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Is technological innovation a push for trade friction?

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ABSTRACT
This study analyses the interrelation between technological innovation (*TI*) and trade friction (*TF*) by applying the bootstrap rolling-window full- and subsample Granger causality test from China in a sample from January 2002 to December 2021. Results show that the influence of *TI* on *TF* is twofold. On the one hand, *TI* is a push for *TF*. This finding is consistent with the 'income effect', which postulates that *TI* leads to more *TF* by affecting the income of other countries. On the other hand, *TI* has a negative influence on *TF*. This result confirms the 'substitute effect', implying that *TI* can benefit consumers by providing more high-quality and cheaper products. In turn, *TF* can hinder *TI* by reducing exporters' profits. Based on these findings, governments should coordinate their efforts toward innovation and trade policies. At the same time, firms should master core technology and develop their high-performance products to avoid the risk of *TF*.

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1. Introduction

This paper investigates the interrelationships between technological innovation (*TI*) and trade friction (*TF*). *TI* and *TF* are essential international trade issues that draw wide attention (Akcigit & Melitz, 2022). *TF* reflects conflicts of trading partners. A country may take trade remedies measures (e.g., anti-dumping, countervailing, and safeguard measures) to protect a particular industry when its economy is threatened by other countries' trade activities, leading to trade conflicts (Tian et al., 2016). As a primary productive force, *TI* has played a vital role in economic and trade growth (Das & Chatterjee, 2021; Kogan et al., 2017; Su et al., 2022a), which is deeply connected with *TF*. *TI* enables a firm to improve the competitiveness of exports and expand overseas markets, which may harm other countries' interests, and thus triggers *TF* (Houser, 2020). For example, according to the U.S. Department of

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Commerce, China's high-tech trade surplus with the U.S. increased from US$21.089 billion to US$114.163 billion from 2003 to 2016, which prompted the Trump Administration to impose several rounds of tariffs on Chinese goods from 2018 (Lawrence, 2018). This event reveals that *TI* may be a push for *TF*. This relationship between *TI* and *TF* can also be observed in other countries. In the 1970s, confronted with the rapid growth in the Japanese semiconductor industry under the 'ultra-large-scale integration' plan formulated by the government, the U.S. took several protective measures such as anti-dumping, anti-investment and anti-merger against the semiconductor industry (Langdon, 1983). Another example is the *TF* between South Korea and Japan. In 2019, in order to restrict the development of the Korean semiconductor industry, the Japanese government limited the export of three core materials for manufacturing semiconductors to South Korea, and the two countries removed each other from the export whitelist of trade facilitation. Therefore, *TI* may positively impact *TF*, which puts firms in exporting countries at risk. However, as *TI* continues to improve, a country may have cheaper and irreplaceable products for export (Das & Chatterjee, 2021), which increases global welfare and causes *TF* to decrease. Conversely, *TF* has a mixed impact on *TI* by reducing overseas markets for exporters. On the one hand, it may hinder *TI* by reducing funds for research and development (R&D). On the other hand, it can stimulate *TI* by increasing firms' incentive to escape from the competition (Liebman & Reynolds, 2013). In general, *TF* is an important issue that draws excellent attention worldwide; whether *TI* is a push for *TF* is controversial. Thus, this paper explores the time-varying correlation between *TI* and *TF* to solve this issue. This research has important implications for the government to formulate strategic trade policies to avoid the risk of *TF* and provides a reference for the government to achieve long-term prosperity through *TI* when confronting *TF*.

As China is implementing a national innovation-driven development strategy, it is already among the world's leading players in some key *TI* indices (Song et al., 2017). According to the World Intellectual Property Organization (WIPO), China ranked first regarding patent applications in 2021. Besides, in the annual ranking of the Global Innovation Index (GII) released by WIPO in 2022, China climbed to the 11th position and ranked first among 36 upper-middle-income economies. *TI*'s improvement helps exports gradually change from labour-intensive to technology-intensive industries, causing high-tech products to become the main target in trade disputes (Jabbour et al., 2019). For instance, the production of Chinese photovoltaic cells ranked first in the world for four consecutive years from 2007 to 2010, leading the European Union (EU) to launch a massive amount of anti-dumping investigation (Voituriez & Wang, 2015; Zhi et al., 2014). In addition, with the development of *TI* in aerospace and communication, the trade surplus in the above fields with the U.S. continues to increase, which prompted the U.S. administration to take protective measures in 2018 (Su et al., 2022b). Thus, we can infer that *TI* is a push for *TF*. However, this conclusion does not always hold. In 2021, the trends of *TI* and *TF* showed opposite directions. The number of authorised patents continued to soar under the government's efforts to encourage *TI*, while the number of *TF* against China dropped significantly. In general, *TI* and *TF* have a close relationship, but whether *TI* is a push for *TF* is still ambiguous. According to China's Ministry of Commerce (MOC), the country was the most prominent target of trade remedies investigations from 2000–2020, and India, the U.S., Ukraine, Argentina, South Korea, and the EU initiated 68.85% of the analyses. This makes *TF* the main risk for Chinese exporters (Jabbour et al., 2019; Miyagiwa et al., 2016). It is noteworthy that the country is upgrading its industrial structure by encouraging *TI* and is building a robust domestic market and a strong trading nation, which may change the relationship between *TI* and *TF*. Thus, the discussion about *TI* and *TF* has special significance for China.

The contributions of this paper are as follows. Firstly, previous literature rarely examines the causal relationship between *TI* and *TF*; they mainly focus on the impact of *TI* on trade and related policy (Miyagiwa & Ohno, 2007; Rossi et al., 2021) or the impact of trade policy on *TI* (Dorn et al., 2020; Guei, 2022; Liu et al., 2021). To our knowledge, this paper is the first to explore the interconnection between *TI* and *TF* by considering the number of *TF* cases that Chinese exporters counteracted worldwide. We find that *TI* and *TF* influence each other significantly. Secondly, existing studies mainly apply the full-sample causality test, neglecting the parameters' structural changes. This paper contributes to the current investigations by using the bootstrap sub-sample rolling-window causality test, which enables us to examine the time-varying relationship between *TI* and *TF*. We find that *TI* is a push for *TF*, which is consistent with the 'income effect' that *TI* of one country leads to *TF* by threatening other countries' income. This view, however, was not valid in 2021, during which period *TI* reduced *TF*. Encouraged by the national innovation-driven development strategy, firms were more capable of developing their high-tech products in 2021, benefiting their trading partners by producing high-quality and cheaper products. As a result, *TF* decreases. This result proves the 'substitute effect', implying that *TI* reduces *TF* by increasing the real purchasing power of consumers. Understanding the correlation between *TI* and *TF* is significant for China to survive in *TF* while achieving innovation-driven development.

The rest of this paper is organised as follows. Section 2 is the literature review. Section 3 analyses the interrelationship between *TI* and *TF* theoretically. The empirical methods and the data are introduced in Sections 4 and 5, respectively. Section 6 shows the empirical results. Section 7 further discusses the results and compares them with previous studies. Section 8 concludes the paper and presents limitations and recommendations for future studies.

2. Literature review

A growing body of literature has recognised *TI*'s important role in *TF*. Samuelson (2004) points out that when one country's export increases through technological progress, other countries' gain from trade will fall, resulting in a trade conflict. Besides, Aggarwal (2004) reveals that innovative exporters are a threat to foreign competitors, which triggers the use of an anti-dumping policy. Niels (2000) also suggest that anti-dumping policies are more used in technological than non-technological industries. Miyagiwa and Ohno (2007) reveal that while cost-saving *TI* facilitates exports, it also increases the likelihood of being arbitrated as a dumping case. In addition, Márquez-ramos et al. (2010) use a gravity trade model and prove a positive effect of *TI* on exports, but they do not further analyse the impact on *TF*. Azar and Ciabuschi (2017) also demonstrate that innovation facilitates exporting activities by strengthening exporters' competitive advantage. Likewise, Rossi et al. (2021) suggest that innovative activities increase the likelihood of starting exporting and lower the probability of exiting foreign markets, which implies that *TI* increases the competition in international trade. Moreover, Tian et al. (2016) further point out that *TF* results from fierce competition.

Unlike most research that *TI* increases export and leads to anti-dumping, Damijan et al. (2010) reveal that product or process innovations have no significant promoting effect on export, implying that *TI* has no impact on *TF*. Besides, Miyagiwa et al. (2016) argue that improving R&D capability in developing countries can help avoid anti-dumping wars with developed countries. In addition, Zhang et al. (2018) point out that innovation is risky, which may impose firms' unbearable financial burdens and discourage exports. In addition, Edeh et al. (2020) conclude that process and marketing innovation promote export performance, but product innovation hinders exports in Nigeria. Furthermore, Dai et al. (2020) suggest an inverted-U relationship between innovation intensity and exporters' survival probability, implying that innovation has a mixed impact on *TF*.

Conversely, *TF* has specific impacts on *TI*, but the conclusion is mixed. Avsar and Sevinc (2019) find that Turkish anti-dumping trade barriers promote R&D expenditures by reducing competition. In addition, Buryi and Lahiri (2019) imply that domestic firms tend to increase R&D investments when there is a rise in import tariffs. Slavtchev (2020) also approves that a protectionist policy is conducive to German R&D inputs by reducing import competition from middle- and low-income countries. In addition, Melitz and Redding (2021) suggest that protectionist policy increases the incentive for innovation of domestic firms. Moreover, Dorn et al. (2020) reveal that trade liberalisation impedes innovation in U.S. manufacturing firms, suggesting that *TF* can promote *TI*. Likewise, Aghion et al. (2021) propose a negative influence of trade liberalisation on the innovative activities of some French firms, implying that *TF* facilitates *TI*.

In contrast, Atkeson and Burstein (2010) develop a general equilibrium model and suggest that trade liberalisation rather than protectionist policy increases exporter's innovation rates. Besides, Lileeva and Trefler (2010) propose that Canadian exporters generate more innovations after Canada and the U.S. sign the free trade agreement. Likewise, Burstein and Melitz (2011) prove that a more extensive market facilitated by tariff cuts promotes innovation. In addition, Akcigit et al. (2018) conclude that reduced trade barriers bring an influx of foreign competitors into domestic markets, which boosts domestic innovation through intensified international competition. Coelli et al. (2022) draw a similar conclusion that the increasing import competition from the reduction in global tariffs contributes to more patents. Moreover, Aghion et al. (2005) suggest that the impact of import competition on innovation when trade is liberalised follows an inverted U shape. Extremely low or high levels of competition result in less innovation. Shu and Steinwender (2019) further imply that when there is no *TF*, the influx of foreign competitors into domestic markets spurs innovation in developing countries, while the impact is mixed in developed countries.

More recent studies have investigated the relationship between *TI* and China-related *TF*. Li and Li (2022) propose that innovation triggers anti-dumping investigations against China primarily via the 'perceived threat' channel. Wang (2022) suggests that technological progress in Huawei, a Chinese company, increases competition and results in the trade conflict. Besides, Wu et al. (2021) indicate that innovation promotes Chinese manufacturing exports, but they do not analyse the further impact on *TF*. Likewise, using firm-level data, Dong et al. (2022) reveal that innovation benefits China's exports. Conversely, China-related international *TF* also influences *TI*. Xie et al. (2020) show that anti-dumping barriers hinder Chinese firms' R&D investment and R&D intensity. Liu and Ma (2020) explore the impact of trade policy uncertainty (TPU) on innovation, finding that a rise in TPU decreases Chinese firms' patent applications. Houser (2020) points out further that the Sino-U.S. *TF* will hinder the worldwide development of *TI*. However, Prud'homme and Cohen (2019) point out that Sino-U.S. *TF* has stimulated a quest for technological 'self-reliance' in China. In addition, Xu et al. (2022) propose that the Sino–U.S. *TF* is conducive to Chinese firms' innovation. Moreover, Li et al. (2022) show that the U.S. tariff escalation increases Chinese firms' R&D expenditure.

Most previous researchers examine the impact of innovation on specific trade policies (e.g., anti-dumping) (Miyagiwa & Ohno, 2007) while ignoring the direct impact of *TI* on *TF*. Although some studies discuss the reason and impact of Sino-U.S. *TF* (Li et al., 2022; Xu et al., 2022), there still needs to be an answer to whether *TI* is a push for *TF*. In addition, although some studies (e.g., Houser, 2020; Xu et al., 2022) show that the effects of *TF* on innovation vary by region, they still need to discuss whether these effects change over time. Furthermore, 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. This study considers the influence of China's *TI* policies when investigating the relationship between *TI* and *TF*. We use the bootstrap subsample rolling-window causality test (Balcilar et al., 2010; Su et al., 2019) to explore the influence of *TI* on *TF* at different periods. This study not only answers the question of whether *TI* is always a push for *TF* but also has implications for the government regarding promoting innovation in the environment of *TF*.

3. *TI* and *TF* interaction mechanism

We use a two-country theoretical framework (Miyagiwa et al., 2016; Samuelson, 2004) to explain the impact of *TI* on *TF*. Consider there are two countries, A and B, and there is intra-industry trade. Suppose *TI* contributes to the cost-reducing production in country A, which drives down the exporting price (Wu et al., 2021). This will increase the market share of country A while diminishing that of country B (Miyagiwa & Ohno, 2007). In this way, *TI* can usually increase the income of exports and promote the economic growth of country A (Dong et al., 2022; Palley, 2006). However, the income of country B falls because of the diminishing market share after country A achieves technological progress, which may cause TF between the two countries (Samuelson, 2004). Let y_B be the export income of country B, and TI_A be technological innovation in country A, then $TF = f(y_B)$, $y_B = g(TI_A)$, which means TF is a function of y_B, and y_B is a function of TI_A. From another perspective, as TI reduces the price of the product, residents in country B can buy more products worldwide at a lower price, which means the real purchasing power of B increases. In this way, TI reduces TF. Let R_B be the real purchasing power of country B, then $R_B = h(TI_A)$, $TF = l(R_B)$, indicating that TI of country A influences R_B, and TF is a function of R_B. As TI influences TF by affecting y_B and R_B, the total impact of TI on TF can be shown as Equation (1):

$$\frac{dTF}{dTI_A} = \frac{\partial TF}{\partial y_B} \times \frac{dy_B}{dTI_A} + \frac{\partial TF}{\partial R_B} \times \frac{dR_B}{dTI_A} \tag{1}$$

As mentioned above, the TI in country A harms the income of country B, then $\frac{\partial TF}{\partial y_B} < 0$. In addition, the reduction of income in country B brings more TF, then $\frac{dTF}{dy_B} < 0$. Therefore, $\frac{\partial TF}{\partial y_B} \times \frac{dy_B}{dTI_A} > 0$, which is defined as '**income effect**', suggesting that the TI of country A brings more TF by reducing the income of country B. Furthermore, as TI in country A raises the real purchasing power of country B, which causes less TF, we can infer that $\frac{dR_B}{dTI_A} > 0$, and $\frac{\partial TF}{\partial R_B} < 0$. Then $\frac{\partial TF}{\partial R_B} \times \frac{dR_B}{dTI_A} < 0$, indicating that TI reduces TF by increasing the real purchasing power of country B. We define this effect as the '**substitute effect**'. In summary, TI has both an income effect and an substitute effect on TF. When the income effect outweighs the substitute effect, TI is a push for TF, and vice versa.

In turn, TF can also influence TI. On the one hand, TF impedes the TI of the exporter for the following two reasons. First, it is generally believed that a more significant market stimulates innovation because fixed costs can be spread over more units of products (Geng & Kali, 2021). When TF occurs, a country can negatively affect other countries' market share by taking protective measures (Crowley et al., 2018), thus reducing firms' inventiveness to innovate in other countries. For instance, when country B takes safeguard measures against subsidised imports or dumped imports from country A, the overseas markets of A shrink, suppressing the innovation motives of firms in country A. Second, TF may reduce the exporters' profit, which negatively impacts the R&D expenditure that TI needs (Melitz & Redding, 2021). For example, the levying of anti-dumping and countervailing duty from country B increases the price of country A's products in country B, which weakens the competitiveness of country A's products and leads to a reduction in profit. Lack of financing is one of the biggest obstacles that innovative firms face (Krastanova, 2014; Wu et al., 2021), so the reduced profit impedes TI. Let $TI = l(TF)$, which means TI is a function of TF. We can infer that $\frac{dTI}{dTF} < 0$, suggesting that TF hinders TI of the exporting country. On the other hand, TF promotes the TI of exporters by increasing the competitive pressure. Exporters may be incentivised to escape from the competition by developing products with higher performance through TI (Aghion et al., 2005; Galdon-Sanchez & Schmitz, 2002; Xu et al., 2022). In this situation, $\frac{dTI}{dTF} > 0$. In summary, TI and TF are interactive, but the exact direction of the impact is uncertain.

4. Methodology

4.1. Bootstrap full-sample causality test

The standard Granger causality test based on the vector autoregression (VAR) model usually assumes that statistics like 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 (Toda and Phillips, 1993, 1994), which can lead to inaccurate estimates. Shukur and Mantalos (1997) suggest that the critical values of residual-based bootstrap (RB) estimation can improve estimation performance. 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, *RB*-based modified-*LR* statistic is applied to explore the causal relationship between *TI* and *TF*. The VAR model is shown in Equation (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, $\mathbf{\Phi}_0, \ \ldots \ \mathbf{\Phi}_p$ are matrixes of coefficients to be estimated and p is the lag length. In this paper, we choose the lag length based on the Akaike information criterion (AIC), Schwarz information criterion (SIC) and Hannan-Quinn information criterion (HQ). In addition, as mentioned in the theoretical analysis that export is related to *TI* and *TF* (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, Equation (2) can be expressed as follows:

$$\begin{bmatrix} TI_t \\ TF_t \end{bmatrix} = \begin{bmatrix} \phi_{10} \\ \phi_{20} \end{bmatrix} + \begin{bmatrix} \phi_{11}{}^{(1)} & \phi_{12}{}^{(1)} & \phi_{13}{}^{(1)} \\ \phi_{21}{}^{(1)} & \phi_{22}{}^{(1)} & \phi_{23}{}^{(1)} \end{bmatrix} \begin{bmatrix} TI_{t-1} \\ TF_{t-1} \\ EX_{t-1} \end{bmatrix} + \ldots + \begin{bmatrix} \phi_{11}{}^{(2)} & \phi_{12}{}^{(2)} & \phi_{13}{}^{(2)} \\ \phi_{21}{}^{(2)} & \phi_{22}{}^{(2)} & \phi_{23}{}^{(2)} \end{bmatrix} \begin{bmatrix} TI_{t-2} \\ TF_{t-2} \\ EX_{t-2} \end{bmatrix} + \ldots + \begin{bmatrix} \phi_{11}{}^{(p)} & \phi_{12}{}^{(p)} & \phi_{13}{}^{(p)} \\ \phi_{21}{}^{(p)} & \phi_{22}{}^{(p)} & \phi_{23}{}^{(p)} \end{bmatrix} \begin{bmatrix} TI_{t-p} \\ TF_{t-p} \\ EX_{t-p} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}. \tag{3}$$

In Equation (3), when $\phi_{21}{}^{(q)} = 0, \ (q = 1, 2, \ \ldots, p)$, *TI* is not a Granger cause of *TF*. Likewise, when $\phi_{12}{}^{(q)} = 0$, *TF* is not a Granger cause of *TI* can be tested. 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 *TI* is the Granger cause of *TF*. Also, *TF* is the Granger cause of *TI* if the null hypothesis that $\phi_{12}{}^{(q)} = 0$ is rejected.

4.2. Parameter stability test

We assume the VAR model parameters to be constant over time in the full-sample causality test, which means only one causality can be obtained in every period

(Su et al., 2020). However, the relationship between dependent and independent variables may undergo structural changes brought about by demand or supply shocks in the economy or may result from 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 and Ozdemir, 2013). Therefore, it is necessary to test the stability of 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 Hansen (1992) 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 sub-sample 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 avoids biases (Qin et al., 2021; Su et al., 2021). 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 more considerable, and therefore, the result is not effective. On the other hand, large subsamples can improve the estimation's validity, but heteroscedasticity may lead to an unreliable result. It is usually believed that bias-minimizing window size should not be less than 20 observations (Pesaran & Timmermann, 2005).

We can then investigate the Granger causal relationship between *TI* and *TF* in each subsample by applying the *RB*-based modified *LR* causality test. The significance of the causality between *TI* and *TF* can be observed by calculating the *p*-value of the *LR* statistic. The impact of *TI* on *TF* 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 *TF* on *TI*. The confidence interval is 90%, with the lower limit equal to the fifth quantiles of $\hat{\phi}_{12}{}^{(q)}$ and the upper limit equal to the 95th quantiles of $\hat{\phi}_{21}{}^{(q)}$ (Balcilar et al., 2010).

5. Data

This study uses monthly data from January 2002 to December 2021. China's accession to the World Trade Organization (WTO) in December 2001 promoted its exports to proliferate. The larger overseas market gives firms a stronger motivation for *TI* (Geng & Kali, 2021). Besides, China has adopted a national strategy of innovation-driven development to improve firms' long-term competitiveness and upgrade industrial structure. Hence, China's granted patents have increased dramatically. In this paper, we use the number of granted patents each month to measure *TI*, which is widely considered a good indicator of innovation (Su et al., 2022a). In addition, with the growth in exports and technological advances, many countries impose remedial measures such as anti-dumping, countervailing and safeguards against China to protect their own industries (Jabbour et al., 2019). According to China's MOC, 27% of global trade remedies investigations are against China, making it the world's biggest target in trade remedies cases since 1995. Confronted with this challenging situation, Chinese exporters respond to the investigations actively to safeguard their interests. This paper uses the number of trade remedies cases that Chinese exporters counteract to measure *TF* (Tian et al., 2016), released by MOC.[1] We can infer that *TI* and *TF* may be correlated, with *TI* seemingly being a push for *TF* in most periods. Furthermore, the relationship between *TI* and *TF* is connected with changes in China's exports (Dong et al., 2022). As China's exports are enormous and continue to grow, its trading partners' market share may decrease, thus leading to *TF* (Samuelson, 2004). This paper uses China's export value to measure *EX* (Jabbour et al., 2019; Xu et al., 2022), which is drawn from the CEIC Data.[2]

Figure 1 shows *TI* and *TF* trends. The solid line indicates the changes in *TF,* while the dashed line describes the changes in *TI*. It can be observed that *TI* has an overall rising trend. It reached to peak in 2021. Besides, a high *TI* coincides with an increase in *TF* in most periods. In addition, as *TI* rises, the trade remedies investigations against China are also shifting from labour-intensive (e.g., textiles) to technology-intensive products. For example, when the growth of *TI* accelerated significantly in 2012, *TF* also increased rapidly. In 2012, the U.S. and EU implemented several rounds of anti-dumping investigations against Chinese photovoltaic cells, which

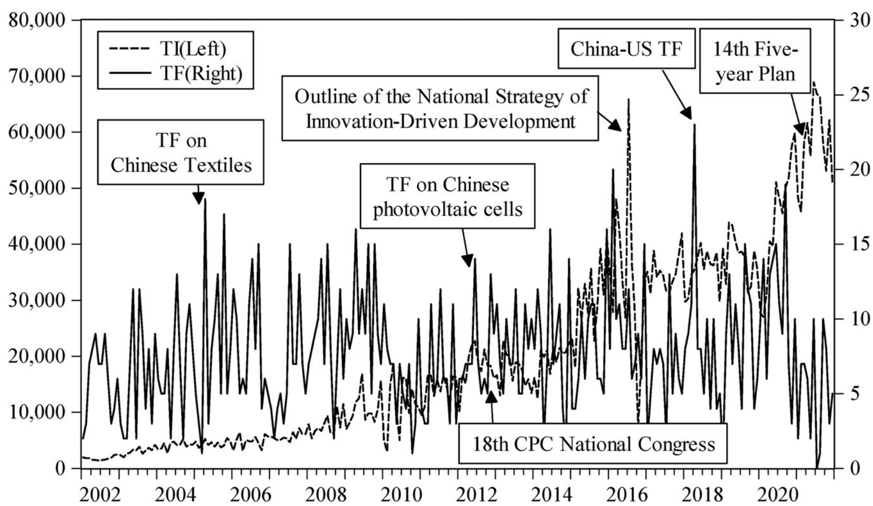

Figure 1. Trends of *TI* and *TF*.
Note: *TI*: technological innovation; *TF*: trade friction; CPC: Communist Party of China
Source: The authors.

substantially negatively impacted the photovoltaic industry (Voituriez & Wang, 2015; Zhi et al., 2014). Similar changes can be observed after the release of the Outline of the National Strategy of Innovation-Driven Development (ONSID) in May 2016. Encouraged by ONSID, Chinese firms allocate more resources to innovation, causing *TI* to rise. The figure shows that *TF* also ascends rapidly in the corresponding period. In particular, *TF* peaked in 2018 when Sino-U.S. trade frictions began. Therefore, we can infer that *TI* is a push for *TF*.

However, the trends of *TI* and *TF* are sometimes different. Affected by the Sino-U.S. trade frictions, the Chinese government emphasises technological 'self-reliance' (Prud'homme & Cohen, 2019), which causes the relationship between *TI* and *TF* to change. According to the Outline of the 14th Five-Year Plan (2021–2025) for National Economic and Social Development, China will make more efforts to achieve innovation-driven development. Besides, the Chinese government is building a robust domestic market and a strong trading nation. These events increase firms' innovation inventiveness, driving *TI* to soar in 2021. However, *TF* drops sharply during this period. Moreover, China's exports affect the relationship between *TI* and *TF*. On the one hand, export is closely connected with *TF*. When China's export is vast, and it keeps a rising trade surplus with its trading partners, the overseas market of other countries may shrink, leading to *TF*. On the other hand, rising export influences *TI* by increasing exporters' profits. If firms attach importance to *TI*, they will invest more export profit in R&D activities, leading to more *TI*. However, if firms can make huge profits only by exporting large quantities of labour-intensive products, they may lack incentives for *TI*. As export is deeply connected with *TI* and *TF*, we choose export (*EX*) as the control variable (Jabbour et al., 2019; Xu et al., 2022). In summary, *TI* and *TF* have a time-varying relationship, which is also connected with exports.

Table 1 shows the descriptive statistics of the variables. The means of *TI* indicates that there are 19833.58 granted patents on average each month. The average value of *TF* suggests that Chinese exporters counteract 7.738 trade remedies cases on average monthly. The average weight of *EX* is US$144523.8 million. All three variables have positive skewness, which means they follow the right-skewed distribution. In addition, the kurtoses of the *TI* and *TF* are more significant than 3, demonstrating a leptokurtic distribution, whereas that of *EX* is less than 3, indicating a platykurtic distribution. Moreover, the Jarque–Bera test shows that *TI* and *TF* obey a nonnormal distribution at the significance of 1%. And *EX* follows a nonnormal distribution at

Table 1. Descriptive statistics of the sequence of *TI*, *TF* and *EX*.

Statistics	*TI*	*TF*	*EX*
Observations	240	240	240
Mean	19833.58	7.738	144523.8
Median	16001.5	7	154916.5
Maximum	68857	23	340498.8
Minimum	1386	0	19137
Std. Dev.	16619.15	3.954	71213.82
Skewness	0.918	0.681	0.030
Kurtosis	3.002	3.570	2.253
Jarque–Bera	33.744***	21.779***	5.616*

Notes: *** indicates that the statistics are significant at the 1% level. The unit of EX is US$million.
TI: technological innovation; *TF*: trade friction; EX: exports.
Source: The authors.

the significance of 10%. Hence, the estimation of parameters is inaccurate when we use the traditional Granger causality test. The subsequent analysis takes all variables from the natural logarithms to avoid potential heteroscedasticity. Besides, *EX* is further transformed by taking the first difference to avoid non-stationary.

6. Empirical results

Before performing the full-sample Granger causality test, this study performs ADF (Dickey & Fuller, 1981) and PP (Phillips & Perron, 1988) unit root tests to ensure the stability of the sequences. Table 2 shows that all sequences are stationary.

Then, we conduct the Granger full-sample causality test by constructing VAR models shown in Equation (3). According to AIC, SIC and HQ, the optimal lag length is 4. The full-sample causality results are presented in Table 3. The null hypothesis that *TI* is not a Granger cause of *TF* and the null hypothesis that *TF* is not a Granger cause of *TI* cannot be rejected at the significance level of 10%. Results show that *TI* and *TF* have no relationship with each other, which is inconsistent with the theoretical analysis.

The traditional full-sample Granger causality test requires that all parameters are constant, and we can get only a single Granger causal relationship within a fixed time interval. However, when structural changes exist in the parameters, the causality of *TI* and *TF* 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 4.

The results of the *Sup-F* tests indicate a sudden shift in the *TI* equation, the *TF* equation is at the 1% significance level. *Mean-F* and *Exp-F* tests are used to test the null hypothesis that parameters follow a martingale process. The results show that the

Table 2. Unit root tests.

Series	ADF	PP
TI	−4.327 (3)***	−10.998[9]***
TF	−14.952 (0)***	−15.261[7]***
EX	−3.051(13)**	−32.072[12]***

Notes: Numbers in parentheses indicate the lag order, which is selected based on the AIC.
Numbers in the brackets refers to the bandwidth, which uses the Bartlett Kernel as suggested by the Newey–West test (1987).
*** and **denote significance at the 1% and 5% levels, respectively.
TI: technological innovation; *TF*: trade friction; EX: exports;.
ADF: Augmented Dickey-Fuller test; PP: Phillips and Perron test.
Source: The authors.

Table 3. Full-sample Granger causality tests.

	H0: *TI* is not a Granger cause of *TF*		H0: *TF* is not a Granger cause of *TI*	
Tests	Statistics	*p*-values	Statistics	*p*-values
Bootstrap *LR* test	2.325	0.660	1.342	0.844

Notes: The null hypothesis is that no causal relationship exists between the variables. p-values are calculated using 10,000 bootstrap repetitions.
TI: technological innovation; *TF*: trade friction; LR: likelihood ratio.
Source: The authors.

Table 4. Parameter stability tests.

	TI equation		*TF* equation		VAR (4) system	
	Statistics	Bootstrap *p*-value	Statistics	Bootstrap *p*-value	Statistics	Bootstrap *p*-value
Sup-F	37.669***	0.000	41.211***	0.000	36.266	0.109
Mean-F	17.251***	0.009	9.373	0.390	20.476	0.243
Exp-F	14.102***	0.001	15.488***	0.000	13.796	0.160
Lc					3.420	0.220

Notes: We calculate p-values using 10,000 bootstrap repetitions. ***indicate significance at the 1% levels. Lc shows the results of the Hansen–Nyblom parameter stability test for all parameters in the VAR jointly.
TI: technological innovation; *TF*: trade friction; VAR: vector autoregression.
Source: The authors.

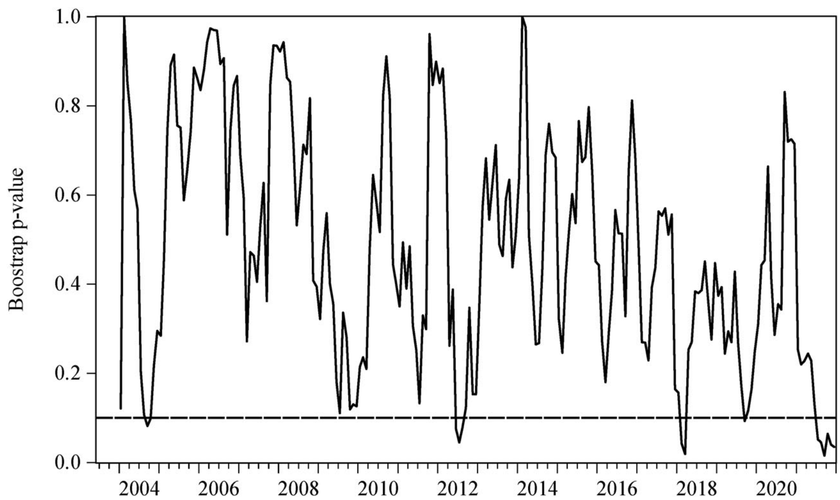

Figure 2. Bootstrap *p*-value of the statistics (the null hypothesis is that *TI* is not a Granger cause of *TF*).
Source: The authors.

null hypothesis is rejected, indicating that the *TI* equation and *TF* equation may evolve gradually with time. In summary, the results above show that parameters are unstable, and there are structural changes in the whole sample. Thus, the full sample Granger causality test results need to be more accurate. To improve the accuracy of the results, we adopt the bootstrap rolling-window Granger causality test to investigate the time-varying causal link between *TI* and *TF* in different subsamples. As the bias-minimizing window size should not be less than 20 observations (Pesaran & Timmermann, 2005), the rolling subsample data includes 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 *TF* as the dependent variable. Results show that the *p*-values are less than 0.1 during 2012:M6–2012:M8, 2018:M2-2018:M3, 2021:M7-2021:M12, indicating that the null hypothesis—*TI* is not the Granger cause of *TF*—is rejected significantly at the 10% level. Figure 3 reports the sum of the rolling-window coefficients for the impact of *TI* on *TF*. Combining Figures 2 and 3, we can see that *TI* influences *TF* positively in 2012:M6–2012:M8 and 2018:M2-2018:M3, suggesting that China's *TI* is a push during this period for *TF*. However, this influence becomes negative in 2021:M7-2021:M12, meaning that *TI* reduces *TF*.

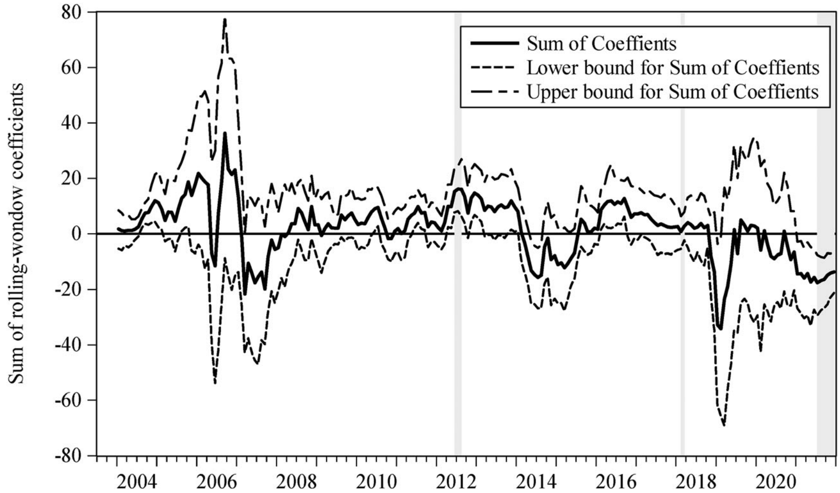

Figure 3. Sum of rolling-window coefficients of *TI*'s influence on *TF*.
Source: The authors.

China has implemented a series of programmatic policies to promote *TI*. For instance, in 2006, the Chinese government promulgated the 'Outline of the National Medium- and Long-Term Science and Technology Development Plan (2006–2020)', aiming to rank top five in the world by 2020 in terms of the number of national granted patents. In 2008, the 'Outline of National Intellectual Property Strategy' was issued, which lists the better protection of intellectual property as one of the strategic goals. Encouraged by such policies of China, the *TI* improves rapidly, promoting the growth of exports of the country. In 2012, several countries conducted trade remedies investigations against China (Qin et al., 2022; Su et al., 2022c), which involved not only labour-intensive (e.g., textiles) and capital-intensive products (e.g., steel and tires) but also technology-intensive products (e.g., photovoltaic). Moreover, 70% of the trade remedies investigations are initiated by developing countries or emerging economies, such as Brazil, India, Argentina and Thailand. The main reason that *TI* increases *TF* during this period is twofold. On the one hand, *TI* facilitates Chinese exports, which reduces its competitors' market share and income. The conflicting interests between the two countries lead to *TF*. On the other hand, many countries have not recovered from the subprime mortgage crisis and the European sovereign debt crisis (Feng et al., 2021; Su et al., 2022d). According to WTO, the global commodity trade grew by only 0.2% in 2012. Such an economic downturn encourages many countries to safeguard against Chinese exports (Baldwin & Evenett, 2009). Therefore, *TI* has a positive influence on *TF* from 2012:M6–2012:M8.

From 2012–2018, China's *TI* accelerates under the national strategy of innovation-driven development (Song et al., 2017; Zhang, 2020). In 2018, for example, Huawei was the company that filed for most patents with the World Intellectual Property Organization (Houser, 2020). With the progress of *TI*, China has encountered multiple trade remedies investigations initiated by India, Mexico, Brazil, Costa Rica, Turkey, the U.S., the EU, and so on from 2018:M2 to 2018:M3. Among them, the investigation initiated by the U.S. has a relatively more considerable influence. The

U.S. administration decided to impose a 25% tariff on more than 1,300 kinds of Chinese imports involving aviation, aerospace, information, and communication technology in 2018. Confronted with such a situation, China also imposes tariffs on U.S. exports (Lawrence, 2018; Li et al., 2020). It is believed that China's rise to technological prominence affects U.S. interests, which leads to Sino-U.S. *TF* (Li & Li, 2022). Therefore, *TI* is a push for *TF* during 2018:M2-2018:M3. This result is consistent with the 'income effect', implying that the *TI* of China brings more *TF* by threatening the export income of other countries.

However, there was a negative impact of *TI* on *TF* in 2021. Guided by the outline of the 14th Five-Year Plan (2021–2025), China has been improving the system for *TI*, encouraging R&D investment, and accelerating the development of *TI*. Besides, the Sino-U.S. *TF* has raised Chinese companies' awareness of developing high-tech products such as semiconductors. Furthermore, the Chinese government makes more efforts to build a robust domestic market and expand overseas markets under the Belt and Road Initiative, which enhances the incentives for Chinese firms' *TI*. It can be observed that while *TI* increased, *TF* dropped sharply in 2021. The reasons are as follows. First, developing Chinese firms' high-tech products enables them to circumvent technical trade barriers, thus decreasing TF. Second, *TI* boosts China's economy and benefits its trading partners by producing high-quality and cheaper products (Dong et al., 2022). Hence, *TI* reduces *TF* during 2021:M7-2021:M12. This finding proves the 'substitute effect', suggesting that China's *TI* reduces *TF* by increasing the real purchasing power of other countries.

Figure 4 presents the rolling bootstrap *p*-values of the *LR* statistic using *TI* as the dependent variable. The *p*-values are less than 0.1 during the periods of 2005:M2–2005:M7, showing that *TF* is the Granger cause of *TI* during this period. Figure 5 depicts the sum of the rolling-window coefficients of *TF*'s influence on *TI*. Specifically, *TF* exerts a negative effect on *TI*, which means that more *TF* hinders *TI* in China during that period.

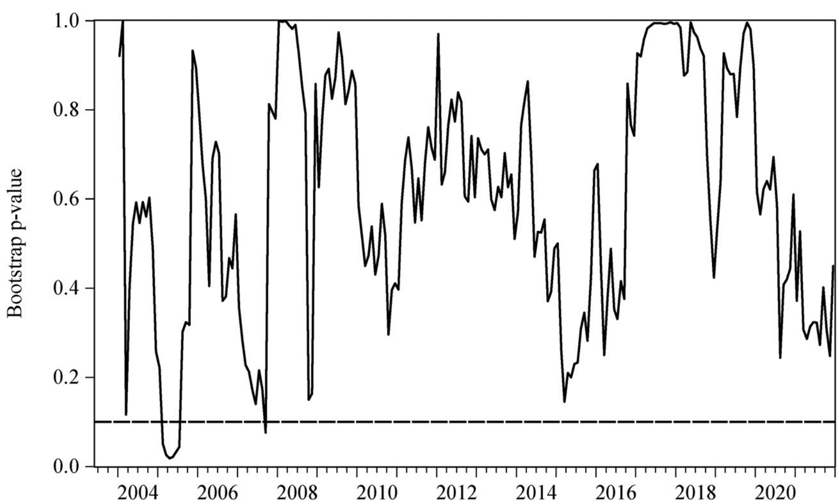

Figure 4. Bootstrap *p*-value of the statistics (the null hypothesis is that *TF* is not a Granger cause of *TI*).
Source: The authors.

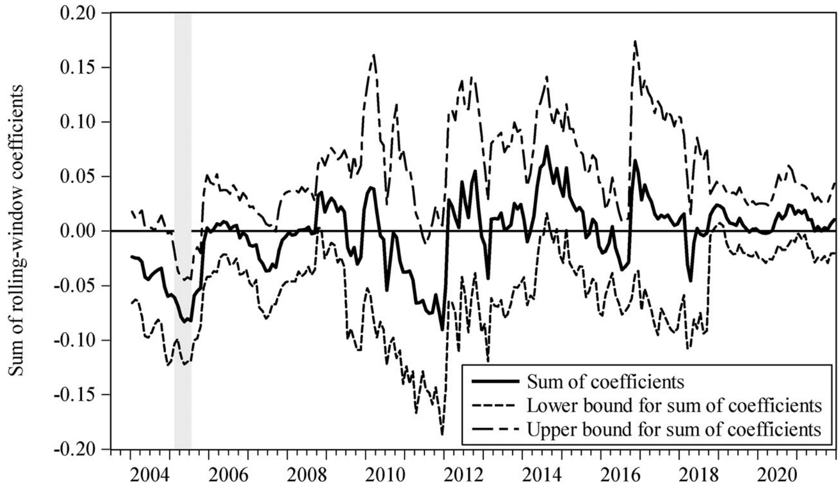

Figure 5. Sum of rolling-window coefficients of *TF*'s influence on *TI*.
Source: The authors.

In 2005, China's exports continued to increase, reaching approximately $1.4 trillion. At the same time, China is the country that receives most trade remedies investigations globally (Jabbour et al., 2019). According to China's MOC, its exporters respond to 43 trade remedies cases from 2005:M2 to 2005:7, involving various labour-intensive products such as textiles, daily necessities, and building materials. Among them, textiles are the most significant target for anti-dumping investigations. It is worth noting that all import quotas for textiles and clothing among WTO members should be abolished from January 1, 2005. As China has a comparative advantage in the textile industry, this event further benefits textiles export (Zhuo and Park, 2019). As the export of textiles threatens other countries' interests, several economies, including the EU, the U.S. and India, decided to take various protectionist measures to restrict imports from China. In response to the protectionist measures and to protect the textile industry, the Chinese government makes many efforts to negotiate with its trading partners. Such *TF* hinders the development of *TI*. First, *TF* reduces the resources for *TI*. China was an export-oriented economy in 2005, whose income depended mainly on exporting labour-intensive products. As *TF* reduces exporters' profits, it limits the R&D expenditure further and ultimately impedes *TI*. Second, the overseas export markets shrink when there is *TF*, which weakens exporters' incentive for *TI*. Hence, *TF* reduces *TI* in 2005:M2–2005:M7.

However, under the national innovation-driven development, the industrial structural upgrade gradually. Chinese firms have realised the important role of *TI* in enterprise development and invested more resources in R&D (Dong et al., 2022; Yi et al., 2013). An increasing number of Chinese enterprises have developed their high-tech products, whose performance has reached or surpassed that of imported products. For example, although the Sino-U.S. trade friction has caused a shrinking overseas market and a plummeted profit for Huawei, the company put more emphasises on *TI*. (Xu et al., 2022). In addition, the Chinese government has been building a robust domestic market and a strong trading nation, which gives firms a greater incentive to innovate (Wu et al., 2021). Since *TF* has less impact on the resources and incentives of *TI* in Chinese firms, there is no significant influence of *TF* on *TI* from 2005:M7 to 2021:M12.

7. Discussion

In the empirical analysis, we apply the bootstrap sub-sample rolling-window Granger causality test to investigate the relationship between *TI* and *TF* in different subsamples and draw three conclusions. Firstly, we find that the influence of *TI* on *TF* is positive in 2012:M6–2012:M8 and 2018:M2-2018:M3, indicating that during these periods, *TI* is a push for *TF*. In 2012, *TI* facilitated Chinese exports, which led to conflicting interests between China and its trading partners. Besides, many countries have not recovered from the subprime mortgage crisis and European sovereign debt Crisis (Feng et al., 2021), leading to a positive influence from *TI* to *TF* in 2012:M6–2012:M8. In 2018, with the continuous progress of *TI*, China encountered multiple trade remedies investigations initiated by India, Mexico, Brazil, Costa Rica, Turkey, the U.S., the EU, and so on. Among them, the research undertaken by the U.S. has a relatively more considerable influence. It is believed that China's rise to technological prominence affects U.S. interests, which leads to Sino-U.S. *TF* (Li & Li, 2022). Therefore, *TI* is a push for *TF* during 2018:M2-2018:M3. This result is consistent with the 'income effect', indicating that the *TI* of China brings more *TF* by threatening the export income of other countries. This finding supports other studies conducted in this area (Aggarwal, 2004; Li & Li, 2022; Miyagiwa & Ohno, 2007), but they mainly focus on the impact of *TI* on anti-dumping. For example, Miyagiwa and Ohno (2007) reveal that while cost-saving *TI* facilitates exports, it also increases the likelihood of being arbitrated as a dumping case. Li and Li (2022) propose that innovation triggers anti-dumping investigations against China primarily via the 'perceived threat' channel. Unlike these studies, this paper uses the number of trade remedies cases (anti-dumping, countervailing and safeguards against China) that Chinese exporters counteract to measure *TF*, drawing a more comprehensive conclusion that China's *TI* is a push for *TF*.

Secondly, *TI* reduces *TF* in 2021:M7-2021:M12. During this period, developing Chinese firms' high-tech products enabled them to circumvent technical trade barriers. Besides, *TI* boosts China's economy and benefits its trading partners by producing high-quality and cheaper products. Hence, *TI* reduces *TF* during 2021:M7-2021:M12. This finding proves the 'substitute effect', suggesting that China's *TI* reduces *TF* by increasing the real purchasing power of other countries. This result differs from most studies that China's *TI* brings more *TF* (Samuelson, 2004; Wang, 2022). For example, Wang (2022) suggests that technological progress in Huawei, a Chinese company, increases competition and results in the trade conflict. In contrast, this paper proves that *TI* can reduce *TF* by promoting producing high-quality and cheaper products and achieving mutual benefit between trading partners. This finding has important implications for the government and firms to engage in *TI*.

Thirdly, it shows that *TF* influences *TI* negatively during the periods of 2005:M2–2005:M7, indicating that *TF* may hinder a country's *TI* when its economic growth mainly depends on exports. From 2005:M2 to 2005:7, Chinese exporters respond to 43 trade remedies cases; among them, textiles are the most significant target for anti-dumping investigations. China was an export-oriented economy in 2005, whose income depended mainly on exporting labour-intensive products (e.g., textiles). As *TF* reduces exporters' profits, it limits the R&D expenditure further and ultimately impedes *TI* (Melitz & Redding, 2021). In addition, the overseas export markets shrink when there is *TF* (Crowley et al., 2018), which weakens exporters' incentive for *TI*. Hence, *TF* reduces *TI* in 2005:M2–2005:M7. This result agrees with related studies (Houser, 2020; Liu & Ma, 2020; Xie et al., 2020), but they fail to investigate the impact of all of the *TF*s that China encounters. For example, Xie et al. (2020) show that anti-dumping barriers hinder Chinese firms' R&D investment and R&D intensity. However, they fail to study the influence of other *TF*s, such as countervailing and safeguards against China. Liu and Ma (2020) focus on the impact of trade policy uncertainty (TPU) on innovation, finding that a rise in TPU decreases Chinese firms' patent applications, which does not discuss *TF* directly. Houser (2020) points out that the Sino-U.S. *TF* will hinder the worldwide development of *TI*, which does not aim to discuss the *TF* between China and other countries. Furthermore, we find that *TF* influences *TI* negatively during the periods of 2005:M2–2005:M7, while the influence is insignificant in different periods. This result differs from some studies (Li et al., 2022; Prud'homme & Cohen, 2019; Xu et al., 2022) that the Sino–U.S. *TF* is conducive to Chinese firms' innovation. This finding implies that in order to promote *TI*, the government and firms should take measures to avoid *TF*. In addition, the Chinese government should build a robust domestic market to reduce the negative impact of *TF* on *TI* in Chinese firms.

8. Conclusion, implication and limitation

8.1. Conclusion

TF is an important issue that draws great attention worldwide. In particular, *TF* has become the main risk for Chinese exporters, deeply connected with *TI*. In this context, this paper aims to analyse whether *TI* is always a push for *TF*. Firstly, we conduct the full-sample Granger causality test. Results show that *TI* and *TF* have no relationship with each other, which is inconsistent with existing literature (Avsar and Sevinc, 2019; Miyagiwa et al., 2016; Samuelson, 2004). Considering that the full-sample Granger causality test assumes that there is only a single Granger causality in the whole sample, it is inaccurate in estimating the relationship between *TI* and *TF*. Then, we apply the parameter stability test, results show that the parameters are unstable and structural changes exist. Therefore, we apply the bootstrap sub-sample rolling-window Granger causality test to examine the time-varying causal relationship between *TI* and *TF* in different subsamples, drawing three main conclusions.

First, in 2005 and 2018, China's *TI* led to more *TF* primarily by threatening trading partners' overseas market share and exporting income. This result supports the 'income effect' in the theoretical analysis, implying that China's *TI* can lead to more *TF* by reducing the income of the other country. This finding also supports other related literature (Aggarwal, 2004; Li & Li, 2022; Miyagiwa & Ohno, 2007), which reveals that *TI* leads to more anti-dumping investigations.

Second, *TI* had a negative effect on *TF* in 2021, during which time the development of Chinese firms' high-tech products enabled them to circumvent technical trade barriers. Besides, *TI* promotes producing high-quality and cheaper products, which helps achieve the mutual benefit between China and its trading partners during this period. This result is consistent with the 'substitute effect' in the theoretical analysis, which suggests that *TI* can reduce *TF* by providing cheaper products, thereby increasing the real purchasing power of consumers. This result differs from most studies that China's *TI* brings more *TF* (Samuelson, 2004; Wang, 2022).

Third, a negative influence from *TF* on *TI* is observed, suggesting that *TF* may hinder *TI* by reducing firms' profit for innovation. In addition, *TF* causes the overseas export markets to shrink, which weakens exporters' incentive for *TI*. This result agrees with related studies (Houser, 2020; Liu & Ma, 2020; Xie et al., 2020).

8.2. Suggestion and implication

Understanding the relationship between *TI* and *TF* is significant for China to survive in *TF* while achieving innovation-driven development. It provides the following insights for policymakers. First, as China's *TI* may lead to *TF* and thus risks trade, policymakers should take some measures to reduce *TF* risks when applying the national innovation-driven development strategy. For example, policymakers should take actions such as bilateral consultation or the WTO dispute settlement mechanism to build a win-win relationship with its trading partner. Second, since *TI* can also help China to survive in *TF* by increasing the welfare of worldwide consumers, policymakers should continue to encourage *TI*. Third, as *TF* can impede technology progress when economic growth relies mainly on exports, the government needs to build a robust domestic market and avoid over-dependence on overseas markets to reduce the risk of *TF*.

Furthermore, the relationship between *TI* and *TF* has important implications for firms. Firstly, firms engaged in *TI* should take measures to reduce *TF* risk. When trade remedy cases against Chinese firms occur, they should respond actively to minimise the loss of profits. Secondly, firms should realise that low-value-added enterprises mainly engaged in processing, assembly, and component manufacturing will suffer more in *TF*. However, when *TI* brings high-quality, low-cost, and irreplaceable products, *TF* may decrease. Therefore, firms should try to master core technology and develop high-performance products to deal with *TF*.

8.3. Research limitations and recommendations

This paper has some limitations that can be considered recommendations for future studies. The first limitation is that this paper focuses on the relationship between *TI* and *TF* in China while not considering other countries. *TF* is a common phenomenon in international trade, and the impact of *TI* on *TF* differs among different countries. Therefore, future studies can examine whether *TI* is always a push for *TF* in other countries and compare the results with ours. However, considering that China has the most patent applications and is the most prominent target of trade remedies investigations, it has special significance to study this issue using China as a sample.

The following limitation is the relatively limited period. Using the sample from January 2002 to December 2021, we find that *TI* reduced *TF* in 2021. This is because Chinese firms pay more attention to developing their high-tech products, enabling them to circumvent technical trade barriers. They also benefit their trading partners by producing high-quality and cheaper products. However, we have yet to determine whether this phenomenon will be a long-term trend. Hence, future studies could extend the sample period to see whether this conclusion still holds. However, the current period is enough to draw a meaningful conclusion that *TI* has both positive and negative effects on *TF*.

Finally, this paper uses the number of trade remedies cases that Chinese exporters counteract to measure *TF*, which does not include the trade remedies investigations that Chinese firms do not respond to. In the first few years after China entered the WTO, Chinese exporters rarely responded to trade remedies investigations such as anti-dumping. As they become familiar with international trade rules, more exporters actively respond to trade remedies cases to safeguard their interests. Research can be continued by considering all of the trade remedies investigations to examine their relationship with *TI*. However, considering this paper aims to investigate *TF* rather than unilateral trade remedies investigations, the number of trade remedies cases that Chinese exporters counteract is a better indicator of the conflict between China and its trading partners.

Notes

1. http://cacs.mofcom.gov.cn/cacscms/view/notice/ckys#
2. https://www.ceicdata.com
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.

Disclosure statement

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