Research Policy 54 (2025) 105210

Contents lists available at ScienceDirect

Research Policy

journal homepage: www.elsevier.com/locate/respol

The impacts of U.S. Section 337 investigations on Chinese technology firms

Jiani Fan [a], Xiuping Hua [b,*], Miao Wang [c], Yong Wang [d], Huayi Zhang [e]

[a] Ningbo University of Finance & Economics, Ningbo, China
[b] Business School, University of Nottingham Ningbo China, Ningbo, China
[c] Centre for English Language Education, University of Nottingham Ningbo China, Ningbo, China
[d] Institute of New Structural Economics (INSE), Peking University, Beijing, China
[e] University of Chicago, 5801 S Ellis Ave, Chicago, IL 60637, United States

ARTICLE INFO

JEL classification:
F10
F23
G12
G14
O24

Keywords:
Firm value
Strategic adaptations
R&D investments
International sales
Government subsidies

ABSTRACT

This paper examines the valuation impact of investigations related to the alleged infringement of American intellectual property (IP) rights, specifically Section 337 investigations, on Chinese technology firms. Evidence suggests that the stock market responds negatively to announcements of Section 337 investigations in the short term; however, the long-term price impact varies significantly across firms. When focal firms actively formulate strategic adaptations, such as increasing R&D investments, diversifying international sales, and seeking government support, they enhance their dynamic capabilities, thereby fostering long-term value creation. Moreover, further analysis shows that state-owned enterprises (SOEs) underperform private firms in strategic adaptation and value creation, while firms without venture capital (VC) backing are also worse positioned than VC-backed firms.

1. Introduction

Given the escalating trade tensions between the U.S. and China recently, research efforts have been directed toward the economic impacts of various protectionist tariffs and trade remedy policies on these two economies (Autor et al., 2013; Amiti et al., 2020; Fajgelbaum et al., 2020). Specifically, amidst the U.S. government's pivot toward protectionism and the structural transformation of Chinese exports, U.S. trade policies have increasingly emphasised technology-intensive manufacturers over labour-intensive goods. As an essential element of the trade remedy laws established by the Tariff Act of 1930 (19 U.S.C. 1337), Section 337 investigations focus on claims of American intellectual property rights (IPR) infringement, including patent, copyright, registered trademark, or mask work by imported goods. The primary purpose is to protect domestic firms from adverse impacts caused by violations of U.S. IP rights by curbing unfair competition and practices in import trade. For instance, in 2020, the U.S. International Trade Commission (USITC) reported that 86 % of investigations involved patent or trademark infringement, with the most frequently accused goods being computer and telecommunications products (25 %), pharmaceuticals and medical devices (18 %), and consumer electronics (9 %).

From 1995 to 2019, the USITC initiated 324 Section 337 investigations targeting China, highlighting a trend where more American companies file complaints about IPR violations than traditional unfair dumping practices. The consequences for Chinese firms are substantially detrimental, as once a violation is found for accused products, the same products originating in the country of the alleged party are likely to be excluded from the U.S. market. Therefore, understanding how American IPR protection affects Chinese technology companies is essential for academics, practitioners, and policymakers.

The significance of IPR protection in economic development has been extensively acknowledged in the literature (Kim et al., 2012; Lee, 2021; Schmiele, 2013). Studies on IPR and trade emphasise the impact of IPR protection on various dimensions, including trade flows (Shin et al., 2016; Campi and Dueñas, 2019), outbound international patenting (Yang and Kuo, 2008), and cross-border mergers and acquisitions (Alimov and Officer, 2017). This body of research suggests that IPR protection in technologically advanced countries is a technological barrier, significantly obstructing exports from developing countries with lower technological capabilities (Lee, 2021; Shin et al., 2016).

* Corresponding author.
E-mail addresses: jiani.fan@nbufe.edu.cn (J. Fan), Xiuping.hua@nottingham.edu.cn (X. Hua), Miao-wang@nottingham.edu.cn (M. Wang), yongwang@nsd.pku.edu.cn (Y. Wang), Huayizhang@uchicago.edu (H. Zhang).

https://doi.org/10.1016/j.respol.2025.105210
Received 10 October 2022; Received in revised form 23 February 2025; Accepted 23 February 2025
Available online 6 March 2025
0048-7333/

However, firms in developing countries can mitigate these IPR-induced barriers to technological catch-up by fostering innovation capabilities through internal R&D efforts (Lee, 2021). Similarly, consistent with dynamic capabilities theory, firms develop unique, difficult-to-replicate capabilities that enable them to effectively adapt, integrate, and reconfigure internal and external resources, skills, and competencies to address the challenges posed by a rapidly changing environment (Eisenhardt and Martin, 2000; Teece et al., 1997; Zollo and Winter, 2002).

Our research builds on a related body of work represented by Amiti et al. (2020), Egger and Zhu (2020), and Huang et al. (2023), which have investigated how protectionist tariffs imposed during the trade war affect the economic performance of companies in related markets. Most of the studies in this stream of literature use event study analysis to assess the influence of trade protection policies that increase trade barriers. They generally indicate that the imposition of trade protection policies negatively affects firms' shareholder wealth in exporting and importing countries (Amiti et al., 2020; Egger and Zhu, 2020; Huang et al., 2023). Similarly, the literature on antidumping and countervailing investigations provides evidence that protectionist and safeguard tariffs adversely affect financial markets in both the domestic economy and the targeted countries in the short run (Crowley et al., 2019; Hua et al., 2019; Li et al., 2014). Additional research on the U.S.-China trade war indicates decreased exporting activity from China to the USA (Jiang et al., 2023) and increased exporting activity in third-party countries like Vietnam, Mexico, etc. (Fajgelbaum et al., 2024).

Our work differs from the prior research by focusing on how Chinese investors and companies react to investigations into Chinese violations of American IPR that culminated in the trade war. We extend previous studies by directly evaluating investors' expectations of changes in companies' future value resulting from U.S. Section 337 investigations (Davies and Studnicka, 2018; Huang et al., 2023). Moreover, we combine the event-study method with regression analysis. This approach, grounded in efficient market theory (Fama, 1970), mitigates endogeneity concerns as stock prices swiftly incorporate new information reflecting investors' expectations of future economic conditions.

Empirically, we assess the overall impact of American IP violation investigations by analyzing investors' expectations of the future performance of Chinese companies, as share prices contain information about future profitability and cash flows (Davies and Studnicka, 2018). For each Section 337 investigation, we estimate cumulative abnormal returns (CARs) and buy-and-hold returns (BHARs) over relevant windows of time surrounding the event dates for the Chinese A-share firms that produce the "named" products in the investigations. We observe significant negative CARs around the announcement of Section 337 investigations, indicating that foreign IP restrictions adversely affect the short-term value of Chinese technology firms.

Building upon the dynamic capabilities framework pioneered by Teece et al. (1997), we then examine the strategic adaptations that drive the heterogeneous long-term value of the affected firms. To address disruptions and overcome barriers, firms strategically reconfigure resources and operations to capitalise on opportunities while minimising adverse economic and social spillovers (Ovuakporie et al., 2021). Empirical evidence demonstrates that some focal firms effectively mitigate regulatory impacts through strategic responses, including enhanced R&D investments, government support acquisition, and market adjustments, collectively enhancing their dynamic capabilities (Brenton, 2001; Huang et al., 2023; Li et al., 2014). These adaptive responses enable firms to maintain competitiveness and positively influence investor perceptions and market valuations, ultimately facilitating long-term value creation through the continuous reconfiguration of resources and capabilities in alignment with environmental demands.

We employ the method of Propensity Score Matching with Difference-in-Differences (PSM-DID) to explore strategic options implemented by focal firms in response to Section 337 investigations, such as increasing R&D investments, diversifying international sales and securing government subsidies. We hypothesize that firms leveraging these dynamic capabilities are able to accommodate trade restrictions, adapt internal and external resources, and upgrade business activities to enhance long-term value. First, as R&D expenditures provide positive signals to investors when they make trading decisions (Chambers et al., 2002), firms with stronger R&D capabilities are less sensitive to adverse shocks of Section 337 investigations in subsequent years. Second, reducing reliance on trade with policy-imposing nations and diversifying international sales contributes to better long-term stock performance (Davies and Studnicka, 2018). Third, according to the antidumping literature, government assistance, including financial support, is as vital as strategic restructuring for companies undergoing investigations related to foreign trade remedy measures (Li et al., 2014).

Our main results reveal that firms producing the "named" products significantly increase their R&D investments, promote non-U.S. sales, and secure more subsidies after investigations. Our findings on long-term corporate value also demonstrate that increasing subsequent R&D investments, adjusting exporting destinations, and securing additional government subsidies are effective and efficient strategies for Chinese technology firms responding to Section 337 investigations. Further analyses indicate that while SOEs are less reluctant to adapt strategically to adverse IPR protection shocks than private counterparties, VC-backed firms saw superior long-term value due to VC's role in assisting strategic adaptations.

This study contributes to the extant literature in several ways. First, our paper provides new insights into the literature on the economic impacts of interstate trade frictions (e.g., Amiti et al., 2020; Fajgelbaum et al., 2020). We contribute most directly to the growing literature on the value impacts of trade policy shocks between the U.S. and China, as indicated in Crowley et al. (2019), Egger and Zhu (2020), Huang et al. (2023), Hua et al. (2019), and Li et al. (2014). Our observations align with the financial market valuations of R&D investments (e.g., Chambers et al., 2002) and find support in antidumping literature emphasising trade reliance reduction and government assistance utilization (Davies and Studnicka, 2018; Fisman et al., 2014; Li et al., 2014). As investors incorporate the future benefits of R&D investment, non-U.S. sales, and government support into share pricing, these capabilities signal firm quality to external investors, contributing to sustained long-term value. We enhance this stream of literature by offering novel evidence on how financial markets react to IP-induced barriers affecting Chinese firms producing products in Section 337 investigations.

Second, we contribute to the strand of literature on the dynamic capabilities framework (Brenton, 2001; Huang et al., 2023; Li et al., 2014; Ovuakporie et al., 2021; Teece, 2007, 2018; Teece et al., 1997). Prior studies remain largely theoretical and focus on the best practice or development of dynamic capabilities (Teece, 2007, 2018; Teece et al., 1997; Zollo and Winter, 2002). We argue that the impact of dynamic capabilities in aligning strategic adaptations could be leveraged to succeed in turbulent external environments. Firms with enhanced innovative capabilities are more adept at alleviating the adverse impacts of more stringent IPR in destination countries. Further analysis shows that SOEs underperform private firms in strategic adaptation and value creation, while firms without VC backing are also worse positioned than VC-backed firms. Our empirical findings provide credible evidence of the importance of firms' dynamic capabilities in navigating complex environments.

Third, we contribute to the literature on the strategic options and actions employed by exporting firms in response to geopolitical disruptions, which includes examining product price adjustments (Avsar, 2013), trade diversion (Brenton, 2001; Ganguli, 2008; Jiang et al., 2023), changes in technology adoption strategies (Crowley, 2006), and government assistance (Li et al., 2014). By focusing on the context of Chinese technology firms facing IP-induced barriers in the U.S. market, we provide a nuanced analysis of how firms can strategically navigate these challenges and transform potential threats into opportunities for innovation and growth. Our research demonstrates the effectiveness of increasing R&D investment, adjusting international sales strategies, and securing substantial government subsidies in mitigating the negative value impact caused by trade and IPR-related frictions on technology firms. Specifically, we expand on the literature linking exporting firms' responses to geopolitical disruptions (Brenton, 2001; Lee, 2021; Jiang et al., 2023; Li et al., 2014; Shin et al., 2016). Our findings add a new dimension to this body of literature by revealing that corporate strategic responses can buffer firms against immediate adverse impacts and promote long-term resilience.

The remainder of this study is organised as follows. Section 2 reviews the literature on the related studies and develops hypotheses. Section 3 outlines the data source, variables, event study method, and empirical models employed in this study. Section 4 presents stock market reactions and the main regression results. Section 5 carries out further analyses, including heterogeneity tests and robustness checks. Finally, Section 6 concludes this study.

2. Literature review and hypothesis development

2.1. Trade protection policies, IPR protection, and financial market effects

Our research relates to several strands of literature examining the economic effects of IPR protection on trade flows (Shin et al., 2016; Campi and Dueñas, 2019), outbound international patenting (Yang and Kuo, 2008), and cross-border M&A (Alimov and Officer, 2017). The literature that links IPR with trade focuses on evaluating how IPR in the receiving (or importing) nation influences exports from the sending country while accounting for various other trade determinants (Ivus, 2010). The IPR and trade literature posits that IPR protection in developed countries is a technology barrier that significantly hampers exports from developing countries. Shin et al. (2016) contend that, given the varying levels of technological advancement among countries, the elasticity of exports to changes in IPR is more pronounced in developed nations than in developing ones. Consequently, the increased stringency of IPR in developed countries may serve as an entry barrier, posing challenges for middle-income countries seeking to penetrate developed country markets by elevating the technological sophistication of their products through innovation (Lee, 2021).

Most prominently, we draw heavily on the body of literature that exploits firms' real-time responses to trade protection actions in financial markets (Egger and Zhu, 2020; Fisman et al., 2014; Li et al., 2014; Hua et al., 2019; Huang et al., 2023). We utilise market-based approaches to capture these real-time responses, grounded in the efficient capital market theory (Fama, 1970), which posits that financial markets operate with at least semi-strong form efficiency. According to this theory, security prices reflect all publicly available information to determine a firm's expected cash flows and profits. Any new information, such as the initiation or conclusion of a patent infringement litigation, prompts the market to reassess its expectations regarding the magnitude or risk of future cash flows and profits. Consequently, the market adjusts the firm's value, which is immediately reflected in changes to the firm's stock prices.

In terms of short-term value impact, Crowley et al. (2019), Fisman et al. (2014), Huang et al. (2023), and Li et al. (2014) provide empirical support for predictions of the efficient capital market theory. Fisman et al. (2014) examine firm equity market responses to Sino-Japanese adverse relationship shocks and the correlation between stock market returns and trade exposure of related firms to these two markets, while Li et al. (2014) study the impacts of U.S. antidumping and countervailing investigations on Chinese firms' equity market performance between 2006 and 2012 and the channels through which tariff announcements affect abnormal returns. Specifically, Li et al. (2014) find that the announcements of U.S. antidumping and countervailing duties significantly reduce the market value of exporting firms in China, and firms with overseas plants in non-subject countries and government subsidies suffer less decline in shareholder wealth in the short run. Huang et al. (2023) find a similar result, showing that U.S. firms with greater exposure to China, directly or indirectly through domestic supply chains, experience larger declines in equity market value around tariff increase announcements.

Inspired by Li et al. (2014) and Huang et al. (2023), we explain the short-term price reactions of Chinese firms to Section 337 investigations based on the efficient market theory (Fama, 1970). According to the theory, new information about potential patent infringements is rapidly incorporated into stock prices, resulting in an initial negative impact due to anticipated disruptions in trade relations and possible legal costs. This also aligns with the findings of Shin et al. (2016), which reveal that stricter IPR protection in countries with higher technology levels hinders exports from nations with lower levels of technology development. Consequently, Hypothesis 1 posits the following:

Hypothesis 1. (H1): *The short-term value of firms producing products named in Section 337 investigations is negatively affected.*

2.2. Dynamic capabilities framework and IPR protection

Dynamic capabilities, as proposed by Teece et al. (1997), are defined as the firm's ability to integrate, build and reconfigure internal and external competencies to address rapidly changing environments. Unlike ordinary capabilities, dynamic capabilities enable organisations to modify their resource base, alter their ordinary capabilities, and thus facilitate continuous learning, adaptation, and increased alignment with the environment (Teece, 2007; Winter, 2012). Over the past decade, their importance has been theoretically and practically amplified, particularly in the global economy and high-tech sectors. Increasing geopolitical disruptions and uncertainty push firms to rethink their strategies to leverage and maintain their competitive advantage and good firm performance. Recently, dynamic capabilities have been further expended, with a major development being their alignment with general systems theory, emphasising the importance of reactivity and feedback mechanisms (Teece, 2018).

In international business, the imposition of 337 sanctions presents a formidable challenge to firms, compelling them to reassess and realign their strategic postures. Some scholars argue that firms under export control might limit the target countries' imitation of new technologies (Branstetter et al., 2011). In contrast, an alternative perspective posits that firms can circumvent these restrictions and achieve technological catch-up by fostering innovation capabilities (Lee, 2021) and implementing strategic adaptations in response to evolving environmental dynamics and trends (Protogerou et al., 2012). According to Huang et al. (2023), firms could mitigate the negative shocks by adjusting their international business strategies and seeking government assistance.

From path-dependent processes, dynamic capabilities involve a firm's organisational routines that enable it to continuously recombine its existing resources (Reed and Defillippi, 1990), develop new ones (Zollo and Winter, 2002), and match capabilities to the challenges posed by outside competitors and markets (Teece, 2018). Consistent with the theory, when focal firms face 337 sanctions, they actively formulate strategic responses, increasing R&D investments, seeking additional external government support, and readjusting overseas sale tactics and resources, thus effectively mitigating negative impacts (Eisenhardt and Martin, 2000; Teece et al., 1997; Zollo and Winter, 2002).

However, as firms formulate strategies to address the adverse impacts of investigations and enhance their dynamic capabilities and performance, investor expectations regarding future performance evolve positively. Consistent with the entry-barrier effect of foreign IPR (Lee, 2021; Shin et al., 2016) and the antidumping literature (Brenton, 2001; Li et al., 2014), promoting R&D initiatives, expanding overseas markets, and obtaining government assistance help mitigate the adverse effects of stricter IPR in destination countries on the exports of source countries. In response to a rapidly changing and turbulent environment, firms that timely and effectively reconfigure strategies and operations to align with external conditions can maintain competitiveness and generate greater long-term value (Lutjen et al., 2019; Ovuakporie et al., 2021). The capital market incorporates these strategic responses, which enhance firms' dynamic capabilities, into stock pricing, thereby mitigating and reversing the initial negative effects, leading to a positive long-term trend in market value. Thus, we propose Hypothesis 2, as indicated in Fig. 1:

Hypothesis 2. (H2): *Responding to Section 337 investigations, firms significantly increase their strategic adaptations by enhancing R&D investments, diversifying international sales, and seeking government support, thereby strengthening their dynamic capabilities.*

2.3. R&D investments and long-term value

A rich body of literature has examined the stock market recognition of R&D investments (e.g., Chambers et al., 2002; Hou et al., 2016; Jiang et al., 2021). R&D initiatives, IPR, advertising and marketing capabilities, and skilled human resources are essential for a firm's long-term survival. The prior literature provides consistent evidence that the equity market reacts favourably to the level and changes of investment outlay in innovative projects and activities as investors incorporate future rewards of R&D into the pricing of stocks (Chambers et al., 2002).

While the previous evidence suggests that the value of R&D investments can be effectively reflected in the current stock price, several recent studies propose that the benefits of R&D are underestimated, either through under-pricing or risk compensation, when explaining excess future returns (Chambers et al., 2002; Chan et al., 2001). One set of research asserts that investors underreact to R&D activity due to the accounting requirement for expensing R&D costs in current financial statements. In line with investors' underreaction hypothesis, Eberhart et al. (2004) provide conforming evidence on the association between R&D increases and long-term stock returns and find that sudden increases in R&D spending result in significant positive abnormal returns over the following five years.

Another set of recent studies on R&D and stock market returns focuses on the risk compensation of stocks of R&D-intensive firms. The R&D capital represents a proxy for extra market risks for which investors are compensated with excess returns. In particular, Chambers et al. (2002) argue that earlier research does not completely control for the unspecified systematic risks of R&D-intensive firms when measuring future excess returns. Therefore, investors of firms doing R&D who bear extra risks are compensated with excess future returns. Consistent with Chambers et al. (2002), Hou et al. (2016) show that stock returns in countries where the market rewards growth opportunities are more sensitive to R&D spending, confirming the risk compensation hypothesis. Jiang et al. (2021) explore the association between R&D intensity and the jump in the volatility of security prices. Their findings suggest that by increasing the voluntary disclosure of R&D information (less mispricing), R&D-intensive firms experience less jump volatility of stock price through higher stock liquidity.

Drawing upon the literature concerning the market valuation of R&D investments, we anticipate that companies with a high R&D investment ratio will exhibit superior performance compared to expectations over the extended duration of Section 337 investigations. We posit that the market responses to patent infringement investigations will demonstrate a more favourable trend for firms deeply involved in R&D activities in the long term. The rationale behind this expectation lies in the proactive and innovative nature of firms with a high R&D investment ratio. By proactively engaging in R&D, such firms may signal resilience, adaptability, and a commitment to innovation, which can contribute to a positive trend in long-term firm value over the extended period of

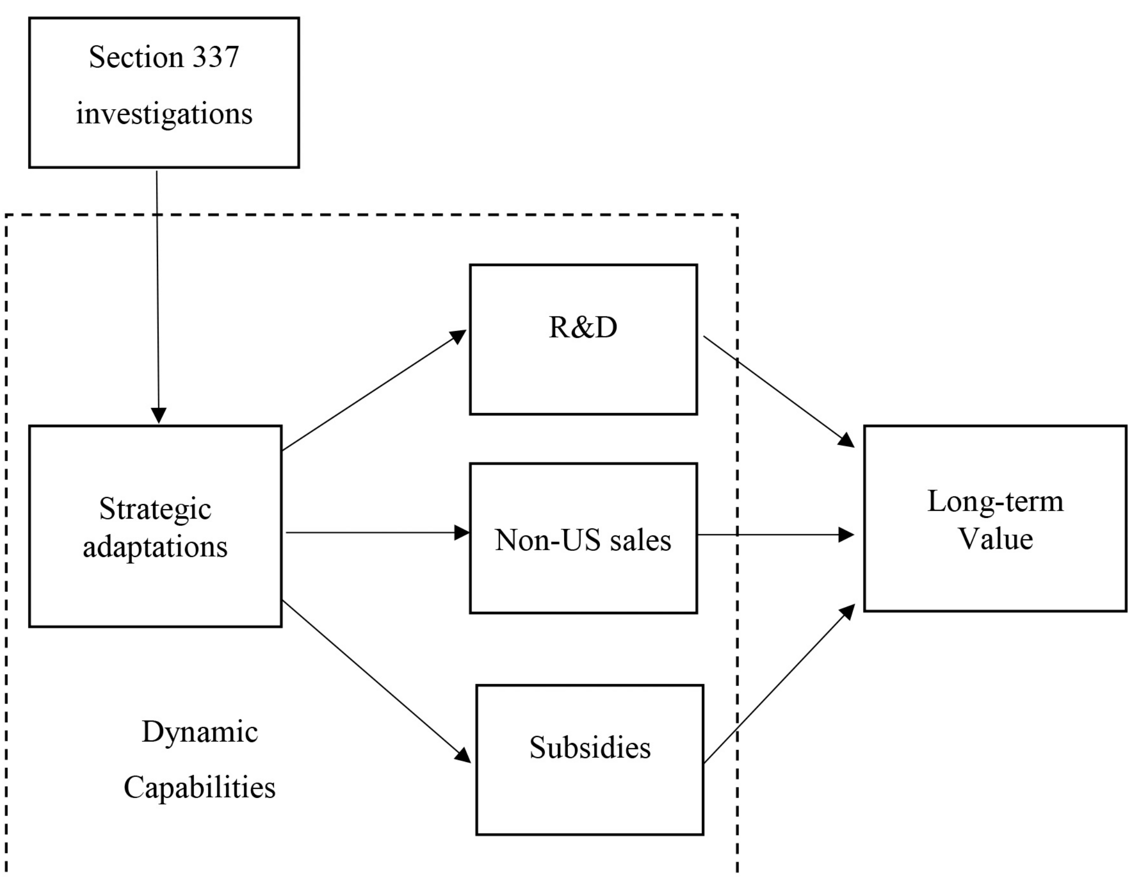


Fig. 1. Section 337 investigations, dynamic capabilities and long-term value.

scrutiny associated with patent infringement investigations. Thus, Hypothesis 3 predicts the following:

Hypothesis 3. (H3): *Firms' strategic response of increasing R&D investments enhances their long-term value in the face of Section 337 investigations*.

2.4. Trade diversification and long-term value

The existing literature on the risk response strategies of foreign firms to antidumping and countervailing duties suggests that business operations and profitability are significantly affected by such trade protection initiatives. The resulting reaction strategies of exporters include product price adjustments (Avsar, 2013), trade diversion (Brenton, 2001; Ganguli, 2008), changes in technology adoption strategy (Crowley, 2006), and government assistance (Li et al., 2014). Brenton (2001) examines the impact of EU antidumping measures and suggests that antidumping policies result in trade diversion, particularly benefiting suppliers outside the EU. Moreover, Fisman et al. (2014) and Davies and Studnicka (2018) propose that firms' stock prices more reliant on trade relations with policy-imposing nations are more likely to underperform significantly when faced with trade barriers and interstate policy shocks. Similarly, Crowley et al. (2019) find that the announcements of the European Union's trade restriction policies have an immediate and significant negative impact on the stock returns of Chinese solar panel firms, with the most export-reliant firms suffering the most significant losses. Furthermore, Li et al. (2014) demonstrate that the stock market reacts more positively to antidumping and countervailing investigations for firms with a high percentage of sales to non-targeted countries.

The prior antidumping literature indicates that firms can mitigate the negative impacts of trade remedy policies by employing response strategies such as trade diversion (Brenton, 2001) and securing substantial government assistance (Li et al., 2014). Exporting firms can change exporting destinations to circumvent the tariff barriers of duty-imposing countries (Brenton, 2001; Ganguli, 2008). For instance, an increase of 5 %–7 % in exports to third countries is observed by Bown and Crowley (2007) as an effective way for Japanese firms to deflect the threats of extra tariffs in the U.S. Particularly in the context of the US-China trade war, negative trade shocks drive export diversion toward closer countries with larger economies, such as Vietnam, Mexico, etc., affecting R&D-intensive, skilled-labour-intensive, high-capital-income-share, and upstream industries (Jiang et al., 2023; Fajgelbaum et al., 2020). Consequently, as firms increase their sales to other countries, they outperform expectations, sending positive signals to investors, who incorporate this information into stock pricing. Thus, Hypothesis 4 predicts the following:

Hypothesis 4. (H4): *Firms' strategic response of promoting overseas sales to non-U.S. countries helps enhance their long-term value in the face of Section 337 investigations*.

2.5. Government support and long-term value

Countries usually aim to upgrade their technological bases to specialise in high-value products within global value chains (Janger et al., 2017), and government support typically plays an important role in creating market leaders for innovation (Beise, 2004). Most recently, one of the major concerns in the Sino-US economic conflicts has been the industry policy and the initial wave of tariffs enforced by the Trump administration on China exports, particularly targeted high-tech industries (Ju et al., 2023). Government plays a pivotal role in trade negotiation and providing direct financial support to affected sectors and firms. For instance, Lee and Baik (2010) discover that complainant firms seeking antidumping relief experience greater benefits when they allocate higher funds to lobbying activities, thereby indirectly highlighting the government's impact on such cases.

In addition to trade negotiation, governments may employ various measures to support domestic sectors facing diminished global demand, including financial assistance. Li et al. (2014) assert that government assistance is crucial in alleviating the adverse impact of antidumping and countervailing investigations. In particular, the Chinese government implemented a stimulus package to counteract the adverse effects of the EU's preliminary ruling imposing antidumping duties on Chinese photovoltaic modules and components (Li et al., 2014). As a result, capital market investors perceive the receipt of government subsidies as a positive signal and incorporate this information into the pricing of stocks that have been negatively affected by foreign trade remedy investigations. Similarly, we expect that obtaining more government subsidies will have a positive firm value effect in response to Section 337 investigations in the long term. Thus, Hypothesis 5 predicts as follows:

Hypothesis 5. (H5): *Firms' strategic response of seeking additional government support helps enhance their long-term value in the face of Section 337 investigations*.

3. Data and methodology

3.1. Sample sources

The data of the analysis are extracted from multiple databases. To calculate the influence of Section 337 on stock returns, we manually collect data from the China Trade Remedies Information (CTRI) website for the information on Section 337 investigations from 2005 to 2019. To certify the validity of the information, we then check the news disclosed by the U.S. Department of Commerce. Initially, 300 release cases of Section 337 investigations are collected. The CTRI website releases records of each 337 case, including information on the investigation number, the name of the complainants and respondents, the commodity involved, the patent number of the allegedly infringed patents, key dates (e.g., date of a complaint filed, dates of institution and determination), and the status of the investigation. We then match 337 involved commodities with public firms' company information and include companies listed on the Shanghai and Shenzhen Stock Exchanges that produced the same commodities involved in the Section 337 cases in the sample.

After matching the respondent firms of Section 337 investigations, we use the release dates of the investigations' institution as the event dates to align stock returns and market synthesis returns across different stock exchanges from 2005 to 2019 for event study analysis. We compile an initial sample of 1903 firms belonging to industries identical to those involved in the 337 cases, based on the 3-digit industry classifications of the China CSRC (2012).

The distributions of the sample events by year and industry are reported in Table 1 and Appendix 1. As shown in Table 1, Section 337 investigations experienced a significant surge following the 'trade war' announcements in 2018, doubling the number of cases in 2019. In terms of industries (see Appendix 1), consistent with the USITC Section 337 statistics, the primary sectors involved in these investigations are Computer, Communication, and Other Electronic Equipment Manufacturing (29 %), Electrical Machinery and Equipment Manufacturing (23 %), and Chemical Materials and Products Manufacturing (7 %). These industries are classified as high-tech manufacturing industries according to the high-tech industry (Manufacturing Industry) classifications (2013) issued by the Chinese State Statistical Bureau (SSB).

We further enrich the dataset by including the control group, non-337-affected firms from the same industry as the focal firms, to test firms' strategic adaptations, resulting in a dataset containing 2488 firms. Firm-level accounting and financial data are used as control variables, including firm size, leverage, Tobin's q, ROA and ownership type (SOE), sourced from the China Stock Market and Accounting Research (CSMAR) database. Then, we collect the stock market data of the

Table 1
Events distribution by year.

Year	No.	Pct.
2005	1	1.85 %
2006	3	5.56 %
2008	4	7.41 %
2009	3	5.56 %
2010	3	5.56 %
2011	4	7.41 %
2012	5	9.26 %
2013	6	11.11 %
2014	3	5.56 %
2015	1	1.85 %
2016	5	9.26 %
2017	4	7.41 %
2018	4	7.41 %
2019	8	14.81 %
Total	54	100 %

Notes: This table presents the sample distribution of Section 337 investigation events by year. The sample contains 54 news releases detailing newly initiated Section 337 investigations by the USITC from 2005 to 2019.

treatment and control groups and complement this dataset by incorporating additional information on overseas sales and government subsidies obtained from CSMAR. Data on R&D investments are extracted from the WIND database. We winsorise all accounting variables at the bottom and top 1 % levels to control for outliers. The descriptive statistics for the key variables employed in regression analyses are summarised in Table 2.

3.2. Measures and model specifications

3.2.1. Measures of abnormal returns and the event study method

To test H1, we follow Davies and Studnicka (2018) and Huang et al. (2023) to estimate the influence of 337 investigations on short-term stock market returns of Chinese public firms. The equity market's response to news releases of Section 337 investigations involving Chinese firms is assessed using the standard market model (Barber and Lyon, 1997). To estimate the abnormal returns, we use historical stock return data from an estimation window of 150 trading days before the news release dates of the initiation of the Section 337 investigations. Consistent with prior research, we use a time window (−180, −31) from day −180 to day −31 (in trading days) before the news release to avoid the influence of the news release itself on the estimation window. For a seven-day event window of (−3, 3), the news release date is defined as Day 0, Day −3 as 3 trading days before the event, and Day 3 as three trading days after the event. The standard market model relates the one-day return, $R_{i,t}$, on firm i at time t to a firm-specific constant, α_i, and the market portfolio return R_{mt}:

Table 2
Descriptive statistics.

Variable	Obs.	Mean	SD	Min	Median	Max
BHAR_two years	6074	0.095	0.667	−2.775	−0.035	7.863
BHAR_three years	6074	0.120	0.831	−1.773	−0.044	6.923
Rdintensity1	6074	0.014	0.015	0	0.010	0.080
Non-U.S._sales	3779	0.279	0.246	0	0.211	0.928
Subsidy_ratio1	4996	0.006	0.010	0	0.003	0.225
Leverage	6074	0.399	0.211	0.053	0.387	1.107
Lnassets	6074	7.963	1.180	5.355	7.828	12.059
TobinQ	6074	1.979	1.273	0	1.616	8.550
ROA	6074	0.041	0.074	−0.298	0.042	0.232
SOE	6074	0.273	0.446	0	0	1
VC dummy	6074	0.261	0.439	0	0	1

Notes: This table reports the summary statistics for Chinese technology firms. The sample comprises 1903 firms operating in the industries targeted by Section 337 investigations. Detailed definitions are provided in Appendix 2. Accounting variables are winorised at the 1 % level.

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + \varepsilon_{i,t}, t \in T \tag{1}$$

where $\varepsilon_{i,t}$ is the error term of stock i on Day t and T is the pre-event estimation window of share price data on which Eq. (1) is estimated. Market return R_{mt} is the composite index return of either the Shanghai Stock Exchange or the Shenzhen Stock Exchange, depending on the place where the stock is traded. In this market model, variations in the average returns across stocks (α_i), the systematic risk of a stock (β_i) and movements in the market portfolio are controlled. The firm's market beta is estimated using historical stock returns over the estimation window (−180, −31). For each stock, the parameters of the standard market model are estimated using ordinary least squares (OLS) regression over the 150-trading day period.

These parameter estimates from Eq. (1) are then used to derive a benchmark return (i.e., expected stock return). The differences between the predicted stock returns and the actual stock returns observed in the market are defined as the abnormal returns in the event window. The daily abnormal return over an event window is then computed by subtracting the benchmark return of the firm from the actual event window stock return.

$$AR_{i,t} = R_{i,t} - E(R_{i,t}) \tag{2}$$

where $AR_{i,t}$ is the daily abnormal return, $R_{i,t}$ is the daily actual return of stock i at time t and $E(R_{i,t})$ is the daily expected normal return obtained from Eq. (1).

We then aggregate the daily abnormal returns over the time around the news release to form the accumulated abnormal return from event day t_1 to event day t_2.

$$CAR_{i,(t_1,t_2)} = \sum_{t=t_1}^{t_2} AR_{i,t} \tag{3}$$

where $CAR_{i,(t_1,t_2)}$ is the aggregated abnormal return from day t_1 to day t_2 for stock i. We follow Hua et al. (2019) and Li et al. (2014) to examine three event windows for our CARs starting from 3 days before the news release and extending as far as 5 days after the news release. According to Breinlich (2014), the employment of the CAR to examine the stock market reaction allows us to observe the net effect of the stock performance, as there might be a net zero effect of the stock return over the longer window (i.e., negative AR on Day t, but positive AR on Day t + 1).

To test the impacts of dynamic capabilities on long-term value, we measure long-run abnormal returns based on BHARs for the sample firms over a three-year period after the institution of Section 337 investigations. The calculation of BHARs involves assessing the disparity between the cumulative returns of the target firms and the selected benchmark index over the holding period (Barber and Lyon, 1997). The method using BHARs helps delineate the differential performance of focal firms relative to the benchmark, facilitates the identification of relative performance trends and discerns the extent to which Section 337 investigations impact the financial performance of focal firms. Following Barber and Lyon (1997), we compute the BHAR for stock i at time t as follows:

$$BHAR_{i,T} = \prod_{t=0}^{T} \left[1 + R_{i,t}\right] - \prod_{t=0}^{T} \left[1 + E(R_{i,t})\right] \tag{4}$$

where $R_{i,t}$ is the actual monthly return of stock i at month t observed in the market, $E(R_{i,t})$ is the predicted monthly return of stock i at month t, and T is the holding period. We subtract the compounded monthly return from the benchmark of the market index of either the Shanghai Stock Exchange or the Shenzhen Stock Exchange depending on the place where the stock is traded. In this study, we examine two-year and three-year buy-and-hold abnormal returns for sample firms.

3.2.2. Method and research model for testing dynamic capabilities

We employ the PSM-DID method to explore strategic options implemented by focal firms in response to Section 337 investigations. The PSM approach, widely established in the literature, mitigates endogeneity concerns arising from selection bias by enabling the construction of a control group comprising non-investigated firms with similar firm-level characteristics to those subject to Section 337 investigations within the same industry (Clò et al., 2022; Guo and Jiang, 2013). Using 1-to-5 nearest-neighbour matching, we first identify non-337 firms that are not directly affected by the investigations but share comparable characteristics with affected firms. Each firm-year observation in the treated group is then matched with a counterpart in the control group based on the closest propensity scores, which estimate the likelihood of a firm being subject to a Section 337 investigation. Building upon this matched sample, we implement a time-varying DID model (Beck et al., 2010) to assess whether Chinese technology firms develop three key dynamic capabilities in response to investigations: R&D intensity enhancement, international market diversification, and institutional support acquisition.

For dependent variables, we use R&D intensity, measured by R&D expenses divided by the market value of assets, as a proxy for technological advancement following Franzen et al. (2007); firms' *non-U.S. sales* as the ratio of a firm's overseas sales in the non-U.S. markets (e.g., Europe, Asia, and South America) to total sales following Fisman et al. (2014); and *subsidy_ratio1* as the ratio of government subsidies to total assets. To test H2, the model specification is as follows:

$$Dependent\ variable_{it} = \beta_0 + \beta_1 Section337_i \times Post_{i,t} + \sum Z_{i,t-1} + \varphi_i + \theta_t + \varepsilon_{i,t} \tag{5}$$

where dependent variables are *Rdintensity1*, *subsidy_ratio1*, and *non-U.S. sales*, which have already been described in this section. $Section337_i$ is a dummy variable that equals one if the firm is affected by Section 337 news, $post_{i,t}$ is a dummy variable that equals one if the time is after the event for respondent firms, $Section337_i \times post_{i,t}$ is an interaction term of $Section337_i$ and $post_{i,t}$, $Z_{i,t-1}$ is standard firm-level control variables, $\varepsilon_{i,t}$ is the error term, and β_1 is the coefficient vector of main interest to us. The industry and year fixed effects are captured by φ_i and θ_t. Results of pre-existing trends and dynamic impacts on *Rdintensity1*, *subsidy_ratio1* and *non-U.S. sales* are reported in Appendix 3.

3.2.3. Method and research models for testing the long-term impact of dynamic capabilities

While the study includes calculations of abnormal returns, another primary objective is to identify the determinants of long-term value creation among focal firms that have strategically enhanced their dynamic capabilities in response to Section 337 investigation announcements. We employ regression analysis to examine firm-specific variables that influence the variation in BHARs across different firms. By adapting the methods of Davies and Studnicka (2018) and Huang et al. (2023), we assess cross-sectional heterogeneity in long-term stock returns. Specifically, we regress BHARs on three key dimensions of dynamic capabilities: R&D intensity, the proportion of non-U.S. sales, and the subsidy ratio. The regression model specifications are presented below.

$$BHAR_{i,T} = \beta_0 + \beta_1 Rdintensity1_{i,t-1} + \sum Z_{i,t-1} + Industry_i + Year_t + \varepsilon_{i,t} \tag{6}$$

$$BHAR_{i,T} = \beta_0 + \beta_1 non-U.S.sales_{i,t-1} + \sum Z_{i,t-1} + Industry_i + Year_t + \varepsilon_{i,t} \tag{7}$$

$$BHAR_{i,T} = \beta_0 + \beta_1 subsidy\_ratio1_{i,t-1} + \sum Z_{i,t-1} + Industry_i + Year_t + \varepsilon_{i,t} \tag{8}$$

where $BHAR_{i,T}$ is BHARs of stock i for T holding period of time, *Rdintensity1*, *non-U.S. sales* and *subsidy_ratio1* are as described previously in Section 3.2.2. $\sum Z_{i,t-1}$ include leverage, the logarithm of total assets, log value of sales, Tobin's q, ROA and SOE, $\varepsilon_{i,t}$ is the residual, and β_1 is the coefficient vector of main interest to us. We also lag one year for the control variables to mitigate the issues related to potential simultaneity for the long-turn abnormal returns based on Fisman et al. (2014). The industry and year fixed effects, captured by $Industry_i$ and $Year_t$, are included to control for macroeconomic conditions and industry-related features and, therefore, mitigate endogeneity from omitted variables. Standard errors are clustered by the firm to control for cross-sectional dependence in the error term.

We lag *Rdintensity1* by one year to account for the time needed for R&D investments to impact firm performance potentially. The expected sign of this regressor is positive, as firms with higher R&D expenditures are perceived as high-technology firms in the capital market, as indicated in H3. These high R&D invested firms are also better equipped to withstand adverse shocks. Similarly, *non-U.S._sales* and *subsidy_ratio1* are also lagged by one year in the BHARs regressions to mitigate potential simultaneity concerns. Firms with a higher ratio of *non-U.S. sales* are less reliant on sales in the U.S. market. Therefore, based on the findings of Fisman et al. (2014) and Jiang et al. (2023), we expect this variable to be positively associated with the BHARs, as presented in H4. Finally, according to Li et al. (2014), government assistance supports struggling sectors facing external shocks and signals institutional backing to investors. Consequently, we anticipate a positive association between *subsidy_ratio1* and BHARs, as outlined in H5.

4. Empirical results

4.1. Short-term stock market reactions

The descriptive statistics for short-term abnormal returns (CARs) over different event windows are presented in Table 3. The t statistics of the mean CARs indicate that CARs estimated over windows from Day −3 to Day 3 (−0.4 %, $p < 0.05$) and from Day −5 to Day 5 (−0.8 %, $p < 0.01$) are both significantly different from zero. On average, investors experience negative returns of 0.4 % and 0.8 % across 7 days and 11 days surrounding the event dates. The median CARs for event windows of (−3, 3), (−5, 5) are −0.5 % and −0.8 %, respectively. The significantly negative CARs thus imply that, on average, firms underperform relative to investors' expectations in event window days surrounding announcements of Section 337 investigations. The results confirm our H1 that the stock market responds negatively to the news release of a Section 337 investigation in the short term.

4.2. Firms' strategic adaptations to section 337 investigations

Given the significance of R&D investment, non-U.S. sales, and government support in facilitating dynamic strategic adaptations to adverse shocks, we now explore firms' strategic responses to geopolitical disruptions, institutional pressures, and constraints arising from foreign IPR protection.

The results of the PSM-DID analysis are reported in Table 4. In Columns (1)–(3) of Table 4, the coefficients on *Section337*post* are both positive and significant (0.003, $p < 0.01$; 0.020, $p < 0.05$; 0.001, $p <$

Table 3
Short-term stock returns: cumulative abnormal return (CAR).

	Mean	Median	*t*-Test
CAR [−3,3]	−0.4 %	−0.5 %	−2.40**
CAR [−5,5]	−0.8 %	−0.8 %	−3.72***

Notes: The table presents mean and median CARs for windows of time surrounding the event days, as estimated from Eq. (3).
*, **, and * indicate the significance at the 10 %, 5 %, and 1 % levels, respectively.

Table 4
The strategic adaptations to Section 337 investigations.

Variable	Rdintensity1	Non-U.S._sales	Subsidy_ratio1
	(1)	(2)	(3)
Section337*post	0.003***	0.020**	0.001**
	(4.630)	(2.069)	(2.332)
Leverage	0.002*	−0.031	0.008***
	(1.745)	(−0.889)	(3.500)
Lnassets	0.001**	0.014	−0.002***
	(2.048)	(1.587)	(−3.752)
TobinQ	−0.002***	−0.004	0.000
	(−17.736)	(−1.535)	(0.802)
ROA	−0.008***	−0.089**	0.018***
	(−4.774)	(−2.512)	(2.914)
SOE	0.001**	−0.015	−0.000
	(2.241)	(−0.714)	(−0.173)
Constant	−0.004	0.251***	0.013***
	(−1.613)	(3.182)	(2.981)
Firm-level Clustering	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
No. of obs.	19,391	8239	12,099
R^2	0.408	0.059	0.069

Notes: (1) PSM-DID regression results. (2) Dependent variable: *Rdintensity1*, R&D expenses divided by market value of assets; *Non-U.S._sales*, overseas sales in countries other than the U.S. divided by total sales; *Subsidy_ratio1*, government subsidies divided by total assets. (3) Independent variable: *Section337*post*, an interaction term between *Section337* dummy and *post* dummy. (4) Definitions of control variables can be found in Appendix 2. (5) All regressions include year and industry-fixed effects. (6) Robust t-statistics clustered by firm are reported in parentheses. (7) $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

0.05) in all specifications, indicating that firms that are affected by patent infringement investigations continuously enhance their research efforts, expand sales to other countries, and obtain increasing government assistance to mitigate their wealth loss in the capital market, supporting H2. In relation to control variables, the leverage ratio is positively associated with non-U.S. sales and government subsidies. Firm assets positively contribute to R&D intensity and non-U.S. sales. *TobinQ* and *ROA* exhibit a negative association with both R&D intensity and non-U.S. sales.

4.3. Regression results on long-term value

Despite the negative short-term stock reactions discussed above, the main focus of this study is on exploring the economic mechanisms that explain the variations of stock reactions to adverse IPR protection shocks targeting technology-intensive firms. The long-term abnormal returns (BHARs) over two years and three years are reported in Table 5. Despite negative median BHARs over the two-year (−7.7 %, $p < 0.05$) and three-year (−8.7 %, $p < 0.01$) periods, the mean BHARs demonstrate a statistically significant positive trend, yielding increases of 3.5 % ($p < 0.05$) and 6.6 % ($p < 0.01$), respectively. The upward trajectory in mean returns suggests that a subset of firms—particularly those implementing effective strategic adaptations—successfully leverage these regulatory challenges to augment their long-term value.

We assess returns over longer and shorter event windows to ensure robustness and conduct additional tests using the CSI High-End Manufacturing Thematic Index as an alternative benchmark. This index includes companies in communication equipment, semiconductors, biotechnology, pharmaceuticals, electronics, automobiles, computers, and aerospace, covering most sectors affected by intensive 337 sanctions. The findings are presented in Section 5.2 and Appendix 4.

Table 5
Long-term stock returns: Buy-and-hold abnormal return (BHAR).

	Mean	Median	*t*-Test
BHAR_two years	3.5 %	−7.7 %	2.23**
BHAR_three years	6.6 %	−8.7 %	3.79***

Notes: The table presents mean and median BHARs over three years after the event. Buy-and-hold abnormal returns are estimated from Eq. (4).
*, **, and * indicate the significance at the 10 %, 5 %, and 1 % levels, respectively.

As outlined in the hypothesis development section, the literature on IPR and trade (Lee, 2021; Shin et al., 2016), along with antidumping studies (Brenton, 2001; Li et al., 2014), suggests that firms in technology-catching-up nations can mitigate the entry-barrier effect of IPR by enhancing their technological capabilities through internal R&D, expanding into alternative foreign markets, and securing increased government assistance. Integrated with the efficient market theory (Fama, 1970), utilizing information on R&D investment, expansions of overseas sales to other countries, and government assistance provides positive signals to investors when assessing the impact of Section 337 investigations.

The regression results of our baseline regressions are reported in Table 6, which presents the results of long-term BHARs on *Rdintensity1*, *non-U.S._sales*, and *subsidy_ratio1*. R&D intensity, vulnerability to U.S. trade, and government subsidies are important in explaining superior equity performance for certain types of firms. For instance, coefficient estimates on *Rdintensity1* in models (1) and (3) are positive and significant at the 1 % level (5.216, $p < 0.01$, and 7.365, $p < 0.01$), indicating that firms with a higher level of R&D investments perform better relative to expectations in the capital market even after two and three years of Section 337 investigations, which supports H3. In Columns (2) and (5), the coefficients for *non-U.S._sales* are 0.125, significant at the 5 % level, and 0.143, significant at the 1 % level, respectively. The results suggest that firms less reliant on the U.S. market perform better in the stock market in subsequent years after the Section 337 investigations, supporting H4.

Government subsidies significantly contribute to the long-term stock prices of affected firms, as demonstrated in both Column (3) and Column (6) of the analysis. The coefficient for *subsidy_ratio1* is 2.435, significant at the 5 % level, and 3.681 at the 1 % level, respectively, supporting H5. Consistent with findings in the previous literature (Fisman et al., 2014; Huang et al., 2023), leverage, total assets, Tobin's q, and SOE are negatively associated with long-run stock market returns, implying that larger firms with high leverage are more prone to the adverse impacts of Section 337 investigations. Moreover, *ROA* positively correlates with BHARs, suggesting that more profitable firms experience enhanced long-term stock performance.

5. Further analyses

5.1. Cross-sectional heterogeneity analysis

In this section, we extend our analysis to examine the cross-sectional determinants of the long-run stock returns related to firm ownership types, such as state ownership and VC investments. This extension aims to provide a more comprehensive understanding of the factors influencing the outcomes of our study. Conducting heterogeneity analysis can help uncover variations across subsets and explain how specific firm characteristics may influence the stock performance of firms affected by Section 337 investigations. Under the communist public ownership principle, China has pursued a partial privatisation process in which the state retains substantial ownership in most firms (Sun and Tong, 2003). As a result, the government still plays a significant role in the Chinese market.

Chinese government ownership and firm performance have been the subject of considerable debate among academics (Sun and Tong, 2003; Allen et al., 2005). Economists argue that SOEs are less efficient, less profitable, and exhibit inferior performance compared with privately owned firms (Boycko et al., 1996). The most mentioned reasons for the underperformance of SOEs are the absence of transferable residual cash flow claims for governments, the excessive labour inputs by

Table 6
Regressions on long-term value.

Variable	BHAR_two years			BHAR_three years		
	(1)	(2)	(3)	(4)	(5)	(6)
Rdintensity1	5.216***			7.365***		
	(5.962)			(6.575)		
Non-U.S._sales		0.125**			0.143*	
		(2.173)			(1.822)	
Subsidy_ratio1			2.435**			3.681***
			(2.391)			(2.984)
Leverage	−0.087	−0.087	−0.011	−0.203***	−0.182*	−0.098
	(−1.547)	(−1.139)	(−0.203)	(−2.774)	(−1.794)	(−1.301)
Lnassets	−0.037***	−0.019	−0.083***	−0.046***	−0.022	−0.100***
	(−3.045)	(−1.206)	(−6.915)	(−2.833)	(−0.991)	(−5.963)
TobinQ	−0.015*	−0.024**	−0.057***	−0.020*	−0.033*	−0.060***
	(−1.786)	(−2.162)	(−7.136)	(−1.789)	(−1.912)	(−5.764)
ROA	0.602***	0.937***	0.727***	0.699***	1.141***	0.923***
	(4.449)	(5.211)	(4.649)	(3.965)	(4.919)	(4.691)
SOE	−0.041*	−0.003	0.034	−0.065**	−0.021	0.034
	(−1.880)	(−0.100)	(1.482)	(−2.206)	(−0.505)	(1.084)
Constant	−0.727**	−1.018***	0.114	−0.396	−1.292***	0.057
	(−2.358)	(−4.776)	(0.997)	(−0.818)	(−4.558)	(0.126)
Firm-level Clustering	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	5351	3209	4707	5351	3209	4707
R^2	0.292	0.257	0.242	0.298	0.271	0.264

Notes: (1) OLS estimation results. (2) Dependent variables: *BHAR_two years*, average BHARs estimated over two years after the events; *BHAR_three years*, average BHARs estimated over three years after the events. (3) Independent variables: *Rdintensity1*, R&D expenses divided by market value of assets, lagged by one year; *non-U.S._sales*, overseas sales in countries other than the U.S. divided by total sales, lagged by one year; *Subsidy_ratio1*, government subsidies divided by total assets, lagged by one year. (4) Definitions of control variables can be found in Appendix 2. (5) All regressions include year and industry fixed effects. (6) Robust t-statistics clustered by firm are reported in parentheses. (7) *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

governments, the employment of politically connected managers, and, more generally, the government's pursuit of social and political goals over profit maximisation (Boycko et al., 1996; Sun and Tong, 2003).

Empirically, Dewenter and Malatesta (2001), among others, offer strong evidence that economic performance is undermined by the government's distortions imposed upon firms based on international analysis. In addition to the voluminous literature on the performance of SOEs internationally, some scholars have claimed that China's partial privatisation through mixed ownership structures of the state and private parties fails to improve firm efficiency and productivity (Lin et al., 1998). Therefore, we predict that SOEs' long-run value is more negatively affected by Section 337 investigations since they own fewer dynamic capabilities.

On the other hand, the VC investors' reputation and certification hypothesis posits that reputable VCs provide positive signals to investors in the capital market regarding the quality of the unproven firms and certify that all relevant inside information is reflected in the stock price. Most studies in the extant literature report a positive influence of VC backing on IPO under-pricing and post-IPO performance (e.g., Jelic et al., 2005). Thus, firms with venture capital certification and support are better positioned for strategic adaptations and are likely to outperform expectations in the long term.

The cross-sectional heterogeneity analysis results are reported in Table 7. In Columns (1)–(4), the coefficient estimates for SOEs are negative and significant at the 5 % level. In contrast, those for the VC dummy are positive and significant at the 5 % level in all regressions. The results indicate that SOEs underperform non-SOEs by 4.6 % and 7.1 % in the two- and three-year periods following Section 337 investigations in equity markets, respectively. In comparison, VC ownership significantly boosts long-run stock performance for affected firms, with 6 % and 8.8 % increases over the same two- and three-year periods, respectively.

5.2. Robustness checks

We conduct a battery of additional tests to confirm the robustness of our results, including alternative event windows for stock market reactions, additional control for industries' technological sophistication, and alternative measures of key variables. Tables 8–11 report the results of these robustness tests.

Table 7
Cross-sectional heterogeneity analysis.

Variable	BHAR_two years		BHAR_three years	
	(1)	(2)	(3)	(4)
SOE	−0.046**		−0.071**	
	(−2.176)		(−2.486)	
VC dummy		0.060**		0.088**
		(2.394)		(2.372)
Constant	−0.811**	−0.933***	−0.503	−0.689
	(−2.554)	(−2.900)	(−0.950)	(−1.286)
Controls	Yes	Yes	Yes	Yes
Firm-level Clustering	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
No. of obs.	5349	5351	5349	5351
R^2	0.287	0.287	0.291	0.290

Notes: (1) OLS estimation results. (2) Dependent variables: *BHAR_two years*, average buy-and-hold abnormal returns (BHARs) estimated over two years after the events; *BHAR_three years*, average BHARs estimated over three years after the events. (3) Independent variables: *SOE*, an indicator variable that equals to one if a firm is a state-owned enterprise, and zero if otherwise.; *VC dummy*, an indicator variable that equals to one if a firm is backed by VC, and zero if otherwise. (4) Controls include: *leverage*, *lnassets*, *TobinQ*, *ROA*, *SOE*, and *lnsales*. Definitions of control variables can be found in Appendix 2. (5) All regressions include year and industry fixed effects. (6) Robust t-statistics clustered by firm are reported in parentheses. (7) *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

5.2.1. Alternative time windows for stock market reactions

We use alternative time windows to estimate CARs and BHARs. Table 8 reports the mean and median of CARs estimated over an eight-day event window from Day −1 to Day 6 and BHARs estimated over a six-month period after the news releases. The mean and median of CARs

Table 8
Short-term stock returns (alternative event windows).

	Mean	Median	*t*-Test
Panel A: Cumulative abnormal return (CAR)			
CAR [−1,6]	−0.27 %	−0.29 %	−3.732***
Panel B: Buy-and-hold abnormal return (BHAR)			
BHAR_six months	−2.81 %	−6.41 %	−4.24***

Notes: The table presents the mean and median CARs for the event window from Day −1 to Day 6 and the mean and median BHARs over the six-month period after the event. Cumulative abnormal returns are estimated from Eq. (3). Buy-and-hold abnormal returns are estimated from Eq. (4). *, ** and *** indicate significance at the 10 %, 5 % and 1 % levels, respectively.

Table 9
The strategic responses to Section 337 investigations (RET sample).

Variable	Rdintensity1	Non-U.S._sales	Subsidy_ratio1
	(1)	(2)	(3)
Section337*post	0.001***	0.033**	−0.001
	(2.624)	(2.360)	(−1.229)
Leverage	0.002*	−0.055	−0.008***
	(1.646)	(−0.943)	(−3.361)
Lnassets	0.002***	−0.002	−0.001
	(5.553)	(−0.199)	(−0.729)
TobinQ	−0.002***	0.003	−0.000
	(−12.065)	(0.323)	(−1.292)
ROA	−0.012***	0.203	0.003
	(−3.734)	(1.437)	(0.597)
SOE	−0.002***	0.043*	0.001
	(−3.117)	(1.807)	(0.913)
Constant	−0.026***	0.175	0.021*
	(−8.450)	(1.637)	(1.790)
Firm-level Clustering	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
No. of obs.	10,262	5431	8090
R^2	0.360	0.031	0.201

Notes: (1) PSM-DID regression results using a sample of RET firms. (2) Dependent variable: *Rdintensity1*, R&D expenses divided by market value of assets; *Non-U.S._sales*, overseas sales in countries other than the U.S. divided by total sales; *Subsidy_ratio1*, government subsidies divided by total assets. (3) Independent variable: *Section337*post*, an interaction term between *Section337* dummy and *post* dummy. (4) Definitions of control variables can be found in Appendix 2. (5) All regressions include year and industry-fixed effects. (6) Robust t-statistics clustered by firm are reported in parentheses. (7) *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

(−1, 6) are −0.27 % and −0.29 %, respectively, both significant at the 1 % level, implying that average firms perform worse than expectations in the face of Section 337 investigations, which is consistent with the findings of H1 in our main estimations. Regarding the medium-term impact, the mean and median of *BHAR_six months* are −2.81 % and −6.41 %, respectively, both significant at the 1 % level, which is consistent with the findings of Table 5.

5.2.2. Alternative sample of firms in technologically sophisticated industries

Although we employ PSM-DID estimation as the primary method for testing H2, industry-level technological sophistication and development may still influence firms' strategic decisions. This potential bias arises because firms with higher R&D intensity, a larger proportion of non-U.S. sales, and substantial government subsidies may reflect industry-specific characteristics rather than the direct effects of Section 337 investigations. To address this concern, we construct an alternative sample of firms with high Rapidly Evolving Technology (RET) scores and apply the PSM technique to create a control group of RET firms unaffected by Section 337 investigations. This approach enables us to account for industry sophistication, mitigate the confounding effects of technological development within the industry, and more effectively isolate the impact of Section 337 investigations on R&D intensity, non-U.S. sales, and government subsidies.

Following the methodology of Bowen et al. (2023), we calculate RET scores based on the textual content of firms' patents to assess whether they pertain to rapidly evolving or stable technological areas. To measure a specific patent's position within the technological landscape, we assess the degree to which its vocabulary is experiencing growth in usage within recent and contemporary patents. Patents are classified as belonging to rapidly evolving technology domains if they employ vocabulary that exhibits significant growth across the entire patent corpus. Firms with RET scores higher than the 5-year mean value of all firms before the 337 investigations are selected as RET firms. This new RET subsample contains both 337 affected firms and non-337 affected firms. Detailed calculation is provided in Appendix 5.

Subsequently, we use the PSM matching technique to create a control group of RET firms. The results of regressions using RET firms are reported in Table 9. In line with the results of H2 in our main estimations, the coefficient estimates for *Section337*post* in Columns (1) and (2) are 0.001 ($p < 0.01$) and 0.033 ($p < 0.05$), respectively. This significant and positive impact of Section 337 investigations yields several important implications. First, the results suggest that Section 337 investigations serve as a catalyst for improving innovation capabilities and market diversification among affected firms, encouraging them to intensify their R&D efforts and seek markets outside the U.S. This adaptive behaviour helps mitigate the immediate negative impact of the investigations while potentially strengthening the firms' long-term competitive positions. Moreover, the significant positive coefficients highlight high-tech firms' resilience and strategic agility in the face of external geopolitical disruptions (Ren et al., 2024), offering valuable insights for policymakers and business leaders on fostering innovation and global market engagement in response to foreign regulatory challenges.

However, we find that the coefficient of *Section337*post* for subsidy ratio is insignificant. A plausible explanation for the insignificant coefficient stems from the characteristics of government support in technologically sophisticated industries. These firms consistently receive substantial subsidies as part of broader industrial and national innovation policies, creating a high baseline level of support across both Section 337-affected firms and the control group. This limited variation in subsidy distribution consequently reduces the model's ability to detect significant differential effects attributable to Section 337 investigations.

5.2.3. Alternative measures of key variables

Third, we use alternative measures of R&D intensity, trade exposure to the U.S. market, and government support in robustness checks. The results are reported in Table 10. As indicated in Columns (1)–(6), the coefficient estimates for *Rdintensity2* (3.330, $p < 0.01$; 4.907, $p < 0.01$), non-U.S. profits (0.245, $p < 0.01$; 0.281, $p < 0.01$), and subsidy_ratio2 (3.504, $p < 0.05$; 4.572, $p < 0.05$) are positive and significant in all specifications. The results support our prediction that firms' research endeavours, efforts to expand the non-U.S. market, and government assistance contribute to the market value of affected firms in the long run after negative IP-related policy shocks. Therefore, technology-intensive firms that focus on building dynamic capabilities by investing more in innovative projects, expanding overseas profits to other countries, and securing more government subsidies can effectively navigate challenges and improve long-term performance.

Moreover, ROA is used as an alternative measure of long-term performance in addition to BHARs. The results are presented in Table 11. As indicated in columns (1) and (4), the coefficient estimates on *Rdintensity1* (0.265 and 0.368) are positive and significant at the 1 % level. In column (5), the coefficient for *non-U.S._sales* is 0.009 and significant at the 5 % level. In columns (3) and (6), the coefficients on *subsidy_ratio1* are 0.073, significant at the 5 % level, and 0.138, significant at the 1 % level, respectively. Consistent with our main results using BHARs as

Table 10
Regressions on long-term value (alternative measures).

Variable	BHAR_two years			BHAR_three years		
	(1)	(2)	(3)	(4)	(5)	(6)
Rdintensity2	3.330***			4.907***		
	(5.115)			(5.194)		
Non-U.S._profits		0.245***			0.281***	
		(3.323)			(2.874)	
Subsidy_ratio2			1.123**			1.471**
			(2.423)			(2.234)
Leverage	−0.135*	−0.052	0.013	−0.282**	−0.141	−0.063
	(−1.735)	(−0.676)	(0.236)	(−2.524)	(−1.402)	(−0.852)
Lnassets	−0.012	−0.023	−0.085***	0.007	−0.027	−0.103***
	(−0.703)	(−1.484)	(−7.021)	(0.292)	(−1.221)	(−6.079)
TobinQ	−0.040***	−0.024**	−0.057***	−0.043***	−0.033*	−0.058***
	(−3.788)	(−2.173)	(−7.131)	(−2.795)	(−1.909)	(−5.697)
ROA	0.544***	0.862***	0.765***	0.754***	1.056***	0.980***
	(3.123)	(4.817)	(4.840)	(3.229)	(4.481)	(4.925)
SOE	0.004	0.004	0.037	−0.043	−0.013	0.038
	(0.120)	(0.128)	(1.609)	(−0.958)	(−0.312)	(1.226)
Constant	0.946***	−1.022***	0.114	0.739***	−1.298***	0.058
	(6.199)	(−4.620)	(1.002)	(3.500)	(−4.535)	(0.131)
Firm-level Clustering	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	2869	3209	4707	2869	3209	4707
R^2	0.313	0.259	0.242	0.341	0.273	0.263

Notes: (1) OLS estimation results. (2) Dependent variables: *BHAR_two years*, average BHARs estimated over two years after the events; *BHAR_three years*, average BHARs estimated over three years after the events. (3) Independent variables: *Rdintensity2*, R&D expenses divided by total assets, lagged by one year; *non-U.S._profits*, overseas gross profits in countries other than the U.S. divided by total sales, lagged by one year; *Subsidy_ratio2*, government subsidies divided by total sales, lagged by one year. (4) Definitions of control variables can be found in Appendix 2. (5) All regressions include year and industry fixed effects. (6) Robust t-statistics clustered by firm are reported in parentheses. (7) *p < 0.1, **p < 0.05, ***p < 0.01.

Table 11
The long-term impacts of R&D, non-U.S. sales, and subsidies on ROA.

Variable	F2.ROA	F2.ROA	F2.ROA	F3.ROA	F3.ROA	F3.ROA
	(1)	(2)	(3)	(4)	(5)	(6)
Rdintensity1	0.265***			0.368***		
	(3.555)			(4.038)		
Non- U.S._sales		0.003			0.009**	
		(0.829)			(2.076)	
Subsidy_ratio1			0.073**			0.138***
			(2.253)			(3.586)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm-level Clustering	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	17,783	15,767	12,880	6847	5665	11,630
R^2	0.113	0.091	0.156	0.117	0.097	0.119

Notes: (1) OLS estimation results. (2) Dependent variable: *ROA*, the return on assets ratio defined as net profit divided by total assets. (3) Independent variable: *Rdintensity1*, R&D expenses divided by market value of assets, lagged by one year; *non-U.S._sales*, overseas sales in countries other than the U.S. divided by total sales, lagged by one year; *Subsidy_ratio2*, government subsidies divided by total sales, lagged by one year. (4) Controls include: *leverage*, *lnassets*, *TobinQ*, *SOE*, and *Rdratio*. (5) Definitions of control variables can be found in Appendix 2. (6) All regressions include year and industry-fixed effects. (7) Robust t-statistics are reported in parentheses. (8) *p < 0.1, **p < 0.05, ***p < 0.01.

measures of long-term financial market performance, the results indicate that R&D intensity, overseas sales to countries outside the U.S., and government subsidies positively contribute to better accounting performance of Chinese firms in the long term.

6. Conclusions and limitations

This study examines the financial market reactions of Chinese technology firms to U.S. Section 337 investigations and analyzes their subsequent strategic adaptations for long-term value enhancement. The event-study methodology mitigates endogeneity concerns by treating Section 337 investigations as exogenous events. Following these investigations, we use the PSM-DID method to estimate firms' strategic responses and dynamic capability changes regarding R&D inputs, international market diversification, and governmental subsidy acquisition. To investigate the channels through which Section 337 investigations influence financial performance, we associate stock returns with firm capabilities that capture the heterogeneous impacts of these investigations.

The empirical findings demonstrate that Chinese firms' stocks initially respond negatively to Section 337 investigation announcements. PSM-DID analysis reveals that firms implement effective strategic responses to augment dynamic capabilities through intensified R&D expenditures, market diversification initiatives, and enhanced government support acquisition. Firms demonstrating improved capabilities contribute significantly to long-term value creation. Further cross-sectional heterogeneity tests reveal that, while SOEs demonstrate inferior market performance, VC-backed firms exhibit superior long-term stock performance.

While our study provides valuable insights, it is crucial to acknowledge its limitations by considering broader economic impacts, including those on non-listed firms and their supply chain networks (e.g., suppliers and customers). Furthermore, exploring other potential strategic adaptations, such as increased government support for enhancing firms' innovation capabilities and foreign direct investments in technologically advanced countries, can contribute to a more comprehensive understanding of how firms navigate adverse impacts from foreign IP-related shocks and improve long-term performance in future research.

CRediT authorship contribution statement

Jiani Fan: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Xiuping Hua:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Data curation, Conceptualization. **Miao Wang:** Writing – original draft, Validation, Methodology, Formal analysis. **Yong Wang:** Writing – original draft, Supervision, Project administration, Funding acquisition, Formal analysis, Conceptualization. **Huayi Zhang:** Writing – review & editing, Validation, Investigation, Formal analysis, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This paper was supported by the Major Program for Philosophy and Social Science at Ministry of Education of China (Project No. 2023J2DZ017), the Key Program for Philosophy and Social Science at Ministry of Education of China (Project No. 23JZD011), Ningbo Science and Technology Bureau for Key Plan Program (Project No. 2022Z243, 2022Z173), and Ningbo Science and Technology Bureau for Soft Science Program (Project No. 2024R034). All errors remain the responsibility of the authors.

Appendix 1. Events distribution by industry

Industry	No.	Pct.
Agricultural	1	1 %
Agricultural and food processing	1	1 %
Automobile manufacturing	1	1 %
Chemical materials and products manufacturing	5	7 %
Coal mining and washing	2	3 %
Comprehensive industry	1	1 %
Computer, communication, and other electronic equipment manufacturing	21	29 %
Electrical machinery and equipment manufacturing	17	23 %
Ferrous metal smelting and calendering	1	1 %
Financial market service	1	1 %
Food manufacturing	1	1 %
Furniture manufacturing	1	1 %
Instrument manufacturing	2	3 %
Metal products	1	1 %
Nonferrous metal smelting and calendering	2	3 %
Other manufacturing	2	3 %
Petroleum processing, coking, and nuclear fuel processing	1	1 %
Pharmaceutical manufacturing	3	4 %
Railway, shipping, aerospace, and other transportation equipment manufacturing	1	1 %
Retail	1	1 %
Rubber and plastic products manufacturing	2	3 %
Special equipment manufacturing	2	3 %
Telecommunications, radio, television, and satellite transmission services	1	1 %
Water transportation	1	1 %
Wood processing and wood, bamboo, rattan, palm, and grass products manufacturing	1	1 %
Total	73	100 %

Notes: This table presents the sample distribution of Section 337 investigation events by industry. The sample includes 54 news releases on Section 337 investigations by the USITC, covering 25 different industries and sectors. Some investigations encompass multiple industries.

Appendix 2. Definition of key variables and data source

Variables	Description	Source
Dependent variables		
BHAR_two years	Average BHARs estimated over two years after the events.	CSMAR
BHAR_three years	Average BHARs estimated over three years after the events.	CSMAR
Independent variables		
Rdintensity1	R&D expenses divided by market value of assets, lagged by one year.	WIND
Rdintensity2	R&D expenses divided by total assets, lagged by one year.	WIND
Non-U.S._sales	Overseas sales in countries other than the U.S. divided by total sales, lagged by one year.	CSMAR
Non-U.S._profits	Overseas gross profits in countries other than the U.S. divided by total sales.	CSMAR
Subsidy_ratio1	Government subsidies divided by total assets, lagged by one year.	CSMAR
Subsidy_ratio2	Government subsidies divided by total sales, lagged by one year.	CSMAR

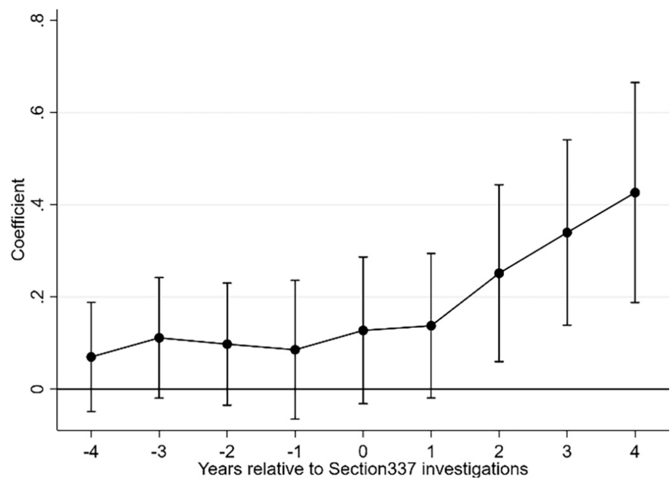
(*continued on next page*)

(*continued*)

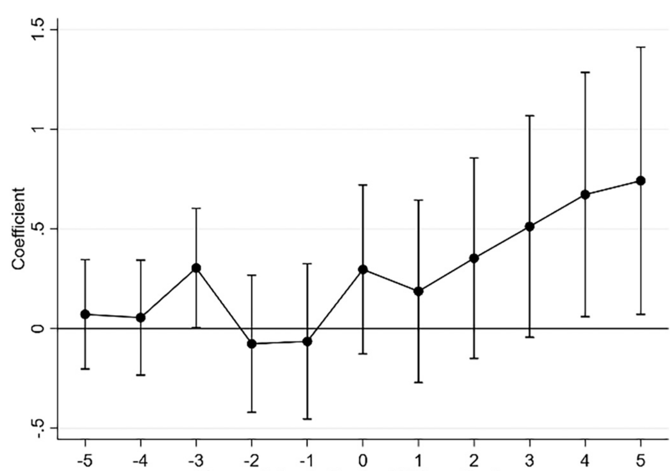
Variables	Description	Source
VC dummy	An indicator variable that equals to one if a firm is backed by VC, and zero if otherwise.	PEdata
Control variables		
Leverage	The sum of short-term and long-term debts divided by total assets.	CSMAR
Lnassets	The log value of total assets.	CSMAR
TobinQ	Firm's market value divided by total assets.	CSMAR
ROA	The return-on assets ratio defined as net profit divided by total assets.	CSMAR
SOE	An indicator variable that equals to one if a firm is a state-owned enterprise, and zero if otherwise.	CSMAR
Rdratio	R&D expenses divided by total sales.	WIND

Appendix 3. Pre-existing trends and dynamic responses

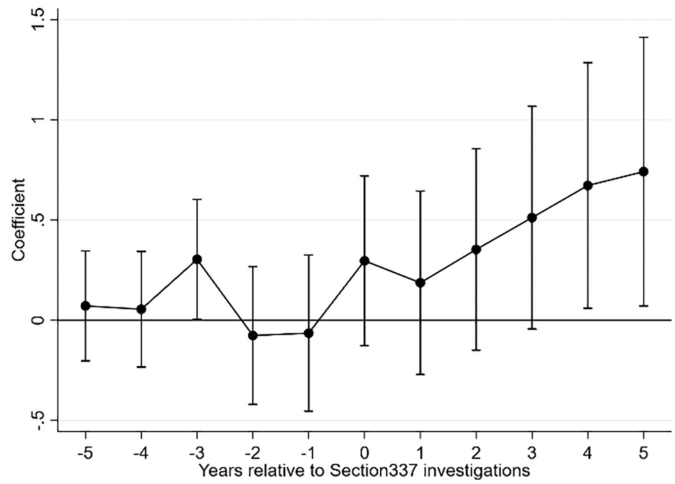
Panel A Pre-existing trends and dynamic responses - R&D intensity



Panel B Pre-existing trends and dynamic responses - non-U.S. sales



Panel C Pre-existing trends and dynamic responses - subsidy ratio



The figures show the dynamic impact of U.S. Section 337 investigations on the R&D intensity, overseas sales to non-U.S. countries and subsidy ratio of Chinese listed firms that manufacture products named in Section 337 investigations.

Appendix 4. Regressions of buy-and-hold abnormal returns (alternative market index)

Variable	BHAR_two years			BHAR_three years		
	(1)	(2)	(3)	(4)	(5)	(6)
Rdintensity1	4.682***			6.279***		
	(4.616)			(5.080)		
Non-U.S._sales		0.136**			0.158*	
		(2.142)			(1.738)	
Subsidy_ratio1			1.923*			2.874***
			(1.719)			(2.745)
Leverage	−0.209***	−0.097	−0.169**	−0.388***	−0.275**	−0.365***
	(−3.082)	(−1.070)	(−2.312)	(−4.351)	(−2.345)	(−3.694)
Lnassets	0.050***	0.060***	0.050***	0.030	0.037	0.026
	(3.460)	(3.317)	(3.412)	(1.566)	(1.530)	(1.367)
TobinQ	0.029***	0.030**	0.011	0.015	0.011	−0.012
	(2.997)	(2.517)	(1.059)	(1.052)	(0.573)	(−0.805)
ROA	0.917***	1.021***	0.827***	0.834***	0.963***	0.672***
	(5.444)	(4.690)	(4.219)	(3.900)	(3.608)	(2.788)
SOE	−0.051*	−0.026	−0.021	−0.059	−0.001	−0.017
	(−1.940)	(−0.667)	(−0.719)	(−1.640)	(−0.023)	(−0.449)
Constant	0.743	0.340	0.692	1.387***	0.602*	1.487***
	(1.284)	(0.400)	(1.151)	(4.115)	(1.860)	(3.727)
Firm-level Clustering	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	2967	1962	2488	3476	2299	2987
R^2	0.323	0.282	0.349	0.455	0.410	0.477

Notes: (1) OLS estimation results. (2) Dependent variables: *BHAR_two years*, average BHARs estimated over two years after the events using High-End Manufacturing Thematic Subindex (HMTS); *BHAR_three years*, average BHARs estimated over three years after the events using HMTS. (3) Independent variables: *Rdintensity1*, R&D expenses divided by market value of assets, lagged by one year; *non-U.S._sales*, oversea sales in countries other than the U.S. divided by total sales, lagged by one year; *Subsidy_ratio1*, government subsidies divided by total assets, lagged by one year. (4) Definitions of control variables can be found in Appendix 2. (5) All regressions include year and industry fixed effects. (6) Robust t-statistics clustered by firm are reported in parentheses. (7) *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Appendix 5. Calculation of RET scores

Following Bowen et al.'s (2023) approach, we assess the technological phase of patents by analyzing whether a patent belongs to rapidly evolving or stable technology areas based on its vocabulary usage compared to the entire existing patent corpus. A patent is classified as belonging to rapidly evolving technology areas if it relies on vocabulary that is experiencing rapid growth across the overall patent corpus. After cleaning and pre-processing patent text data, we tally the annual count of unique terms and evaluate their year-to-year variations. Subsequently, we calculate average annual change values for each patent's vocabulary. The study then proceeds to measure the relative positioning of patents in technology cycles, involving three key steps.

First, the paper calculates the number of vocabulary words that appear in all patents each year and computes the annual changes in each vocabulary word, resulting in the vector Z_t:

$$Z_t = \frac{1}{|P_t|}\sum_{k=1}^{P_t}\frac{V_{k,t}}{V_{k,t}\cdot\mathbf{1}} \tag{1}$$

For any given patent k, the text of the patent is first converted into a vector form, $V_{k,t} = [v_{1,t}, v_{2,t}, \ldots, v_{N,t}]$. N represents the number of vocabulary words that appeared in all patents in year t, and the vector $V_{k,t}$ contains $v_{n,t}$, representing the number of times vocabulary word n appeared in patent k in year t. To mitigate the impact of patent length, the paper further normalizes vector $V_{k,t}$ by dividing it by the length of patent k, $V_{k,t}\cdot\mathbf{1}$, where vector $\mathbf{1}$ consists of values that are all 1, and this normalized vector is dot-multiplied with the patent text vector. Furthermore, the paper sums all the vectors for year t and divides the result by the total number of patents in that year, $|P_t|$, to standardize the values and reduce the impact of varying numbers of patents each year.

The second step involves calculating the vector of changes in vocabulary words for year t, denoted as Δ_t, based on the standardized vocabulary word count vectors Z_t and Z_{t-1}. $\Delta_t = [\Delta_{1,t}, \Delta_{2,t}, \ldots, \Delta_{N,t}]$ is the vector of vocabulary word change percentages, where $\Delta_{n,t}$ represents the percentage change in vocabulary word n between year $t-1$ and year t.

$$\Delta_t = \frac{Z_t - Z_{t-1}}{Z_t + Z_{t-1}} \tag{2}$$

The third step involves calculating the rapidly evolving technology index for each patent based on the annual changes in vocabulary words. Specifically, the paper de-duplicates the vocabulary words in each patent text to obtain a 0/1 vector $B_{k,t} = [b_{1,t}, b_{2,t}, \ldots, b_{N,t}]$, where $b_{n,t}$ indicates whether vocabulary word n appears in patent k in year t (1 if it does, 0 if it does not). Similar to the first step, this vector is normalized by dividing it by the number of vocabulary word categories for that patent $B_{k,t}\cdot\mathbf{1}$ to reduce irrelevant effects of the patent's language features. Furthermore, the normalized vector is dot-multiplied with the vector of vocabulary word change percentages to obtain the patent's rapid technological advancement index, denoted as $PRET_{k,t}$:

$$PRET_{k,t} = \left(\frac{B_{k,t}}{B_{k,t}\cdot\mathbf{1}}\cdot\Delta_t\right) \times 10000 \tag{3}$$

Finally, the average rapidly evolving technology index for relevant patents of company i in year t is calculated, resulting in the company's rapid technological advancement index for year t:

$$RET_{i,t} = \frac{1}{K_{i,t}}\sum_{1}^{K_{i,t}} PRET_{k,t} \tag{4}$$

Data availability

Data will be made available on request.

References

Alimov, A., Officer, M.S., 2017. Intellectual property rights and cross-border mergers and acquisitions. Finance 45, 360–377.

Allen, F., Qian, J., Qian, M., 2005. Law, finance, and economic growth in China. J. Financ. Econ. 77, 57–116.

Amiti, M., Kong, S.H., Weinstein, D., 2020. The Effect of the U.S.-China Trade War on U. S. Investment. National Bureau of Economic Research downloaded on 10 May 2021 from. https://www.nber.org/papers/w27114.

Autor, D.H., Dorn, D., Hanson, G.H., 2013. The China syndrome: local labour market effects of import competition in the United States. American Economic Review 103, 2121–2168.

Avsar, V., 2013. Antidumping, retaliation threats, and export prices. World Bank Econ. Rev. 27, 133–148.

Barber, B.M., Lyon, J.D., 1997. Detecting long-run abnormal stock returns: the empirical power and specification of test statistics. J. Financ. Econ. 43, 341–372.

Beck, T., Levine, R., Levkov, A., 2010. Big bad banks? The winners and losers from bank deregulation in the United States. J. Financ. 65, 1637–1667.

Beise, M., 2004. Lead markets: country-specific drivers of the global diffusion of innovations. Research Policy 33 (6/7), 997–1018.

Bowen, D.E., Frésard, L., Hoberg, G., 2023. Rapidly evolving technologies and startup exits. Manag. Sci. 69 (2), 940–967.

Bown, C.P., Crowley, M.A., 2007. Trade deflection and trade depression. J. Int. Econ. 72, 176–201.

Boycko, M., Shleifer, A., Vishny, R.W., 1996. A theory of privatisation. Econ. J. 106, 309–319.

Branstetter, L., Fisman, R., Foley, C.F., Saggi, K., 2011. Does intellectual property rights reform spur industrial development? Journal of International Economics 83 (1), 27–36.

Breinlich, H., 2014. Heterogeneous firm-level responses to trade liberalization: a test using stock price reactions. Journal of International Economics 93, 270–285.

Brenton, P., 2001. Anti-dumping policies in the EU and trade diversion. Eur. J. Polit. Econ. 17, 593–607.

Campi, M., Dueñas, M., 2019. Intellectual property rights, trade agreements, and international trade. Research Policy 48, 531–545.

Chambers, D., Jennings, R., Thompson, R.B., 2002. Excess returns to R&D-intensive firms. Rev. Acc. Stud. 7, 133–158.

Chan, L.K., Lakonishok, J., Sougiannis, T., 2001. The stock market valuation of research and development expenditures. J. Financ. 56, 2431–2456.

Clò, S., Frigerio, M., Vandone, D., 2022. Financial support to innovation: the role of European development financial institutions. Research Policy 51 (10), 104566.

Crowley, M.A., 2006. Do safeguard tariffs and antidumping duties open or close technology gaps? Journal of International Economics 68, 469–484.

Crowley, M.A., Meng, N., Song, H., 2019. Policy shocks and stock market returns: evidence from Chinese solar panels. Journal of the Japanese and International Economies 51, 148–169.

Davies, R.B., Studnicka, Z., 2018. The heterogeneous impact of Brexit: early indications from the FTSE. Eur. Econ. Rev. 110, 1–17.

Dewenter, K.L., Malatesta, P.H., 2001. State-owned and privately owned firms: an empirical analysis of profitability, leverage, and labor intensity. American Economic Review 91, 320–334.

Eberhart, A.C., Maxwell, W.F., Siddique, A.R., 2004. An examination of long-term abnormal stock returns and operating performance following R&D increases. J. Financ. 59, 623–650.

Egger, P.H., Zhu, J., 2020. The US–Chinese trade war: an event study of stock-market responses. Econ. Policy 35, 519–559.

Eisenhardt, K.M., Martin, J.A., 2000. Dynamic capabilities: what are they? Strategic Management Journal 21, 1105–1121.

Fajgelbaum, P.D., Goldberg, P.K., Kennedy, P.J., Khandelwal, A.K., 2020. The return to protectionism. Q. J. Econ. 135, 1–55.

Fajgelbaum, P., Goldberg, P., Kennedy, P., Khandelwal, A., Taglioni, D., 2024. The US-China trade war and global reallocations. American Economic Review: Insights 6 (2), 295–312.

Fama, E.F., 1970. Efficient capital markets: a review of theory and empirical work. J. Financ. 25, 383–417.

Fisman, R., Hamao, Y., Wang, Y., 2014. Nationalism and economic exchange: evidence from shocks to Sino-Japanese relations. Rev. Financ. Stud. 27, 2626–2660.

Franzen, L.A., Rodgers, K.J., Simin, T.T., 2007. Measuring distress risk: the effect of R&D intensity. J. Financ. 62, 2931–2967.

Ganguli, B., 2008. The trade effects of Indian antidumping actions. Rev. Int. Econ. 16, 930–941.

Guo, D., Jiang, K., 2013. Venture capital investment and the performance of entrepreneurial firms: evidence from China. Finance 22, 375–395.

Hou, K., Hsu, P.H., Wang, S., Watanabe, A., Xu, Y., 2016. Corporate R&D and stock returns: international evidence. J. Financ. Quant. Anal. 57 (4), 1–72.

Hua, X., Jiang, Y., Sun, Q., Xing, X., 2019. Do antidumping measures affect Chinese export-related firms? Rev. Quant. Finan. Acc. 52, 871–900.

Huang, Y., Lin, C., Liu, S., Tang, H., 2023. Trade networks and firm value: evidence from the US-China trade war. Journal of International Economics 145, 103811.

Ivus, O., 2010. Do stronger patent rights raise high-tech exports to the developing world? Journal of International Economics 81 (1), 38–47.
Janger, J., Schubert, T., Andries, P., Rammer, C., Hoskens, M., 2017. The EU 2020 innovation indicator: a step forward in measuring innovation outputs and outcomes? Research Policy 46 (1), 30–42.
Jelic, R., Saadouni, B., Wright, M., 2005. Performance of private to public MBOs: the role of venture capital. J. Bus. Financ. Acc. 32, 643–682.
Jiang, C., John, K., Larsen, D., 2021. R&D investment intensity and jump volatility of stock price. Review of Quantitative Finance and Accounting 57, 235–277.
Jiang, L., Lu, Y., Song, H., Zhang, G., 2023. Responses of exporters to trade protectionism: inferences from the US-China trade war. Journal of International Economics 140, 103687.
Ju, J., Ma, H., Wang, Z., Zhu, X., 2023. Trade wars and industrial policy competitions: understanding the US-China economic conflicts. J. Monet. Econ. 141, 42–58.
Kim, Y.K., Lee, K., Park, W.G., Choo, K., 2012. Appropriate intellectual property protection and economic growth in countries at different levels of development. Research Policy 41, 358–375.
Lee, K., 2021. China's Technological Leapfrogging and Economic Catch-Up. Oxford University Press.
Lee, S.H., Baik, Y.S., 2010. Corporate lobbying in antidumping cases: looking into the Continued Dumping and Subsidy Offset Act. J. Bus. Ethics 96, 467–478.
Li, W., Yan, Z., Sun, W., 2014. The effect of antidumping and countervailing investigations on the market value of firms. Int. Rev. Financ. Anal. 36, 97–105.
Lin, J.Y., Cai, F., Li, Z., 1998. Competition, policy burdens, and state-owned enterprise reform. Am. Econ. Rev. 88, 422–427.
Lutjen, H., Schultz, C., Tietze, F., Urmetzer, F., 2019. Managing ecosystems for service innovation: a dynamic capability view. J. Bus. Res. 104, 506–519.
Ovuakporie, O.D., Pillai, K.G., Wang, C., Wei, Y., 2021. Differential moderating effects of strategic and operational reconfiguration on the relationship between open innovation practices and innovation performance. Research Policy 50 (1), 104146.
Protogerou, A., Caloghirou, Y., Lioukas, S., 2012. Dynamic capabilities and their indirect impact on firm performance. Ind. Corp. Chang. 21 (3), 615–647.
Reed, R., Defillippi, R.J., 1990. Causal ambiguity, barriers to imitation, and sustainable competitive advantage. Acad. Manag. Rev. 15 (1), 88–102.
Ren, M., Chugh, R., Gao, H., 2024. Fencing or balancing? An exploratory study of Australian and New Zealand exporters' strategic responses during the US-China trade war. Int. Mark. Rev. 41 (3/4), 642–682.
Schmiele, A., 2013. Intellectual property infringements due to R&D abroad? A comparative analysis between firms with international and domestic innovation activities. Research Policy 42, 1482–1495.
Shin, W., Lee, K., Park, W.G., 2016. When an importer's protection of IPR interacts with an exporter's level of technology: comparing the impacts on the exports of the north and south. World Econ. 39, 772–802.
Sun, Q., Tong, W.H., 2003. China share issue privatization: the extent of its success. J. Financ. Econ. 70, 183–222.
Teece, D.J., 2007. Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance. Strateg. Manag. J. 28, 1319–1350.
Teece, D.J., 2018. Dynamic capabilities as (workable) management systems theory. J. Manag. Organ. 24 (3), 359–368.
Teece, D.J., Pisano, G., Shuen, A., 1997. Dynamic capabilities and strategic management. Strategic Management Journal 18, 509–533.
Winter, S.G., 2012. Capabilities: their origins and ancestry. J. Manag. Stud. 49, 1402–1406.
Yang, C.H., Kuo, N.F., 2008. Trade-related influences, foreign intellectual property rights and outbound international patenting. Res. Policy 37, 446–459.
Zollo, M., Winter, S.G., 2002. Deliberate learning and the evolution of dynamic capabilities. Organ. Sci. 13 (3), 339–351.