Digital Infrastructure and Export of SMEs: Evidence from China

Zhuoran Bai[A], Junliang Ge[B], Danyang Zhang[C,†], and Yan Zhang[D]

Abstract

This paper shows that digital infrastructure development improves SMEs' performance on the international market in China. Using a staggered Difference-in-Differences (DID) design and data from SMEs listed on the A-share SME and ChiNext board (2009-2020), we find that the Broadband China policy significantly boosts SME exports. On average, SMEs located in the pilot cities enjoyed a 6.3% larger increase in export-to-revenue compared to those located elsewhere. Our results are robust to the use of new DID estimators, Goodman-Bacon (2021) decomposition, Propensity Score Matching (PSM), pre-trend analysis, placebo tests, and alternative samples. The impact of the policy varies with firm size, industry, and executive team composition. The Broadband China policy promotes digital transformation of SMEs, which facilitates export through enhanced direct market access, reduced transactional costs, and alleviated financial constraints. We also provide evidence that rules out improvements in productivity or imports as drivers of the observed export expansion.

[A] Institute of World Economics and Politics, Chinese Academy of Social Sciences, Beijing, China.
[B] Central University of Finance and Economics, School of International Trade and Economics, Beijing, China.
[C,†] Corresponding author. New Mexico State University, College of Business, Las Cruces, USA. Email: dzhang@nmsu.edu.
[D] Central University of Finance and Economics, School of International Trade and Economics, Beijing, China.

Plain English Summary

This paper finds that the development of digital infrastructure promotes export for SMEs in China. We apply the staggered DID and demonstrate that SMEs located in the pilot cities of the Broadband China policy went through a larger increase in export-to-revenue. The size of the policy impact varies with firm size, industry, and executive team composition. Our results imply that the government should invest in the development of digital infrastructure to facilitate the digital transformation of SMEs, which benefits the SMEs through enhanced direct market access, reduced transactional costs, and alleviated financial constraints.

Keywords: SMEs, Digital Infrastructure, Export, Executive Team, Broadband China
JEL Codes: F14, H54, L26, O14

Statements and Declarations

The authors declare no known financial or non-financial interests that relate to the research described in this paper. This research does not involve interaction with human subjects nor identifiable information of them. No IRB approval is required. This paper uses confidential data from Chinese Customs as well as data with limited access from Wind Database and China Stock Market & Accounting Research Database. On request, the authors could provide a version of the final dataset that removes the identifiable information of the firms. Opinions expressed here are those of the authors and not of any institution.

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1. Introduction

Small and medium enterprises (SMEs) play a major role in the world economy today, representing about 90% of businesses and more than 50% of employment worldwide.[1] For developing countries, SMEs are the nucleus of economic activities – in 2022, SMEs account for over 90% of registered enterprises in China, contributing to about 80% of employment, over 60% of GDP, and 50% of tax revenue.[2] SMEs also make substantial contribution to the key driver for China's economy – international trade. In 2023, with a total value of $3.06 trillion, SMEs accounts for 53.5% of China's international trade.[3]

Despite their vital role in the economy, SMEs encounter several major obstacles on the export markets, including low productivity (Owalla et al., 2022; Chen & Lee, 2023), high transaction cost (Nooteboom, 1993), high regulatory cost (Crain & Crain, 2011), financial constraints (Custódio et al., 2013; Carbó-Valverde et al., 2016; Lekkakos & Serrano, 2016; Cheng et al., 2021; Pietrovito & Pozzolo, 2021), and a lack of information (Lin & Ho, 2019). Compared to larger enterprises, SMEs face resource constraints, and the absence of economies of scale contribute to their lower productivity and higher transaction cost on average (Nooteboom, 1993; Owalla et al., 2022; Chen & Lee, 2023). With lower productivity and higher transactional and regulatory costs, SMEs have limited export capacity compared to the larger enterprises. As established in the literature, the most productive firms export (Melitz, 2003), and the exporters are larger, pay higher wages, and have higher growth (Bernard and Jensen, 1999, 2004; Bernard et al., 2007). There is high entry cost into the export market (Roberts and Tybout, 1997; Melitz, 2003; Das et al., 2007), since these costs rise less than proportionally with trade volume (Roberts and Tybout, 1997), this will put the SMEs at

[1] World Bank. https://www.worldbank.org/en/topic/smefinance.
[2] National Bureau of Statistics of China, the Fourth National Economic Census Series Report of the National Bureau of Statistics (https://www.stats.gov.cn/sj/tjgb/jjpcgb/qgjpgb/).
[3] General Administration of Customs of China (http://www.customs.gov.cn/customs/xwfb34/302330/5625690/index.html).

disadvantage. As pointed out in the World Trade Report, "SME participation in trade remains relatively limited".[4] Financial constraint is another pervasive issue for SMEs. With their smaller size and lower credit ratings, SMEs often struggle to access adequate credit support (Custódio et al., 2013; Carbó-Valverde et al., 2016). Cheng et al. (2021) finds that the financial constraints faced by Chinese SMEs lower their export both at intensive and extensive margins. SMEs also suffer from a lack of information with insufficient knowledge of changes in target market demand, trade policies, and cultural differences (Lin & Ho, 2019).

The development of Information and Communication Technology (ICT) provides SMEs an opportunity to tackle some of the above-mentioned problems and expand to the international market. The advancement of cross-border e-commerce platforms and logistics systems provide SMEs with new avenues for international trade (Tolstoy et al., 2021). With the digital platforms, SMEs can directly interact with global customers, relaxing the geographic and time constraints inherent in traditional trade models. The use of cross-border e-commerce platforms also mitigates risks related to insufficient information and reduces transportation and warehousing costs for SMEs. Digital infrastructure construction can therefore promote international trade among the SMEs by supporting these e-commerce platforms and facilitating the logistic systems.

In the recent years, China has witnessed fast development of ICT and undergone prioritized development in digital infrastructure (Ji & Wang, 2024). In 2014, China initialized the Broadband China policy which aimed at enhancing Internet speed and coverage and promoting the adoption of big data, e-commerce, and digital technology. This policy was implemented in three waves, covering a total of 117 pilot cities (municipalities and prefectural-level) – first wave in 2014 in 41 pilot cities, second wave in 2015 in 38 cities, and third wave in 2016 in 38 cities. In 2012, China's Internet penetration rate was only 42.1%, while in 2024, the Internet penetration rate increased to 78.6%, higher than the global average of 68.4%.[5] The implementation of Broadband

[4] See World trade report 2016: Levelling the trading field for SMEs at https://www.wto.org/english/res_e/booksp_e/world_trade_report16_e.pdf.

[5] Internet penetration rate is the ratio of Internet user number over the resident population. Data is from

China policy promotes the digital transformation in Chinese enterprises and is more pronounced among the non-state-owned enterprises (Jia et al., 2024; Li et al., 2025).

This study focuses on SMEs and their export performance. We use data from A-share companies listed on the SME and ChiNext boards of the Shenzhen Stock Exchange between 2009 and 2020.[6] We then follow the Chinese classifications to only keep the medium, small, and micro firms based on employment, operating revenue, and total assets. With a staggered Difference-in-Differences (DID) design, we find the Broadband China policy significantly boosts SME exports in China – on average, SMEs located in the pilot cities enjoyed a 6.3% larger increase in export-to-revenue compared to those located elsewhere after the implementation of the policy. To get over the problems using staggered DID with two way fixed effects as discussed in the literature (Borusyak et al., 2024; Goodman-Bacon, 2021; Sun & Abraham, 2021), we use the new DID estimators proposed by de Chaisemartin and D'Haultfœuille (2020), Callaway and Sant'Anna (2021), and Borusyak et al. (2024), as well as carry out the decomposition suggested by Goodman-Bacon (2021). Our results are very robust to these alternative methods. We observe no significant pre-trends (where we apply the fully dynamic event study design), no result in placebo tests (where we randomly assign fictitious treatment groups and repeat 1,000 times), and very similar results further applying Propensity Score Matching (PSM) in our DID design.

The size of the impact of the policy varies with firm size, industry, and workforce composition. With absence of economies of scale (Nooteboom, 1993; Owalla et al., 2022; Chen & Lee, 2023), SMEs face a lack of information (Lin & Ho, 2019) and would benefit more from improved Internet access. Consistently, we find small and micro firms experienced a larger increase in export-to-revenue than the medium firms. Across

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The 55th Statistical Report on China's Internet Development (released by China Internet Network Information Center) and the International Telecommunication Union (https://www.itu.int/en/ITU-D/Statistics/pages/stat/default.aspx).

[6] In our research period (2009-2020), Shanghai Stock Exchange and Shenzhen Stock Exchange are the only two stock exchanges in the mainland of China. Shanghai Stock Exchange mainly serves large and mature firms. Shenzhen Stock Exchange exclusively operates the SME Board and ChiNext markets, which focuses on serving SMEs, private firms and other growing firms. Compared to the Main Board, the SME Board and ChiNext set lower bars for listed firms in profitability, asset size and shareholding structure.

industries, firms operating in industries where information and digital technology matter more should benefit more from Broadband China policy, and we find a more pronounced expansion in export-to-revenue for firms in industries with higher digital technology adoption rates. Previous literature has documented the significant impact of firms' executive team characteristics on their performance, including team members' age, gender, education, and professional background (Flabbi et al., 2019; Choi et al., 2022; Cheng et al., 2024; Tsolmon, 2024; Xu & Shi, 2025). Firms with fitter workforce will benefit more, and we find that SMEs went through a more pronounced expansion in export if a higher share of their executive teams are younger, male, highly-educated or with technical, financial, and overseas background. To better explain the promotional effect on firms' exports, we study the mechanisms and provide supporting evidence at both city and firm level. At the city level, Broadband China policy promotes cross-border e-commerce, enhances industrial agglomeration, and facilitates digital infrastructure development. At the firm level, the policy promotes digital transformation, which in turn improves direct market access, lowers transactional costs, and reduces financial constraints. We also show that the export expansion we observe is not driven by increase in imports or productivity.

This paper contributes to the literature studying the impact of digitization and digital infrastructure development. Previous literature has explored the impact of digitization on firm performance, including productivity (Syverson, 2011; Acemoglu et al., 2014; Nucci et al., 2023), innovation (Liu et al., 2023; Zheng et al., 2025), digital transformation (Jia et al., 2024; Li et al., 2025), and export performance (Lin, 2015; Herman et al., 2023; Chiappini & Gaglio, 2024). Our paper, however, focuses on SMEs, which face distinct challenges in global markets due to constraints in resources, technology, and scale. This paper then addresses the unique dilemmas SMEs encounter in the export market by exploring how digital infrastructure development enhances SMEs' export performance. The existing literature also examines the regional effects of digital infrastructure on governance (Wang et al., 2023), knowledge diffusion (Paunov & Rollo, 2016), and labor misallocation (Hua & Zhang, 2024). Compared to papers studying the regional effects, this paper provides micro-level evidence using firm data.

Li et al. (2025) and Jia et al. (2024) also use microdata and explore the natural experiment of Broadband China policy, but both of them focus on the digital transformation of firms instead of export performance. This paper also relates to the literature on entrepreneurship and firm performance and complements previous studies between firm performance and executive team member characteristics, including age (Christensen et al., 2015; Cheng et al., 2024), gender (Flabbi et al., 2019; Tsolmon, 2024), education attainment (Choi et al., 2022), and background/experience (Jiang & Liu, 2020; Pan & Xu, 2024; Wu, 2024; Xu & Shi, 2025).

The remainder of this paper is organized as follows. Section 2 introduces the Broadband China policy. Section 3 describes data and outlines our empirical strategy. Section 4 present empirical results, including baseline results, robustness checks, and heterogeneity studies. Section 5 discusses the mechanism and provides supporting evidence. Finally, section 6 concludes.

2. Broadband China Policy

The Internet went through fast proliferation in the 1990s globally. China, however, remained comparatively underdeveloped in digital infrastructure at the beginning of the 21st century. By 2012, China's broadband penetration rate was only 12.9%, significantly below the OECD average of 26.7%, and its average Internet speed was 1.6 Mbps, lower than the global average of 2.9 Mbps.[7]

To promote digital infrastructure development, the Chinese government launched "the Broadband China Strategy and Implementation Plan" on August 1, 2013, which prioritized broadband development as a national strategy. The Ministry of Industry and Information Technology (MIIT) and the National Development and Reform Commission (NDRC) then released a list of the Broadband China pilot cities in three waves, covering a total of 117 cities (including 4 municipalities directly under the central government and 113 prefectural-level cities) – first wave in 2014 with 41 pilot cities, second wave in 2015 with 38 cities, and third wave in 2016 with 38 cities.[8] Figure 1 illustrates the geographic distribution of the pilot cities in different waves, and we list out the names of pilot cities in each wave in Appendix Table A1.

The Broadband China policy sets out well-defined goals and timetables (see Appendix Table A2), including a set of targeted policies to enhance regional digital infrastructure and improve enterprise-level broadband adoption rates.

First, the policy accelerates broadband network upgrade, with a special focus on international Internet connection. For example, the policy mandates an increase in Fiber-to-the-Home (FTTH) coverage from 130 million households in 2013 to 300 million by 2020. It prioritizes the enhancement of global connection by raising the international Internet bandwidth from 2,500 Gbps in 2013 to 6,500 Gbps by 2015.

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[7] Broadband penetration rate is a core indicator used internationally to measure the level of fixed broadband penetration in a country, which is equal to the number of broadband subscribers in a country divided by the total population of the country in that year. Data is from *China Broadband Development White Paper* (http://www.caict.ac.cn/kxyj/qwfb/bps/201910/P020191031512605025697.pdf), released by the China Academy of Information and Communications Technology (CAICT). Internet speed data is from *State of the Internet Reports 2012* from Akamai (https://content.akamai.com/PG2636-State-of-the-Internet-Report-Q4-2012.html). Note that the Internet penetration rate is more broadly defined than the broadband penetration rate.

[8] In 2014, there are 4 municipalities directly under the central government (namely, Beijing, Chongqing, Shanghai and Tianjin) and a total of 333 prefecture-level cities and autonomous prefectures in China.

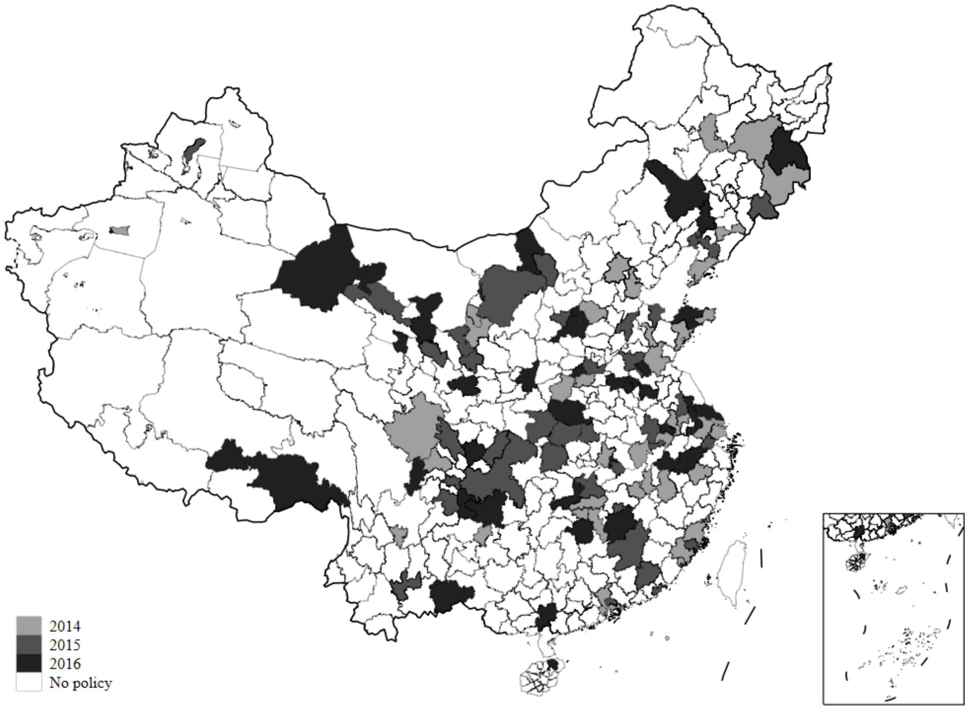

Fig. 1 Distribution of Pilot Cities for Broadband China Policy

Notes: Data from the Ministry of Industry and Information Technology and the National Development and Reform Commission.

Second, the policy promotes broadband network adoption, especially for SMEs. The policy plans to carry out a broadband application demonstration project for SMEs by subsidizing broadband equipment upgrade, providing technical training for 1.2 million SME employees, and promoting Internet integration into firms' production and business processes. The policy also encourages firms to join e-commerce platforms and plans to increase e-commerce transactions from 10 trillion Chinese yuan in 2013 (about 1.52 trillion dollars) to 18 trillion Chinese yuan in 2015 (about 2.74 trillion dollars).[9]

The 45th Statistical Report on the Development of the Internet in China summarizes the achievements of the Broadband China policy.[10] Based on the National Bureau of Statistics, China's Internet penetration rate was 45.8% and had 359.45 million Internet broadband access ports in 2013. In 2017, after the implementation of

[9] The average exchange rate between Chinese yuan and the US dollar in 2009-2020 is 1 US Dollar for 6.5620 Chinese Yuan. Exchange rate data is from the World Bank.

[10] Data from China Internet Network Information Center (CNNIC) at https://www.cac.gov.cn/2020-04/27/c_1589535470378587.htm.

Broadband China policy, these two numbers increased to 55.8% and 775.99 million. The Internet transmission rates also witnessed fast growth – the International Outlet Bandwidth (which measures the network transmission rate and the rate of international information exchange and delivery) has nearly quadrupled in the 20-year period from 2013 to 2022 (see Figure 2).[11]

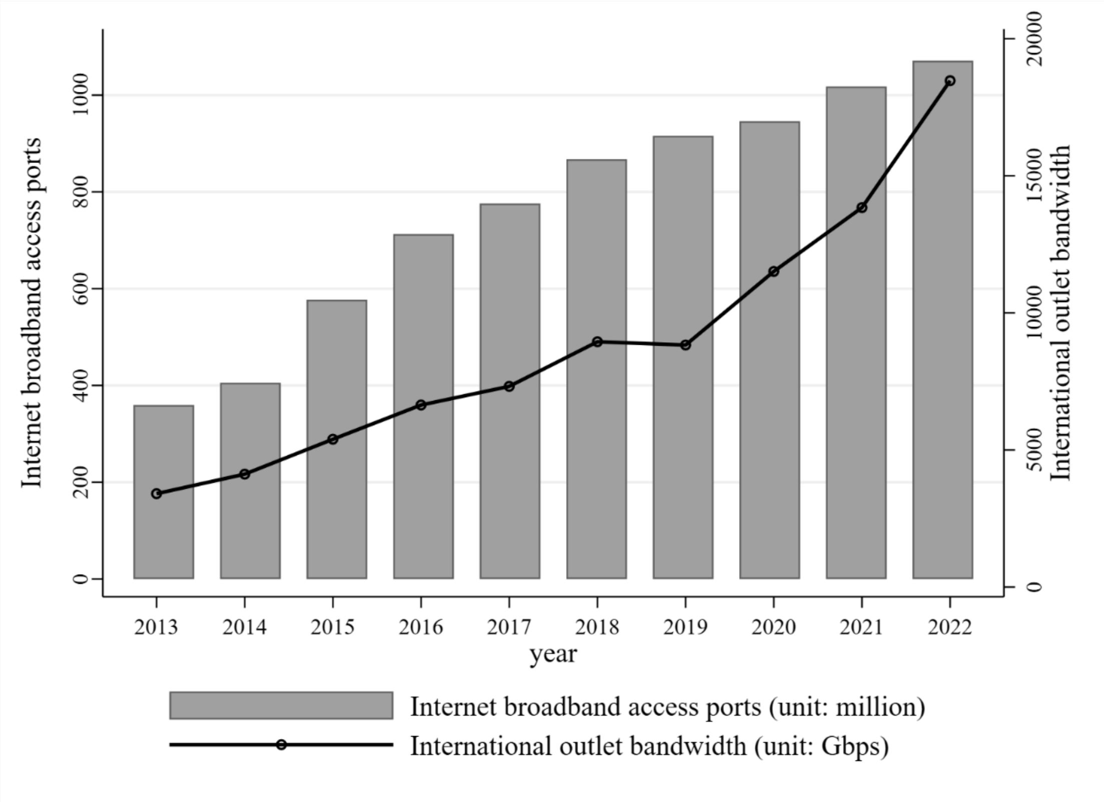

Fig. 2 Internet Broadband Development in China, 2013-2022

Notes: The bar chart shows the number of Internet broadband access ports in China (unit: million), and the line chart shows the International Outlet Bandwidth (Gbps). Data from the China Statistical Yearbook.

[11] International Outlet Bandwidth refers to the data transmission capacity leased by domestic telecom operators through submarine cables or satellite links to connect with global networks. Greater bandwidth directly correlates with higher data transfer speeds and lower latency, fundamentally determining the efficiency of cross-border digital interactions.

3. Data and Empirical Strategy

3.1. Data Introduction

3.1.1. SMEs

We restrict our study to the firms listed on the SME Board and ChiNext markets at the Shenzhen Stock Exchange between 2009 and 2020. Compared to the Shanghai Stock Exchange, which mainly serves large and mature firms, the Shenzhen Stock Exchange exclusively operates the SME Board and ChiNext markets, which focuses on serving SMEs, private firms and other growing firms. As a result, SMEs are typically listed on the Shenzhen Stock Exchange. Compared to the Main Board, the SME Board and ChiNext set lower bars for listed firms in profitability, asset size and shareholding structure.[12] At the end of 2020, there are 994 and 892 listed firms in the SME Board and ChiNext markets, respectively.

Based on the criteria set by the National Bureau of Statistics of China (NBS) in 2017, Chinese firms are divided into four categories, namely large, medium, small, and micro.[13] The classification combines information on employee number, operating revenue, and total assets, and the exact criteria vary by industry (details listed in Appendix Table A3, A4, and A5).[14] In this paper, we define the SMEs as the medium, small, and micro firms based on the classification criteria in China, and the sample comes down to 596 unique SMEs in the research period. Table 1 presents comparison between SMEs and all A-share market firms in several key indicators, and we observe significantly fewer employees, lower operating revenues and smaller total assets among the SMEs. The return on total assets (*ROA*, the ratio of net income to total assets) and

[12] As of 2019, the Main Board usually requires firms to have accumulated net profits of 30 million Chinese yuan for three consecutive years, net cash flows of 50 million Chinese yuan for the last three years, and a total share capital of 50 million Chinese yuan after issuance. The SME Board holds similar standards as the Main Board but requires lower outstanding share capital. ChiNext lowers the share capital requirement to 30 million Chinese yuan and relaxes the listing requirements in accumulated net profits to 10 million Chinese yuan for the last two years or net profits of 5 million Chinese yuan for the last year.

[13] Policy listed at https://www.stats.gov.cn/xw/tjxw/tzgg/202302/t20230202_1893916.html.

[14] For example, a firm in the manufacturing industry has to employee less than 1,000 workers and earn an operating revenue less than 0.4 billion Chinese yuan to be defined as SME, but a firm in the computer service and software industry will be classified as SME in our paper as long as it hires less than 300 employees and earn an operating revenue less than 0.1 billion Chinese yuan. A firm needs to satisfy all criteria to be on the “larger” scale standard – for example, if a firm is large by employee number, medium by operating revenue, and small by total assets, then this firm is classified as small by the government.

total factor productivity (*TFP*, measured following Levinsohn & Petrin, 2003) of SMEs are also lower, hinting less efficient production and operation among the SMEs. The leverage ratio (*LEV*, the ratio of total liabilities to total assets) of SMEs is lower, implying the higher financing constraints SMEs face.

Table 1: SMEs and A-share Firms (Mean Only)

Variables	2012		2009-2020	
	A-share	SMEs	A-share	SMEs
Total Asset	46.803	3.355	56.868	3.121
Employee	6.246	0.974	6.271	0.887
Revenue	8.558	0.898	9.111	1.300
ROA	0.050	0.044	0.048	0.038
LEV	0.466	0.308	0.467	0.312
TFP	8.094	7.406	8.253	7.514
Observations	2,494	251	35,094	4,005

Notes: The full sample covers all firms listed on the A-share market, including the Main Board, SME Board, and ChiNext Board. The SMEs include only the medium, small, and micro firms as specified by the NBS standard. Total asset is measured by one trillion Chinese yuan (about $0.16 trillion). Employee number is measured in thousands. Revenue is measured in one trillion Chinese yuan. *ROA*, return on assets, is the ratio of net income to total assets. *LEV*, leverage ratio, is the ratio of total liabilities to total assets. *TFP*, total factor productivity, is measured by the LP method (Levinsohn & Petrin, 2003).

3.1.2. Data Source

This paper combines multiple data sources. We refer to the above-described list of SMEs and use stock code to match the firms with their annual reports to obtain more information. These data are released by the China Stock Market and Accounting Research Database (CSMAR) and the Wind Database, and they provide information on firms' financial indicators (e.g., export value, number of employees, ROA, equity structure) and executive board member characteristics (e.g., age, gender, education, previous experience).[15] Based on the zip code provided, we can identify the location of firms.

We collect information on each city's economic development from the China City Statistical Yearbook, including GDP, technology development, etc.

In some specifications, we further integrate the China Customs Data, which provides transaction-level data on the time, value, quantity, export destination country,

[15] The CSMAR is a research-oriented comprehensive database focusing on China's economy/finance and is widely used in the literature. The Wind provides detailing financial data of listed firms and the broader economy, including stocks, bonds, funds, foreign exchange, financial derivatives, commodities, macroeconomics, financial news and others.

and trade mode for China's international trade. We aggregate the Customs Data by firm and year, and match with our main data using firm name.

3.1.3. Data Treatment

As standard treatment, we follow three steps to keep only the valid observations. (1) We exclude firms in the financial industry for their different asset-liability structure and regulatory policies. (2) We exclude listed firms which are exiting the stock market (marked by the "ST" or "*ST" in the listing status). (3) We exclude firms with missing key variables. The final sample contains a total of 4,005 observations in the panel data, covering 589 unique SMEs from 2009 to 2020.[16]

3.2. Empirical Strategy

To study the impact of the Broadband China policy, we adopt the staggered DID design, as specified below:

$$Export_{ict} = \beta_0 + \beta_1 DI_{ct} + \beta_2 X_{it} + \beta_3 X_{ct} + \eta_i + \eta_t + \varepsilon_{ict} \tag{1}$$

Here subscripts i, c, and t denote firm, city, and year, respectively. The dependent variable $Export_{ict}$ denotes the export-to-revenue ratio. DI_{ct} is our key variable of interest, which is a dummy variable that equals 1 if city c is already included in the Broadband China pilot cities in year t, and 0 otherwise. We include the firm fixed effects η_i which take care of constant firm features and year fixed effects η_t which take care of common shocks over time.[17] The random error is denoted by ε_{ict}.

We include both firm-level and city-level control variables. For firm-level control variables X_{it}, we include total factor productivity (*TFP*, estimated based on Levinsohn & Petrin, 2003), firm size (*lnSize*, the natural log of a firm's total assets), return on total assets (*ROA*, the ratio of net income to total assets), leverage ratio (*Lev*, the ratio of total liabilities to total assets), growth rate of operating revenues (*Growth*, the annual growth rate of a firm's operating revenues), percentage of shares held by the largest shareholder (*TOP1*, the ratio of the number of shares held by the first largest shareholder to the total number of shares), and Tobin's Q ratio (*TobinQ*, which measures the market value of a company in relation to the replacement cost of its assets).[18] For the choice of firm-level

[16] The panel is unbalanced in nature, since firms enter the SME and ChiNext Board in different years. For a firm that was listed but later exited the market, we include the data before it exited the market.
[17] There are no firms switching cities in the sample period and we did not include the city fixed effects.
[18] For *TOP1*, if there are multiple largest shareholders holding the same number of shares, we only count it once. The formula for calculating *TobinQ* is (market value of outstanding shares + number of shares of non-outstanding shares × net assets per share + book value of liabilities)/total assets.

control variables, we followed Bharadwaj et al. (1999), Bernard and Jensen (2004), Yu (2015), Cheng et al. (2020), Wang et al. (2021), Du et al. (2025), and Li et al. (2025).

For city-level control variables X_{ct}, following He et al. (2024), we include variables to control for regional economic development ($lnGDP$, the natural log of GDP per capita, in Chinese yuan), science and education expenditure ($lnTech$, the natural log of the sum of expenditure on education and science, in 10 thousand Chinese yuan), fiscal expenditure (Gov, the share of the general budget expenditure of the local treasury in GDP), and financial development (Fin, the balance of loans of financial institutions at the end of the year over GDP). We also include import-to-GDP ratio since import plays a vital role in a firm's export performance and it might also respond to the policy.[19]

Table 2: Summary Statistics

	Observations	Mean	S.D.	Min	Max
Firm-Level Variables					
Export-to-Revenue	4,005	0.178	0.203	6.70e-06	0.999
lnSize	4,005	21.125	0.860	16.412	27.298
ROA	4,005	0.038	0.078	-0.332	0.231
Lev	4,005	0.312	0.312	0.031	0.942
Top1	4,005	32.361	13.193	3.890	79.730
Growth	4,005	0.163	1.444	-0.997	67.951
TobinQ	4,005	2.561	3.530	0.765	122.190
TFP	4,005	7.514	0.795	4.748	12.709
City-Level Variables					
ln*GDP*	1,134	11.041	0.530	9.102	12.579
ln*Tech*	1,134	13.530	1.282	4.225	16.569
Gov	1,134	0.168	0.149	0.044	2.349
Fin	1,134	1.702	0.819	0.398	6.039
Import_GDP	1,134	0.130	0.197	5.270e-5	0.990

Notes: *Export-to-Revenue* is the ratio of total exports value to revenue. *lnSize* is the natural log of a firm's total asset in Chinese yuan. *ROA* is the ratio of net income to total assets. *Lev* is the ratio of total liabilities to total assets. *Growth* is the annual growth rate of a firm's operating revenues. *TOP1* is the number of shares held by the first largest shareholder over the total number of shares. *TobinQ* is (market value of outstanding shares + number of shares of non-outstanding shares × net assets per share + book value of liabilities)/total assets. *TFP* is measured based on Levinsohn and Petrin (2003). *lnGDP* is the natural log of GDP per capita in Chinese yuan. *lnTech* is the natural log of total expenditure on education and science in 10 thousand Chinese yuan. *Gov* is the share of the general budget expenditure of the local treasury in GDP. *Fin* is the balance of loans of financial institutions at the end of the year over GDP. *Import_GDP* is the share of the city's imports in GDP.

[19] CSMAR database does not provide import value and the customs data we have do not specify the firm names in 2017-2020, but firm name is what we mainly rely on to match the listed firms with the customs data (e.g., see Yu, 2015). Appendix Table A9 shows the number of firms in each year, and dropping 2017-2020 will greatly decrease our sample size. With the data limitation, we include city-level import-to-GDP ratio in the controls, obtained from the China City Statistical Yearbook. In Table 14 where we match with Customs Data, we have a smaller sample but we replace city-level import-to-GDP ratio as firm-level total values of import, share of imports of capital goods, and share of import of intermediate goods.

4. Baseline Results, Robustness Checks, and Heterogeneity Studies

4.1. Baseline Results

Table 3 presents the baseline results on the impact of digital infrastructure development on SMEs' export. Specifically, column 1 includes only the independent variable *DI*, column 2 adds the firm fixed effects and year fixed effects, and column 3 further includes the firm-level and city-level control variables. We find the Broadband China policy significantly boosts SME exports – on average, firms located in the pilot cities enjoyed a 6.3% larger increase in export-to-revenue compared to those located elsewhere after the implementation of the policy. This result provides direct evidence that SMEs benefit from the development of digital infrastructure in China with higher integration into the international market.

By analyzing all the policy documents in 1980-2020 in China, Wang and Yang (2025) points out that there exists positive selection in the policy experimentation sites concerning local socio-economic conditions, and that the policy impacts might be unrepresentative if the policies are widely applied in the entire country. In our paper, however, findings in Wang and Yang (2025) would not pose serious questions on the interpretation of our results. First, in our regressions, we already control city-level socio-economic conditions, which vary both by city and over time. We also include the firm fixed effects, which potentially take care of many unobserved heterogeneities.[20] Second, for the assumption of applying DID, we do not observe any significant pre-trend (which we will show in Section 4.2.2). This guarantees the comparability of the treated and control groups in our sample. Third, for the external validity, the Broadband China policy itself is already widely implemented, which supports the representativeness of our results. Table A6 below shows the share of pilot cities among all cities (in count of cities and in GDP, respectively). With all three rounds of the policy, 34.72% cities have been included as pilot cities, representing about 60% of GDP in the research period.

[20] We do not observe any firm changing cities in the sample period.

Table 3: Baseline Results

	Export-to-Revenue Ratio		
	(1)	(2)	(3)
DI	0.039***	0.062***	0.063***
	(0.011)	(0.013)	(0.012)
lnSize			0.011
			(0.008)
ROA			0.063*
			(0.036)
Lev			-0.027
			(0.028)
Top1			0.001
			(0.001)
Growth			0.005
			(0.004)
TobinQ			0.002
			(0.002)
TFP			-0.042***
			(0.013)
lnGDP			0.026
			(0.027)
lnTech			-0.026
			(0.023)
Gov			0.010
			(0.022)
Fin			0.020
			(0.015)
Import_GDP			0.000
			(0.018)
Firm FE	No	Yes	Yes
Year FE	No	Yes	Yes
Firm Obs	4,005	4,005	4,005
City-year Obs	1,134	1,134	1,134
R-squared	0.009	0.739	0.747

Notes: Robust standard errors clustered at the city level in parenthesis, ***p<0.01, **p<0.05, *p<0.1.

4.2. Robustness Tests

4.2.1. New DID Estimator and Goodman-Bacon Decomposition

As discussed in the literature, the estimator using staggered DID with two-way fixed effect can be biased, and is essentially a weighted average of the treatment effects over different groups and periods (Borusyak et al., 2024; Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Sun & Abraham, 2021). To deal with the potential problems, we apply the new DID estimators proposed by de Chaisemartin and D'Haultfœuille (2020), Callaway and Sant'Anna (2021), Borusyak et al. (2024) and the decomposition suggested by Goodman-Bacon (2021).

Table 4 presents the results using the new estimators. After the Broadband China policy, on average, SMEs in the pilot cities showed a 5.2% to 5.8% larger expansion in export-to-revenue compared to those in other cities, depending on the estimator. This estimate is similar to our baseline result and is also significant at 1%. To save space, we suppress the results on control variables and we list the corresponding full-length tables in Appendix E.

Table 4: New DID Estimators

	Export-to-Revenue Ratio		
	de Chaisemartin and D'Haultfœuille (2020)	Callaway and Sant'Anna (2021)	Borusyak et al. (2024)
DI	0.052***	0.052***	0.058***
	(0.007)	(0.020)	(0.012)
Controls	No	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm Obs	1,540	2,739	3,074
City-year Obs	N/A	1,022	1,090

Notes: Robust standard errors clustered at the city level in parenthesis, ***p<0.01, **p<0.05, *p<0.1. We apply the new DID estimator proposed by de Chaisemartin and D'Haultfœuille (2020) in column 1, Callaway and Sant'Anna (2021) in column 2, and Borusyak et al. (2024) in column 3.

Table 5 presents the decomposition proposed by Goodman-Bacon (2021), which shows the weighted average of all possible 2 × 2 DID estimates. The first two groups (earlier treatment versus later control; later treatment versus earlier control) have smaller weights (0.035 and 0.050), and the group of treatment versus never treated has a larger weight of 0.426. The average DID estimate among the treatment versus never treated group is 0.053, which is slightly lower than our baseline estimate of 0.063. None of the four groups have a negative estimated coefficient.

Combining the new DID and the decomposition results, the baseline result we get in Table 3 is very robust.

Table 5: Bacon decomposition

Bacon decomposition	Weight	Average DID estimate
Earlier Treatment vs. Later Control	0.035	0.033
Later Treatment vs. Earlier Control	0.050	0.076
Treatment vs. Never treated	0.426	0.053
Treatment vs. Already treated	0.490	0.024

Notes: We apply the decomposition proposed by Goodman-Bacon (2021).

4.2.2. Parallel Trend Test

The proper application of DID builds on the assumption of parallel trend. In this paper, it means that before the implementation of the Broadband China policy, we would see similar time trends for the treatment and control groups. To test this assumption, we adopt a fully dynamic event study design including all possible relative time periods with no truncation, as specified below.

$$Export_{ict} = \sum_{k=-\infty}^{\infty} \beta_k DI_{ck} + \theta X_{it} + \gamma X_{ct} + \eta_i + \eta_t + \varepsilon_{ict} \quad (2)$$

Here k is the relative time measured with k = t – K, where t is the absolute time (year) and K is the first year a city is included in the pilot cities (e.g., k = -1 means the last year right before a city is ever included in the pilot cities). In this paper, we set k = -1 as the benchmark. We include the same control variables and fixed effects as specified for equation (1). Here β_k is the coefficient for the lead (k<0) and lag (k>0) periods. Figure 3 plots the estimated coefficients β_k with 95% confidence intervals, and shows no significant pre-trend before the implementation of the policy. We also see relatively constant size in the impact of the policy over time, which is no longer significant starting year six post the inclusion into the pilot cities. For the rest of the pre-trend figures, we put them into Appendix D and we do not observe any figures with significant pre-trend at 5%.

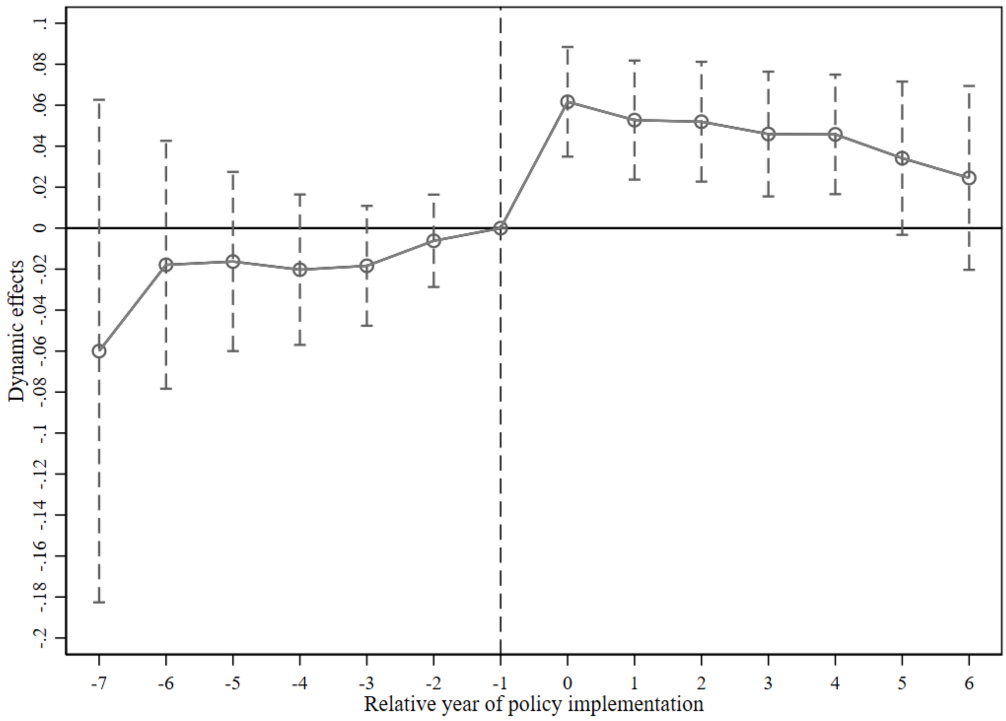

Fig. 3 Parallel Trend Test

Notes: This figure plots the point estimates and associated 95% confidence intervals for the relative time dummies. We designate the time preceding the enforcement of the policy as the baseline period (β_{-1}=0).

4.2.3. Placebo Test

We carry out the placebo tests following established practices in literature (e.g., Alpert et al., 2021) to randomly assign the treatment group. Specifically, we follow the same timeline and number of pilot cities as the Broadband China policy, but now the cities are randomly assigned to the treatment group (or pilot cities).[21] With the pseudo-treatment group, we then re-estimate the treatment effects the same way as in the baseline analysis. We repeat this process for 1,000 times and Figure 4 plots the estimated coefficients against the p-values at each trial in scatter graph. More than 85.6% of the estimated pseudo-coefficients are not significant at 10%, and only 4 trials (out of 1000) have a p-value below 0.001, while the p-value in the baseline result is 0.000. The estimates are centered around zero and conform to a normal distribution, as expected for placebo tests. In none of the trials did we get an estimate as large as the actual policy

[21] If n cities are designated as pilot cities in year t, we then randomly select n cities that have never been chosen as pilot cities to form the new treatment group in year t.

impact (0.063), as represented by the grey dashed line in graph.[22] Based on the placebo results, we are very confident that our finding is not driven by some (unobserved) random factors and that our results are very robust.

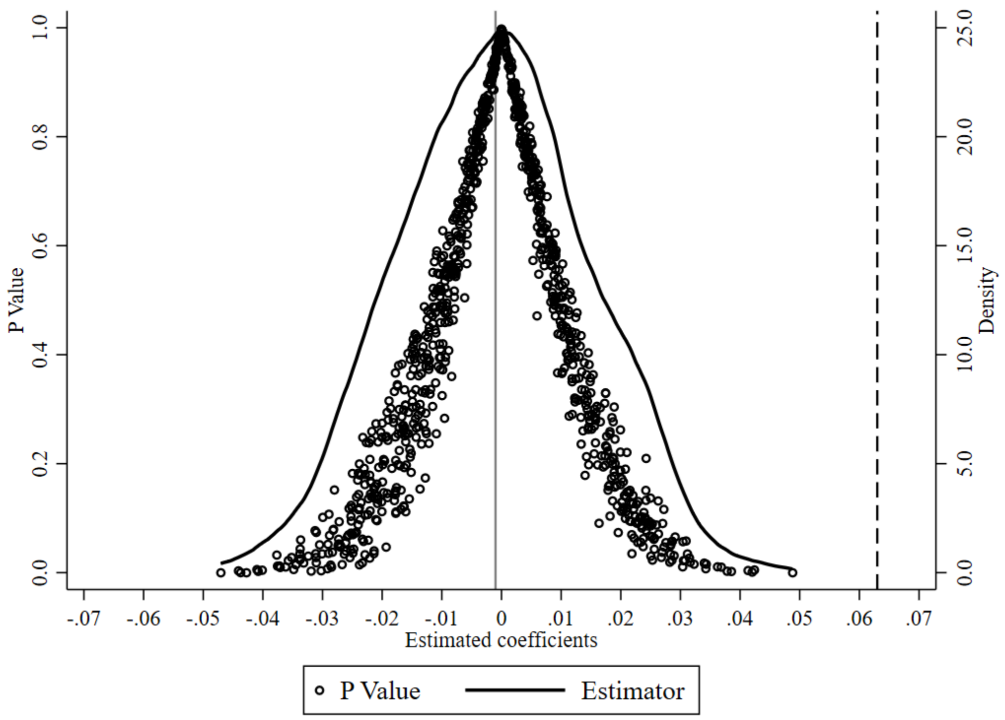

Fig. 4 Distribution of Estimated Coefficients and p-values in Placebo Tests

Notes: This figure plots the estimated coefficients (x-axis) against their corresponding p-values (y-axis) across 1,000 pseudo-treatment trials. The black vertical dashed line marks the actual policy effect (0.063) in our baseline result. The grey vertical solid line indicates the mean coefficient (-0.001) derived from the 1,000 placebo tests.

4.2.4. Propensity Score Matching

We combine the Propensity Score Matching (PSM) in our DID analysis to increase the compatibility between the treatment and control groups. We match firms on the following dimensions – firm size, return on total assets, financial leverage ratios, operating income growth rates, the proportion of shares held by the largest shareholder, and Tobin's Q. We carry out the matching process under three different algorithms – nearest-neighbor, kernel, and radius matching.[23]

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[22] The largest estimate we got from the 1,000 trials was 0.049, below the actual policy impact 0.063.

[23] For the nearest-neighbor matching, we identify the two closest control group firms in propensity score for each treated firm, retaining only the matched pairs for estimation. Kernel matching matches each

We then conduct the same baseline analysis in the matched sample, and the results are reported in Table 6. All three matching algorithms generate similar coefficients as in the baseline results, and the PSM-DID coefficients are all statistically significant at 1%. The PSM-DID results provides further support for the robustness of our baseline results.

Table 6: PSM-DID Results

	Export-to-Revenue Ratio		
	(1)	(2)	(3)
	Nearest-neighbor	Kernel	Radius
DI	0.066***	0.063***	0.063***
	(0.014)	(0.012)	(0.012)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm Obs	2,124	3,957	3,964
City-year Obs	925	1,129	1,130
R-squared	0.784	0.753	0.753

Notes: Robust standard errors clustered at the city level in parenthesis, ***p<0.01, **p<0.05, *p<0.1. In columns 1-3, we use 1:2 nearest-neighbor matching, kernel matching, and radius matching for PSM analysis, respectively.

4.2.5. Other Robustness Checks

We carry out another two robustness checks and results are put in the Appendix Table A7. Starting 2018, U.S. imposed comprehensive tariffs on Chinese imports and several adjustments to these tariffs afterwards. In column 1, we therefore restrict our sample period to pre-2018 to get around potential impacts of the trade war between U.S. and China. Firms in different industries may encounter different tariffs, non-tariffs and other trade policies, and in column 2 we include industry by year fixed effects in our baseline regression. Both columns show similar and significant results as the baseline.[24]

4.3. Heterogeneity Studies

4.3.1. Firm Size

In the literature, there is wide discussion on the absence of economies of scale for SMEs (Nooteboom, 1993; Owalla et al., 2022; Chen & Lee, 2023) and Lin and Ho

treated firm to all control firms but assigns weights inversely proportional to the propensity score distance, with higher weights for smaller differences. Radius matching pre-defines a maximum acceptable propensity score difference (here, 0.01) and each treated firm to all controls within this range.

[24] In our final sample, there are 492 unique industry-year cells.

(2019) points out the lack of information among the SMEs. Based on the literature, we would expect smaller firms to benefit more from improved Internet access. We further split the SMEs in our sample into medium and small-micro firms and replicate our main analysis. Results are in Table 7. As expected, SMEs of different sizes both benefit from improved Internet access but we observe larger increase in export-to-revenue in the small-micro firms than the medium ones, and the difference is significant at 10%.

Table 7: Medium and Small-Micro Firms

	Export-to-Revenue Ratio	
	(1) Medium	(2) Small and Micro
DI	0.036*	0.059***
	(0.021)	(0.015)
Group Difference	0.023*	
Controls	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
Firm Obs	1,205	2,764
City-year Obs	548	969
R-squared	0.787	0.789

Notes: Robust standard errors clustered at the city level in parenthesis, ***p<0.01, **p<0.05, *p<0.1. In column 1, we further restrict the sample to the medium-sized listed firms. In column 2, we restrict the sample to small and micro listed firms.

4.3.2. Industry

Across industries, firms operating in industries where information and digital technology matter more should benefit more from Broadband China policy. To test this, we then divide firms based on their industries' degree of digital transformation. We followed the OECD's classification on digital technology adoption and classify industries into high and low digital technology based on adoption rates of digital technologies and business practices as in Calvino et al. (2018). Results are in Table 8. Consistent with our expectation, we find that firms in high digital technology industries benefit more from improved access to Internet, and the difference is significant at 10%.

Table 8: Firms in High and Low Digital Technology Industries

	Export-to-Revenue Ratio	
	(1)	(2)
	High-digital Tech	Low-digital Tech
DI	0.089***	0.060***
	(0.029)	(0.016)
Group Difference	0.030*	
Controls	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
Firm Obs	1,086	2,878
City-year Obs	487	976
R-squared	0.763	0.760

Notes: Robust standard errors clustered at the city level in parenthesis, ***p<0.01, **p<0.05, *p<0.1. Column 1 and 2 use the firms in the high and low digital technology industries, respectively. We follow the OECD's classification on the digital technology adoption for industries measured by adoption rates of digital technologies and business practices as in Calvino et al. (2018).

4.3.3. Executive Team

Previous literature has documented the significant impact of a firm's executive team characteristics on its performance, including team members' age, gender, education, and professional background (Flabbi et al., 2019; Choi et al., 2022; Cheng et al., 2024; Tsolmon, 2024; Xu & Shi, 2025). Firms with fitter workforce shall benefit more from the policy, and we take a closer look at the compositions of the executive teams.

In data, we can observe the individual characteristics of a firm's executive team members, which include the chief executive officer (CEO), chief financial officer (CFO), general manager, vice general manager, etc.[25] These individual characteristics include age, gender, educational attainment, educational background, and previous experience.[26] We then aggregate the individual-level information to firm-level and

[25] In our data, 15.64% of the executive team members are CEO and general manager, 14.52% are CFO, 0.16% are both CEO/general manager and CFO, and the rest are others (including vice general manager).

[26] For education attainment, we see whether the executive member has education levels of below college, college, four-year university, master and doctor. For occupation background, we see whether they have worked in the following categories: production (10.9%), R&D (19.00%), designing (2.83%), human resource (3.54%), management (80.18%), marketing (24.49%), finance (15.91%), accounting (20.70%), law (2.15%), and others (0.31%). Note that one executive member might have occupation background in more than one of the categories, so the percentages sum up to be more than 100%. For overseas experience, we know whether the board member has previous working (3.87%) or studying (2.79%) experience overseas. For working experience, we see whether they have worked in one of the following types of financial firms/institutions: regulatory agency (0.40%), policy banks (0.06%), commercial banks (2.01%), insurance company (0.49%), securities (2.28%), fund management (0.42%), security

match back to our sample described in the data section. Table A8 lists the descriptive statistics of the executive team characteristics in our sample - the average executive team consists of 6.5 members, has a mean age of 46.4 years, is predominantly (81.3%) male, and 46% of the board members have master or doctor degrees. Based on the executive team member's background/experience (occupation background, overseas working/studying experience, and financial working experience), we construct three variables on firm-level representing the percentage of executive team members who has technical, overseas, or financial background.[27] On average, 28.8% of the executive team members have technical background, but only 7.0% and 5.4% of them have financial or overseas background, respectively.

Table 9: Executive Team – Age, Gender, Education and Background

	Export-to-Revenue Ratio					
	(1) Age	(2) Male	(3) Master	(4) Financial	(5) Technical	(6) Overseas
DI	0.075***	0.057***	0.051***	0.054***	0.053***	0.051***
	(0.013)	(0.013)	(0.014)	(0.011)	(0.013)	(0.012)
Interaction	-0.022**	0.018*	0.020*	0.039*	0.024**	0.040*
	(0.010)	(0.010)	(0.011)	(0.022)	(0.012)	(0.022)
Group Variable	0.017*	-0.017*	-0.010	-0.021	-0.011	-0.042*
	(0.009)	(0.010)	(0.011)	(0.028)	(0.011)	(0.022)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Obs	4,005	4,005	4,005	4,005	4,005	4,005
City-year Obs	1,134	1,134	1,134	1,134	1,134	1,134
R-squared	0.747	0.747	0.747	0.748	0.747	0.748

Notes: Robust standard errors clustered at the city level in parenthesis, ***p<0.01, **p<0.05, *p<0.1. In each column, we construct a group dummy based on the demographic composition of executive team members and include the group dummy as well as the interaction term between the group dummy and DI in the regression. In column 1, the group dummy equals 1 if the executive team members' average age is above median. In column 2, the group dummy equals 1 if the share of male executive team members is above median. In column 3, the group dummy equals 1 if the share of executive team members with master/doctorate degree is above median. In columns 4-6, the group dummy equals 1 if the share of executive team members with financial (column 4), technical (column 5), or overseas (column 6) occupation/working/studying experience is above median.

For each of the variables listed in row 2 to row 7 in Table A8, we then rank the

registration and clearing (0.00%), futures (0.25%), investment banks (0.11%), trust (0.54%), investment management (0.98%), trading (0.09%), others (1.47%), and no financial background (92.82%).

[27] An executive member is classified as having technical background if her occupation background falls into production, R&D, or designing. An executive member is classified as having overseas background is she has worked or studied overseas. An executive member is classified as having financial background if she worked in any type of financial firms listed above.

firms in our sample on each of the variables and divide a firm into subgroups based on whether the firm is above or below median on each variable.[28] Table 9 lists the results where we carry out the baseline analysis adding the group dummy as well as the interaction term between the group dummy and our key variables of interest (*DI*).

For age, previous literature finds mixed evidence on age and entrepreneurship – young people are more capable in producing big ideas and less restricted by the existing paradigms of thought and practice (Azoulay et al., 2019), but they also possess less human capital, social capital, or financial capitals than their older counterparts (Dunn & Holtz-Eakin, 2000), and researchers also observe changing relationship between age and innovation over time (Jones, 2010). As for technology, young people may lack scientific knowledge to produce or manage effective R&D (Jones, 2010), but they are also more receptive to emerging technologies (Hong et al., 2023). In our paper, we find that the firms with a younger executive team benefit more from the Broadband China policy.

For gender, it is well noted in literature that men and women differ in several psychological dimensions including preference for competition (e.g., Markowsky & Beblo, 2022), confidence (e.g., Barber & Odean, 2001), and risk attitudes (e.g., Croson & Gneezy, 2009), which might lead to different behaviors in management style (Carmona et al., 2018), investment (Charness & Gneezy, 2012), leadership (Ertac & Gurdal, 2012), entrepreneurship (Guzman & Kacperczyk, 2019), and technology adoption (Venkatesh et al., 2000). Similar to our paper, Bansak et al. (2011) aggregate gender ratio at firm-level and find lower risk taking for firms with a higher share of women on the senior management team. In our data, we observe a larger increase in export-to-revenue for firms with a higher share of men on the executive teams.

Education, social network, and previous working/studying experience also play an important role in the managing behavior of the executive team members. Simoes et al. (2016) summarize the previous findings on entry into self-employment and one's

[28] Since the share of executive team members with financial or overseas background is really low, all of the firms in the below-median group in financial/overseas background have no executive members with any financial/overseas background.

education, experience, and access to financial resources. Van de Sluis et al. (2008) document the positive correlation between schooling and entrepreneurship performance. Based on data from listed firms in China, Choi et al. (2022) find higher values for firms with more educated executives. Lusardi and Mitchell (2023) record sharp differences in financial literacy across education levels, and we would expect executive team members with more education can better process information on economic policy. Empirically, we find firms benefit more from the Broadband China policy if a higher share of their executive team members has a master or doctorate degree.

For occupation/working/studying background, Wu (2024) finds that technology-based executive teams are more technologically sensitive and efficient in R&D. Pan and Xu (2024) also document the promotional effect of managers' information technology experience on firms' digital transformation. Using the listed firms in China, Xu and Shi (2025) find higher levels of digital transformation among firms with higher shares of executive team members with financial background. Jiang and Liu (2020) also use the listed firms in China and find a positive relationship between overseas experience of the CEOs and a firm's R&D expenditure. Consistent with the literature, we find that firms with the executive board members with more financial/technical/overseas experience benefit more from improved Internet access.

5. Discussion on Mechanism

In this section, we provide more explanations on the promotional effect of Broadband China policy on SMEs' export. Overall, the policy promotes the digital transformation of SMEs, which in turn improves direct market access, lowers transactional costs, and alleviates the financial constraints faced by SMEs. We provide more supporting evidence of the promotional impact using both firm-level and city-level data, and we find SMEs leaning on direct market access experienced a larger increase in export-to-revenue, and that the export expansion is not purely driven by improved imports or productivity.

5.1. Explanations on the Promotional Effect – Firm Level

The Broadband China policy promotes the establishment of fast and stable Internet connection, which facilitates the adoption of information technology and digital tools such as cloud computing and big data analysis. For example, digital supply chain management and online sales channel management could help SMEs to enhance operational efficiency, and data integration and analysis could help SMEs to improve decision-making accuracy. These digital tools can reduce information friction, negotiation costs, and export risks for SMEs. The digital transformation of firms can then promote export growth. To measure digital transformation at firm level, we apply the digital transformation degree index and speed index as in Wu et al. (2021) and Du and Ma (2024), respectively.[29] As shown in column 1 and 2 of Table 10, the SMEs located in the pilot cities witnessed higher levels and faster growth of digital transformation compared to those in other cities. With deeper digital transformation, firms can optimize production process, improve operational efficiency, and promote cross-border e-commerce, which will ultimately enhance their export performance.

[29] Basically, both papers analyze the annual report of firms, and construct the degree and speed index of digital transformation through the search and identification of a bunch of key words related to digital technology application (e.g., e-commerce, Fintech, mobile payment), artificial intelligence (e.g., machine learning, deep learning, natural language processing), big data (e.g., text mining, data visualization, augmented reality), cloud computing (e.g., stream computing, Internet of things, converged infrastructure), and blockchain (e.g., digital currency, distributed computing, differential privacy).

Table 10: Digital Transformation

	(1) Degree	(2) Speed
DI	0.173**	0.087***
	(0.086)	(0.031)
Controls	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes
Firm Obs	4,005	4,005
City-year Obs	1,134	1,134
R-squared	0.819	0.174

Notes: Robust standard errors clustered at the city level in parenthesis, ***p<0.01, **p<0.05, *p<0.1. Column 1 uses the digital transformation degree index in Wu et al. (2021). Column 2 uses the digital transformation speed index in Du and Ma (2024).

As widely recognized in the literature, financial constraints pose major obstacles for firms on the international market, especially for SMEs (Custódio et al., 2013; Carbó-Valverde et al., 2016; Lekkakos & Serrano, 2016; Cheng et al., 2021; Pietrovito & Pozzolo, 2021). The development of digital infrastructure could alleviate financial constraints for firms by reducing information friction between different parties. For example, the use of big data could improve credit assessment by assisting financial institutions to obtain accurate and comprehensive credit information of SMEs and enabling supply chain partners to track the real-time metrics including orders, inventories and deliveries. Easier access to fintech platforms and online financial services provide SMEs with innovative financial solutions such as digital inclusive finance and supply chain finance tailored for trade-oriented SMEs. Adoption of smart contracts and automated systems lowers the cost for SMEs by reducing manual review processes and intermediaries.

To measure the degree of financial constraints faced by firms, we follow Whited and Wu (2006) to construct the WW index where a larger index indicates greater financial constraints. As shown in column 1 of Table 11, digital infrastructure development significantly reduces financial constraints. To take a closer look, we look at the short-term loans and Supply Chain Financing (SCF, financing obtained through commercial credit) respectively. We do not have data specifying bank loans, but as stated in Liu et al. (2017), short-term loans are a common way firms borrow from banks since long-term loans pose higher risks for the banks and higher interest rates for the firms. As in the literature, we use the ratio of short-term borrowings to total assets to gauge bank loan financing, and a lower ratio signifies more pronounced bank financing constraints.[30] SCF provides SMEs alternative opportunities to obtain financial support besides the traditional channels (Gelsomino et al., 2016). To measure SCF, we follow Mateut (2014) and Petersen and Rajan (1997) to construct an indicator where a larger value means greater supply chain financing constraints.[31] Results in column 2 and 3 of Table 11 show that the Broadband China policy alleviates the financial constraints for firms by increasing both financing from banks and SCF, which then facilitates the export growth of SMEs.

For transaction costs, the Broadband China policy lowers the market specific cost of trade and information cost, which promotes international trade (Freund & Weinhold, 2004; Arkolakis, 2010; Lin, 2015). Column 4 and 5 of Table 11 look at the transaction cost of firms. Internal transaction cost covers expenses incurred during a firm's internal management and operation, and we measure it using the the sum of financial and administrative expenses expressed as a proportion of total assets. External transaction cost covers expenses related to negotiations and contract execution due to market transactions, as well as costs associated with obtaining various administrative approvals (e.g., export licenses). As in Zhang et al. (2024), we measure the external cost using the sum of "other cash paid for operating activities" and selling expenses divided by the total assets. This ratio captures firm-level expenditures associated with market intermediation, contractual enforcement, and supply chain coordination, and could reflect the frictional costs of engaging in external economic activities. Our result shows that digital infrastructure development helps to lower both the internal and external transaction cost for SMEs. With digital infrastructure development, the efficiency of cross-departmental collaboration, information transfer, and organizational management

[30] Short-term borrowing is calculated using current liabilities minus accounts payable, wages payable, benefits payable, and taxes payable.

[31] Specifically, supply chain financing constraints are measured as the ratio of "accounts receivable + notes receivable + prepayments - accounts payable - notes payable - receipts in advance" to total assets. The sum between accounts receivable, notes receivable and prepayments reflect the commercial credit extended to downstream enterprises, while the sum between accounts payable, notes payable and advance receipts indicates the commercial credit relationship with upstream suppliers.

can be improved, which reduces the internal cost. It also grants SMEs easier access to communication platforms, cross-border payment systems, and streamlined administrative approval processes, which reduces the external cost.

Table 11: Promotional Effects on Firm-Level

	(1)	(2)	(3)	(4)	(5)
	WW	*Short-term Loans*	*Supply Chain Financing*	*Internal Costs*	*External Costs*
DI	-0.008***	0.015**	-0.013*	-0.015***	-0.020*
	(0.003)	(0.007)	(0.007)	(0.005)	(0.011)
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Firm Obs	4,005	4,005	3,668	4,001	3,992
City-year Obs	1,134	1,134	1,094	1,134	1,131
R-squared	0.944	0.930	0.824	0.494	0.477

Notes: Robust standard errors clustered at the city level in parenthesis, ***p<0.01, **p<0.05, *p<0.1. Column 1 uses the index in Whited and Wu (2006) which indicates the degree of firms' overall financial constraints, and a larger index means greater financial constraints. Column 2 uses the ratio of short-term borrowings to total assets, which indicates the degree of firms' constraints on financing from bank channels and a lower ratio signifies more pronounced bank financing constraints. Column 3 follows Petersen and Rajan (1997) and Mateut (2014) to construct an indicator that reflects the degree of firms' constraints on financing from supply chain commercial credit channels, where a larger value means greater supply chain financing constraints. Columns 4 studies the internal transactional costs measured by the sum of financial and administrative over total assets. Column 5 studies external transactional costs, and we follow Zhang et al. (2024) to use the sum of "other cash paid for operating activities" and selling expenses over total assets.

5.2. Explanations on the Promotional Effect – City Level

At the city level, the Broadband China policy promotes cross-border e-commerce, enhances industrial agglomeration, and facilitates digital infrastructure development, and all these changes can contribute to the faster export growth of firms located in the pilot cities.

Broadband China policy accelerates the growth of cross-border e-commerce, which offers SMEs a new pathway to export, especially when traditional export channels are impeded (Tolstoy et al., 2021). Access to e-commerce platforms such as Alibaba, Jingdong International, and Temu helps SMEs to overcome traditional entry barriers and engage directly with overseas consumers. These platforms also provide SMEs with advanced market research tools and data analytics, assisting SMEs to better understand demand fluctuations, consumer preferences, and the competitive landscape in target markets. This reduces transaction costs and broadens market coverage for

SMEs, which in turn boosts exports.

We do not have direct measurement of cross-border e-commerce at city level. However, since cross-border e-commerce retail goods typically reach consumers via express delivery, we can use cross-border express delivery as its proxy. We only have cross-border express delivery data at province level, so we estimate city-level scale (number of packages) and revenue of cross-border express delivery based on a city's share in all express delivery business in the province.[32] Column 1 and 2 of Table 12 shows the significant and positive impact of the Broadband China policy on cross-border e-commerce at city level.

The development of broadband infrastructure facilitates industrial agglomeration. High-quality digital infrastructure can attract more firms to concentrate in the region, thereby fostering scale effects. This agglomeration benefits SMEs with shared labor markets, intermediate goods, and knowledge spillovers, which helps mitigate their production and operational constraints and eventually boosts their exports. Digital infrastructure development also optimizes regional resource allocation, reducing the dependence on traditional factors of production such as land and labor. This then mitigates the negative crowding effect typically associated with industrial clustering.

To test this mechanism, we follow Keeble et al. (1991) to construct the location entropy to measure the level of regional industrial agglomeration, as specified below.

$$AGG_{irt} = \left[\frac{E_{irt}}{\sum_i E_{irt}}\right] / \left[\frac{\sum_r E_{irt}}{E_{Total,t}}\right]$$

Here E_{irt} denotes the number of workers employed in industry *i* in year *t* in region *r*. In this paper, we use manufacturing agglomeration (*MAGG*) and service agglomeration (*SAGG*) to measure the level of specialized agglomeration in the region.

Based on the results in column 3 and 4 in Table 12, digital infrastructure development promotes both manufacturing and service agglomeration, but the impact in manufacturing is not significant. This disparity may be attributed to the service

[32] To be specific, we multiply the share of a province's express delivery business volume for a city with the total cross-border express delivery at provincial level to estimate that city's scale and revenue of cross-border express delivery.

industry's high reliance on digital resources, such as network platforms and data processing. Industries such as finance, logistics, and e-commerce can substantially reduce their production and operational costs through digital platforms. In contrast, manufacturing development is more contingent upon traditional physical infrastructure and factor supply.

Broadband China policy significantly enhanced regional digital infrastructure. The policy emphasized the optimization and upgrade of broadband networks, improving both network coverage and speed. These advancements enable more firms to access the Internet and digital technology platforms easily – stable and fast network provide better support to daily operations, improved access to big data and cloud computing increases their flexibility and responsiveness to fluctuations in the international market, and better digital infrastructure promotes the growth of modern service such as e-commerce, logistics, and digital finance.

We use two indicators to measure urban digital infrastructure development – the number of urban broadband Internet access subscribers and the per capita volume of postal and telecommunications services (*PTS volume*). Results in column 5 and 6 from Table 12 show that the Broadband China policy leads to faster digital infrastructure development in the pilot cities.

Table 12: Promotional Effects on City-Level

	(1)	(2)	(3)	(4)	(5)	(6)
	Cross-border E-commerce Scale	*Cross-border E-commerce Revenue*	*SAGG*	*MAGG*	*Internet Access Subscribers*	*PTS Volume*
DI	0.185*	0.132*	4.531**	1.912	0.237***	262.794**
	(0.108)	(0.072)	(1.813)	(2.144)	(0.056)	(112.347)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
City-year Obs	897	897	1,045	1,045	914	919
R-squared	0.975	0.988	0.935	0.936	0.992	0.757

Notes: Robust standard errors clustered at the city level in parenthesis, ***p<0.01, **p<0.05, *p<0.1. Column 1 and 2 studies the scale and revenue of cross-border e-commerce, respectively. In column 3 and 4, we follow Keeble et al. (1991) to construct the location entropy to measure the level of regional industrial agglomeration for service and manufacturing, respectively. In column 5 and 6, we study digital infrastructure. Column 5 uses the number of urban broadband Internet access subscribers and column 6 uses per capita volume of postal and telecommunications services.

5.3. Direct and Indirect Exporters

As explained in the previous part, improved Internet access and digital transformation promote direct market access. Consequently, firms that more actively engage in accessing foreign markets directly are expected to benefit more from the policy. In this part, we then compare direct exporters with indirect exporters (which trade via intermediaries). To collect information on whether a firm engages in direct export, we match our data with the customs data using firm names as in the literature (e.g., Yu, 2015). Following Bai et al. (2017), if a listed firm is matched in the customs with exporting record, it would be a direct exporter; a listed firm with export data but not matched in the customs would be an indirect exporter.

Results are put in Table 13. In column 1 and 2, we use 2009-2020 as in the main analysis, and in column 3 and 4, we restrict our sample to 2009-2016 to exclude years 2017-2020 with missing information on firm names in customs.[33] Comparing the direct and indirect exporters, both samples (2009-2020 and 2009-2016) show smaller and insignificant impact for the indirect exporters, compared with the larger and significant (at 1%) impact for the direct exporters. This comparison provides further support for our explanation of export expansion as a result of improved direct market access.

In the next part (Table 14), we further include information from the customs and find a significant increase in number of destination countries a firm exports to, which also provides support for our explanation through direct market access. In Appendix Table A10, we separately look at the policy impacts among existing and new

[33] For 2017-2020, the customs data we have do not provide information of firm names, which is key for matching our main sample from CSMAR with customs data. For column 1 and column 2 using 2009-2020, if a firm has export record in 2009-2016 in the customs data, it is a direct exporter. Otherwise, it is an "indirect exporter". The "indirect exporters" identified this way is not clean since it contains some direct exporters in 2017-2020 which are not correctly identified due to data limitation. To have a cleaner sample, in column 3 and 4, we only use 2009-2016, but since the Broadband China policy was carried out in three rounds (2014, 2015, and 2016), we only keep the first two rounds of policy and drop the SMEs located in pilot cities announced in the 2016 rounds for lack of observations post-policy (e.g., for third round in 2016, we can only observe the response of the firms right at the policy year but nothing after that). This gives us a cleaner sample, but at the cost of much smaller sample size as seen in column 3 and 4. This is because the panel is not balanced for the listed firms – over time, there is a growing number of listed firms in the sample (see Table A9).

exporters.[34] Both types of exporters can benefit from increased direct market access – a new exporter would have an easier time accessing a foreign market, while an existing exporter would have an easier time expanding their business to more foreign markets.

Table 13: Direct versus Indirect Exporters

	Export-to-Revenue Ratio			
	2009-2020		2009-2016	
	(1) Direct	(2) Indirect	(3) Direct	(4) Indirect
DI	0.070***	0.038	0.065***	0.020
	(0.014)	(0.023)	(0.018)	(0.026)
Group Difference	0.032*		0.045*	
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm Obs	3,360	630	1,082	220
City-year Obs	1,066	329	422	148
R-squared	0.769	0.792	0.762	0.862

Notes: Robust standard errors clustered at the city level in parenthesis, ***p<0.01, **p<0.05, *p<0.1. Column 1 and 3 study direct exporters. Column 2 and 4 study the indirect exporters. In column 1 and 2, we use data in 2009-2020. In column 3 and 4, we use data in 2009-2016.

5.4. Productivity and Import

In the seminal work of Melitz (2003), the foundation of New-New Trade Theory, firm productivity is a key driver behind the exporting behavior of firms. In Appendix B, we also find improved productivity of SMEs following the implementation of Broadband China policy. However, the expansion in export-to-revenue is not driven by increase in firm productivity. Throughout the analysis, we have included TFP in our controls. This is also supported by comparing the baseline results in column 2 and 3 of Table 3 – once the firm and year fixed effects are included, the coefficient of variable of interest is very similar when we further add the full set of controls (including TFP). In the Appendix Table A11, we also show the comparison of results with and without TFP in the controls, and results are very similar.

Imports play a vital role in a firm's export performance. Feng et al. (2016) finds the Chinese firms which expanded their imports in intermediate products also expanded

[34] We divide firms into existing and new exporters based on their previous export record before the implementation of the Broadband China policy. To be specific, for a SME located in a pilot city, if it has any previous export record before the year the policy is implemented, then it is classified as existing exporters. If not, then it is classified as new exporters – for example, for a SME located in the third round of pilot cities (implemented in 2016), if it has no export record till 2015, but starts to export in 2017, then it is a new exporter.

in their export (volume and scope). To address the concern that the increased export could be a result of cheaper imported intermediate and capital goods, we further include imports in our controls (respectively, the natural log of total import value, share of import for capital goods, and share of import for intermediates goods). To collect import information, we integrate data from the China Customs matching the firms by name and look at other export measurements including quality, variety, and destinations.[35] For the classification on capital goods and intermediate goods, we follow Arkolakis et al. (2008), Koopman et al. (2012), and Feng et al. (2016) – we apply the Broad Economics Classification (BEC) classification released by the United Nations and match to our customs data by the Harmonized System (HS) code.

Results are in Table 14. For export-to-revenue, now we directly use the export value reported in the Customs data, aggregated at firm-year level (compared to previous results that use the export value reported by the CSMAR). With data limitation, the sample now only covers 2009-2016, and we only adopt the 2014 and 2015 Broadband China policy based on the sample period. We exclude firms located in pilot cities in the 2016 waves to keep the control group clean.[36] Comparing column 1 and 2 of Table 14, the coefficients are similar when imports are controlled and the expansion in export observed is not driven by imports. As in the baseline result, the SMEs in the pilot cities show a larger expansion in export-to-revenue following the Broadband China policy. We also show the policy's promotional impact on product quality, variety (number of different products by HS6 code), and number of destination countries a firm exports to. For the estimation of export product quality, we follow the methods proposed by Hallak and Schott (2011) and Khandelwal et al. (2013) to first estimate product quality at firm-

[35] Since there is no consistent firm code across the database, matching by name is commonly used empirically for use of firm data in China. For example, Yu (2015) matched the Chinese industrial firm data and China Custom data based on firm name.

[36] For the main results, we are using data from CSMAR, including data on the export value of a firm. Unfortunately, CSMAR does not provide import value – for import, variety, export product quality, and number of destination countries that a firm exports to, we can only collect firm-level information by aggregating the transaction-level information from the customs. In the customs data we have, years 2017-2020 do not specify the firm name, and firm name is what we mainly rely on to match the listed firms with the customs data since the two datasets do not have a consistent firm ID which can allow us to match the firms (e.g., see Yu, 2015 for more details). As shown in Table A9, we lose many observations when dropping 2017-2020 since there are more listed SMEs in the sample in the later years than earlier years.

product level and then aggregate to firm level (see Appendix C for details on the estimation). The increase in number of destinations countries among the treated SMEs provides further support for our explanation of improved direct market access from the Broadband China policy.

Table 14: Other Export Performance – Controlling Import

	(1)	(2)	(3)	(4)	(5)
	Export-to -Revenue	*Export-to -Revenue*	*Quality*	*Variety*	*Destination*
DI	0.037***	0.038***	0.064***	0.162**	0.111**
	(0.012)	(0.011)	(0.012)	(0.065)	(0.056)
lnTotal Import		0.007	0.008	-0.012	-0.015
		(0.005)	(0.006)	(0.032)	(0.031)
Import Capital		-0.009*	-0.019	-0.108	-0.106
		(0.005)	(0.013)	(0.092)	(0.065)
Import Intermediate		-0.018	-0.020	-0.038	-0.082
		(0.012)	(0.017)	(0.086)	(0.106)
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Firm Obs	1,990	1,990	1,555	1,990	1,990
City-year Obs	607	607	504	607	607
R-squared	0.770	0.771	0.737	0.856	0.913

Notes: Robust standard errors clustered at the city level in parenthesis, ***p<0.01, **p<0.05, *p<0.1. Export data from China Customs data, aggregated at firm-year level. Column 1 and 2 study the export-to-revenue. Column 3 studies the quality of exported products, following Hallak and Schott (2011) and Khandelwal et al. (2013). Column 4 studies product variety represented by the count of different products (by HS6 code) that firms export. Column 5 studies the count of different destination countries a firm exports to. For product quality, the sample size is smaller because we follow Hallak and Schott (2011) and Khandelwal et al. (2013) to estimate export product quality, and we need product quantity and price to estimate quality, but we only have export value data in 2016.

6. Conclusion

In the context of reverse globalization and ongoing adjustments in global value chains, firms encounter numerous challenges in the international market. Despite the important role SMEs play in the world economy today, they face unique problems due to absence of economies of scale and resource constraints. In this paper, we find the promotional effect of digital infrastructure development on SME's performance on the international market in China. Applying the staggered DID design, we find that on average, SMEs located in the pilot cities of the Broadband China policy enjoyed a 6.3% larger increase in export-to-revenue compared to those located elsewhere.

The findings of this paper carry important policy implications. Considering the high share of business activities engaged by the SMEs nowadays, to boost economic growth, countries should invest in the improvement of digital infrastructure, especially for the developing economies. The government should strengthen policies that promote e-commerce and encourage local firms to interact with global e-commerce platforms, including preferential tax policies, logistics systems investments, training programs on digital technology, streamlined regulatory processes, and targeted financial support for SMEs with e-commerce.

This paper uses data on all listed SMEs at the SME Board and ChiNext market in Shenzhen Stock Exchange in China for more than a decade, which guarantees the representativeness of the sample and allows us to study the impact of the Broadband China policy up to 7 years post-policy. In future, it would be interesting to see whether the policy has a persistent impact over time (e.g., after a decade).

Since our research is limited to listed firms, it also remains an open question as to how much of our findings can be generalized to the unlisted firms. There is established literature discussing the difference between the listed and unlisted firms (e.g., Boyne, 2002). Compared to the listed firms, their unlisted peers are more responsive to investment opportunity changes (Asker et al., 2011), rely more on trade credit (Abdulla et al., 2017), show larger ranges and variability (Vos, 1992), face higher financial friction but have less cash holdings (Gao et al., 2013), have slower growth (Capasso et al., 2007), and Bernstein (2015) finds firms to be less novel in internal innovation following initial public offering. Considering the systematic differences across listed and unlisted firms found in the literature, as pointed out by Vos (1992), researchers should be careful to use the listed firms' performance ratios on the unlisted firms. In our paper, we find the small-micro firms benefit more in export expansion than the medium-sized firms, and this result is consistent with Zwick and Mahon (2017), which finds small firms respond more than the large firms to the temporary tax incentives on equipment investment. Asker et al. (2011) also documents higher responsiveness to changes in investment opportunities for unlisted firms compared to their listed counterparts. These observations might point to larger impacts among unlisted firms, but export expansion of listed firms also leads to rising competition on the international market for unlisted firms in the equilibrium. It then remains an open question how much unlisted firms would benefit from the Broadband China policy, and we will leave that for future research.

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