−4.139)	(−3.849)
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
N	7541	7541	7541
Adj R^2	0.143	0.290	0.284

Note: (1) As export trade and innovation may have an industry cluster effect, our matching process is treated by industry.[We thank an anonymous referee for several valuable comments on conducting PSM by industry that helped to greatly improve the paper.] In addition, our industry division method follows the classification method used in the mainstream literature; that is, the manufacturing industry is divided according to the CSRC 2012 Industry Classification and all other industries are divided according to the CSRC 2012 Industry Classification. (2) Control variables are included in all of the above models; (3) T-statistics based on robust standard errors clustered at the firm level are reported in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 9
Treatment of endogeneity problems: two-stage system generalized method of moments.

Variables	(1)	(2)	(3)
	$RD_{i,t}$	$Total_{i,t}$	$Invent_{i,t}$
$RD_{i,t\text{-}1}$	0.2350*		
	(1.811)		
$Total_{i,t\text{-}1}$		0.2447***	
		(4.496)	
$Invent_{i,t\text{-}1}$			0.2526***
			(4.461)
$Treat_i \times Post_t$	0.0193*	3.4028***	2.7499***
	(1.875)	(5.094)	(6.125)
Constant	0.0344	−23.5889***	−22.9229***
	(0.254)	(−3.221)	(−2.813)
AR(1)	0.022	0.000	0.000
AR(2)	0.426	0.284	0.606
Hansen	0.352	0.258	0.147
Year fixed effects	Yes	Yes	Yes
N	9,005	9,005	9,005

Note: (1) Control variables are included in all of the above models; (2) T-statistics based on robust standard errors clustered at firm level are reported in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

invention patent applications (*Invent*) of the listed companies. The results of the Hansen test and the residual sequence correlation test support the validity of the instrumental variable in the model, the residual first-order sequence correlation (*AR (1)*), and the second-order sequence correlation (*AR (2)*).

In addition, Table 9 shows that after controlling the explained variables of the lagging period and using two-stage system GMM to solve problems of endogeneity, the coefficient estimates of $Treat_i \times Post_t$ are still significantly positive at the 1% or 5% level. This again indicates that export trade promotes the innovation activities of listed companies in terms of both innovation input and innovation output.

(2) Instrumental variable method

Next, we address the endogeneity problem associated with trade policy to improve the reliability of the conclusions of this paper. We use the IV method as the final robustness estimation, taking the lag term of enterprise export trade volume as the IV.

Specifically, we first take the natural logarithm of export trade volume and then take the lag term of the logarithmic export trade volume as the IV (*IV*). Generally, the export behavior of Chinese enterprises is characterized by persistence (Chen et al., 2012; Dai and Zheng, 2015). The larger an enterprise's export trade volume in the previous year, the higher the probability of the enterprise's engaging in export behavior in the current year. Therefore, the lag term of enterprise export trade volume, selected as the IV of export trade, satisfies the correlation hypothesis. In addition, to satisfy the exclusivity hypothesis of the IV approach, there must be no direct correlation between the export trade volume of the previous period and enterprise innovation in the current period. That is, the technological innovation level of the enterprise in the current period must not affect its export trade volume in the previous period. In sum, our IV is valid.

The regression results are shown in Table 10, in which column (1) presents the results of the first stage of the IV regression and columns (2)-(4) report the results of the second stage of the instrumental variable regression. First, the estimation results of the first stage show that the greater the export trade volume of listed companies in the previous period, the more willing enterprises are to export in the current period. The estimation results of the second stage show that after the use of the IV, export trade still significantly improves the innovation input and output of listed companies. Therefore, the results after addressing endogeneity problems again support the conclusions of this paper.

Table 10
Treatment of endogeneity problems: instrumental variable regression.

	First stage	Second stage		
Variables	(1)	(2)	(3)	(4)
	$Treat_i \times Post_t$	$RD_{i,t}$	$Total_{i,t}$	$Invent_{i,t}$
$Treat_i \times Post_t$		0.0079**	0.9245***	1.0550***
		(2.411)	(2.886)	(3.726)
IV	0.0142***			
	(11.023)			
Constant	−0.3797**	0.0240*	−7.2671***	−5.1453***
	(−2.154)	(1.951)	(−5.182)	(−4.135)
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
N	9005	9005	9005	9005

Note: (1) Control variables are included in all of the above models; (2) T-statistics based on robust standard errors clustered at the firm level are reported in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

4.5. Additional analysis

4.5.1. Mechanism analysis

The results above indicate that engaging in export trade promotes the technological innovation of listed companies. It is also important to explore the paths and mechanisms of this effect. According to the theoretical analysis for economies of scale and of risk-taking, first, an increase in market demand leads enterprises to expand their production scale and increase their input of production factors to achieve economies of scale, thus promoting enterprise innovation. Second, competition and learning effects by exporting significantly improve enterprise management, production technology, and product process and increase enterprises' risk-taking, thereby enhancing their technological innovation. Based on this, we estimate the following models:

$$Yi,t = \gamma 0 + \gamma 1 Treati \times Postt + \sum Controls + \sum Firm + \sum Year + \varepsilon i,t \tag{3}$$

$$RiskTi,t = \eta 0 + \eta 1 Treati \times Postt + \sum Controls + \sum Firm + \sum Year + \varepsilon i,t \tag{4}$$

In model (3), the explained variable $Y_{i,t}$ represents economies of scale, measured by the logarithm of the number of employees, intermediate product input, operating income, and profits (He et al., 2020). In model (4), $RiskT_{i,t}$ represents the risk-taking level of an enterprise. Referring to John et al. (2008), Boubakri et al. (2013), and Yu et al. (2013), we choose as our primary measure of corporate risk-taking ($RiskT_{i,t}$) the volatility of a firm's industry-adjusted return on assets ($ADJ\_ROA_{i,t}$) over three-year overlapping periods (i.e., $t-1$, t, $t+1$). The calculation process is as follows:

$$RiskTi,t = \sqrt{\frac{1}{N}\sum_{t=1}^{N}\left(ADJ\_ROAi,t - \frac{1}{N}\sum_{t=1}^{N} ADJ\_ROAi,t\right)^2 \mid N = 3} \tag{5}$$

$$ADJ\_ROAi,\mathrm{t} = \frac{EBITDAi,t}{ASSETSi,t} - \frac{1}{X}\sum_{t=1}^{X}\frac{EBITDAi,t}{ASSETSi,t} \tag{6}$$

where $EBITDA_{i,t}$ is the earnings before interest, taxes, depreciation, and amortization of firm i in year t, and $ASSETS_{i,t}$ denotes the total assets of the enterprise at the end of the period. Table 11 reports the estimation results of the mechanism test. First, export trade significantly increases the number of employees, input of intermediate products, operating income and profits of the listed companies, expanding the scale of their production and sales in terms of input and output. This realizes economies of scale, reduces unit product costs, obtains cost advantages, and improves enterprise competitiveness, thereby promoting enterprise innovation. Second, export trade significantly increases enterprises' risk-taking, reducing the risk associated with R&D investment and increasing technological innovation.

Table 11
Export trade and corporate innovation: mechanism test.

Variables	(1)				(2)
	Employee	*MI*	*Sales*	*Profit*	*RiskT*
$Treat_i \times Post_t$	0.0737**	0.0631**	0.0430*	0.0865*	0.0058***
	(2.109)	(2.297)	(1.762)	(1.952)	(2.704)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
N	9799	9557	9827	8836	8798
Adj R^2	0.504	0.890	0.924	0.725	0.715

Note: (1) Control variables are included in all of the above models; (2) T-statistics based on robust standard errors clustered at the firm levels are reported in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

4.5.2. Heterogeneity analysis

In recent years, numerous scholars have studied heterogeneous trade theory, according to which a company's type affects its export trade behavior (Jing et al., 2013; Li et al., 2016; Liu and Tong, 2017). Accordingly, we further examine the relationship between export trade and the technological innovation of the sampled listed companies with reference to the nature of ownership, technology level, location, export destination country type, and export trade type.

The regression results are shown in Table 12. Panel A shows that export trade plays a key role in promoting the innovation of state-owned enterprises but does not significantly promote the innovation of private enterprises, and even has a significant inhibitory effect on the appearance design patent applications of private enterprises. This indicates that compared with private enterprises, state-owned enterprises have lower production efficiency and innovation efficiency (Wu, 2012; Dong et al., 2014), leaving more room to improve their export learning (Jing et al., 2013). Second, state-owned enterprises show a significantly lower level of risk-taking (Li and Yu, 2012) than private enterprises do. Therefore, after state-owned enterprises start exporting, they take significantly more risks. Finally, because of their large scale and protection by the government (Yu et al., 2019), state-owned enterprises are more likely than private enterprises are to obtain economies of scale, making them better able to compete in the international market. Therefore, engaging in export trade has a greater positive effect on innovation ability for state-owned listed companies than their private counterparts.

The innovation behavior of enterprises may be affected by industry differences. Previous studies have shown that export trade promotes technological innovation mainly for enterprises in high-tech industries and medium–high-tech industries. It has no significant positive effect—and may even have a negative effect—on the technological innovation behavior of enterprises in low-tech industries (Li et al., 2016). Following previous studies, based on the High-tech Industry (Manufacturing) Classification (2017) and High-tech Industry (Service Industry) Classification (2018)[7,8,9] issued by China's National Bureau of Statistics, we classify the sampled enterprises as high-tech or non-high-tech to explore the impact of export trade on the technological innovation of listed companies from the perspective of technological development level. The regression results are shown in Table 12, Panel B. The estimation results show that export trade has a significant positive impact on the technological innovation of non-high-tech listed companies. The possible reasons are as follows. First, non-high-tech enterprises have a lower technological starting point than high-tech enterprises do and thus more room for improvement. Second, compared with non-high-tech enterprises, high-tech enterprises engaging in export trade are more vulnerable to technological blockades by Western developed countries. Third, high-tech enterprises need to invest heavily in R&D to support their high-tech activities. Providing protection for high-risk R&D activities itself incurs considerable risk. Therefore, the effect of export trade on high-tech enterprises' level of risk-taking is not pronounced. Fourth, because of their high technical level, high-tech

[7] The relevant documents are available from the National Bureau of Statistics.

[8] The High-tech Industry (Manufacturing) Classification (2017) is available at http://www.stats.gov.cn/tjsj/tjbz/201812/t20181218_1640081.html.

[9] The High-tech Industry (Service Industry) Classification (2018) is available at http://www.stats.gov.cn/tjsj/tjbz/201805/t20180509_1598315.html.

enterprises can establish certain technical barriers in the domestic market to obtain economies of scale and reduce the marginal cost of their products. Therefore, as high-tech enterprises already have a certain degree of economies of scale, engaging in export trade has little substantial impact on their economies of scale. Based on these points, export trade is particularly beneficial to non-high-tech enterprises in enhancing their innovation ability.

In addition, regions are often heterogeneous in their level of export trade and/or level of enterprise innovation. Therefore, according to the regions in which they are located, we classify the listed companies as either enterprises in eastern China or enterprises in central or western China. The regression results are shown in

Table 12
Export trade and corporate innovation: heterogeneity test.

Panel A:From the perspective of nature of ownership						
Variables	*State-owned*			*Non-state-owned*		
	(1) $RD_{i,t}$	(2) $Total_{i,t}$	(3) $Invent_{i,t}$	(4) $RD_{i,t}$	(5) $Total_{i,t}$	(6) $Invent_{i,t}$
$Treat_i \times Post_t$	0.0075**	0.8660***	0.8365***	0.0049	0.0783	0.3187
	(2.217)	(3.293)	(3.497)	(1.272)	(0.267)	(1.203)
Constant	0.0331*	−8.7731***	−6.3988***	−0.0108	−4.5509*	−4.9028**
	(1.789)	(−3.133)	(−2.692)	(−0.275)	(−1.729)	(−2.082)
N	3240	3240	3240	2039	2039	2039
Adj R^2	0.124	0.322	0.299	0.133	0.190	0.216
Panel B:From the perspective of technology level						
Variables	*High-tech*			*Non-high-tech*		
	(1) $RD_{i,t}$	(2) $Total_{i,t}$	(3) $Invent_{i,t}$	(4) $RD_{i,t}$	(5) $Total_{i,t}$	(6) $Invent_{i,t}$
$Treat_i \times Post_t$	0.0059	−0.2443	0.0801	0.0065***	0.8495***	0.8649***
	(0.919)	(−0.907)	(0.289)	(3.277)	(3.292)	(3.840)
Constant	0.0459	−10.8588***	−13.2561***	0.0192	−4.8308**	−3.6171**
	(0.668)	(−2.714)	(−3.505)	(1.557)	(−2.561)	(−2.406)
N	1295	1295	1295	4106	4106	4106
Adj R^2	0.254	0.374	0.363	0.082	0.251	0.240
Panel C: From the perspective of location						
Variables	*Centralleastern region*			*Western region*		
	(1) $RD_{i,t}$	(2) $Total_{i,t}$	(3) $Invent_{i,t}$	(4) $RD_{i,t}$	(5) $Total_{i,t}$	(6) $Invent_{i,t}$
$Treat_i \times Post_t$	0.0083***	0.6483***	0.7295***	0.0006	0.1591	0.4126
	(3.091)	(2.768)	(3.572)	(0.186)	(0.334)	(0.897)
Constant	0.0083	−6.6887***	−5.3947***	0.0325*	−6.3458*	−5.1467*
	(0.435)	(−2.932)	(−2.658)	(1.654)	(−1.830)	(−1.695)
N	4297	4297	4297	1104	1104	1104
Adj R^2	0.111	0.268	0.259	0.229	0.288	0.263
Panel D:From the perspective of export destination country type						
Variables	*Developed countries*			*Developing countries*		
	(1) $RD_{i,t}$	(2) $Total_{i,t}$	(3) $Invent_{i,t}$	(4) $RD_{i,t}$	(5) $Total_{i,t}$	(6) $Invent_{i,t}$
$Treat_i \times Post_t$	0.0141**	0.7506	0.8168*	0.0065***	0.6153***	0.7120***
	(2.053)	(1.326)	(1.753)	(2.968)	(3.053)	(4.025)
Constant	0.0229	−5.2135***	−4.1470**	0.0156	−5.7330***	−4.7335***
	(1.452)	(−2.585)	(−2.356)	(0.990)	(−2.997)	(−2.810)
N	4887	4887	4887	5493	5493	5493
Adj R^2	0.086	0.232	0.218	0.111	0.259	0.248

Panel E: From the perspective of export trade type

Variables	*General trade*			*Processing and mixed trade*		
	(1) $RD_{i,t}$	(2) $Total_{i,t}$	(3) $Invent_{i,t}$	(4) $RD_{i,t}$	(5) $Total_{i,t}$	(6) $Invent_{i,t}$
$Treat_i \times Post_t$	0.0087***	0.4736***	0.6013***	0.0135	0.5030	0.5881
	(2.769)	(2.909)	(3.984)	(1.386)	(1.278)	(1.640)
Constant	0.0078	−6.4110***	−4.6439***	0.0252	−5.4628**	−4.8340**
	(0.572)	(−3.839)	(−3.172)	(1.217)	(−2.254)	(−2.315)
N	6318	6318	6318	3895	3895	3895
Adj R^2	0.103	0.231	0.222	0.064	0.170	0.161

(1) To improve the robustness of the results, the samples used in the above models were PSM paired after excluding listed companies that export but then exit the export market. (2) Control variables are included in all of the above models. (3) T-statistics based on robust standard errors clustered at the firm level are reported in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 12, Panel C. The estimation results show that export trade mainly promotes the technological innovation of enterprises in central and eastern China; it does not significantly promote the technological innovation of enterprises in western China. This indicates, first, that the development of modern industry in the western region is slow, lacking precision production equipment, an appropriate financial environment, and scientific and technological human resources. Therefore, after engaging in export trade, even if western Chinese enterprises have learned from international advanced technology, the transformation efficiency of their innovation achievements is relatively low because they lack the environment and human resources conducive to innovation. Second, because western China is geographically far from the main export markets of Europe and the U. S., the cost of entering these export markets is highest for western Chinese enterprises (Tong and Liu, 2014). Therefore, the export costs incurred by these enterprises are relatively high and their resulting export profits are relatively low, resulting in relatively little investment in innovation.

Furthermore, previous studies have shown that newly industrialized economies and developing countries can improve their independent innovation capability (Aw et al., 2000; De Loecker, 2007; Alvarez and Lopez, 2005) by participating in international competition to learn from and absorb advanced technology from developed countries. However, this effect has not been confirmed in the vast majority of developed industrialized countries (Bernard and Jensen, 1999; 2004a; Wagner, 2002; Greenaway and Yu, 2004). Therefore, the role of export trade in promoting corporate innovation may vary between countries based on their export destination type.[10] Therefore, according to the division of the Human Development Index[11], we classify the export destination countries of the sampled listed companies as developed or developing economies to conduct comparative analysis. As shown in Table 12, Panel D, export trade significantly promotes the innovation level of enterprises in developed countries but only slightly promotes the innovation output of enterprises in developing countries. This indicates that export trade has a significant positive effect on the innovation level of enterprises that export to developed countries, but only slightly promotes the innovation output of enterprises that export to developing countries. The more developed an enterprise's export destination country, the higher the enterprise's degree of innovation knowledge, resulting in higher enterprise innovation.

Finally, according to Dai et al. (2014), processing trade with low technological content is the main reason for the productivity paradox observed among Chinese enterprises. Processing trade enterprises may not experience learning by exporting effects (Xiang and Ma, 2013). Therefore, the promoting effect of export trade on enterprise innovation may vary with the mode of export trade. Therefore, following Li et al. (2016), we distinguish between modes of trade for further analysis.[12] The regression results are shown in Table 12, Panel E. First, export trade significantly promotes the innovation of enterprises that are mainly engaged in general

[10] We thank an anonymous referee for several valuable comments on heterogeneity analysis that helped to greatly improve the paper.

[11] Human Development Index is available at http://hdr.undp.org/sites/default/files/hdr2019.pdf. (p. 300–311).

[12] Following Li et al. (2016), if the proportion of processing trade of their total export trade is less than 25%, we classify exporting enterprises as mainly engaged in general trade. If the proportion of processing trade of their total export trade is more than 75%, we classify exporting enterprises as mainly engaged in processing trade. We classify the others as mainly engaged in mixed trade.

trade, but has no significant impact on the innovation level of enterprises mainly engaged in processing and mixed trade. This indicates that, unlike enterprises mainly engaged in general trade, enterprises mainly engaged in processing and mixed trade do not experience the export learning effect, consistent with previous findings.

5. Conclusion

The performance of export trade at the micro level of enterprises has long been a hot topic of research on international trade. Based on data on Shanghai and Shenzhen A-share listed companies from 2000 to 2015, we use a multi-DID model to study the relationship between export trade and technological innovation. The findings indicate that export trade promotes the technological innovation of listed companies in terms of both innovation input and innovation output. From the perspective of patent output, export trade significantly promotes listed companies' applications for invention patents and utility model patents with a high technical content. The conclusions report in this paper remain robust after a series of robustness tests. Export trade behavior generally leads enterprises to expand their production scale, increase their input of production factors to achieve economies of scale, and increase their risk-taking, thereby raising their level of technological innovation. In terms of enterprise heterogeneity, export trade mainly promotes the technological innovation of state-owned enterprises, non-high-tech enterprises, enterprises in central and eastern China, enterprises that export to developed economies, and enterprises that are mainly engaged in general trade.

At the time of writing, the trade negotiations resulting from Sino–U.S. trade frictions have reached an impasse. The U.S. launches a trade war against China primarily to restrain the development of China's high-tech enterprises by imposing punitive tariffs to curb China's scientific and technological innovation (Huang et al., 2018a; 2018b). Given the U.S.'s zero-sum thinking, i.e., seeking to maintain its status as a great power while curbing China's development, the trade conflict is complex and likely to be long-lasting (Yu et al., 2018a; 2018b). Since the U.S.'s announcement of tariffs against China Sino-US trade friction on March 22, 2018[13], Chinese enterprises' volume of export trade to the U.S. has decreased significantly, and the value-innovation chain of Chinese export enterprises has been damaged (Young, 1991; Gibbon et al., 2008). Today, with rapid economic globalization, national strength is ultimately measured by the capacity for innovation. At present, China is on the brink of entering the ranks of the world's most innovative countries. The conclusions of this paper are of practical significance for Chinese enterprises seeking to strengthen their export trade and improve their scientific and technological innovation against the background of Sino–U.S. trade frictions. This may in turn help China to emerge as an innovative country by breaking down the scientific and technological blockade erected by the U.S. and eliminating its high-tech dependence on the U.S.

Declaration of Competing Interest

The author declare that there is no conflict of interest.

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[13] On March 22, 2018, the U.S. government plans to impose tariffs of up to 25% on China's imports of US $50 billion, which is regarded as the beginning of Sino-US trade friction (Huang et al., 2018).

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