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DOES TECHNOLOGICAL PROGRESS PROMOTE OR PREVENT TRADE CONFLICT? EVIDENCE FROM CHINA

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Abstract. Using the bootstrap rolling-window subsample Granger causality test from China, this study analyses the influence of technological progress (*TP*) on trade conflict (*TC*). The results show that *TP* can both promote and prevent *TC*. In 2012 and 2018, *TP* led to more trade conflicts between China and its trading partners. This result proves the "trade-loss effect", suggesting that *TP* in one country promotes *TC* by threatening other countries' income. However, *TP* had a negative influence on *TC* in 2021 and 2022. This finding is consistent with the "welfare effect", implying that *TP* can prevent *TC* by providing more high-quality and cheaper products for worldwide consumers. This study suggests that the government should adopt appropriate trade policies when encouraging *TP* to promote bilateral trade. Furthermore, firms should develop their own high-quality irreplaceable products through technological innovation to address *TC* risk.

Keywords: technological progress, trade conflict, rolling-window, bootstrap.

JEL Classification: C32, F13, O32.

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1. Introduction

This paper aims to answer the question of whether technological progress (*TP*) promotes or prevents trade conflict (*TC*). The impact of TP on TC can be observed in many countries. In 2019, confronted with the rapid development of the Korean semiconductor industry, Japan decided to control the export of three core materials that are essential for the Korean production of semiconductors. The Korean government responded by removing Japan from the export whitelist of trade facilitation (Kim, 2021). Such an event reveals that *TP* may promote *TC*. Another example is Sino-U.S. TC. China has become a growing leader in technology, which seems to spur the protectionist activities of the United States (Houser, 2020). Since 2018, President Trump has approved several rounds of tariffs on imports from China. The Chinese government also instituted antidumping duties on a series of U.S. products (Park, 2020). Therefore, *TP* may lead to *TC*. However, the promoting effect of *TP* on *TC* is not conclusive.

Fast *TP* in less developed countries may threaten the interests of technologically advanced countries, leading to more *TC* initially, but it may prevent *TC* when the technology achieves further advancement. In particular, *TP* can facilitate the production of cheaper and irreplaceable products (Das & Chatterjee, 2021), which increases global welfare and contributes to free trade, thereby preventing *TC*. In general, *TC* among different countries is becoming increasingly fierce in international trade (Liu et al., 2020). *TC* not only puts related firms at risk but also influences neighboring countries, impacting global value chains and even international political relations (Shin & Balistreri, 2022). *TC* is related to *TP* (Akcigit & Melitz, 2022), but whether *TP* promotes or prevents *TC* is still controversial in different stages of economic development. Thus, this paper explores the time-varying correlation between *TP* and *TC* to solve this issue. This research has important implications for the government to formulate strategic trade policies to avoid the risk of *TC* in the process of *TP*.

China has been implementing a national innovation-driven development strategy since 2012, which has greatly promoted the advancement of technology (Song et al., 2017). According to the World Intellectual Property Organization, China ranked first in the world in terms of patent applications in 2021. With the progress of technology, Chinese exports increase dramatically, making the country the largest exporter worldwide (Jenkins, 2022). In the meanwhile, according to China's Ministry of Commerce (MOC), the country became the most prominent target of trade remedy investigations (e.g., anti-dumping, countervailing, and safeguarding) during 2000–2020. Before 2012, products that were involved in trade remedy cases were mainly labor-intensive and capital-intensive. With the rapid development of technology-intensive industries during 2013–2018, more high-tech products became the target of anti-dumping investigations (Jabbour et al., 2019). For example, in the Sino-U.S. *TC*, several Chinese high-tech companies are subject to trade sanctions (Houser, 2020). Hence, TP may be a driver of TC. However, this relationship is not conclusive. In 2021, the number of authorized patents continues to soar, while the number of *TCs* against China drops significantly. Therefore, whether *TP* promotes or prevents *TC* is uncertain. In general, *TC* has become the main risk for Chinese exporters, which is connected with *TP*. Furthermore, the country is upgrading its industrial structure by encouraging technological innovation (Su et al., 2022a), which may change the relationship between *TP* and *TC*. Thus, the discussion about *TP* and *TC* has special significance for China.

The contributions of this paper are as follows. First, previous literature mainly focuses on the impact of technological innovation on trade and related policy (Dai et al., 2020) or the impact of trade liberalisation on innovation (Dorn et al., 2020; Aghion et al., 2021; Coelli et al., 2022). To our knowledge, this paper is the first to explore the influence of *TP* on *TC* by considering the number of *TC* cases in which Chinese exporters are involved. Second, existing studies mainly apply the full-sample causality test, which fails to investigate the time-varying relationship when there are structural changes. This paper uses the bootstrap subsample rolling-window causality test, which enables us to examine the time-varying relationship between *TP* and *TC*. We find that *TP* promotes *TC*, which is consistent with the "trade-loss effect" that *TP* of one country may lead to a loss for other countries. This result, however, is not valid in 2021 and 2022, during which period *TP* reduces *TC*. This result proves the "welfare effect", suggesting that *TP* raises the real purchasing power of consumers in other countries by reducing the cost, which increases the welfare of other countries. Understanding the influence of *TP* on *TC* provides implications for the government to avoid *TC* risk when promoting technological progress.

The rest of this paper is organized as follows. Section 2 is the literature review. Section 3 theoretically analyses the relationship between *TP* and *TC*. The empirical methods and the data are introduced in sections 4 and 5, respectively. Section 6 discusses the empirical results. The last section concludes the paper.

2. Literature review

The literature on *TP* and *TC* mainly focuses on the impact of trade on *TP*, and most researchers believe that *TC* impedes *TP*. By developing a Ricardian trade model, Eaton and Kortum (2002) propose that free trade is conducive to the spread of new technologies, which implies that *TC* hinders the *TP*. Bernard et al. (2011) also suggest that *TC* reduces the technology advantage and technical efficiency of firms. Likewise, Bustos (2011) proves that the reduction in trade tariffs increases Argentinean firms' investment in technology, implying that *TC* hinders *TP*. Hwang et al. (2016) find that trade liberalisation promotes a firm's R&D, indicating that *TC* blocks *TP*. In addition, Olper et al. (2017) reveal that *TC* can diminish firms' ability to acquire essential technology. Using the samples of Ghana and Tanzania, Esaku and Krugell (2020) show that firms that have better access to international markets are more likely to invest in technology, indicating that *TC* is a brake of *TP*. Farrokhi and Pellegrina (2021) draw a similar conclusion that the reduction of trade costs in the agricultural sector induces shifts from traditional technology to modern ones, implying that *TC* can block *TP* by increasing trade costs. Moreover, Coelli et al. (2022) reveal that the reduction in global tariffs increases import competition, which increases firms' incentives for technological innovation. However, the negative influence of *TC* on *TP* is not conclusive. Cervellati et al. (2018) point out that trade liberalisation may limit technology adoption, implying that *TC* facilitates *TP*. Shu and Steinwender (2019) suggest that trade liberalisation has a mixed impact on *TP* in developed countries. In addition, Slavtchev (2020) shows that a protectionist policy increases German R&D inputs by reducing import competition from middle- and low-income countries. Likewise, Melitz and Redding (2021) suggest that protectionist policy increases domestic firms' incentives for innovation, which facilitates *TP*. In another study, Dorn et al. (2020) propose that innovation in U.S. manufacturing firms is hindered by trade liberalisation. Moreover, Aghion et al. (2021) find a negative influence of trade liberalisation on the innovative activities of some French firms, suggesting that *TC* promotes *TP*.

Conversely, some literature recognizes the role of *TP* in *TC*, but the conclusion is mixed. Samuelson (2004) demonstrates that the *TP* in one country promotes exports, which reduces other countries' gains from trade, resulting in *TC*. Miyagiwa and Ohno (2007) draw a similar conclusion that while cost-saving technological innovation increases exports, it also increases the possibility of anti-dumping investigations by other countries. In addition, Niels (2000) notes that technological sectors are more likely to encounter anti-dumping investigations than nontechnological sectors. In another study, Azar and Ciabuschi (2017) suggest that technological innovation strengthens exporters' competitive advantage, but they do not discuss the further impact on *TC*. Furthermore, Tian et al. (2016) point out that *TC* results from fierce competition. Unlike the aforementioned research that *TP* facilitates exports and leads to anti-dumping, Miyagiwa et al. (2016) argue that developing countries can avoid anti-dumping conflicts with developed countries by improving their R&D capability. In addition, Dai et al. (2020) suggest an inverted-U relationship between innovation intensity and exporters' survival probability, implying that *TP* has a mixed impact on *TC*.

An increasing number of studies have investigated the impact of the Sino-US *TC* on the financial market (Shi et al., 2021), global value chains (Javorcik, 2020; Zhu & Zheng, 2022), and technology. Houser (2020) notes that the Sino-U.S. *TC* will hinder the worldwide development of *TP*. In addition, by analysing China's Belt and Road Initiative (BRI) on the innovation ability of firms, Li et al. (2022) suggest that *TC* hinders *TP* by impeding firms' innovation ability. However, Liu et al. (2020) propose that *TC* increases the consumption cost of fossil fuels, which leads to the substitution of renewable energy, thereby promoting *TP* in renewable energy. Sun et al. (2022) show that the uncertainty of the trade environment promotes green technological innovation, which is conducive to *TP*. Moreover, Xu et al. (2022) find that the Sino–U.S. *TC* increases Chinese firms' innovative activities.

Conversely, *TP* in China is also considered a significant influencing factor of *TC*. Deng and Liu (2019) point out that the industry with faster *TP* in China will receive more anti-dumping investigations from other countries. In addition, Li and Li (2022) demonstrate that the *TP* triggers anti-dumping investigations against China primarily via the "perceived threat" channel. Wang (2022) suggests that *TP* in Huawei, a Chinese company, increases competition and results in *TP*.

Most previous researchers investigate the impact of trade liberalisation on *TP* (Aghion et al., 2021; Coelli et al., 2022) or the influence of Sino-U.S. *TC* (Houser, 2020; Xu et al., 2022) while ignoring the impact of *TP* on *TC*. Although some research discusses the influence of *TP* on certain trade policies (e.g., anti-dumping) (Li & Li, 2022), it ignores the direct impact of *TP* on *TC*. In addition, related research does not use time-varying parameters in the models, neglecting the structural changes in the full-sample time series, which may lead to inaccurate results. Considering that the changes in China's industrial structure and technological policies may alter the relationship between *TP* and *TC*, we use the bootstrap subsample rolling-window causality test (Balcilar et al., 2010; Su et al., 2023a) to explore the influence of *TP* on *TC* in different periods. This study helps to answer the question of whether *TP* promotes or prevents *TC*, which has implications for the government to avoid *TC* risk and promote bilateral trade in the process of *TP*.

3. Theoretical analysis of *TP* and *TC*

We apply a two-country theoretical model (Samuelson, 2004; Miyagiwa et al., 2016) to explain the impact of *TP* on *TC*. Suppose there are two countries, A and B. The technology of country A is progressing. The *TP* in country A reduces the production cost, driving down the exporting price (Tao et al., 2022; Su et al., 2022c). This will increase the competitive power of country A. However, the overseas markets of B may shrink, and its export income may decrease. In particular, if B is a more advanced country than A, then B may suffer from the narrowing of its technological lead. Hence, the technological progress of country A leads to the loss of country B (Grossman & Helpman, 1995; Miyagiwa & Ohno, 2007). Let l_B be the loss of trade for country B and TP_A be the technological progress of country A; then, $l_B = f(TP_A)$, which means l_B is a function of TP_A. From another perspective, since TP_A reduces the exporting price of country A, residents in country B can buy more products worldwide at a lower price, which means that the welfare of B increases (Grossman & Helpman, 1995). Let W_B be the welfare that country B obtained from international trade; then, $W_B = g(TP_A)$, which suggests that W_B is a function of TP_A.

Then, country B needs to weigh the loss and gain before deciding whether to take protective measures against country A. Let TC be the trade conflict between countries A and B, then $TC = h\ (l_B, W_B)$, which shows that TC depends on l_B and W_B. As TP influences TC by affecting l_B and W_B, the total impact of TP_A on TC can be shown as Eq. (1):

$$\frac{dTC}{dTP_A} = \frac{\partial TC}{\partial l_B} \times \frac{dl_B}{dTP_A} + \frac{\partial TC}{\partial W_B} \times \frac{dW_B}{dTP_A}. \tag{1}$$

As mentioned above, the TP_A leads to the loss of trade for country B, then $\frac{dl_B}{dTP_A} > 0$. In addition, the loss of trade for country B brings more TC, then $\frac{\partial TC}{\partial l_B} > 0$. Therefore, $\frac{\partial TC}{\partial l_B} \times \frac{dl_B}{dTP_A} > 0$, which is defined as the *"trade-loss effect"*, suggesting that the TP_A brings more TC by leading to the loss of trade for country B (Samuelson, 2004). Furthermore, as TP_A raises the real purchasing power of country B, which causes less TC, we can infer that $\frac{dW_B}{dTP_A} > 0$ and $\frac{\partial TC}{\partial W_B} < 0$. Then, $\frac{\partial TC}{\partial W_B} \times \frac{dW_B}{dTP_A} < 0$, indicating that TP reduces TC by increasing the welfare of country B. We define this effect as the *"welfare effect"*. In summary, TP has both a trade-loss effect and a welfare effect on TC. When the trade-loss effect outweighs the welfare effect, TP promotes TC; otherwise, TP prevents TC.

In turn, TC can also influence TP. On the one hand, when country B takes protective measures against country A, the overseas markets of country A will shrink, and exporters' profit will decrease, which negatively impacts the R&D funds that the TP needs (Melitz & Redding, 2021). TC may also lead to inefficiency in knowledge diffusion, which weakens firms' ability to acquire advanced technology through international trade, impeding TP (Eaton & Kortum, 2002; Olper et al., 2017; Farrokhi & Pellegrina, 2021). On the other hand, TC can also promote the TP of country A. Exporters may have the incentive to escape from the competition by developing products with higher performance through technological innovation (Xu et al., 2022), which is conducive to TP. In summary, TP and TC are interactive, but the exact direction of the impact is uncertain.

4. Methodology

4.1. Bootstrap Causality Test based on the Vector Autoregression (VAR) Model

The standard Granger causality test based on the VAR model usually assumes that statistics such as the likelihood ratio (*LR*) or Lagrange multiplier (*LM*) obey the standard asymptotic distribution in full samples (Sun et al., 2021). However, such an assumption may not hold because of structural changes in the time series (Sims et al., 1990; Toda & Phillips, 1993, 1994), which can lead to inaccurate estimates. Shukur and Mantolos (1997) suggest that the critical values of residual-based bootstrap (RB) estimation can be used to improve the performance of estimation. Furthermore, Shukur and Mantalos (2000) prove that *RB*-based corrected *LR*-statistics exhibit relatively better power and size properties even in small samples, which can increase the robustness of the Granger test.

Therefore, the *RB*-based modified-*LR* statistic is applied to explore the causal relationship between *TP* and *TC*. The VAR model is shown in Eq. (2):

$$\mathbf{y}_t = \mathbf{\Phi}_0 + \mathbf{\Phi}_1 \mathbf{y}_{t-1} + \ldots + \mathbf{\Phi}_p \mathbf{y}_{t-p} + \boldsymbol{\varepsilon}_t,\ t = 1, 2, \ldots, T, \tag{2}$$

where $\mathbf{y}_t$ is a column vector of variables, $\boldsymbol{\varepsilon}_t$ is the white-noise vector, T is the number of samples, $\mathbf{\Phi}_0$,..., $\mathbf{\Phi}_p$ are matrixes of coefficients to be estimated and p is the lag length. In addition, as mentioned in the theoretical analysis that exports are related to *TP* and *TC* (Dong et al., 2022), we use exports (*EX*) as the control variable in the VAR model (Jabbour et al., 2019; Xu et al., 2022). Thus, Eq. (2) can be expressed as follows:

$$\begin{aligned}
\begin{bmatrix} TP_t \\ TC_t \end{bmatrix} &= \begin{bmatrix} \phi_{10} \\ \phi_{20} \end{bmatrix} + \begin{bmatrix} \phi_{11}{}^{(1)} & \phi_{12}{}^{(1)} & \phi_{13}{}^{(1)} \\ \phi_{21}{}^{(1)} & \phi_{22}{}^{(1)} & \phi_{23}{}^{(1)} \end{bmatrix} \begin{bmatrix} TP_{t-1} \\ TC_{t-1} \\ EX_{t-1} \end{bmatrix} + \ldots + \\
&\begin{bmatrix} \phi_{11}{}^{(2)} & \phi_{12}{}^{(2)} & \phi_{13}{}^{(2)} \\ \phi_{21}{}^{(2)} & \phi_{22}{}^{(2)} & \phi_{23}{}^{(2)} \end{bmatrix} \begin{bmatrix} TP_{t-2} \\ TC_{t-2} \\ EX_{t-2} \end{bmatrix} + \ldots + \\
&\begin{bmatrix} \phi_{11}{}^{(p)} & \phi_{12}{}^{(p)} & \phi_{13}{}^{(p)} \\ \phi_{21}{}^{(p)} & \phi_{22}{}^{(p)} & \phi_{23}{}^{(p)} \end{bmatrix} \begin{bmatrix} TP_{t-p} \\ TC_{t-p} \\ EX_{t-p} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}.
\end{aligned} \tag{3}$$

In Eq. (3), when $\phi_{21}{}^{(q)} = 0$, (q=1, 2, ..., p), *TP* is not a Granger cause of *TC*. Likewise, when $\phi_{12}{}^{(q)} = 0$, *TC* is not a Granger cause of *TP*. In this study. *RB*-based modified-*LR*-statistics and p-values are used to test full-sample causality. If the null hypothesis that $\phi_{21}{}^{(q)} = 0$ is rejected, then *TP* is the Granger cause of *TC*. Additionally, *TC* is the Granger cause of *TP* if the null hypothesis that $\phi_{12}{}^{(q)} = 0$ is rejected.

4.2. Parameter stability test

The VAR model parameters are assumed to be constant over time in the full-sample causality test, which means that only one causality can be obtained in every period (Su et al., 2022b; Yuan et al., 2022). However, the relationship between dependent and independent variables may undergo structural changes, which may be brought about by demand or supply shocks in the economy or may be the result of institutional shifts. In this situation, it is highly possible that the parameters will not be constant, which leads to an unreliable result of the full-sample Granger causality test (Balcilar & Ozdemir, 2013). Therefore, it is necessary to test the stability of the parameters. This study uses the *Sup-F*, *Mean-F*, and *Exp-F* tests proposed by Andrews (1993) and Andrews and Ploberger (1994) to check the stability of the parameters. In addition, we apply the *Lc* test proposed by Nyblom (1989) and Hanson (2002) to test the long-term parameter stability. These tests can be used to check the stability of the parameters to determine whether structural changes exist at unknown time points.

4.3. Rolling-window subsample causality test

When structural mutations exist in the full-sample, although devices such as dividing the samples or using dummy variables can be employed to solve this problem, biases still exist, which affect the results of the Granger causality test. Thus, this study uses the bootstrap subsample rolling-window Granger causality test (Balcilar et al., 2010), which not only allows the causality between variables to change over time but also enables us to observe the difference caused by structural changes in different subsamples and avoid biases (Su et al., 2022e, 2023b, 2023c). This method divides the whole sample into fixed-size subsamples for causality testing. Suppose the full-sample length is T and each subsample includes L observations; then, the subsamples are $\tau - L + 1, \tau - L + 2, \ldots, \tau$, where $\tau = L, L + 1, \ldots T$. In this way, we can obtain $T - L + 1$ subsamples. When deciding the size of subsamples, L, there is no uniform standard (Balcilar et al., 2010). On the one hand, small subsamples can reduce the impact of potential heteroscedasticity, but the estimated variance will be larger, and therefore, the result is not effective. On the other hand, large subsamples can improve the validity of the estimation, but the existence of heteroscedasticity may lead to an unreliable result. It is usually believed that the bias-minimizing window size should not be less than 20 observations (Pesaran & Timmermann, 2005).

We can then investigate the Granger causal relationship between *TP* and *TC* in each subsample by applying the *RB*-based modified *LR* causality test. The significance of the causality between *TP* and *TC* can be observed by calculating the *p*-value of the *LR* statistic. The impact of *TP* on *TC* can be obtained using the formula $N_b^{-1}\sum_{q=1}^{p}\hat{\phi}_{21}{}^{(q)}$, where N_b is the frequency of bootstrap iterations, and $\hat{\phi}_{21}{}^{(q)}$ is the bootstrap estimator in the VAR model. Similarly, $N_b^{-1}\sum_{q=1}^{p}\hat{\phi}_{12}{}^{(q)}$ shows the impact of *TC* on *TP*. The confidence interval is 90%, with the lower limit equal to the fifth quantile of $\hat{\phi}_{12}{}^{(q)}$ and the upper limit equal to the 95th quantile of $\hat{\phi}_{21}{}^{(q)}$ (Balcilar et al., 2010).

5. Data

This study uses monthly data from 2002:M1 to 2022:M10. China became a member of the World Trade Organization (WTO) in December 2001, which led to a larger overseas market for Chinese firms, thereby facilitating *TP* (Geng & Kali, 2021). In this paper, we use the number of granted patents to measure *TP*, which is widely considered a good indicator of *TP*

(Paunov, 2016; Aghion et al., 2019). More patents indicate a higher level of *TP*. In addition, China's entrance to the WTO contributes to its fast-growing exports, and many countries impose remedial measures such as anti-dumping, countervailing, and safeguards against China to protect their own industries (Jabbour et al., 2019). Confronted with this situation, Chinese exporters actively respond to investigations to safeguard their interests. This paper uses the number of *TC* cases between China and other economies to measure *TC* (Tian et al., 2016), released by MOC[1]. We can infer that *TP* and *TC* may be correlated, with *TP* seemingly being a push for *TC* in most periods. Furthermore, the relationship between *TP* and *TC* is connected with changes in China's exports (Dong et al., 2022). The increase in China's exports may intensify the competition between China and other economies, thus resulting in more *TC* (Samuelson, 2004). This paper uses China's export value to measure *EX* (Xu et al., 2022), which is drawn from the CEIC Data[2].

Figure 1 shows *TP* and *TC* trends. The solid line indicates the changes in *TC*, while the dashed line describes the changes in *TP*. It can be observed that *TP* has an overall rising trend with some fluctuations. The value of *TP* skyrocketed after the release of the Outline of the National Strategy of Innovation-Driven Development (ONSID) in May 2016. After that, *TP* continues to rise and reaches its peak in 2022. In addition, the value of *TC* fluctuates year-round, with some local peaks in 2005, 2016, and 2018. In addition, *TC* shows an obvious downwards trend after 2020. Moreover, a high *TP* coincides with an increase in *TC* in some periods. For example, when *TP* rose in 2012, *TC* also increased rapidly. Similar changes can be observed at the beginning of 2018 when *TP* shows an obvious rising trend. In the corresponding period, *TC* also ascends. In particular, *TC* peaked in 2018 when Sino-U.S. *TC* began. Hence, we can infer that *TP* promotes *TC*. However, the trends of *TP* and *TC* are not always the same. In 2021, the outline of the 14th Five Year Plan (2021–2025) for national economic and social development was released, proposing to develop artificial intelligence, integrated circuits, and

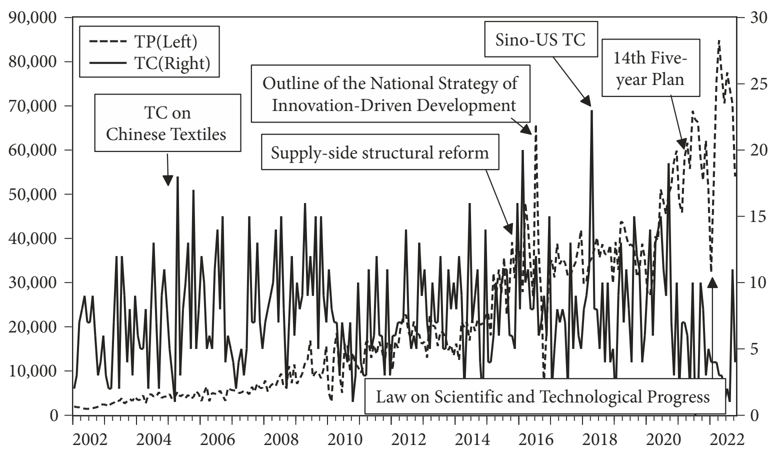

Figure 1. Trends of *TP* and *TC*

[1] http://cacs.mofcom.gov.cn/cacscms/view/notice/ckys#

[2] https://www.ceicdata.com

so on, which drive the *TP* to soar. In addition, the Law on Scientific and Technological Progress (LSTP) (2021 Revision) comes into force in January 2022, which further protects property rights, thereby promoting *TP*. However, *TC* drops sharply during 2021–2022. Furthermore, the relationship between *TP* and *TC* will be affected by China's exports. On the one hand, China's increasing exports may negatively affect the overseas market share of other countries, leading to *TC*. On the other hand, rising exports influence *TP* by increasing exporters' profits. As exports are deeply connected with *TC* and *TP*, we choose exports (*EX*) as the control variable (Xu et al., 2022). In summary, *TP* and *TC* have a time-varying relationship, which is also connected with exports.

Table 1 shows the descriptive statistics of the variables. The mean of *TP* indicates that there are 21716.43 granted patents on average each month. The average value of *TC* suggests that Chinese exporters are involved in 7.576 TC cases on average monthly. In addition, the positive skewness of *TP*, *TC*, and *EX* shows that they follow a right-skewed distribution. Furthermore, the Jarque–Bera test demonstrates that *TP* and *TC* obey a nonnormal distribution at the significance of 1%. *EX* obeys a nonnormal distribution at the significance level of 10%. Hence, the estimation of parameters is inaccurate when we use the traditional Granger causality test. In the subsequent analysis, all of the variables are taken from the natural logarithms to avoid potential heteroscedasticity. In addition, *EX* is further transformed by taking the first difference to avoid nonstationarity.

Table 1. Descriptive statistics of the sequence of *TP*, *TC* and *EX*

Statistics	TP	TC	EX
Observations	250	250	250
Mean	21716.43	7.576	150754.6
Median	16326.5	7	162616.2
Maximum	84828	23	340498.8
Minimum	1386	0	19137
Std. Dev.	18963.33	3.990	76486.8
Skewness	1.076	0.682	0.162
Kurtosis	3.511	3.516	2.395
Jarque–Bera	50.922***	22.155***	4.906*

Notes: *** indicates that the statistics are significant at the 1% level. The unit of *EX* is US$ million.

6. Empirical results

Before constructing VAR models, we need to conduct unit root tests. Table 2 shows that all sequences are stationary. Thus, we can conduct the Granger full-sample causality test based on VAR models. According to the Akaike information criterion (AIC), final prediction error (FPE), Schwarz information criterion (SIC) and Hannan-Quinn information criterion (HQ), the optimal lag length is 4.

Table 2. Unit root tests

Series	ADF	PP	KPSS
TP	−4.547 (3) ***	−11.032[9] ***	0.109[9]
TC	−14.711 (0) ***	−15.2353[8] ***	0.139[6]
EX	−3.184(13) **	−30.106[13] ***	0.078[12]

Notes: Numbers in parentheses indicate the lag order, which is selected based on the AIC. Numbers in the brackets refer to the bandwidth, which uses the Bartlett Kernel as suggested by the Newey–West test (1987). The null hypothesis for KPSS is that the time series is stationary. *** and * *denote significance at the 1% and 5% levels, respectively.

The traditional full-sample Granger causality test requires that all parameters are constant, and we can obtain only a single Granger causal relationship within a fixed time interval. However, when structural changes exist in the parameters, the causality of *TP* and *TC* may change over time. In this situation, the results of the traditional full-sample Granger causality test may deviate from the actual situation (Zeileis et al., 2005). Hence, the stability test is performed to determine the presence of structural mutations. As mentioned above, this study uses *Sup-F*, *Mean-F*, *Exp-F*, and *Lc* tests to test the stability of parameters in the VAR models. The results are shown in Table 3.

Table 3. Parameter stability tests

	TP equation		*TC* equation		VAR (4) system	
	Statistics	Bootstrap *p*-value	Statistics	Bootstrap *p*-value	Statistics	Bootstrap *p*-value
Sup-F	37.334***	0.000	37.757***	0.000	39.298*	0.053
Mean-F	18.549***	0.005	12.115	0.131	23.279*	0.098
Exp-F	13.977***	0.001	14.378***	0.000	15.319*	0.076
Lc					4.020*	0.068

Notes: We calculate p-values using 10,000 bootstrap repetitions. *** and * indicate significance at the 1% and 10% levels, respectively. Lc shows the results of the Hansen–Nyblom parameter stability test for all parameters in the VAR jointly.

The results of the *Sup-F* tests indicate a sudden shift in the *TP* equation, *TC* equation, and VAR system. *Mean-F* and *Exp-F* tests are used to test the null hypothesis that parameters follow a martingale process. The results show that the null hypothesis is rejected, indicating that the *TP* equation, *TC* equation, and VAR system may evolve gradually with time. In addition, the *Lc* test is used to test the null hypothesis that parameters in the VAR model follow a random walk process. The result shows that the null hypothesis is rejected at the 10% level of significance. In summary, the results above show that the parameters are unstable, and there are structural changes in the whole sample. Thus, the results of the full sample Granger causality test are inaccurate. To improve the accuracy of the results, we adopt the bootstrap rolling-window Granger causality test to investigate the time-varying causal link between *TP* and *TC* in different subsamples. As the bias-minimizing window size should not be less than 20 observations (Pesaran & Timmermann, 2005), the rolling subsample data include 24[3] months of observations to ensure the reliability of the test.

Figure 2 shows the rolling bootstrap of the *p*-values of the *LR*-statistics using *TC* as the dependent variable. Figure 3 reports the sum of the rolling-window coefficients for the impact of *TP* on *TC*. Figures 2 and 3 reveal that the *TP* has both positive (June 2012–August 2012, February 2018 to March 2018) and negative (July 2021–April 2022) influences on *TC*.

The positive influence of *TP* on *TC* indicates that *TP* can promote *TC*. From 2001 to 2012, heavy industry (steel, metallurgy, machinery, energy, chemistry, materials, etc.), was the leading industry in China. According to the National Bureau of Statistics, the contribution of heavy industry to the gross industrial output value increased from 51.3% in 2001 to 71.4% in 2010.

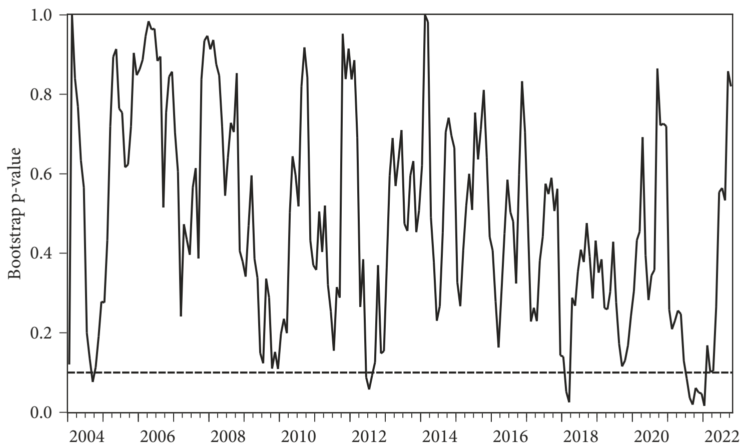

Figure 2. Bootstrap *p*-value of the statistics (the null hypothesis is that *TP* is not a Granger cause of *TC*)

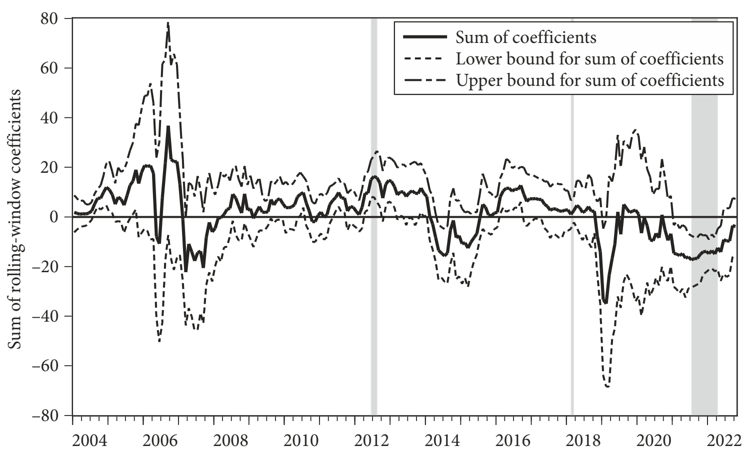

Figure 3. Sum of rolling-window coefficients of *TP*'s influence on *TC*

[3] This paper also uses the rolling-window widths of 20-, 28- and 32- months to explore the causality, and the results do not change significantly, which proves the robustness of the results.

In June 2012, the Ministry of Science and Technology issued the "Guidance on Encouraging Private Capital to Support Technological Innovation", which leads to substantial private capital to support the dominant heavy industry, thereby facilitating *TP*. The *TP* has increased production efficiency and reduced production costs, thereby reducing the export price and improving the international competitiveness of products in heavy industry (Su et al., 2022d, 2022f). However, this has also intensified international competition for similar products, leading to several anti-dumping investigations against China (e.g., Brazil's anti-dumping investigation against China's seamless carbon steel pipes in June 2012 and Turkey's anti-dumping investigation against Chinese diesel engines in August 2012). Therefore, *TP* had a positive influence on *TC* from June 2012 to August 2012.

Technology-intensive industries developed rapidly during 2013–2018. China began to adopt a national strategy of innovation-driven development in November 2012 when the 18th National Congress of the Communist Party of China (CPC) took place. In May 2016, the government further released the Outline of the National Strategy of Innovation-Driven Development (ONSID), which promoted *TP* in information, manufacturing, clean energy, etc. In addition, China has begun to promote supply-side structural reform since 2015, aiming to reduce the capacity of heavy industries such as steel and coal. Under the aforementioned policies, China's industrial structure has been continuously upgraded. In 2017, the share of high-tech industries' output in total industrial output increased by 4.41% compared with 2013, reaching a historical peak of 31.1%. Among them, automobile manufacturing, communication, and other electronic equipment manufacturing became the industries with the most output (Zhou & Chang, 2019). Hence, the international competitiveness of technology-intensive products has been significantly enhanced, leading to several *TC*s in 2018. Some economies, such as the US, EU, India, Mexico, Argentina, and Turkey, took several protective measures against China's products. Among them, the Sino-U.S. *TC* had a relatively more considerable influence (Lawrence, 2018; Li et al., 2020), which not only affects global value chains but also increases world uncertainty (Su et al., 2022g, 2023d; Wang et al., 2023; Qin et al., 2023). Therefore, *TP* promoted *TC* during 2018:M2–2018:M3. This result confirms the "trade-loss effect", suggesting that the *TP* of China brings more *TC* by intensifying the competition in exports and leads to the loss of trade for other countries.

However, *TP* has a negative influence on *TC* in 2021:M7–2022:M4. In March 2021, the outline of the 14th Five Year Plan (2021–2025) for national economic and social development was released, proposing to promote emerging industries of strategic importance (e.g., artificial intelligence, quantum information, integrated circuits, aerospace, deep sea, etc.). In addition, Chinese firms have realized the importance of developing irreplaceable high-tech products since the Sino-U.S. *TC*, which contributes to the increase in *TP*. This enables Chinese firms to circumvent technical trade barriers, and thus, *TC* decreases. Furthermore, the Law on Scientific and Technological Progress (LSTP) (2021 Revision) came into force in January 2022, which further protects property rights, thereby promoting *TP*. The progress of technology not only boosts China's economy but also benefits its trading partners by producing high-quality and cheaper products (Dong et al., 2022). Hence, *TP* reduces *TC* during 2021:M7–2021:M12. This finding proves the "welfare effect", suggesting that China's *TP* reduces *TC* by increasing the welfare of other countries.

Figure 4 presents the rolling bootstrap *p*-values of the *LR* statistic using *TP* as the dependent variable. Figure 5 depicts the sum of the rolling-window coefficients of *TC*'s influence on *TP*. Figures 4 and 5 show that *TC* exerts a significant negative effect on *TP* from February 2005 to July 2005, indicating that *TC* hinders *TP* in China during that period.

The gross industrial output of labour-intensive industries was higher than that of capital-intensive industries from 1952 to 2017 (Zhou & Chang, 2019), and China has a comparative advantage in labour-intensive products such as textiles. For example, China was the world's largest exporter of textiles and clothing in 2014, accounting for 21% of global textiles and clothing exports. It is worth noting that all import quotas for textiles and clothing among WTO members were abolished on January 1, 2005, which further promoted Chinese textile exports. However, fast-growing exports lead to several *TC*s between China and other economies (e.g., the EU, the U.S., and India). Such *TC* reduces Chinese exporters' profits, which further

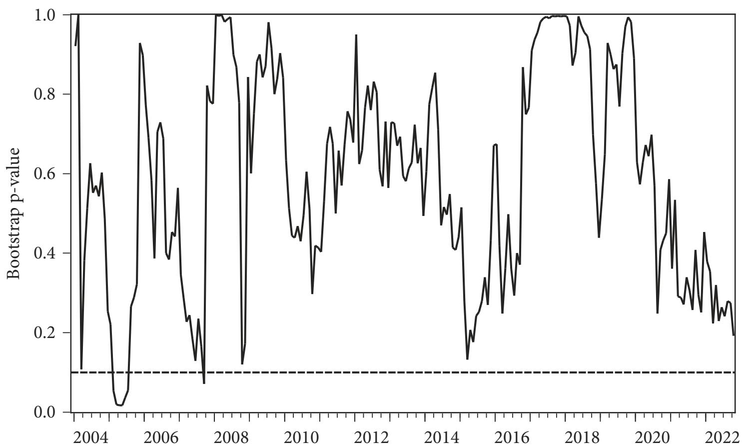

Figure 4. Bootstrap *p*-value of the statistics (the null hypothesis is that *TC* is not a Granger cause of *TP*)

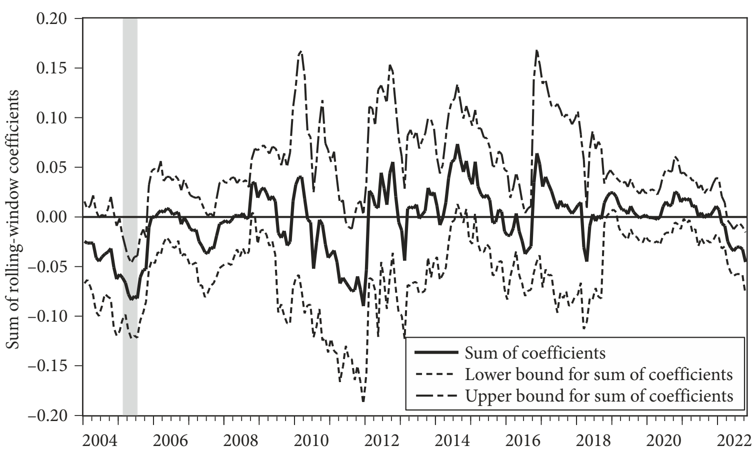

Figure 5. Sum of rolling-window coefficients of *TC*'s influence on *TP*

limits R&D expenditure and ultimately impedes *TP*. In addition, *TC* shrinks the overseas markets and reduces the income for exporters, which weakens firms' incentive for technological innovation. Hence, *TC* impedes *TP* in 2005:M2–2005:M7.

In summary, the full-sample Granger causality test is inaccurate in estimating the relationship between *TP* and *TC* because it assumes that there is only a single Granger causality in the whole sample. The parameter stability test shows that the parameters are unstable and structural changes exist. Therefore, we apply the bootstrap subsample rolling-window Granger causality test to examine the time-varying causal relationship between *TP* and *TC* in different subsamples. We find that the influence of *TP* on *TC* is positive in 2012:M6–2012:M8 and 2018:M2–2018:M3, indicating that during these periods, *TP* promotes *TC*. However, this impact becomes negative in 2021:M7–2022:M4, suggesting that *TP* can prevent *TC* primarily by promoting the production of high-quality and cheaper products and achieving mutual benefit between trading partners. Furthermore, it shows that *TP* enables firms to circumvent technical barriers to trade by developing high-quality and high-tech products. These results prove that *TP* has both positive and negative impacts on *TC*, which is consistent with the "trade-loss effect" and "welfare effect" in theoretical analysis. In turn, *TC* can influence *TP* negatively, indicating that *TC* may hinder a country's *TP*.

7. Conclusions

This paper discusses whether *TP* promotes or prevents *TC* by investigating the time-varying causal relationships between *TP* and *TC*. We find that *TP* both positively and negatively affects *TC* in China. In 2005 and 2018, China's *TP* led to more *TC* primarily by threatening trading partners' overseas market share and exporting income. This result supports the "trade-loss effect" in the theoretical analysis, implying that China's *TP* can lead to more *TC* by leading to the loss of trade for another country. However, *TP* has a negative effect on *TC* in 2021 and 2022, during which time *TP* not only boosts China's economy but also benefits its trading partners by producing high-quality and cheaper products. This result is consistent with the "welfare effect" in the theoretical analysis, suggesting that *TP* can reduce *TC* by increasing the welfare of other countries.

The influence of *TP* on *TC* provides the following insights for the government. On the one hand, when China's *TP* promotes exports and economic growth, it may also lead to *TC* and thus risk trade. Hence, the government should take measures such as bilateral consultation or the WTO dispute settlement mechanism to build a win–win relationship with its trading partner. It is also essential for the government to build a robust domestic market and avoid overdependence on overseas markets to reduce the risk of *TC*. On the other hand, since *TP* can increase the welfare of consumers and prevent *TC*, the government should take all efforts to encourage technological innovation. Furthermore, the relationship between *TP* and *TC* has important implications for firms. Since producing irreplaceable and high-value-added products may help to prevent *TC*, firms should try to master core technology and develop their own high-performance products.

This paper has some limitations that can be considered recommendations for future studies. First, this paper uses the sample from 2002 to 2022 and finds that *TP* reduces *TC* in 2021 and 2022. We believe this is mainly because the *TP* in China benefits its trading partners by producing high-quality and cheaper products. However, limited to the time span, we have yet to determine whether this phenomenon will be a long-term trend. Hence, future studies can extend the sample period to see whether this conclusion still holds. Second, this paper uses the number of *TC* cases between China and other economies to measure *TC*, which enables us to analyse the overall impact of *TP* on *TC*. However, as the largest exporter and the most prominent target of trade remedy investigations, China has *TC* with both developed and emerging economies. Future studies could classify the samples according to the country category and investigate whether *TP* has the same impact on *TC* between China and different types of trading partners. Third, China has a wide range of export products (e.g., agricultural products, industrial products), which are all involved in *TC* between China and other economies. Hence, future studies could discuss whether *TP* has the same impact on the *TC* of different products.

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