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Does exporting to China spur firm innovation activities in developing countries?

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ABSTRACT

Trading with developed countries has been shown to promote technological progress. However, it remains unclear whether trade between developing countries promotes or hinders technological progress. To address this gap, the present study utilizes micro data from the 2006–2021 World Bank Enterprise Surveys for 139 developing countries to assess the link between exports to China and innovation activities. We analyze the relationship between exports to China and various proxies for firm-level innovation activities in other developing countries. Our findings suggest that exports to China significantly enhance innovation in other developing countries, regardless of the innovation measures used. The heterogeneous analysis shows that the effects are more pronounced for mature firms and exporters, while young firms and non-exporters are more likely to introduce process innovation directly, rather than spending more on R&D. This effect becomes more pronounced after the implementation of China's Belt and Road Initiative in 2013. The underlying mechanism is that exporting to China (only for capital-intensive goods) could increase the demand for skilled labor, thereby contributing to higher innovation activities among firms in developing countries, as evidenced by firms hiring a greater proportion of skilled labor. These labor adjustments could contribute to the increase in the likelihood of firms introducing process innovation and spending on R&D by 38% and 47%, respectively.

1. Introduction

International trade is commonly acknowledged as a crucial pathway to promote technological progress (Bloom et al., 2016), and trade with developed countries (or technological front-runner countries) has been widely proven to promote technological progress (Gorodnichenko et al., 2019). So, does trade between developing countries promote or hinder technological progress? The answer to this question is of great value in understanding the benefits of trade and how trade promotes technological progress.

On the one hand, if there are no technological differences between trading countries or the traded goods are non-high-tech products (Ghizzi, 2021), the promotion of technological progress through trade between developing countries may be limited. Additionally, if only trade with developed countries can promote technological progress, trade between developing countries may hinder technological progress by crowding out trade with developed countries (Liu & Qiu, 2016). On the other hand, existing research also suggests that trade between developing countries may promote technological progress through various channels. Firstly, the expansion of

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production brought about by trade can promote technological progress through increased demand. Secondly, the accumulation of capital brought about by trade can provide a foundation for the introduction of technology. In addition, the learning from production expansion itself may also promote technological progress (Chen et al., 2017). Finally, the competition brought about by trade may also promote technological progress- (Melitz & Redding, 2021; Aghion et al., 2005; Gong & Xu, 2017). Therefore, the impacts of international trade between developing countries on technological progress is theoretically uncertain and can only be answered through empirical estimation.

We use trade data between China and other developing countries to test whether trade between developing countries can promote technological progress. In the past 20 years, compared with developed countries, China is clearly not at the forefront of technology. However, China's trade with many other developing countries provides an ideal testing ground for this research. Our research results lead to the following conclusion: trade itself can promote technological progress, and this promotion does not require trade with more developed countries.

Over the span of just three decades, China has rapidly transited from a technologically lagging nation into the 3rd-largest global manufacturer and a hotspot for research and innovation, as highlighted by extant reports (Kroll & Frietsch, 2022). This impressive growth has sparked a vigorous political and academic debate over how China's continued economic rise and global economic engagement impact firms' performance worldwide, as explored in studies by Bloom et al. (2016). While the current literature has focused on examining how the imports from China are affected by the corporate R&D endeavors and innovation in developed countries (Autor et al., 2020), the question of whether and how exports to China, or China's demand shock, affect firm innovation activities in developing countries remains unanswered.

Using rich microdata provided by the 2006–2021 World Bank Enterprise Surveys (WBES) in 139 developing countries, we empirically clarify how exports to China casually affect the corporate innovation activities. However, uncovering the causal effect is not straightforward due to many omitted determinants of firms' innovation activities that are correlated with exports to China, and the estimation suffers from severe reverse causality. To address this, we use an instrument based on the “China shock” approach of Autor et al. (2013), which leverages the time variation of Chinese imports from other developing countries.

Our results show that exports to China contribute to more active innovation in developing nations. To further confirm the existence of the causal relationship, we employ the instrumental variable model based on heteroskedasticity, following the approach of Lewbel (2012). This instrument is constructed through multiplication of the auxiliary equation residuals by the exogenous variables centered on mean. The positive association is robust to other econometric strategies, alternative instruments, and different measures of firm innovation. The heterogeneous analysis shows that the effects are more pronounced for mature firms and exporters, while young firms and non-exporters are more likely to introduce process innovation directly, rather than spending more on R&D. This effect becomes more pronounced after the implementation of China's Belt and Road Initiative in 2013.

Our analysis then delves into explaining how exports to China lead to higher firms' innovation activities in developing countries. The innovation-driven effect is ascribable primarily to the elevated share of R&D employees within firms when exporting to China. In substantial existing studies (Romer, 1990; Gennaioli et al., 2012; Gu et al., 2021; Sun, Li, & Ghosal, 2020), high-skilled labor has been found to contribute to corporate innovation activities. Our results, after addressing endogeneity issues, show that exports to China contribute to a higher employment share of skilled labor, as well as a lower share of unskilled labor within firms. Inspired by the approach of Gu et al. (2021), the results estimated from using a two-step regression method show that these dynamic labor adjustments could contribute to the increase in the likelihood of firms introducing process innovation and spending on R&D by at least 38% and 47%, respectively. An explanation for why exporting to China triggers firm innovation activities is that, with the expansion of the Chinese market, the price of exporting products (only for capital-intensive goods) increases, driving a relatively higher marginal benefit of employing R&D workers than unskilled workers. Exports to China can contribute to the dynamic adjustment of a firm's labor force structure, in turn boosting firms' innovation activities.[1]

We contribute to the extant literature in three chief aspects. First of all, we investigate the innovation effects of exports to China in developing countries. Trade globalization has been recognized as a significant driver of technological innovation over the past three decades (Coelli et al., 2022). However, innovation is impacted differently by trade depending on the country, industry, firm type, and innovation efforts (Akcigit & Melitz, 2022). China's extraordinary increase in exports has presented an innovative competition source for enterprises in advanced countries, and it remains unclear how the import competition influences innovation in high-income countries are still. For example, Autor et al. (2020) have demonstrated that 40% of the innovation deceleration from 1999 to 2007 among US enterprises is ascribable to imports from China, while Bao and Chen (2018) have discovered that enterprises in >100 countries respond to the external competition threat through the innovation enhancement. Contrastively, in a study by Gong and Xu (2017), import penetration from China is not detrimentally influential to innovation in the U.S. Import competition plays an essential role in innovation activities in developed countries. However, for developing countries with weaker economic stability and vulnerability to changes in the trade environment, understanding whether exports to China trigger firms' innovation activities remains poor.

Our second contribution is to uncover how trading with China leads to an increase in innovation. To enter China's market, firms in developing countries must provide relatively high-quality products to compete with international competition (Yang & Tsou, 2022). The products exported from developing countries can be considered innovative labor resource-intensive products (Grossman & Rossi-Hansberg, 2008). This paper aims to investigate whether exports to China contribute to firms' labor hiring adjustment, showing agreement with substantial literature related to the “China shock” and labor market that began with the pioneering work by David

[1] To further support our findings, in online appendix A, we formally make the argument by modeling China's innovation-driven mechanism through the adjustment of labor structure, following Gu et al.'s (2021) procedure.

et al. (2013). Our study analyzes how the China shock impacts both the innovation and labor market within a single framework.

Our third contribution relates to the broader academic debate on the "China syndrome," which has attracted attention from politicians and economists. Import penetration from China has been accused for decline in manufacturing jobs in higher-income countries (David et al., 2013). Among the studies concerning the influence of China shock over labor market, Acemoglu et al. (2016) have been among the most influential. Their findings show that the unemployment caused by rising import penetration from China between 1999 and 2001 totaled 2.0–2.4 million. Pierce and Schott (2016) have focused on the manufacturing labor market in the US, associating its decline with the US government's cancellation of the increase in import tariffs on Chinese imports.

The reminder of the present work is arranged as follows. Section 2 establishes a series of stylized facts regarding developing countries' exports to China and firm innovation activities. In Section 3, the identification strategy, variables, and data are described. In Section 4, empirical results are detailed regarding the effect that exports to China has on firm's innovation activities. Section 5 uncovers the mechanism of the innovation-driven effect of exports to China and estimates the contribution level of exports to China to firm innovation activities. The last section offers conclusions.

2. Is exporting to China so special for firm innovation in developing countries?

2.1. Exporting to China

Since the 21st century, China's economy has become increasingly integrated into the world and has emerged as one of the countries benefiting the most from the wave of trade liberalization. China is emerging as a truly global economic and political power. As a dominant player in international trade, China can not only compete with importing countries' domestic and third-country markets for developed countries but also provide a huge export market for these emerging countries (Feenstra & Sasahara, 2018). As shown in the following Fig. 1, almost all developing countries have exports to China. Some countries, such as Brazil, Russia, India, Mexico, and others, have significant export volumes to China, exceeding 15 billion US dollars in trade volume. China has been and continues to be a robust trade partner and a game-changer for world trade.

To compare the import volumes from developing countries such as Mexico, India, Brazil, and China, we have created a visual representation showcasing the total import from other developing countries. As depicted in Fig. 2, it is evident that China has consistently held the largest imports from other developing countries among the four nations. Notably, starting from 2001, there has been a gradual widening gap between developing country exports to China and the other three countries. This significant increase in imports from other developing countries can be primarily attributed to China's accession to the World Trade Organization (WTO) in

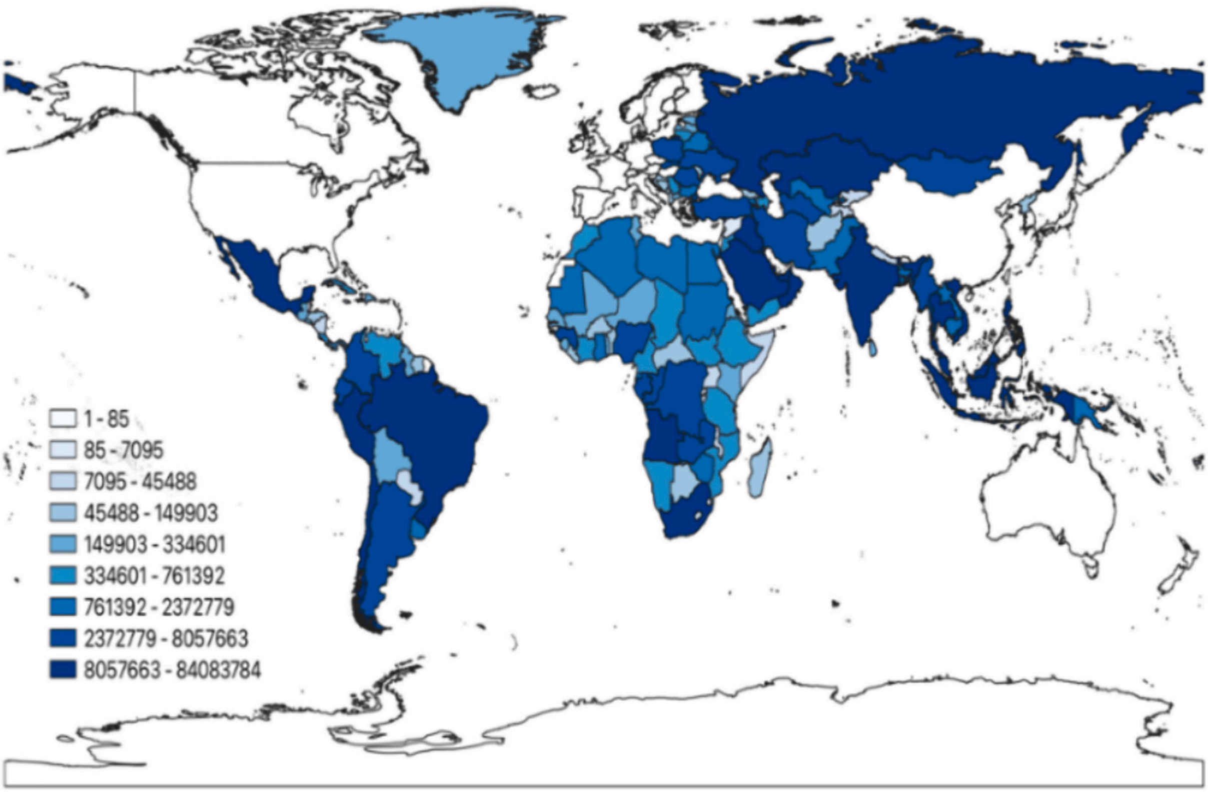

Fig. 1. Distribution of developing country exports to China (2000) (1000 Current USD).

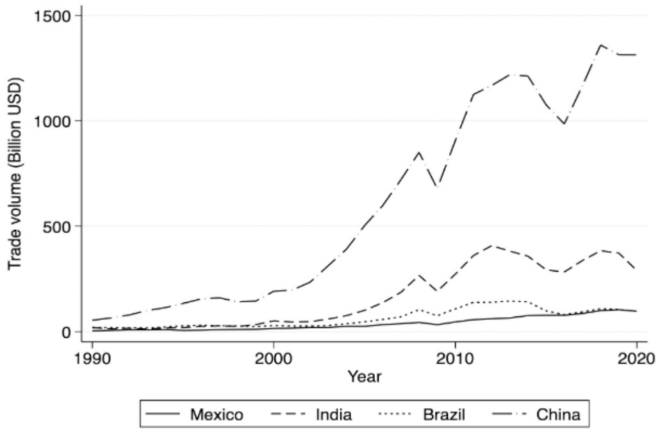

Fig. 2. Comparison of trade volume between developing countries exporting to Mexico, India, Brazil and China (1990–2020).
Data source: CEPII.

2001. Based on the above analysis, China has been a crucially important and special exporting market for developing countries.

2.2. Innovation in China and firm innovation in developing countries

In order to demonstrate that China is a special exporting destination that potentially triggers firm innovation activities in developing countries, we use Fig. 3 to illustrate total innovation activities compared with other large developing countries. Fig. 3, employing patent applications as a proxy for innovation, shows that China's total innovation consistently increases and sharply rises after the year 2010. Comparing with other developing countries, such as Mexico, India, and Brazil, the innovation gaps between China and the other three large developing countries have been widening.

The rise of China as a trade powerhouse has had profound implications for developing countries over the past three decades. Whether exporting to China could drive innovation activities in developing countries has attracted lots of attention. Fig. 4 displays the evolutions of exports to China and total patent applications in developing countries. Fig. 4 illustrates a clear positive correlation, suggesting that exporting to China from developing countries potentially spurs their innovation activities. This indicates that China has made significant progress in innovation, and trading with China may provide greater incentives for firm innovations in other developing countries.

In this paper, spending on R&D and introducing new technology are employed as indicators to measure firm innovation activities. Fig. 5 plots the correlation between the average of exports to China and the average of firm innovation activities in developing countries, showing a significant positive correlation. Specifically, starting from 2013, there is a stronger alignment between innovation activities among developing countries and their exports to China. This may be attributed to the implementation of China's "Belt and Road Initiative," which leads to an increase in exports from developing countries to China. The rise in innovation behavior among developing countries can be driven by China's import demand. As a result, there is a more consistent trend observed between exports to China and firm innovation activities since 2013.

Fundamental innovation is costly, risky, and path-dependent, and to date, groundbreaking innovation is highly concentrated in a few rich countries. Compared with developed countries, the firms in developing countries are more likely to introduce innovation processes directly rather than spending on R&D due to limited human capital and facilities. Another feature of innovation in developing countries depends heavily on technology transfer from developed countries. However, currently, international technology transfer is restricted by trade and technical barriers from the rich countries. Thus, the priority of developing countries is to build a skilled workforce capable of innovations. Innovation is regularly recognized as a critical component of industrialization and catch-up in developing countries. This paper documents a new channel that helps firms enhance their innovation performance through skilled labor adjustment driven by exporting to China.

3. Data sources, variables, and identification strategy

3.1. Dependent variable

To empirically test how exports to China affect firms' innovation activities, the corporate-level database from the WBES was utilized herein.[2] This dataset covers a broad spectrum of developing nations during the period 2006–2021 and includes a stratified stochastic selection of 119,509 enterprises from 139 countries. To collect data, face-to-face interviews were conducted with owners and

[2] World Bank Enterprise Surveys:https://www.enterprisesurveys.org/en/enterprisesurveys

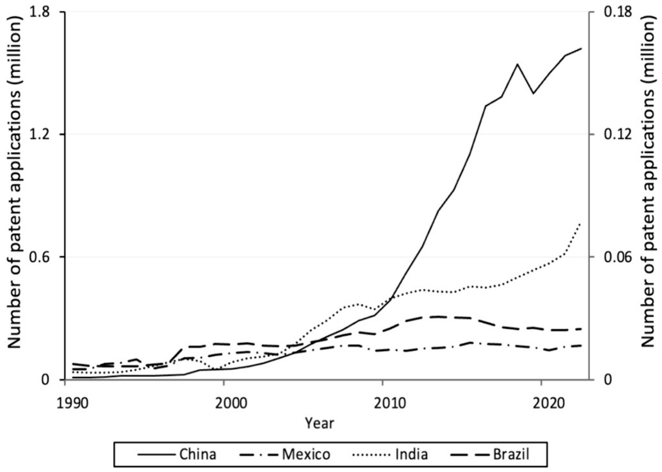

Fig. 3. Patent applications in China, Mexico, India and Brazil.
***Notes*:** The number of patents in China is shown on the left vertical axis, while the number of patents in the other three countries is shown on the right vertical axis.

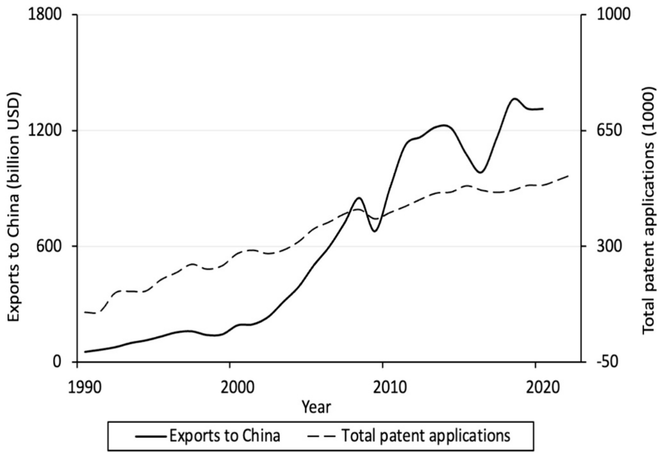

Fig. 4. Exports from developing countries to China and patent applications of developing countries at the aggregate level (1990–2022).
Data source: World Intellectual Property Organization.

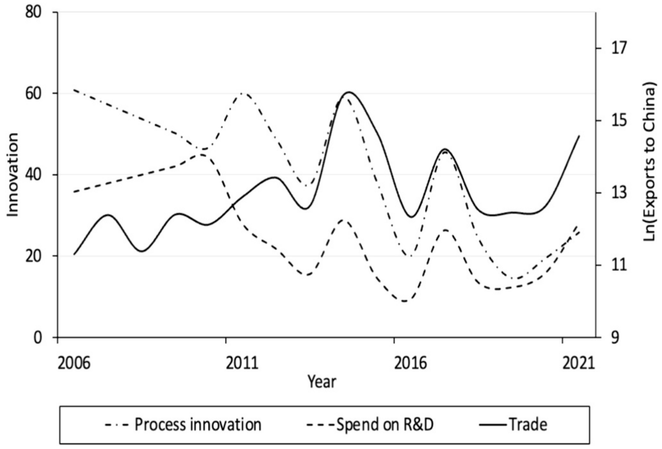

Fig. 5. Average exports to China and innovation behavior among developing Countries (2006–2021).

managers. The dataset contains information on firms' innovation activity, which we use as the dependent variable.

Metrics of innovation activities include innovation input (e.g. R&D spending) and innovation output (Liu & Qiu, 2016). Since R&D spending is an ordinary observable input index for innovation (Aghion et al., 2005), for our baseline specifications, we measure the dependent variable by whether the firm spends on R&D. Additionally, compared to enterprises in developed nations, those in developing nations may introduce new technology directly from other firms or countries. Thus, we also use whether technological innovation is introduced by enterprises as an alternative measurement of innovation activity. Finally, in our robustness checks, we use whether enterprises introduced a novel service/product and whether the firm adopted technology licensed from foreign companies as proxies for innovation activities.

The reader could be concerned that these dependent variables only capture the extensive margin of innovation, but not the intensive margin. Due to the limitation of other measurements of firm innovation, the paper only tries to explore whether and how exports to China trigger firms' innovation activities from the extensive margin of innovation. Fortunately, these innovation measurements benefit us in exploring the trade effects on innovation choices between introducing the innovation process or spending on R&D by different types of firms. Our contribution to the literature is achieved through the examination of how trade induces technology adoption behavior in developing countries beyond the traditional literature.

3.2. Variable of interest

Exposure of a local market to export expansion is determined primarily by the export to China exposure alteration per employee in a region, with the apportionment of exports achieved to the region depending on its share of national industry employment and the measurement is motivated by Autor et al. (2013). As a dominant player in international trade, China provides a significant export market for emerging economies in addition to competing with domestic markets of developed nations, as well as third-country markets (Feenstra & Sasahara, 2018). The growing purchasing power of China has contributed to a remarkable increase in exports to the emerging countries, rising to US$2.134 trillion in 2018 from US$27.12 billion in 1992, with an astonishing growth of 2549%. Furthermore, the innovation environment and incentives for firms in developing countries are particularly vulnerable and sensitive to changes in the world trade environment, such as the China shock. We assess the growth alterations of exports to China across sectors and regions in a narrow sense. For every industry j in region u of nation i in year t, the metric for the rise of exposure to export expansion to China in the change in the export expansion ratio:

$$Exportshock_{iujt} = \sum_{uj} \frac{L_{iujt}}{L_{ijt}} \frac{E_{ijt}}{L_{iut}} \tag{1}$$

where L_{iujt} stands for the commencement of period employment for industry j in region u of nation i; L_{ijt} represents such commencement for industry j in nation i; L_{iut} refers to such commencement in region u.[3] E_{ijt} denotes the actual exports to China for industry j in country i. As clarified by the export expansion ratio, the transregional disparities in $Exportshock_{iujt}$ are attributed to the structural alteration of local industry employment in the initial period t (Autor et al., 2013).

Before presenting our regression results, Fig. 6 displays the correlation between the average exports to China and the average percentage of a firm's innovation activities, measured by spending on R&D (the left panel) and introducing process innovation (the right panel). The fitted lines are estimated from a univariate ordinary least square (OLS) regression with fixed effects of firm innovation activities against the average exports to China. Obviously, the fitting lines are inclined to the top right, which shows that with the increase in exports to China, the firms experienced higher innovation activities.

3.3. Control variables

The control variables are included from both the individual and macroeconomic perspectives. Macroeconomically, we control for GDP (10 billion USD) and the population (10 million) of the export countries. At the micro-firm level, we explain a range of variables frequently adopted in firms' innovation analysis, such as firm's age, firm's productivity, whether trade restriction is a major constrain, whether firms competing against unregistered or informal firms, percentage of female worker, access to land, labor regulations, corruption, tax rates, and transport. Controlling for those variables could help to reduce the omitted variable biases. These control variables are also from the dataset of WBES and CEPII.

In the final part, we try to explore how export to China affect firm's innovation activities. Theoretically, exporting to China increases the marginal return of skilled workers[4], thereby making their proportion and quantity higher and larger. In addition, we also test whether exports to China can contribute to the increase in formal training as an alternative way to confirm the wages and compensation for skilled and R&D workers. These variables are used in the mechanism analysis in Section 5. The definitions and summary statistics for the main variables are shown in the following Table 1, and the involved developing countries are listed in Appendix Table B1.

[3] The firms are categorized into a state or province for different countries. It does not affect the construction of our indicators, since the employment share is used as a weight within one specified country. The names of the regions are listed in Table B2 in the Appendix.

[4] Skilled workers are professionals or technicians whose tasks require extensive theoretical and technical knowledge.

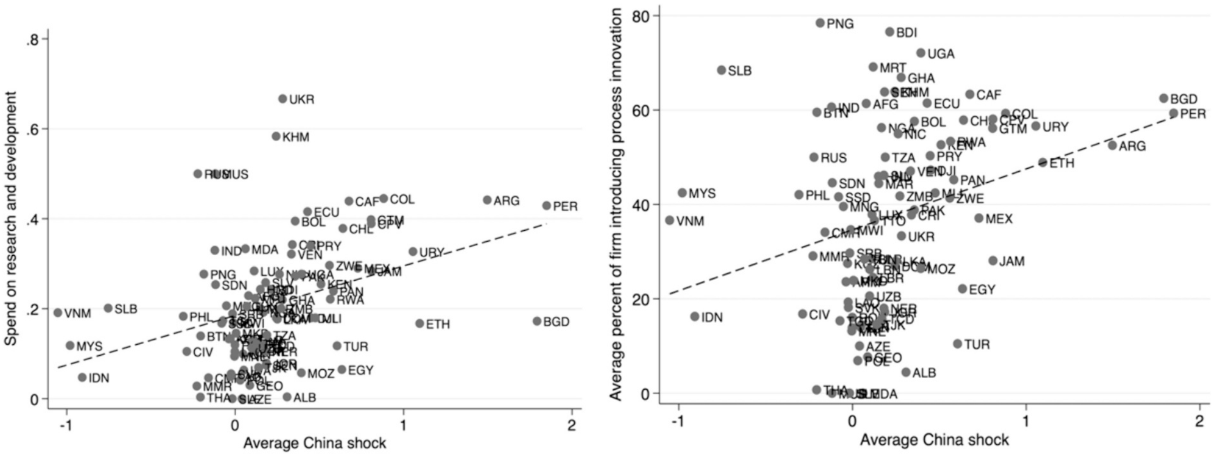

Fig. 6. Exports to China and the firm's innovation activity.

3.4. Identification strategy

Our regression assessment comprises three steps. Initially, ordinary least squares (OLS) with nation-, region-, industry- and year-fixed effects are applied. Next, Two-Stage Least Squares (2SLS) are used. Finally, we obtain causal estimates by exploiting conditional heteroskedasticity for identification. We also estimate binary dependent variables for innovation activity with a linear probability model, thereby achieving better coefficient interpretation. Our specification is formulated as follows (Eq. 2):

$$Innovation_{iujft} = \gamma_0 + \gamma_1 lnExportshock_{it} + \gamma_2 X^{'}_{ijfut} + \gamma_3 Z^{'}_{it} + \mu_t + \gamma_i + \delta_j + \eta_u + \varepsilon_{ijuft} \tag{2}$$

where $Innovation_{iujft}$ indicates whether an enterprise spends on R&D, and whether the firm introduced a process innovation of firm f in country i in region u in industry j in year t. $Exportshock_{it}$ measures the increase in exposure to export expansion to China for country i in year t. $X^{'}_{ijft}$ represents the firm-level controls, and $Z^{'}_{it}$ capture the country level controls. Adding the observed control variables helps our causal identification satisfy conditional independence assumption. Year-specific events are explained through incorporation of the year-fixed effect μ_t, which captures time-dependent shocks typical to the entire developing nations. We also add industry-level and region-level fixed effects to control for industry-specific and regional unobserved factors that may contaminate the relationship be-

Table 1
Definitions of all the variables and summary statistics.

Variable	Obs	Mean	Std. dev.	Min	Max
Depended variable					
Introduced process innovation	70,395	41.253	49.229	0	100
Spend on R&D	70,639	22.970	42.064	0	100
Interested variable					
Ln(*Exportshock*)	118,103	12.753	2.899	0.062	17.876
Instrumental variable					
$lnIV_{oujt}$	118,103	28.993	0.592	27.071	30.235
Control variables					
Firm productivity	118,390	0.714	0.107	0	2
Age	117,426	18.961	16.087	0	221
Trade constraint	108,929	0.152	0.359	0	1
Compete	100,371	0.519	0.500	0	1
Female worker (%)	101,387	0.300	0.282	0	1
Domestic sale ratio	118,519	89.315	89.315	0	100
Access to land	113,350	0.029	0.168	0	1
Regulations	113,350	0.038	0.192	0	1
Corruption	113,350	0.074	0.263	0	1
Tax rates	113,350	0.112	0.316	0	1
Transport	113,350	0.030	0.171	0	1
GDP	119,295	32.056	58.500	0.028	209.678
Population	119,360	14.646	35.046	0.005	129.386
Mechanism test variables					
Skilled worker (%)	58,780	70.248	31.163	0	100
Number of skilled workers	59,753	34.558	52.693	0	200
Whether firms offering formal training	99,108	37.443	48.398	0	100
Formal training worker (%)	19,963	58.444	33.783	0	100

tween exports to China and firm innovation activities. The observed regional factors, such as labor market conditions, infrastructure, and local policies, are all used as control variables. γ_i is the time-invariant country-fixed effect. Owing to the incorporation of these fixed effects, the latent omitted-variables biases can be alleviated. For instance, capture of temporally-invariant cultural ties or historical traits would affect exporting to China and firms' innovation activities. Finally, ε_{ujft} is the idiosyncratic error term, representing unobserved components that affect firm's innovation activities, showing regional-industry clustering, that is, the aggregation degree of the variable of interest.

Estimation of fixed effects is valid in controlling those confounders we cannot easily observe or control for. However, it does not resolve the issue of reverse causality and other omitted variables that vary with time and country. Specifically, our estimation may be affected by the correlation between realized exports to China and China's import demand shock, which could understate the true impact of elevating exports to China on firm innovation activities in developing countries.

To clarify the causal effect of increasing exports to China on firms' innovation activities, we adopt an instrumental-variables scheme inspired by Eichenauer et al., 2018 that accounts for the potential endogeneity of export exposure in developing countries. Drawing inspiration from Autor et al. (2013), who focused on the supply power of China, we argue that much of the developing countries' exports to China stems from China's rising demand strength from developing countries and its lowering of trade barriers, as well as WTO entry.

To address the endogeneity of exports to China, we use an instrumental variable constructed based on the interplay of a time-dependent exogenous variable with a parameter varying along the cross-sectional dimension. We introduce the export expansion of other developing countries as the exogenous variation. The other developing countries do not include those located on the same continent as the country itself. For example, the export exposure of Chinese goods in non-Latin American developing countries is adopted for constructing a time-varying variable exogenous to our sample countries to instrument exports to China for Latin American countries. Based on this exogenous variable, we construct an interaction term between the export expansion of other developing

Table 2
Benchmark results.

	(1)	(2)	(3)	(4)
VARIABLES	Introduced process innovation		Spend on R&D	
	OLS	Probit	OLS	Probit
Ln(Exportshock)	8.286***	0.236***	2.441***	0.108***
	(0.865)	(0.024)	(0.865)	(0.033)
Margin		0.073***		0.027***
		(0.008)		(0.008)
Productivity	5.950	0.250	27.054***	1.220***
	(10.939)	(0.313)	(5.615)	(0.220)
Age	0.079***	0.002***	0.127***	0.004***
	(0.018)	(0.001)	(0.024)	(0.001)
Trade constraint	6.054***	0.188***	4.076***	0.154***
	(0.991)	(0.029)	(0.999)	(0.031)
Compete	2.900***	0.094***	−0.566	−0.023
	(0.479)	(0.015)	(0.416)	(0.016)
Female worker (%)	2.630	0.086	1.955*	0.082*
	(1.576)	(0.054)	(1.021)	(0.045)
Access to land	−1.720	−0.056	0.140	0.006
	(1.893)	(0.060)	(1.168)	(0.051)
Regulations	1.673	0.051	1.894*	0.064*
	(1.451)	(0.044)	(1.013)	(0.034)
GDP	−0.554*	−0.012	−0.130	−0.004
	(0.319)	(0.008)	(0.240)	(0.006)
Population	0.821*	0.016	0.055	−0.003
	(0.486)	(0.015)	(0.397)	(0.014)
Corruption	−2.175**	−0.066***	0.758	0.022
	(0.824)	(0.025)	(0.868)	(0.031)
Tax rates	−0.969	−0.031	−1.198*	−0.051**
	(0.703)	(0.025)	(0.596)	(0.025)
Transport	−0.777	−0.026	0.336	0.012
	(1.170)	(0.040)	(0.858)	(0.036)
Other control variables	Yes	Yes	Yes	Yes
Year-fixed effect	Yes	Yes	Yes	Yes
Region-fixed effect	Yes	Yes	Yes	Yes
Industry-fixed effect	Yes	Yes	Yes	Yes
Constant	−23.909**	−2.253***	18.125	−1.739***
	(10.222)	(0.316)	(12.165)	(0.459)
Observations	46,378	46,125	46,457	45,724
R-squared	0.232		0.193	
Pseudo R-squared		0.187		0.177

Notes: Robust standard errors in parentheses are clustered at the regional industry level. *$p < 0.1$, **$p < 0.05$, and ***$p < 0.01$.

countries and the geographic distance of Beijing from the respective nation's capital, which representing an exogenous parameter representing trade costs. This strategy has been applied in prior work (Eichenauer et al., 2018), and is shown in Eq. (2) below.

$$IV_{oujt} = \sum_{uj} \frac{L_{iujt}}{L_{ijt}} \frac{E_{ojt} * Distance_{ci}}{L_{iut}} \tag{2}$$

This measure relies on mapping national changes in exports to China at the regional level. Following the testing methods proposed by Goldsmith-Pinkham et al. (2020), we subsequently assess the plausibility of the shift-share instrumental variable. Firstly, the identification hinges on the exogeneity of the initial industry shares. We test this assumption by examining the relationship between local industry and regional labor market characteristics and the aforementioned industry shares, which is referred to as the balance test. The correlations are presented in Table B3 in the appendix. Panel A of Table B3 presents the results of our industry-level and firm-level balance tests. All control variables are found to be unrelated to the shift-share instrument variable during this period. Panel B of Table B3 displays the regional balance tests, and we again find no statistically significant relationship between these regional-level variables and our instrument variable. Additionally, we conduct a regional "pre-trend" analysis by regressing the pre-trend variables against the shift-share instrument variable. The results are shown in Panel C of Table B3. We find no significant relationship between the shift-share instrument and the employment shares in 2000 and 2003, which are the years just before and after China's accession to the WTO in 2001. These falsification tests provide sufficient evidence for the validity of the shift-share instrument.

4. Empirical results

4.1. Baseline results

The benchmark outcomes with the country-, year-, region-, industry-fixed effects are detailed in Table 2. This method has the

Table 3
Instrument variable estimation results.

	(1)	(2)	(3)	(4)
VARIABLES	Introduced process innovation		Spend on R&D	
	2SLS	IV-Probit	2SLS	IV-Probit
Ln(Exportshock)	10.438**	0.293***	8.269***	0.269***
	(4.004)	(0.102)	(3.021)	(0.096)
Productivity	5.659	0.241	26.382***	1.203***
	(11.103)	(0.315)	(6.102)	(0.369)
Age	0.079***	0.002***	0.127***	0.004***
	(0.019)	(0.000)	(0.024)	(0.000)
Trade constraint	6.058***	0.188***	4.091***	0.154***
	(0.998)	(0.018)	(1.001)	(0.020)
Compete	2.895***	0.093***	−0.582	−0.023
	(0.478)	(0.014)	(0.413)	(0.016)
Female worker (%)	2.620	0.005	0.086***	1.925*
	(1.589)	(0.006)	(0.029)	(1.021)
Access to land	−1.753	0.012*	−0.057	0.050
	(1.889)	(0.006)	(0.039)	(1.173)
regulations	1.651	0.007**	0.050	1.838*
	(1.431)	(0.004)	(0.032)	(0.998)
GDP	−0.572*	−0.013***	−0.180	−0.005
	(0.292)	(0.004)	(0.218)	(0.005)
Population	0.809*	0.015	0.031	−0.004
	(0.463)	(0.016)	(0.365)	(0.017)
Corruption	−2.208***	−0.067***	0.665	0.019
	(0.802)	(0.025)	(0.884)	(0.026)
Tax rates	−0.935	−0.031	−1.110*	−0.048**
	(0.723)	(0.022)	(0.616)	(0.024)
Transport	−0.784	−0.027	0.314	0.011
	(1.161)	(0.041)	(0.863)	(0.046)
First stage				
lnIVdis1	−4.761***	−4.761***	−4.742***	−4.742***
	(0.507)	(0.062)	(0.511)	(0.062)
AR-Test		8.27***		7.85***
F statistic	88.04		86.25	
Year-fixed effect	Yes	Yes	Yes	Yes
Region-fixed effect	Yes	Yes	Yes	Yes
Industry-fixed effect	Yes	Yes	Yes	Yes
Observations	46,378	46,125	46,457	45,724
R-squared	0.006		0.004	

Notes: Robust standard errors in parentheses are clustered at the regional industry level. *p < 0.1, **p < 0.05, and ***p < 0.01.

advantage of solving the problem of omitted variables and alleviating part of the endogeneity issues. The level of enterprise innovation is determined by two indicators. In the initial two columns, "whether the firm introduced an innovation process" is employed as the dependent parameter, while columns (3) and (4) use "whether the firm spends on research and development." As our dependent variables are binary, using OLS regression may lead to biased results. Therefore, we also employ the Probit model for complementary analysis.

The Table 2 findings display the influence of exporting to China on developing country firms' innovation. The entire coefficients of interest are statistically significant at the 1% level and positive, consistently showing that exports to China favorably impacts firms' innovation activities. The average marginal effect calculated by the Probit model on the sample observation value is consistent with the coefficient of the OLS regression. The marginal effect of China's shock on the two innovation indicators is 0.073 and 0.027, respectively. With other variables held constant, a 1% rise of demand shock in China is linked to a 0.236% elevation in the probability of an enterprise introducing a process innovation and a 0.108% increase in the probability of spending on research and development. This result indicates that the firm innovation activities in developing nations are affected predominantly by positive experiences with exports to China.

In terms of these control variables, most of their effects are consistent with theoretical predictions. A firm's productivity has a strong positive effect on spending on R&D, and mature firms are more likely to invest in innovation activities. If a firm faces more informal competition, it is more likely to engage in innovation activities. Readers may have concerns regarding the issue of endogeneity in firm productivity. While it is true that endogeneity of productivity could result in a biased coefficient of productivity, it should not bias the estimated effect of exports to China on firm innovation activities. In our regression model, firm productivity is included as a control variable. This allows us to account for the correlation between firm productivity and exports to China, regardless of its endogeneity. By controlling for this variable, we can obtain an unbiased estimator for our variable of interest.

Corruption and higher tax rates would lower firms' innovation activities, implying that domestic institutions have a significant effect on firm innovation performance. However, the effect of GDP on firm innovation is negative in developing countries, and trade restrictions have a positive effect on firm innovation activities. This can be explained by the infant industry protection theory, suggesting that higher trade protection may benefit the growth of firms, and import competition would dampen firm innovation activities in developing countries. For developing countries, exporting to China opens a window of opportunity to spur firm innovation activities, as evidenced by our empirical results.

4.2. Endogeneity issue

Table 3 shows the results of using an interaction term between the export expansion and the geographic distance of Beijing from respective nation's capital as an instrument variable (IV). As expected, the first-stage regression demonstrates a negative coefficient on the interaction variable, indicating that countries that are closer to China experienced a greater increase in demand than those further away. The F-statistic much higher than the cutoff value of 10 recommended by Staiger and Stock (1997), while significance is found in the AR test outcomes at the 1% level. Suggestively, the weak instrumental variable issue can be eliminated. As demonstrated by the second-stage regression, the trade shock in China impacted the firm innovation favorably. Specifically, a 1% rise of China shock is linked to a 0.293-point probability elevation of a firm introducing process innovation.

It was found that the second-stage regression outcomes are consistent with the benchmark regression when controlling for endogeneity, and the coefficient slightly increases. For each percent increase in China's demand shock, enterprises can introduce innovation processes by 0.293 units, and the probability of R&D investment will increase by 0.296. This finding conforms to the prior finding which implies that through the "learning-by-exporting" effect, exporting countries can improve their innovation ability and productivity level in the technology diffusion process in the host country.

4.3. Robustness checks

4.3.1. A supplementary instrumental variable approach

Readers may be concerned about the endogeneity issue, arguing that the instrumental variable is not purely exogenous. To address this concern, we adopt the estimation method proposed by Lewbel (2012) as a supplementary instrumental variable approach, which does not rely solely on exclusion constraints. The two-stage estimator for heteroskedasticity-based identification formulated by Lewbel (2012) is implemented, where identification is accomplished without any exclusion constraints in case the errors are heteroskedastic and certain exogenous parameters are present in the structural equation. In our work, the aforementioned exports to China was adopted as the exogenous variable (denoted as Z vector).

To be specific, the endogenous parameter is regressed against the entire control parameters during the first stage, and the residuals are retrieved. Thereafter, instrumental parameters are created with the utilization of these residual estimates. The second stage regression is then estimated using the instrument variables and control variables. Specifically, in the opinion of Lewbel (2012), there are two steps to achieve identification. Initially, the endogenous variable is regressed against the control variables and the residuals $\widehat{\varepsilon_{it}}$ are retrieved. Second step is multiplication of the residual estimate $\widehat{\varepsilon_{it}}$ by $(z-\overline{z})$, with z denoting our IVs (the weighted China shock of other developing countries) and $\overline{z}$ denoting its mean as shown in Eq. (3). The instrumental variable can be considered exogenous in case several exogenous parameters exist in the instrumental variable equation in regression, and the error has heteroscedasticity.

$$Lewbel\_IV = (z-\overline{z})\ \widehat{\varepsilon_{it}} \tag{3}$$

Table 4 shows the instrumental variable approach outcomes based on the Lewbel_IV method. As suggested by the first-stage F-test, the instrumental variable is strong, whereas the AR-Test suggests that the weak instrumental variable assumption is rejected. Significance is found in the first-stage regression outcomes at the 1% level, indicating the effectiveness of the instrumental variable. In the second stage, the innovation index coefficients remain positivity and statistical significance at the 1% level, whose values are 0.195 and 0.099, respectively, which are relatively close to those in the benchmark regression.

4.3.2. An alternative firm innovation indicator

There are various indicators that can measure firms' innovation ability, and it is possible that China demand shocks have different effects on firm innovation in developing countries, depending on the indicator used. To address this, we explore using alternative variables to represent the corporate innovation capacity. In our robustness check, we further consider "whether introducing a new product/service" as alternative measures of the firm's creativity. The outcomes for these regression analyses are displayed in Table 5. (1)–(2) columns do not control for macro variables, while the (3)–(4) columns do. Columns (1) and (3) present the 2SLS estimation results, and the remaining columns present IV-Probit estimation results. (See Table 5.)

The results presented in this series are consistent with previous findings. A 1 % increase in China's trade shock leads to a 14.104% probability rise of an enterprise incorporating an innovative product or service. Thus, it can be concluded that, in general, exports to China influences the corporate innovation in developing nations significantly favorably, providing robust evidence to support our results.

4.3.3. Adding the proportion of firms' domestic sales as an additional control variable

Addressing the concern about whether these products are consumed domestically, potentially influencing firms' innovation activities, we have added the proportion of firms' domestic sales as an additional control variable, as presented in Table 6. The F-statistic and AR value have passed the test, eliminating the weak instrumental variable issue. The results reveal a negative relationship between the proportion of firms' domestic sales and firm innovation activities, both in terms of introducing process innovation (Columns 1 and 2) and spending on R&D (Columns 3 and 4). This suggests that firms with higher domestic sales exhibit lower innovation activities, confirming that innovation activities are indeed driven by exports to China.

4.3.4. The lagging effects of exports to China

Another concern is that exports to China may have a lagging impact on firm innovation behavior. To address this, we conducted an additional robustness check using the one-year lag of exports to China as the variable of interest in the regressions, as shown in Table 7. Columns (1) and (2) present the lagging effects of exports to China on whether a firm introduces process innovation, while the lagging effects on spending on R&D are reported in Column (3) and (4). All the regressions still yield significantly positive results, with instrumental variables passing the test. This further supports our results from the benchmark regressions.

4.4. Heterogeneous analysis

4.4.1. The role of firm age

Prior research suggests that younger firms may benefit more from international knowledge acquisition for innovation (Bouncken et al., 2021). To assess how the innovation performance of an enterprise is affected by its age in developing countries in the face of Chinese demand, we conducted group regression based on the length of time the corporation had been operating. Since the firms in our sample exhibited a median age of 15 years, we divided them into two groups: young firms, which had been operating for <15 years, and mature firms, which had been in business for longer. Panel A in Table 7 shows that firms of different ages have different responses

Table 4
Applying heteroskedasticity of error term as the instrumental variable.

	(1)	(2)	(3)	(4)
VARIABLES	Introduced process innovation		Spend on R&D	
	2SLS	IV-Probit	2SLS	IV-Probit
Ln(Exportshock)	7.112***	0.195***	2.017***	0.099**
	(0.969)	(0.041)	(0.679)	(0.044)
First stage				
$lnIV_{oujt}$	0.021***	0.021***	0.021***	0.021***
	(0.001)	(0.000)	(0.001)	(0.000)
AR-Test		22.85***		5.06**
First-stage F statistics	405.26		429.09	
Other control variables	Yes	Yes	Yes	Yes
Year-fixed effect	Yes	Yes	Yes	Yes
Region-fixed effect	Yes	Yes	Yes	Yes
Industry-fixed effect	Yes	Yes	Yes	Yes
Observations	46,378	46,125	46,457	45,724
R-squared	0.006		0.005	

Notes: Robust standard errors in parentheses are clustered at the regional industry level. *$p < 0.1$, **$p < 0.05$, and ***$p < 0.01$.

Table 5
New firm innovation indicator estimations.

	(1)	(2)	(3)	(4)
VARIABLES	Introduced a new product/service			
	2SLS	IV-Probit	2SLS	IV-Probit
Ln(Exportshock)	7.753***	0.215**	14.104***	0.419***
	(2.816)	(0.094)	(2.782)	(0.110)
First stage				
$lnIV_{oujt}$	−4.669***	−4.669***	−4.762***	−4.762***
	(0.476)	(0.059)	(0.508)	(0.062)
AR-Test		14.51***		5.24**
First-stage F statistics	96.16		87.81	
Country controls	No	No	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	46,740	46,554	46,590	46,404
R-squared	0.005		0.006	

Notes: Robust standard errors in parentheses are clustered at the regional industry level. *p < 0.1, **p < 0.05, and ***p < 0.01.

Table 6
Adding domestic sales as an additional control variable.

	(1)	(2)	(3)	(4)
VARIABLES	Introduced process innovation		Spend on R&D	
	2SLS	IV-Probit	2SLS	IV-Probit
Ln(Exportshock)	8.654*	0.249**	6.475*	0.234**
	(4.367)	(0.114)	(3.654)	(0.106)
Domestic sale	−0.129***	−0.004***	−0.181***	−0.007***
	(0.014)	(0.000)	(0.015)	(0.000)
First stage				
$lnIV_{oujt}$	−4.702***	−4.702***	−4.684***	−4.684***
	(0.593)	(0.069)	(0.593)	(0.069)
AR-Test		8.69***		3.03*
First-stage F statistics	62.98		62.37	
Year-fixed effect	Yes	Yes	Yes	Yes
Region-fixed effect	Yes	Yes	Yes	Yes
Industry-fixed effect	Yes	Yes	Yes	Yes
Observations	46,066	45,813	46,149	45,416
R-squared	0.011		0.018	

Notes: Robust standard errors in parentheses are clustered at the regional industry level. *p < 0.1, **p < 0.05, and ***p < 0.01.

Table 7
The lagging effect that exports to China has on firm innovation.

	(1)	(2)	(3)	(4)
VARIABLES	Introduced process innovation		Spend on R&D	
	2SLS	IV-Probit	2SLS	IV-Probit
Lag_ *Ln(Exportshock)*	9.991*	0.277**	7.576**	0.250**
	(5.296)	(0.108)	(3.066)	(0.102)
First stage				
Lag_lnIV_{oujt}	−4.319***	−4.319***	−4.313***	−4.313***
	(0.404)		(0.406)	
AR-Test		6.59**		6.00**
First-stage F statistics	114.22		112.63	
Other control variables	Yes	Yes	Yes	Yes
Year-fixed effect	Yes	Yes	Yes	Yes
Region-fixed effect	Yes	Yes	Yes	Yes
Industry-fixed effect	Yes	Yes	Yes	Yes
Observations	47,387	47,134	47,466	46,733
R-squared	0.006		0.004	

Notes: Robust standard errors in parentheses are clustered at the regional industry level. *p < 0.1, **p < 0.05, and ***p < 0.01.

to the China shock, with mature firms exhibiting a more intense innovation reaction than young firms. Interestingly, the results show that the effects are more pronounced for mature firms, and the young firms are more likely to introduce process innovation directly, rather than spending more on R&D.

4.4.2. *Heterogeneous effects on exporters and non-exporters*

In our paper, the export shock is constructed at the industry level, and this shock may have spillover effects on non-exporters. To address this concern, we examine the heterogeneous effects that exports to China have on both exporters and non-exporters. The results, presented in Panel B of Table 8, indicate that exports to China stimulate firm innovation behavior among exporters, manifesting in increased spending on R&D and the introduction of process innovation. Conversely, for non-exporters, the impact is observed in the introduction of process innovation rather than increased spending on R&D.

Comparing the different effects of exports to China on process innovation and R&D spending among different groups of firms, we find that young firms and non-exporters are more likely to prioritize the introduction of process innovations over increased R&D expenditure. While increased R&D spending can benefit firms in terms of product innovation and quality upgrading, young firms and non-exporters often find it more feasible to directly introduce process innovations. Firstly, introducing process innovations is a cost-saving alternative compared to allocating resources to R&D spending. Given their potentially limited funding capacity, young firms and non-exporters may face challenges in supporting large-scale R&D investments. Secondly, introducing process innovations entails lower risk compared to R&D-based innovation. These firms cannot guarantee that increased investment in R&D will yield scientific research results that definitively improve product quality.

4.4.3. *The role of the "One Belt and One Road Initiative"*

Since 2013, there has been a stronger alignment between innovation activities among developing countries and their exports to China, as shown in Fig. 5. This enhanced relationship may be driven by the "One Belt and One Road Initiative" (BRI) launched by China in 2013. To explore the heterogeneity of China's shock on firm innovation before and after the BRI, we employ the triple-difference method to uncover the causal effect. The triple-difference method relies on three levels of variation. The first involves variation in firm export destinations, treating BRI-involved countries as the treatment group, and the countries along the BRI route are presented in Table B4 in the Appendix. The second variation is presented by the time before or after the launch of BRI in 2013. The third variation (*lnExportshock*) is developing countries' exports to China, treated as a continuous treatment to capture the firm innovation driven by exports to China rather than total trade. However, developing countries' export to China is time-varying and may introduce simultaneity bias into the estimates. To address this issue, we use the ex-ante export value as the third variation to avoid potential simultaneity bias. We choose the ex-ante export value in 2011 rather than 2012 to avoid the potential expectation effect before the

Table 8
Group analysis.

	(1)	(2)	(3)	(4)		(5)	(6)	(7)	(8)
Panel A: **Firm's Age**									
VARIABLES	Introduced process innovation					Spend on R&D			
	Young firm		Mature firm			Young firm		Mature firm	
	2SLS	IV-Probit	2SLS	IV-Probit		2SLS	IV-Probit	2SLS	IV-Probit
Ln(Exportshock)	11.290**	0.325**	11.050***	0.389***		4.031	0.068	18.465***	1.062***
	(4.702)	(0.160)	(3.100)	(0.142)		(4.225)	(0.198)	(3.584)	(0.375)
First stage									
$lnIV_{oujt}$	−4.313***	−4.313***	−5.128***	−5.128***		−4.295***	−4.296***	−5.116***	−5.195***
	(0.797)	(0.076)	(1.045)	(0.101)		(0.793)	(0.077)	(1.052)	(0.102)
AR-Test		4.11**		7.45***			0.12		8.04***
F statistic	29.31		24.07			29.36		23.64	
	Controls; Year FE, Country FE, Region FE, Industry FE								
Observations	21,944	21,682	24,430	24,241		22,003	21,201	24,450	23,603
R-squared	0.005		0.007			0.004		−0.002	
Panel B: **whether the enterprise is an exporter**									
	Non-Exporters		Exporters			Non-Exporters		Exporters	
Ln(Exportshock)	8.467*	0.252**	11.898**	0.450***		4.183	0.181	15.839***	0.744**
	(4.955)	(0.126)	(4.873)	(0.166)		(3.447)	(0.121)	(4.714)	(0.354)
First stage									
$lnIV_{oujt}$	−4.539***	−4.539***	−7.329***	−7.328***		−4.525***	−4.539***	−7.328***	−7.297***
	(0.590)	(0.070)	(1.146)	(0.142)		(0.591)	(0.070)	(1.144)	(0.141)
AR-Test		3.99**		7.36***			2.23		4.42**
First-stage F statistics	59.12		40.87			58.65		41.03	
Other control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region-fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	38,263	37,995	7825	7641		38,306	37,113	7864	7636
R-squared	0.006		0.008			0.004		−0.001	

Notes: Robust standard errors in parentheses are clustered at the regional industry level. *p < 0.1, **p < 0.05, and ***p < 0.01.

implementation of BRI in 2013. The triple-difference model is set as the following Eq. (4), and the effect of BRI on firm innovation is captured by π.

$$Innovation_{iujft} = \gamma_0 + \pi lnExportshock_{2011}*Year13*Country + \varnothing lnExportshock_{it}*Year13 + \beta Year13*Country + \gamma_2 X'_{ijfut} + \gamma_3 Z'_{it}\varphi + \mu_t + \gamma_i + \delta_j + \eta_u + \varepsilon_{ijuft} \tag{4}$$

Table 9 presents the main results using the triple-difference method, which demonstrate that exports to China had an increasingly positive impact on firm innovation in developing nations following the initiation of the BRI. Regardless of the dependent variable being used, as shown from column (1) to column (4), the effects consistently demonstrate positive and significant results. Careful control has been exercised over all other control variables, two interaction terms, and fixed effects. This finding is consistent with the conclusions drawn by Wu and Si (2022), who also observed a significant and favorable impact of the BRI on corporate technological innovation. Therefore, our findings suggest that the implementation of the BRI has strengthened the already positive effects that exports to China have on firm innovation activities.

Additionally, we utilize the BRI as a natural experiment and conduct a 2SLS analysis. Specifically, we adopt a DID strategy by incorporating the BRI and a post-2013 dummy variable to predict a country's exports to China. Subsequently, we regress firm innovation on the predicted export value. The 2SLS estimation results, presented in Table B4 in the Appendix, align with the results obtained through the triple-difference approach. To further analyze the dynamic effect of the BRI on firm innovation activities, Fig. C1 in the Appendix indicates an insignificant coefficient prior to 2013, which subsequently evolves into a significant effect. As anticipated, the implementation of the BRI in 2013 exhibits a lasting and escalating impact on promoting firm innovation activities in developing countries.

5. Mechanism analysis

5.1. Exports to China and labor adjustment

One possible mechanism by which China demand shocks affect firm innovation in developing countries is through the dynamic adjustment of the firm labor force. Developing country firms may adjust the structure of their labor force through internal transformation and external employment in response to market demand in their export trade with China. Changes in different types of workers may directly impact the corporate innovation performance. At the market demand dimension, the fierce competition pressure from third countries may lead to a pursuit of higher efficiency and lower labor costs. However, developing countries also require skilled workers to navigate complex export trade, including language and cultural barriers, laws, and regulations of the importing country, among others. With the expansion of the Chinese market, the price of exporting products increases, leading to a relatively higher marginal benefit of employing R&D workers compared to unskilled workers. As a result, firms may prefer to employ a locally educated or professionally trained workforce (Doms et al., 2010). The China's innovation-driven mechanism through the adjustment of labor structure as per Gu et al.'s (2021) procedure is modelled as shown in the Appendix.

Based on these discussions, we conducted an empirical analysis of China shocks and the structure of the enterprise labor force and estimated how the adjustment of the enterprise labor force structure affected enterprise innovation. Our results suggest that exports to China can contribute to the dynamic adjustment of a firm's labor force structure, which in turn boosts firms' innovation activities. Table 10 presents the regression results for the demand shock effect in China on the dynamic adjustment of enterprise labor force. Columns (1) to (3) and (4) to (6) show the regression results with the quantity and proportion of skilled employees as the dependent variables, respectively. Both models use the IV approach.

Table 9
The role of "One Belt and One Road Initiated" launched in 2013.

	(1)	(2)	(3)	(4)
VARIABLES	Introduced process innovation		Spend on R&D	
	OLS	Probit	OLS	Probit
$Lnexportshock_{2011}$*year*country	3.714***	0.125***	1.170**	0.042*
	(0.962)	(0.036)	(0.513)	(0.022)
Two-interaction terms	Yes	Yes	Yes	Yes
Other control variables	Yes	Yes	Yes	Yes
Year-fixed effect	Yes	Yes	Yes	Yes
Region-fixed effect	Yes	Yes	Yes	Yes
Industry-fixed effect	Yes	Yes	Yes	Yes
Constant	38.824***	−0.203	51.816***	−0.239
	(6.435)	(0.214)	(7.878)	(0.233)
Observations	46,378	46,330	46,931	49,339
R-squared	0.181		0.137	

Notes: Robust standard errors in parentheses are clustered at the regional industry level. *$p < 0.1$, **$p < 0.05$, and ***$p < 0.01$.

Columns (1) and (6) reveal that exports to China contribute to a higher quantity and proportion of skilled labor. When we decompose exports into higher capital-intensive and lower capital-intensive goods, the results indicate that the enhancement of innovation activity occurs predominantly through capital-intensive goods. Specifically, for every 1% increase in export trade to China, developing country firms witness an 18-unit increase in the number of skilled workers and an almost 6% rise in the proportion of skilled workers among the total workforce. From columns (2) and (5), it is evident that sectors with lower capital intensity experience a decline in both the proportion and number of skilled workers. However, when considering the overall perspective, export activities to China foster an increase in the employment proportion and quantity of skilled labor. This aligns with theoretical predictions, suggesting that exporting capital-intensive products to China could raise the marginal revenue of skilled labor, thereby directly impacting firm innovation performance. The main reasons could be twofold. Firstly, skilled workers function as human capital to complement physical capital in developing countries, as physical capital is relatively scarce in these less developed nations. Secondly, exporting to China requires skilled workers to perform quality upgrading tasks. These two potential mechanisms can encourage firms to hire more skilled workers rather than unskilled workers. If this premise holds true, the export of high R&D intensive goods will also lead to an increase in skilled labor, while the export of low R&D intensive goods will have the opposite effect. The empirical tests are presented in Table B6 in the Appendix, and the results further confirm our arguments.

According to the concept of motivating workers to acquire higher skills and engage in higher-paying jobs, further stimulating the growth of skilled labor (Suzuki, 2023), in developing countries, workers often cannot exploit opportunities for premium wages in skill-intensive sectors due to insufficient education facilities. In this paper, we further explore whether exports to China could incentivize firms to provide more formal training as a means to favor skilled workers, enabling them to access wage premiums and compensations. Formal training would also facilitate the transition from unskilled to skilled workers, thereby increasing firms' innovation activities.

Building on this premise, we investigate changes in the proportion of enterprises providing formal training under the influence of exports to China. The results, presented in Table 11, indicate that exports to China have increased the likelihood of developing country companies providing formal training (as shown in Columns (1) and (2)) and raised the proportion of employees receiving formal training within the firms (as shown from Column (3) to Column (4)).

5.2. *How much does labor adjustment contribute to firm innovation*

The critical readers may be concerned about how much labor adjustment contributes to firm innovation. In this section, we employ a two-step regression method proposed by Gu et al. (2021) to analyze the extent to which innovation benefits from an increase in the number of skilled laborers in a firm driven by total exports to China. As indicated in Table 12, exports to China significantly increase the number of skilled workers (Column 3). We observe a positive correlation between exports to China and the number of R&D personnel, with a coefficient of 4.2. This implies that for every 1% increase in trade volume, there is a 12.1% increase in the number of skilled laborers. Next, we examine the overall impact of trade on innovation activities and investigate the extent to which this impact can be attributed to the increase in the number of skilled workers.

Based on the coefficients shown in columns (1)–(2) of Table 11, a 1% increase in exports to China results in a 12.3-unit increase in the likelihood of firms introducing innovation, equivalent to a 30% increase (12.281/41.252, the coefficient of Ln(ΔExportshock) divided by the mean of Y). For a 1 percentage point increase in the number of skilled labor due to exogenous demand shocks from China, there is a 1.1 increase in the likelihood of firms introducing innovation processes.

Columns (4)–(5) indicate that a 1% increase in exports to China leads to an 8.6-unit increase in the likelihood of firms investing in R&D, equivalent to a 38% increase (8.629/22.970). Moreover, a 1 percentage point increase in the number of skilled labor due to exogenous demand shocks from China results in a 0.971 increase in the likelihood of firms engaging in R&D activities. Since every 1% increase in exports to China is associated with a 4.2-unit increase in the number of skilled laborers (see column (3)), our conclusion is that approximately 37.86% of the increase in the likelihood of firms introducing innovation processes due to export to China is attributed to the increase in the number of skilled labor (1.112*4.181/12.281 = 37.86%), and approximately 47.05% of the increase in the likelihood of firms engaging in R&D activities is attributed to the increase in the number of skilled labor (0.971*4.181/8.629 = 47.05%).

6. Concluding remarks

China plays a crucial role as an international trade participant. A chief debated topic in the United States is the influence exerted by severer import competition from China over the employment. As China's international status and economy continue to rise, more and more countries seek trade opportunities with China. At the micro level, companies engage in innovative activities to gain a competitive advantage in commodity trade and secure a place in the global market. To further understand how China's trade development affects the innovation performance of enterprises in developing countries, the present work focuses on China's import trade with developing countries and examines its impact from a labor perspective.

Using micro-data from 128 developing countries spanning 2006–2021 provided by the WBES, China's imports with several agents of enterprise innovation input and output were assessed, and the mechanism behind it was further explored. Findings of the present work have profound implications for the development paths and workforce adjustment of developing countries participating in international trade, especially those that are increasingly engaged with the Chinese market.

The foremost argument and primary contribution of the present work is that the gross increase in China's imports could significantly spur firm innovation activities in developing countries. Compared to young enterprises, such a positive association is more distinct among mature ones, indicating that mature firms are more likely to improve innovation performance in reaction to the demand

Table 10
The effects of exports to China on firms' hiring structure of skilled workers.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Number of skilled workers			Proportion of skilled workers (%)		
Capital intensity level	High	Low	All	High	Low	All
Ln(Exportshock)	18.770*	−5.797*	4.724**	5.776***	−3.328***	5.791*
	(9.794)	(2.748)	(2.021)	(1.109)	(0.960)	(2.989)
First stage						
$lnIV_{oujt}$	−8.650***	−6.501***	−10.921***	−8.570***	−11.369***	−4.732***
	(1.009)	(0.548)	(1.747)	(1.000)	(2.224)	(1.006)
First-stage F statistics	73.41	140.91	39.09	73.44	26.12	22.13
Other control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year-fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Region-fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,768	32,606	47,128	15,566	30,206	40,087
R-squared	0.027	0.013	0.016	0.002	0.001	0.003

Notes: Standard errors in parentheses are clustered at the regional industry level. $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

Table 11
The effects of exports to China on firms' provision of formal training.

	(1)	(2)	(3)	(4)
VARIABLES	Whether firms offering formal training		Proportion of workers offered formal training (%)	
	2SLS	IV-Probit	2SLS	IV-Probit
Ln(Exportshock)	4.030*	0.123*	3.746**	0.246***
	(1.997)	(0.071)	(1.781)	(0.033)
First stage				
$lnIV_{oujt}$	−5.734***	−5.733***	−1.233***	−0.999***
	(0.669)	(0.070)	(0.243)	(0.061)
First-stage F statistics	73.45		25.68	
AR-Test		2.99*		3.79*
Other control variables	Yes	Yes	Yes	Yes
Year-fixed effect	Yes	Yes	Yes	Yes
Region-fixed effect	Yes	Yes	Yes	Yes
Industry-fixed effect	Yes	Yes	Yes	Yes
Observations	66,145	65,832	60,099	44,700
R-squared	0.005		0.002	

Notes: Robust standard errors in parentheses are clustered at the regional industry level. $^{*}p < 0.1$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

Table 12
Exports to China, firm innovation, and the number of skilled workers.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Introduced process innovation		Number of skilled workers	Spend on R&D	
Ln(Exportshock)	12.281**		4.181*	8.629***	
	(5.152)		(2.374)	(2.688)	
Number of skilled workers		1.112***			0.971**
		(0.350)			(0.434)
First stage					
$lnIV_{oujt}$	−4.427***	−47.198***	−1.344***	−4.430***	−66.587***
	(0.407)	(17.810)	(0.229)	(0.410)	(25.343)
First-stage F statistics	118.17	10.30	34.46	116.66	10.13
Other control variables	Yes	Yes	Yes	Yes	Yes
Year-fixed effect	Yes	Yes	Yes	Yes	Yes
Region-fixed effect	Yes	Yes	Yes	Yes	Yes
Industry-fixed effect	Yes	Yes	Yes	Yes	Yes
Mean Y	41.252	41.252	34.558	22.970	22.970
Observations	29,913	32,616	40,636	29,980	26,709

Notes: Standard errors in parentheses are clustered at the regional industry level.; ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

shocks in China, while the young firms only introduce process innovation directly, rather than spending more on R&D. China's imports not only benefit the exporters but also have a spill-over effect on non-exporters. However, the non-exporters would gain from introducing process innovation directly, rather than spending on R&D. It was also discovered that the positive effect of China's demand shocks on the innovation performance of enterprises in developing countries has further been facilitated by the Belt and Road Initiative launched by China in 2013.

We then delve into the possible impact mechanism, which involves China promoting the innovation of enterprises in developing nations through the quantity and proportion increases in skilled labor. The increase in skilled labor is only driven by capital-intensive exports to China, which is consistent with the prediction of our theoretical model. This influx of skilled workers brings advanced technology and professional skills that facilitate the introduction of innovation processes or independent research, ultimately improving the innovation performance of enterprises. Using a two-step regression method, we find that these labor adjustments could contribute to the increase in the likelihood of firms introducing process innovation and spending on R&D by 38% and 47%, respectively.

Data availability

Data will be made available on request.

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Appendix A. How does exporting to China drive firm labor adjustment?

Building on the dynamic enterprise model proposed by Gu et al. (2021), we demonstrate that when enterprises in developing countries face China shocks, the expanded import demand leads to spontaneous adjustments in enterprises and workers. Through the flow of different types of workers within and across firms, non-R&D workers reduce while R&D workers increase, providing a theoretical basis for the mechanism analysis. Unlike Gu et al. (2021), who focused on the adjustment path of the labor force of enterprises in response to import competition in developed economies, our study mainly examines the dynamic adjustment mechanism of the enterprise labor force in developing countries caused by various factors such as enterprises' export preference and price changes when facing the huge import demand from China.

When firms in developing countries export to other countries, they need provide relatively high-quality products and labor to cope with fierce international competition. To obtain competitive advantages, they prefer to introduce advanced technology, employ high-skill labor to improve the production efficiency, and actively expand its own scale. Therefore, compared with domestic products, the export products of developing countries can be called innovative labor resource-intensive products (Grossman & Rossi-Hansberg, 2008). Firstly, we assume that there are two types of firms $f = \{1\ ,\ 2\}$, they all produce two kinds of goods $g\ = \{N, E\}$, and provide two kinds of jobs $x = \{n\ ,\ r\}$. Especially, jobs and workers are presented by $\{n\ ,\ r\}$. Among them, N represents the low-tech products of domestic trade, which are manufactured by non-R&D staff n_f. The expression for its production function is shown below:

$$y_f^N = zn_f^{\alpha} \tag{A-1}$$

Where z represents productivity, the price of goods N p_0 is exogenous which is determined by domestic market.

Product E is a high-tech product exported to China (that is, affected by China's trade shock), and is produced by skilled workers γ_f. Its production function is expressed as Eq. (A-2):

$$y_f^E = a_f r_f^{\alpha} \tag{A-2}$$

Where a_j is innovation productivity and p_i specifies price of product E.

Except for the difference in innovation ability ($a_j\ = \{a_1\ ,\ a_2\}$), the other conditions of the two companies are the same. In general, we assume that f_1 is more productive than f_2 in producing innovative products, that is, $a_1\ > a_2$.

Next, consider the two ways in which firm f conduct labor adjustment: internal labor transfer and external hiring to bring workers into R&D jobs r_f and non-R&D jobs n_f. We assume that in each period, the exogenous rate of workers leaving their own positions is $0 < s < 1$, and in a stable state, the conversion of these two pathways can be carried out simultaneously. We assume the labor conversion within the firm as i_f, and $i_f > 0$ (non-R&D workers are converted to R&D workers). In addition, we use h_x to represent hiring from external channels such as other companies, colleges, and universities, where $x\ = \{n_f\ ,\ r_f\}$, representing the hiring of non-R&D workers and R&D workers from outside, respectively.

The spending on external employment and internal conversion is a quadratic function of the employee quantity with the parameter ρ. Specifically, the cost of internal conversion (non-R&D workers into R&D workers) is $\frac{\rho}{2}i_f^2$, the cost of externally hired R&D personnel is $\frac{\rho}{2}h_{r_f}^2$, , and the cost of non-R&D workers is $\frac{\rho}{2}h_{n_f}^2$.

For the R&D and non-R&D personnel, their incomes are determined after negotiation between the company and the workers, and the two wages are determined separately. According to the Nash equilibrium, this wage is the equilibrium wage that maximizes the surplus of workers and firms:

$$S_x = MV_x + W_x \tag{A-3}$$

Where $x = \{n_f\ ,\ r_f\}$ represents two types of job, $W_X = w_x - b_x$, b_x is unemployment benefits for different types of workers. Therefore, W_X is the net benefit for the x-type worker from unemployment to employment. MV_x is the marginal benefits that the firm earns by hiring workers of type x.

Defining the bargaining power of workers as $0 < \theta < 1$, the wages that reach Nash equilibrium are in Eq. (A-4):

$$w_x^* = argmax_{wx}(MV_x)^{1-\theta}(W_x)^{\theta} \tag{A-4}$$

Consider the maximization problem that company f is most concerned about in production and operation:

$$MV\left(n_f\ ,\ r_f\ ,\ p_0\right) = \max_{i_f\ ,\ h_{n_f}\ ,\ h_{r_f}} \pi_f + E\beta MV\left(n_f^{'}, r_f^{'}, p_0^{'}\right) \tag{A-5}$$

$$\text{s.t.} p_0 z n_f^{\alpha} + p_i a r_f^{\alpha} = \pi_f + w_{n_f}^* n_f + w_{r_f}^* r_f + \frac{\rho}{2} i_f^2 + \frac{\rho}{2} h_{r_f}^2 + \frac{\rho}{2} h_{n_f}^2 \text{ (cost)} \tag{A-6}$$

$$n_f^{'} = (1-s)n_f - i_f + h_{n_f} \tag{A-7}$$

$$r_f^{'} = (1-s)r_f + i_f + h_{r_f} \tag{A-8}$$

$$w_{n_f}^* = argmax_{w_{n_f}}\left(MV_{n_f}\right)^{1-\theta}\left(W_{n_f}\right)^{\theta} \tag{A-9}$$

$$w_{r_f}^* = argmax_{w_{r_f}}\left(MV_{r_f}\right)^{1-\theta}\left(W_{r_f}\right)^{\theta} \tag{A-10}$$

Where π_f is firm fs profit and $0 < \beta < 1$ refers to discount rate.

Considering the above, we demonstrate the model from several aspects. Firstly, we set up a basic model of two companies, two products, and two types of workers. And based on previous literature, we assume that developing economies, in the face of China shocks, tend to export higher-tech products produced by R&D workers and sell lower-tech products domestically produced by non-R&D workers. Secondly, according to the Nash equilibrium, we figure out two labor prices that maximize the enterprise's surplus. In the next section, we will use the function to represent the state alterations in the corporate labor force before and after the China shocks (that is, increases) and the transition path of the change.

Substitute the maximization function of the company's production and operation (Eq. A-5) into the company's cost function (Eq. A-6), and take the derivation of the external employment of non-R&D workers, R&D workers, and internal transformation, respectively.

$$\rho h_{n_f} = \beta E\left[p_0 z a n_f^{'\alpha-1} - w_{n_f}^{*'} + (1-s)\rho h_{n_f}^{'}\right] \tag{A-11}$$

$$\rho h_{r_f} = \beta E\left[p_i a_f \alpha r_f^{'\alpha-1} - w_{n_f}^{*'} + (1-s)\rho h_{r_f}^{'}\right] \tag{A-12}$$

$$\rho i_f = \rho h_{r_f} - \rho h_{n_f} \tag{A-13}$$

$$w_{n_f}^* = \theta\left[p_0 z a n_f^{\alpha-1} + (1-s)\rho h_{n_f}\right] + (1-\theta)b_{n_f} \tag{A-14}$$

$$w_{r_f}^* = \theta\left[p_i a_j \alpha r_f^{\alpha-1} + (1-s)\rho h_{r_f}\right] + (1-\theta)b_{r_f} \tag{A-15}$$

The marginal cost for externally hiring R&D and non-R&D employees is indicated in the left part of Eq. (A-11), (A-12), whereas the marginal benefit of external employment is indicated in the right part. Similarly, Eq. (A-13) states that the marginal cost and benefit of internal conversion is also equal to the net benefit of externally hiring R&D workers (available in Eq. A-11) minus the marginal cost for non-R&D worker employment (available in Eq. A-12). According to Eq. (A-14) and Eq. (A-15), the workers' wage refers to the weighted sum of the unemployment pension and benefits of hiring two kinds of workers, respectively.

In the equilibrium state, we substitute the wages of Eqs. (A-11) and (A-12) into Eqs. (A-14) and (A-15), and the above five equations can be transformed into the following three:

$$\rho i_f = \rho h_{r_f} - \rho h_{n_f} \tag{A-16}$$

$$1 - [\beta(1-s)(1-\theta)]\rho h_{n_f} = \beta(1-\theta)\left(p_0 z a n_f^{\alpha-1} - b_{n_f}\right) \tag{A-17}$$

$$1 - [\beta(1-s)(1-\theta)]\rho h_{r_f} = \beta(1-\theta)\left(p_i \alpha \gamma_f^{\alpha-1} - b_{r_f}\right) \tag{A-18}$$

According to the above equations, we can get two conclusions. Firstly, the salary is higher among the R&D staff compared to the non-R&D staff. When $i_f > 0$ (non-R&D workers are converted into R&D workers), according to Eq. (A-13), it can be obtained: $\rho h_{r_f} > \rho h_{n_f}$ and we substituted it into Eqs. (A-16), (A-17), assuming $b_{r_f} > b_{n_f}$, then $p_i \alpha r_f^{\alpha-1} > p_0 z a n_f^{\alpha-1}$. At this point, according to Eqs. (A-14) and (A-15), we can deduce that $w^*_{r_f} > w^*_{n_f}$. Secondly, when developing countries face China shocks, companies export products with high technology to the Chinese market, commodity prices p_i will rise due to costs and import tariffs. In the equilibrium state, according to Eq. (A-16), h_{r_f} will also increase, which means more R&D workers are hired externally and the overall quantity of R&D workers increases. An intuitive explanation for this is that rising p_i will lead to a marginal benefit improvement for externally hiring R&D staff. Besides, from Eq. (A-13), as h_{r_f} rises, i_f also rises, that is, more internal non-R&D workers are converted into R&D workers. From the perspective of the enterprise, R&D workers bring higher marginal benefits, and from the perspective of workers, the higher wages of R&D workers attract more non-R&D workers to switch into R&D workers.

Appendix B. Tables

Table B1
List of countries (regions).

Afghanistan	Djibouti	Lesotho	Russian Federation
Albania	Dominica	Liberia	Rwanda
Angola	Dominican Republic	Lithuania	Samoa
Antigua and Barbuda	Ecuador	Luxembourg	Senegal
Argentina	Egypt, Arab Rep.	Madagascar	Serbia
Armenia	El Salvador	Malawi	Sierra Leone
Azerbaijan	Eritrea	Malaysia	Slovak Republic
Bahamas, The	Estonia	Mali	Solomon Islands
Bangladesh	Eswatini	Mauritania	South Africa
Barbados	Fiji	Mauritius	South Sudan
Belarus	Gabon	Mexico	Sri Lanka
Belize	Gambia	Micronesia, Fed. Sts.	St. Kitts and Nevis
Benin	Georgia	Moldova	St. Lucia
Bhutan	Germany	Mongolia	Vincent and the Grenadines
Bolivia	Ghana	Montenegro	Suriname
Bosnia and Herzegovina	Grenada	Morocco	Tajikistan
Botswana	Guatemala	Mozambique	Tanzania
Brazil	Guinea	Myanmar	Thailand
Bulgaria	Guinea-Bissau	Namibia	Timor-Leste
Burkina Faso	Guyana	Nepal	Togo
Burundi	Honduras	Nicaragua	Tonga
Cambodia	India	Niger	Trinidad and Tobago
Cameroon	Indonesia	Nigeria	Tunisia
Central African Republic	Iraq	North Macedonia	Uganda
Chad	Jamaica	Pakistan	Ukraine
Chile	Jordan	Panama	Uruguay
Colombia	Kazakhstan	Papua New Guinea	Uzbekistan
Congo, Dem. Rep.	Kenya	Paraguay	Venezuela, RB
Congo, Rep.	Kyrgyz Republic	Peru	Vietnam
Costa Rica	Lao PDR	Philippines	Yemen, Rep.
Croatia	Latvia	Poland	Zambia
Côte d'Ivoire	Lebanon	Romania	Zimbabwe

Table B2
List of regions (state or city).

Abia	Djibouti City	Maharashtra	RRP
Abidjan	DKI Jakarta	Managua	Sabaragamuwa
Accra	Durban	Mandalay	Saint-Louis
Addis Ababa	Durres	Manicaland	Sal
Aden	Dushanbe	Manila	Samarkandskaya
Aegean	East	Manzini	Samdrup Jongkhar
Al Hudaydah	East Coast	Maputo	Samoa
Al Mukalla	East Malaysia	Maracay	San Jose
Alexandria	Eastern	Maradi	San Pedro
Al-Najaf	Eastern Macedonia	Margibi	San Pedro Sula
Amazonas	Elbasan	Marmara	San Salvador
Amhara	Entire Country	Maseru	Sanaa
Amman	Enugu	Matadi	Santa Catarina
Andhra Pradesh	Estado de Mexico	Mato Grosso	Santa Cruz

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Table B2 (*continued*)

Abia	Djibouti City	Maharashtra	RRP
Antananarivo	Far East	Matola	Santiago
Antofagasta	Fiji	Matsapha	Santo Domingo
Antsiranana	Francistown	Mazar	Sao Paulo
Aqaba	Free Town	Mbabane	Sao Vicente
Aranski & Gorno-Shirvanski	Gaborone	Mbale	Sarajevo
Arbil	Gelephu/Sarpang	Mbarara	Savannakhet
Arequipa	Gharbiya	Mbeya	Segou
Arunachal Pradesh, Nagaland, Manipur, T	Giandja-Kazakhski & Sheki-Zakatalski	Medellin	Sfax
Arusha	Giza	Mekong River Delta	Sharqia
Assam	Goias	Mendoza	Shida Kartli
Asuncion	Gomelskaya	Metro Cebu	Siberia
Azuay	Grand Casablanca	Mexico DF	Siem Reap
Babil	Grodnenskaya	Midlands	Sihanouk Ville
Baghdad	Guatemala City	Minas Gerais	Sikasso
Bago	Guayas	Minsk	Sindh
Bahia	Gujarat	Minskaya	Skopje
Bahri	Harare	Mmtskheta-Mtianeti	Slavonia
Baku & Apsheronski	Haryana	Mogilevskaya	Snnp
Bali	Herzegovina	Mombasa	Sofia
Balochistan	Himachal Pradesh	Montevideo	Sogdiskaya
Balqa	Hirat	Montserrado	Sokoto
Bamako	Honiara	Monywa	South
Bangkok	Huambo	Mopti	South Coast/West
Bangui	Ibb	Mount Lebanon	South East
Banjul	Imereti	Nabatieh	South Lebanon
Banten	Interior	Nairobi	South Macedonia
Barranquilla	Irbid	Nakuru	South Muntenia
Basrah	Issyk-Kul Oblast	Nampula	South West
Battambang	Istra i hrvatsko primorje	NCR Excluding Manila	Southeast
Bauchi	Jalalabad	N'Djamena	South-East
Beira	Jalisco	Ndola	Southern
Beirut	Jawa Barat	Niamey	Southern Central Costal
Bekaa Valley	Jawa Tengah	Nimba	Southwest
Belgrade	Jawa Timur	Nimule	South-West
Benguela	Jharkhand	Nineveh	Southwest Oltenia
Berberati	Jinja	North	Stredne Slovensko
Bihar	Johannesburg	North East	Sulawesi Selatan
Bishkek	Juba	North Lebanon	Suleimaniyah
Bissau	Kabul	North-Central	Sumatera Utara
Black Sea - Eastern	Kaduna	Northeast	Taiz
Bobo-Dioulasso	Kafr-El-Sheikh\Menoufiya\Beheira	Northern	Takoradi
Bogota	Kakheti	Northern croatia	Tamale
Bosnia	Kampala	Northern Red Sea	Tamil Nadu
Brasilia DF	Kampong Cham	Northwest	Tashkent
Bratislava	Kandahar	North-West	Tashkentskaya
Brazzaville	Kano	North-West & West Macedonia	Taunggyi
Brestskaya	Kaolack	North-Western	Tblisi
Bucharest	Karnataka	Nouadhibou	Tegucigalpa
Buenos Aires	Kenema	Nouakchott	Thimphu/Paro
Bujumbura	Kerala	Nuevo Leon	Thi-Qar
Bulawayo	Kerbela	Ogun	Thiès
Burgas	Khangai	Om Durman	Tigray
Butare	Khartoum	Orissa	Timor Leste
Bío Bío	Khatlonskaya	Oromya	Tirana
Cairo	Kiev	Osh Oblast	Toamasina
Calabarazon	Kigali	Others	Tongatapu
Cali	Kindia	Ouagadougou	Torit
Canelones	Kingston	Owendo	Total
Cape Town	Kinshasa	Panama City	Tunis
Caracas	Kirkuk	Parana	Ulaanbaatar
Ceara	Kisangani	Pemba	Upper Egypt
Center	Kisumu	Pernambuco	Ural
Central	Kitwe	Peshawar	Uttar Pradesh
Central Anatolia	KMC	Phnom Penh	Uttaranchal
Central and South	Kumasi	Phuentsholing	Uva
Central Luzon	Kurzeme	Pichincha	Valencia
Central North	Kvemo Kartli	Pieriga	Valparaíso
Champasack	La Paz	Plateaux, Centrale, Kara	Varna
Chhattisgarh	Lae	Plovdiv	Veracruz
Chiclayo	Lagos	Pohnpei	Vidzeme

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Table B2 (*continued*)

Abia	Djibouti City	Maharashtra	RRP
Chihuahua	Lampung	Pointe-Noire	Vientiane
Chittagong	Latgale	Port Elizabeth	Vilniaus
Chui Oblast	Lenkoranski & Kuba-Khachmazski	Port Louis	Vitebskaya
Coahuila de Zaragoza	Libreville	Port Moresby	Vlora
Coast	Likabanovina	Port Of Spain	Vojvodina
Coast and West	Lima	Port Said\Suez\Ismalia	Volgo-Viatsky
Coastal	Lira	Port-Gentil	Vychodne Slovensko
Cochabamba	Livingstone	Puebla	Walvis Bay
Colon	Lome	Punjab	West
Conakry	Lomé	Qualyubia	West Bengal
Cordoba	Los Lagos	Rabat-Sale-Zemmour-Zaer	Western
Cotonou	Luanda	Rajasthan	Windhoek
Cross river	Luang Prabang	Red River Delta	Yamoussoukro
Dakahliya	Lubumbashi	Red Sea\Matrouh\Wadi Al Jadid\Sinai	Yangon
Dakar	Lusaka	Republic of Serbia	Yei
Dalmacija	Luxembourg	Rest of the country	Yerevan
Damietta	Madhya Pradesh	Resto del pais	Zagreb and surroundings
Dar es Salaam	Maekel	Riga	Zapadne Slovensko
Debub	Lesotho	Rio de Janeiro	Zarqa
Delhi	Liberia	Rio Grande do Sul	Zemgale
Dhaka	Mahajanga	Rosario	

Table B3
Falsification tests.

Balance variable	Coef.	SE
Panel A: Industry-level and firm-level balance		
Start-of-period % of manufacturing share	0.004	(0.005)
Firm productivity	−0.737	(1.252)
Age	−0.142	(0.327)
Trade constraint	0.017	(0.008)
Compete	0.019	(0.009)
Female worker (%)	2.045	(0.755)
Access to land	0.354	(0.057)
Regulations	0.002	(0.000)
Panel B: Regional balance		
ln(GDP)	−0.363	(0.082)
ln(Population)	−0.639	(0.148)
Corruption	−0.004	(0.002)
Tax rates	0.007	(0.012)
Transport	−0.007	(0.002)
Panel C: Pre-trend tests		
Manufacturing employment growth, 2000	−0.006	(0.001)
Manufacturing employment growth, 2002	−0.012	(0.005)
Manufacturing employment growth, 2005	−0.008	(0.002)

Table B4
List of countries along “the Belt and Road”.

Afghanistan	Kazakhstan
Armenia	Latvia
Azerbaijan	Lebanon
Bangladesh	Lithuania
Belarus	Malaysia
Bhutan	Mongolia
Bosnia and Herzegovina	Montenegro
Bulgaria	Nepal
Cambodia	Pakistan
Croatia	Philippines
Czech Republic	Poland
Egypt	Romania
Estonia	Sri Lanka
Georgia	Tajikistan
Hungary	Thailand
India	Turkey
Indonesia	Ukraine
Iraq	Uzbekistan
Israel	Vietnam
Jordan	

Table B5
The role of "One Belt and One Road Initiated" -IV method.

	(1)	(2)	(3)	(4)
VARIABLES	Introduced process innovation		Spend on R&D	
	2SLS	IV Probit	2SLS	IV Probit
lntrade	6.440*	0.153***	5.142*	0.167***
	(3.349)	(0.056)	(2.928)	(0.050)
First stage				
IV: lnexport(predicted)	1.314***	1.314***	1.331***	1.330***
	(0.332)	(0.020)	(0.283)	(0.018)
First-stage F statistics	15.71		22.10	
AR-Test		7.36***		11.26***
Other control variables	Yes	Yes	Yes	Yes
Year-fixed effect	Yes	Yes	Yes	Yes
Region-fixed effect	Yes	Yes	Yes	Yes
Industry-fixed effect	Yes	Yes	Yes	Yes
Observations	53,608	53,351	51,785	51,095
R-squared	0.001		0.007	

Notes: Robust standard errors in parentheses are clustered at the regional industry level. *$p < 0.1$, **$p < 0.05$, and ***$p < 0.01$.

Table B6
R&D intensive goods and labour adjustment.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Number of skilled workers			Proportion of skilled workers (%)		
R&D intensity level	High	Low	All	High	Low	All
Ln(*Exportshock*)	9.552***	−6.622**	4.724**	4.615***	−3.768***	5.791*
	(2.871)	(2.637)	(2.021)	(0.822)	(1.051)	(2.989)
First stage						
ln*IV*	−14.953***	−6.542***	−10.921***	−8.465***	−11.181***	−4.732***
	(4.709)	(0.562)	(1.747)	(1.036)	(2.078)	(1.006)
First-stage F statistics	10.08	135.59	39.09	66.71	28.94	22.13
Other control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year-fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Region-fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,505	34,953	47,128	13,184	32,391	40,087
R-squared	0.002	0.012	0.016	0.003	0.000	0.003

Notes: Standard errors in parentheses are clustered at the regional industry level. *$p < 0.1$, **$p < 0.05$, and ***$p < 0.01$.

Appendix C. Figures

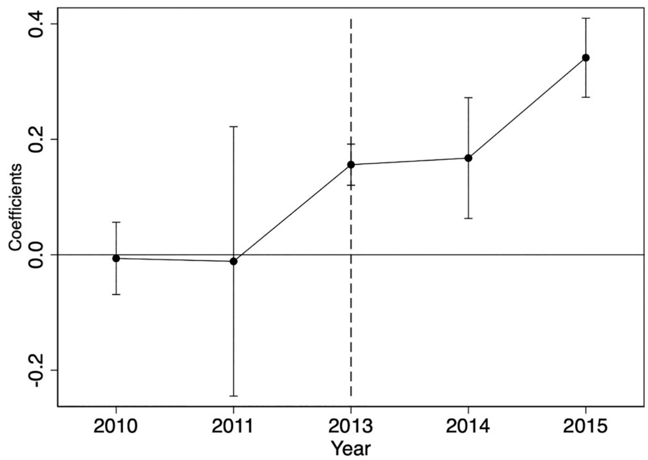

Fig. C1. Dynamic effect that BRI has on firm innovation activities.

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