THE IMPACT OF THE DEVELOPMENT OF THE DIGITAL ECONOMY ON CHAINA'S EXPORT COMPETITIVENESS

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MASTER OF SCIENCE
IN DIGITAL INNOVATION AND FINANCIAL TECHNOLOGY

CHIANG MAI UNIVERSITY
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AN INDEPENDENT STUDY SUBMITTED TO CHIANG MAI UNIVERSITY IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF SCIENCE IN DIGITAL INNOVATION AND FINANCIAL TECHNOLOGY

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To

Tanarat Rattanadamrongaksorn

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หัวข้อการค้นคว้าอิสระ ผลกระทบของการพัฒนาเศรษฐกิจดิจิทัลต่อความสามารถในการแข่งขันด้านการส่งออกของจีน

ผู้เขียน นาย ซิหมิง หยาน

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บทคัดย่อ

บทความนี้ศึกษาผลกระทบของเศรษฐกิจดิจิทัลต่อความสามารถในการแข่งขันด้านการส่งออกของจีน โดยเฉพาะอย่างยิ่งเมื่อพิจารณาถึงภูมิทัศน์ทางเศรษฐกิจของจีนที่เปลี่ยนแปลงไปและการเพิ่มขึ้นของการค้าดิจิทัล การศึกษานี้ได้สำรวจพื้นฐานทางทฤษฎีของการพัฒนาเศรษฐกิจดิจิทัล ความสามารถในการแข่งขันของการส่งออกและจุดตัดระหว่างทั้งสองอย่างลึกซึ้ง การศึกษานี้ใช้ข้อมูลแผงจาก 31 มณฑลของจีนตั้งแต่ปี 2555 ถึง 2565 และใช้แบบจำลองทางเศรษฐกิจมาตรวิทยาเพื่อวัดผลกระทบของดิจิทัลต่อประสิทธิภาพการส่งออก มีการบูรณาการตัวชี้วัดที่สำคัญ เช่น รายได้จากธุรกิจซอฟต์แวร์ การลงทุนด้านไอซีที และบริการโทรคมนาคม เป็นต้นแบบ เพื่อประเมินผลกระทบเชิงประจักษ์ต่อความสามารถในการแข่งขันด้านการส่งออก ผลการวิจัยเน้นว่าความก้าวหน้าของเศรษฐกิจดิจิทัลโดยเฉพาะอย่างยิ่งการพัฒนาอุตสาหกรรมดิจิทัลและการกำกับดูแลข้อมูลได้เพิ่มขีดความสามารถในการส่งออกของจีนอย่างมากโดยการเพิ่มประสิทธิภาพการผลิตลดต้นทุนและส่งเสริมนวัตกรรม การศึกษายังระบุถึงความแตกต่างของภูมิภาคในการพัฒนาเศรษฐกิจดิจิทัลและผลกระทบต่อความสามารถในการแข่งขันด้านการส่งออก โดยให้ข้อมูลเชิงลึกว่าภูมิภาคต่างๆ สามารถปรับตัวและได้รับประโยชน์จากการเปลี่ยนแปลงทางดิจิทัลอย่างไร มีข้อสรุปและข้อเสนอแนะเชิงนโยบายเพื่อยกระดับสถานะการค้าโลกของจีนด้วยการพัฒนาโครงสร้างพื้นฐานด้านดิจิทัลต่อไป สร้างความสมดุลในการเติบโตในภูมิภาค และส่งเสริมการลงทุนจากต่างประเทศ ข้อเสนอเหล่านี้เป็นแนวทางยุทธศาสตร์ในการใช้ความก้าวหน้าทางเศรษฐกิจดิจิทัลเพื่อรักษาการเติบโตทางเศรษฐกิจและการส่งออกที่แข่งขันได้

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ABSTRACT

This thesis examines the impact of the digital economy on China's export competitiveness, particularly in light of the country's evolving economic landscape and the rise of digital trade. The study delves into the theoretical underpinnings of digital economy development, export competitiveness, and the intersection of the two. Utilizing panel data from 31 Chinese provinces between 2012 and 2022, this research employs econometric modeling to quantify the influence of digitalization on export performance. Key indicators such as software business revenue, ICT investment, and telecommunications services are integrated into the model to empirically assess their effect on export competitiveness. The findings highlight that advancements in the digital economy, especially in digital industrialization and data governance, have substantially improved China's export capabilities by increasing production efficiency, reducing costs, and promoting innovation. The research also identifies regional disparities in the digital economy's development and its implications for export competitiveness, offering insights into how different regions have adapted to and benefited from digital transformation. The conclusions with policy recommendations aims at enhancing China's global trade position through further digital infrastructure development, balanced regional growth, and the promotion of foreign investment. These recommendations offer a strategic pathway for

leveraging digital economy advancements to sustain economic growth and competitive exports.

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CHAPTER 1

Introduction

The pervasive integration of digital technology into all business sectors has emerged as one of the most attractive research subjects of today. The increasing scale of the digital economy has a significant and complex effect on export competitiveness. The objective of this study is to investigate the correlation between the growth of the digital economy and the export competitiveness of China. The goal is to pinpoint regional differences and potential advantages that contribute to China's overall position in global markets.

1.1 Background

China's primary advantage in recent decades has been eroded by the increasing cost of labor, which has consequently posed a challenge to its manufacturing. Fortunately, the implementation of technology more than offsets the reduced competitive capacity. Innovation yields prevalent advantages such as time and cost savings, as well as enhancements in quality and efficient operations. Moreover, the conventional obstacles to trade are reduced by the improvement of communication and market accessibility, therefore giving rise to a novel commercial model known as the digital economy. This phenomenon is vividly evident in the recent surge in operations, particularly in China's export sector. Furthermore, apart from the difficulties presented by demographic shifts and limitations in resources, the digital economy has a substantial influence on export competitiveness. Digitized technologies optimize manufacturing, minimize expenses, and promote product innovation, therefore enhancing the competitiveness of exports (Smith, 2020).

1.2 Motivation

Integrating theoretical insights from current literature with an empirical investigation of the processes via which the digital economy influences export channels is crucial for obtaining a thorough knowledge of the impact of the digital economy on international trade. The present synthesis aims to enable an investigation into the impact of the digital economy on trade dynamics and its consequences on export performance. The developed theoretical framework will serve as the foundation for the econometric model used to quantitatively evaluate the influence of the digital economy on exports. By subjecting the identified mechanisms to rigorous testing, this model will demonstrate that the digital economy greatly improves the competitiveness of China's exports. Hence, this study emphasizes the capacity of the digital economy to enhance China's export capacities, in line with research that emphasize the revolutionary impact of digitalization on global trade environments.

1.3 Research Procedure

The flowchart in Figure 1.1 depicts the research procedure that provides an approach to investigating the impact of digital economy on the competitiveness of China's export.

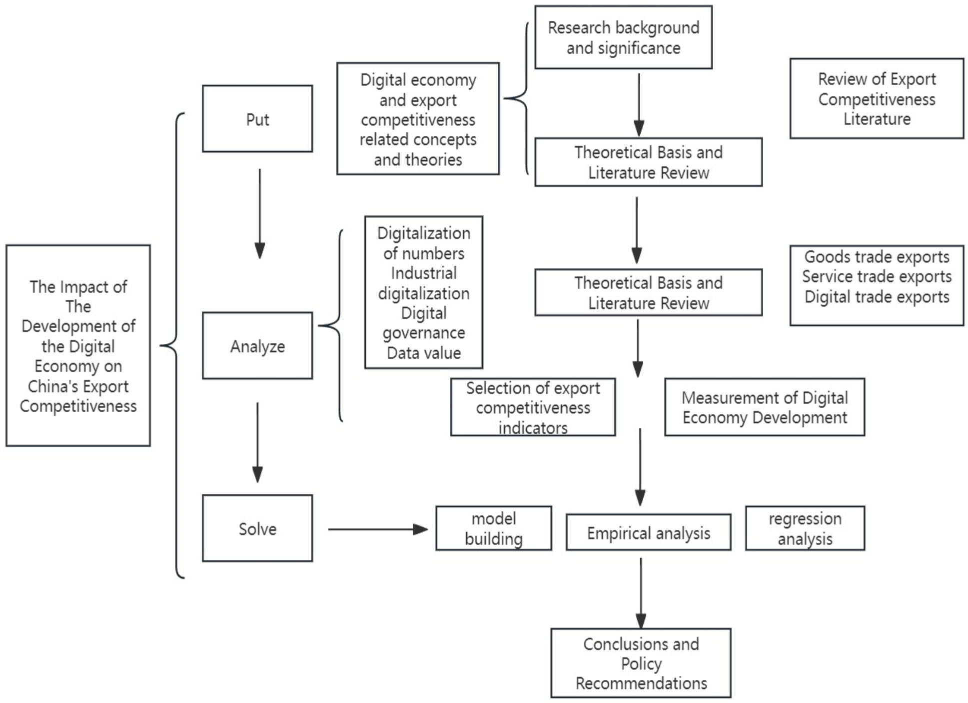

Figure 1.1 Research Procedure

The study commences with examining the research context and purpose, thereby establishing the significance of the research in comprehending the influence of the digital economy on China's export competitiveness. The theoretical framework and literature analysis explore the concepts and theories of the digital economy and export competitiveness. This section provides an overview of the current body of research on export competitiveness, encompassing exports of products trade, service trade, and digital commerce. Furthermore, it analyzes the process of converting numerical data into digital format, industrial digitalization, digital governance, and the overall worth of data.

The framework continues by selecting export competitiveness indicators and determining the suitable quantitative measures to accurately assess export competitiveness. Subsequently, the assessment of the progress of the digital economy involves the establishment of many criteria. Model construction and regression analysis are utilized to carry out empirical analysis. The objective of this stage is to empirically examine the correlation between the development of the digital economy and export competitiveness by employing specific indicators and econometric models.

The conclusions and policy recommendations succinctly outline the results of the empirical study and offer strategic suggestions to improve China's foreign trade competitiveness by fostering the growth of the digital economy. The method entails thorough examination of results and suggesting remedies derived from the acquired insights. Ultimately, this paradigm provides evidence-based policy recommendations by systematically integrating theoretical foundations with empirical analysis to investigate the relationship between the digital economy and export competitiveness.

1.4 Thesis Organization

The opening chapter of this work presents a concise summary of the research context and the importance of this study. Presently, the digital economy is experiencing a phase of swift technical transformation, as both local and international nations acknowledge the significance of its growth and implement various policies tailored to the digital economy. Given the prevailing global economic instability, it is advisable for the country to take use of the prospects offered by digital economic growth in order to elevate its competitiveness. The current global economic landscape is marked by ambiguity and the increasing inclination towards protectionism, hence complicating the dynamics of globalization. Simultaneously, the endeavor of domestic economic reform has grown increasingly challenging. Given these conditions, it is crucial to take use of the possibilities for the growth of the digital economy and maximize its advantages to improve export competitiveness.

In the second chapter, the interconnected notions of the digital economy and export competitiveness are introduced, together with their literature studies considering both domestic and international settings. That encompasses study on both the qualitative and quantitative dimensions of the digital economy. Furthermore, the notion of export competitiveness is clarified, and several elements that impact export competitiveness are consolidated by examining both domestic and international literature. Lastly, a summary is provided on the research on the influence of digital economy growth on export competitiveness.

Furthermore, the chapter focuses on the present condition of China's digital economy and its exportations. Initially, a thorough overview of the present state of the digital economy is presented, followed by a detailed examination of its fundamental progress, digital industrialization, and industrial digitalization. Following that, a comprehensive analysis of the present state of export is conducted, encompassing three key areas: commodities, services, and technology. This paper presents an analysis of the existing condition of China's digital economy by examining digital infrastructure, the magnitude of the digital economy, and digital technologies. An exhaustive study is undertaken on exports, exploring many facets such as total export, export mode, and export product composition.

In the third chapter, the research study methodology is introduced, which involves an empirical investigation of the influence of digital economy development on China's export competitiveness. The empirical analysis of the relationship between the digital economy and export competitiveness is conducted by constructing a model. Firstly, the selection of the export competitiveness index is based on panel data at the regional level. The Export Competitiveness Index (ECI) is considered the metric used to quantify export competitiveness. Furthermore, the digital economy is assessed based on four key dimensions: information business, telecommunication business, Internet business, and industrial digitization. An econometric study was conducted at the regional level using panel data from 31 provinces and cities spanning the years 2012 to 2022. The purpose of this procedure was to acquire the findings of the association between the digital economy and export competitiveness. Detailed findings and analysis will be presented in the fourth chapter.

The fifth chapter provides the final findings. The advancement of the digital information sector can support more export competitiveness, while the degree of Internet development can also bolster export competitiveness. Hence, the following suggestions are put forward: giving priority to the development of the digital economy, strengthening the infrastructure of the digital economy, striving for balanced regional growth, encouraging foreign investment, and expanding trade openness.

CHAPTER 2

Literature Review

The economic value can be measured by four production factors: consumption, government expenditure, investment, and net exports. Final consumer expenditure, gross capital formation, and net exports of goods and services are frequently seen as the three major drivers of economic growth in economic theory. Exports have long been a crucial fundamental element of China's economy. Exports have played a crucial role in propelling national growth in both industrialized and developing nations. This phenomenon is discernible in nations that have undergone the industrial revolution, such as those in the Western countries, as well as in countries currently undergoing economic transition. In an era of global development and rapid scientific and technical progress, the determinants of a nation's import and export activities are experiencing a significant conversion. Given the shift from traditional economic activities to the digital economy as the main drivers of China's exports, it is clear that a comprehensive comprehension of the correlation between export competitiveness and the growth of the digital economy is crucial. This comprehension can thereafter be used to guide modifications in the structure of China's export competitiveness, by incorporating the knowledge acquired from these accomplishments. Comprising e-commerce, Internet technology, data analytics, and other sectors, the digital economy has emerged as a substantial element of the global economy. The digital economy of China is undergoing robust expansion, propelled by the rising prominence of technologies like e-commerce, mobile payments, and artificial intelligence, which significantly contribute to the rise of exports. Furthermore, it plays a pivotal role in China's ongoing sustained economic growth. The present chapter is dedicated to the examination of the correlation between the digital economy and export competitiveness. Subsequently, the relevant literature is systematically organized and analyzed.

2.1 Related Concepts

The initial section of the chapter introduces two interconnected notions of the digital economy and export competitiveness, which are crucial in this study. These concepts are further elaborated in the subsequent two subsections.

2.1.1 Digital Economy

According to Tapscott, in the contemporary economy, information is conveyed through data, and this digitized economic model can be considered as a knowledge-driven economic model that relies on the distribution of knowledge and relevant information. The author examines the attributes of the digital economy from three perspectives: the digital economy itself and its constituent components, the business and governance structures within the framework of Internet development, and the ability to adjust to transformation and change. A research institution（The U.S. Department of Commerce, 1998) announced the Digital Economy Act, yet there remains a lack of unanimity over its definition, with academics providing diverse views. One researcher (Brent Moulton, 1999) observed that the connotation of the digital economy is uncertain, but it is primarily constituted by information technology and Internet trade. He posited that the digital economy encompasses both information technology and e-commerce, and that it is the primary driver of the bullish stock market and the productivity recovery. The digital economy, as described by a research institution (The G20, 2016), refers to a set of economic activities that make vital use of digitized knowledge and information as primary production elements, modern information networks as crucial carriers, and ICT as a driving force. This definition emphasizes the importance of the digital economy, specifically: The digital economy concept is founded on the amalgamation of sophisticated science and technology, data, and the contemporary Internet as the primary gateway for network information technology. This integration is employed to augment efficiency, facilitate economic and social structural transformation, and ultimately attain the objective of economic growth. The China Academy of Information and Communications Technology (CAICT,2018) provides a broader definition of the digital economy, which includes not just information technology but also the digital attributes of conventional businesses and the digital governance of society. With the refinement of the digital economy concept by CAICT, the domain of Internet technology has expanded to include a broader spectrum of digital technologies and the digital attributes of the Internet, as well as the administration of society. This has resulted in a more extensive advancement of the digital economy, as Hypothesized by researchers （Fei Yin and Xingxing Hu ,2022). They perceive the digital economy as an innovative economic model capable of restructuring all aspects of socio-economic production, distribution, allocation, and consumption. Furthermore, they perceive it as a novel catalyst for economic progress.

Based on the aforementioned interpretations of the digital economy by both local and international scholars and research institutions, as well as the specific features of the research reported in this paper, it can be contended that the digital economy is a sophisticated technological method for improving productivity by integrating data, circulating data, and sharing data, among other elements. This facilitates the integration of intelligence, data-driven approaches, and network-oriented structures into the production, sales, and services of the manufacturing business.

In the present age of informationization, the significance of the digital economy is becoming more apparent, and the study on this topic is steadily emerging. The prevailing consensus among researchers is that the digital economy has a defined role in fostering the advancement and growth of society. One scholar (Tapscott, 1994) demonstrates that in the digital economy, the internet has profoundly transformed the methods of conducting business and people's everyday lives, offering unparalleled exceptional offerings and advantages for individuals. An organization（The U.S. Department of Commerce, 1998) said that the use of information technology can enable a substantial degree of economic expansion, while also generating job prospects for a considerable number of people, mitigating inflationary forces, and fostering overall societal progress. The researchers, (Liao Jinqiu and Zhang Xiaofeng, 2001) posit that the digital economy offers significant convenience in the storage and circulation of data, information, and commodities, and will be the dominant development trend in the global economy. One researcher (Zhang Xinhong, 2016) examines the pivotal role of the digital economy in China's economic growth, emphasizing the country's infrastructure, latecomer advantages, and institutional strengths. Another researchers (Hayakawa and Mukunoki， 2019) conducted a study to investigate the impact of foreign direct investment (FDI) in the service industry on a company's export competitiveness. The researchers analyzed Chinese company-level export data and found that FDI contributes to enhancing export competitiveness. This effect is particularly pronounced for non-state-owned enterprises or those operating in regions with looser command-and-control (CAC) environmental regulations. One researcher (Patricia, 2023) asserts that science, technology, and innovation are essential for evaluating the growth of the digital economy. The advancement of science and technology is a driving force behind the growth of the digital economy, which, in turn, stimulates further innovation in science and technology. This mutually reinforcing relationship is of paramount importance for the sustainable development of the digital economy.

With regards to quantitative analysis of the digital economy, researchers and institutions now involved in studying its measurement define it from two primary perspectives. The first approach is direct measurement, which involves quantifying the magnitude of value added in the digital economy based on the given definition. For instance, the China Academy of Information and Communications Technology (AICT) and the U.S. Department of Commerce quantify the benefits obtained from the digital economy using precise numerical values. An alternate strategy is the indirect comparison method, which utilizes several dimensions and indicators to indirectly represent the progress of the digital economy. As an illustration, the OECD and the International Telecommunication Union (ITU) have used several digital economy indicators to assess distinct facets of the digital industrial sector. Furthermore, these indicators undergo a weighted analysis approach, which allows for the comparison of digital economy indices across various locations. The definition and quantitative analysis of the digital economy have been extensively debated globally and have been steadily enhanced during the implementation of digital technologies and the broadening of digitization. This section provides a comprehensive summary of the quantitative research carried out by several reputable institutes and organizations on the digital economy, as seen in the table below.

As shown in Table 2-1, these literatures offer unique insights in different dimensions, including measurement, index system, and scope definition. This paper provides a theoretical basis for the measurement of the digital economy.

Table 2.1 of the system of indicators related to the digital economy

Index	Publisher	Measurement Dimension	Key Indicators
DESI	EU	Broadband access Human capital Internet Application Digital technology application Degree of digitization of public services	Mobile Broadband Enterprise Digital digitalization, e-commerce, e-government, etc.
Digital Economy Review Recommendations	U.S. Department of Commerce, Commission on the Digital Economy	The extent of digitization in the economy Economic activity Impact of economic indicators such as GDP and production abundance Monitoring of emerging areas of digitization	
Measuring the digital economy	OECD	Investing in Smart Infrastructure Innovation Capabilities Empowering Society ICT for economic growth and job creation	Broadband penetration rate Cross-border e-commerce ICT Industry Innovation ICT Investment Internet Users
IDI	International Telecommunication Union	ICT Access ICT use ICT skills	Fixed-line coverage, average international Internet bandwidth per user, Internet subscription rate, broadband utilization rate, etc.
Digital Economy Index	China Academy of Information and Communications Technology	Big Data Investment and Financing Cloud Computing Services Market Size Number of IoT End Users Mobile Internet Access Traffic Number of Broadband Users Fixed Broadband Access Hours	ICT main business income, Internet investment and financing, total import and export of electronic information industry, scale of e-commerce, etc.

Through the synthesis of existing research literature on the development effects of the digital economy, together with qualitative and quantitative analyses, it becomes clear that the meaning and definition of the digital economy have never been uniformly established. Hence, academics and research institutions both domestically and internationally are actively involved in a continuous process of investigation and invention, aiming to gather necessary expertise for future research endeavors.

2.1.2 Export Competitiveness

In this context, a research institution defines export competitiveness as the ability of enterprises to provide goods and services at home and abroad at more advantageous prices and qualities within the context of their economic and social environments (World Economic Forum, 1985) Export competitiveness, as defined by a research institution, refers to the capacity of firms to offer products and services both domestically and internationally at reduced costs and superior quality, considering the economic and social conditions in which they operate (World Economic Forum, 1985). The Forum's fundamental perspective is that competitiveness is derived from the distinctive advantage of superior quality and favorable pricing.

The Forum's core view is that competitiveness is based on the differentiation advantage of quality and price. One researcher (Lall, 1998) defines export competitiveness as the advantage of a country's products over those of other countries in terms of research and development, production, sales, and service, among other factors. He notes that export competitiveness can be expressed as the proportion of exports of a given commodity in the total exports in the international market. The higher this proportion, the stronger the export competitiveness. One researcher (Lu, 2014) demonstrated that the productivity improvement of export enterprises effectively contributes to the change of technological complexity of China's exports. This suggests that improving enterprise productivity is the key to realizing product upgrading as well as maintaining the sustainability of China's export competitiveness.

At present, the majority of studies on the digital economy and international trade focus on import and export. Only a few studies examine the link between the digital economy and export competitiveness. Furthermore, there is a lack of sufficient theoretical analysis in this area. The digital economy represents a novel economic approach that has emerged in conjunction with the rapid development of the Internet. (Freund and Weinhold, 2004) suggested that the utilization of the Internet and information and communication technologies (ICTs) can significantly enhance exports of trade in services. They also suggest that the Internet exerts a more pronounced impact on trade with developed countries than with developing countries. In this context, the researchers (Freund and Weinhold, 2011) emphasized the pivotal role of the digital economy in the advancement of international trade and its influence on export competitiveness. One researcher (Nuray, 2011) posited that the advancement of e-commerce will markedly augment the volume of import and export, predominantly in developed countries in the near term, and will exert a more profound influence on developing countries in the long term. The researchers (Liu and Nath, 2017) assumed that the advancement and implementation of information and communication technologies can guarantee that firms have access to timely information about foreign markets. This, in turn, enables exporting firms to adjust their export production plans, reduce risks, and promote trade growth.

A review of the literature on the impact of the digital economy on export competitiveness in various industries shows that some studies have been conducted on the impact of the digital economy on export competitiveness in specific industries. The researchers (Duan Xiaomei and Chen Luoxu, 2021) employed spatial econometric models to empirically analyze the impact of the digital economy on the export competitiveness of high-technology industries. Their findings indicate that the digital economy exerts a positive influence on the export competitiveness of high-technology industries in the Yangtze River Economy, particularly in terms of investment, output, and environmental factors. The reduction of trade costs through digitization and the increase in investment in innovation are key factors affecting the export competitiveness of high-tech industries. One researcher (Yao Zhanqi, 2022) empirically analyzed the impact mechanism of the digital economy on the export competitiveness of the manufacturing industry. The results indicate that the digital economy significantly promotes the export competitiveness of the manufacturing industry. Furthermore, the digital economy mediates export competitiveness through innovation efficiency, synergistic aggregation, and human capital accumulation. One researcher (Fan Xin, 2021) employed a heterogeneous stochastic frontier model to empirically analyze the impact of the digital economy on export efficiency across different regions of China. The results indicate that the digital economy can enhance export efficiency by reducing export costs and optimizing resource allocation. However, there are notable geographical variations in this impact.

A substantial corpus of literature exists on export competitiveness. However, this paper primarily focuses on the research on the factors influencing export competitiveness. The majority of domestic and foreign researchers and scholars concur that the input of technology exerts a positive influence on export competitiveness. The researchers (D. Keesing and W. Gruber, 1992) demonstrated that the researches and development activities of industrial industries can enhance a country's export competitiveness. Furthermore, the depth and breadth of these activities can contribute to a stronger export performance. Empirical modeling conducted by T. Lowinger revealed a positive correlation between research and development activities and export competitiveness in the United States. The researchers, (Zhu, Shi-e, and Yang, Rudai, 2008) discovered that there are spillover effects in certain policy areas, which can facilitate the advancement of regional economies. Consequently, the introduction of foreign investment into underdeveloped regions will have a more pronounced impact on exports, and concurrently, it can also facilitate the balanced economic development of these regions. The researchers (Wang Qingyi and Zhou Dapeng, 2010) proposed that the transformation of explicit knowledge into tacit knowledge can enhance the competitiveness of exports. They further argued that this process should be facilitated by technological and capital inputs, which would then promote the upgrading and transformation of industries. Some scholars have also demonstrated that trade freedom exerts a certain influence on the enhancement of export competitiveness. The researchers (Shen Guobing and Zhang Xuejian, 2018) conducted empirical analysis and discovered a significant correlation between the intensity of China's intellectual property rights protection and export competitiveness. They found that as the intensity of intellectual property rights protection increases, export competitiveness will continue to grow, reaching a peak value. However, after reaching this peak, export competitiveness will gradually decline. Consequently, the intensity of intellectual property protection should be increased moderately to circumvent any adverse effects on export competitiveness. At the same time, it is also necessary to reinforce the research and development capacity of digital technology in order to sustainably enhance the maximum value of export competitiveness. One researcher (Cai Wangchun, 2018) proposed that the export competitiveness of enterprises could be enhanced by improving product quality and implementing differentiated R&D subsidies, as well as considering R&D subsidies for applied high-tech enterprises. One researcher（Mao Qilin, 2019) employed panel data to construct an empirical model, the results of which indicate that trade liberalization enhances the domestic value-added rate of enterprises' exports in terms of R&D innovation and profit margins. The interrelationship is influenced by the degree of processing trade, with a higher degree of processing trade leading to a weaker relationship.

2.2 Current Situation of China's Economy

In order to gain a comprehensive understanding of the global development context of the digital economy and China's scale and exports in this area, this chapter will present a detailed analysis of the current situation. The analysis will encompass the overall development of the digital economy and the specifics of export. First, we will examine the development of the digital economy from a macroeconomic perspective, followed by a detailed analysis of digital industrialization and the digital transformation of industries. With regard to export, we will elaborate on three dimensions: overall exports, software industry exports, and cross-border e-commerce.

2.2.1 International environment for the development of the digital economy

The continuous development of digital information technology, cloud computing, big data, intelligent manufacturing, and other new industries is gradually maturing, and the era of digital economy is leading the world. The contemporary world is undergoing an information revolution, with developing countries able to catch up with the rapid economic growth that has been witnessed in the West. Alongside this, the advent of the digital revolution has led to the launch of a new era of intense international competition.

In terms of total volume, the global digital economy continues to expand. All major countries have recognized the potential of the digital economy as a means of mitigating the impact of the pandemic and enhancing economic resilience. This has led to accelerated development in areas such as semiconductor manufacturing, artificial intelligence, digital infrastructure, e-commerce, and e-government. These developments have ushered in a new phase of growth for the global digital economy. In 2022, the global digital economy is projected to reach a value of 41.4 trillion U.S. dollars, representing an increase of 2.9 trillion U.S. dollars compared to the previous year. This growth is expected to be driven by the expansion of major economies, with the digital economy of the world's 51 largest economies projected to reach 38.6 trillion U.S. dollars in 2021. In 2022, the scale of the digital economy of the 51 major economies in the world will be 41.4 trillion U.S. dollars, representing an increase of 2.9 trillion U.S. dollars compared to the previous year. This represents a year-on-year growth of 7.8 percent. In terms of proportion, the digital economy has become an important support for global economic development. In 2022, the proportion of the digital economy in GDP of 51 major economies in the world will be 46.1 percent, compared with 44.3 percent of the previous year, an increase of 1.8 percent year-on-year. This indicates that the status of the digital economy in the national economy has been steadily improving (China Global Digital Economy White Paper, 2023, 2024).

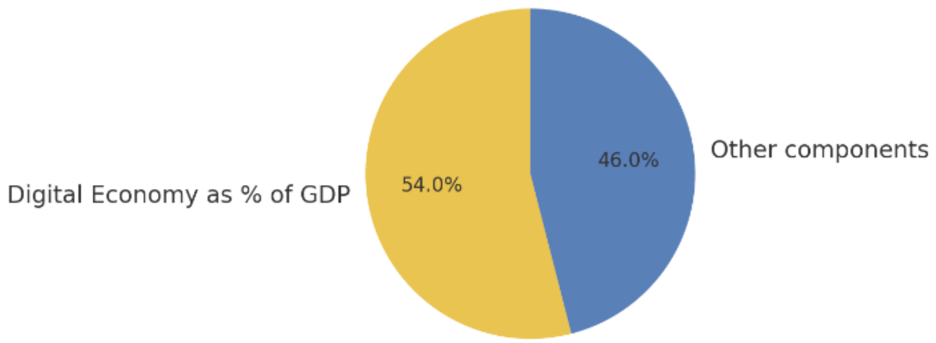

Figure 2.1 Internal structure of the digital economy

In terms of growth rate, the digital economy has become a significant contributor to global economic growth. In 2022, the digital economy of 51 major economies in the world exhibited a growth rate of 7.4 percent year-on-year in nominal terms, which was higher than the nominal GDP growth rate of 4.2 percent during the same period. This growth effectively supported the sustained recovery of the global economy. In terms of structure, industrial digitization continues to be the primary driving force behind the global digital economy. The application of digital technology has been accelerated in traditional industries. In 2022, the scale of digital industrialization of 51 major economies in the world will be USD 6.1 trillion, representing 14.7 percent of the digital economy and 6.8 percent of GDP. Meanwhile, the scale of industrial digitization will be USD 35.3 trillion, accounting for 85.3 percent of the digital economy and 39.3 percent of GDP. This represents an increase of approximately 1.8 percent over the previous year (China Global Digital Economy White Paper, 2023, 2024).

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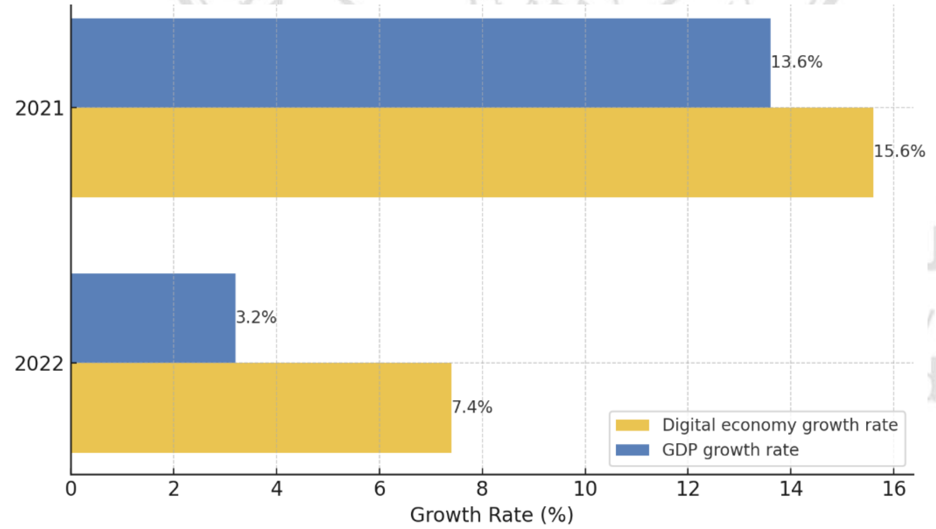

Figure 2.2 GDP and digital economy growth rates

The strategic competition in the field of digital industrialization has intensified, and the frontier technology industry continues to innovate and upgrade. The key hardware and software and cutting-edge technology industries are significant components of digital industrialization. In 2022-2023, South Korea released the

"Semiconductor Superpower Strategy, " which outlines a plan to guide enterprises to complete 340 trillion won of semiconductor investment by 2026. The strategy also includes a proposal to expand tax incentives for semiconductor R&D and equipment investment, upgrade factories, and promote the development of the semiconductor industry. In 2022, South Korea released the "Semiconductor Superpower Strategy, " which outlines a plan to guide enterprises to complete 340 trillion won of semiconductor investment by 2026. The strategy also proposes a support program for the development of the semiconductor industry, including expanding tax incentives for investment in semiconductor R&D and equipment, increasing the capacity of factories, and cultivating professionals. Japan has announced the "establishment of a next-generation semiconductor design and manufacturing base" plan, which aims to produce 2 nm advanced logic integrated circuits by 2027. This will be achieved through the strengthening of the Internet of Things semiconductor production base construction, deepening the global cooperation in the establishment of the future of the technology infrastructure, and other methods. The objective is to enhance Japan's development and production of cutting-edge semiconductor capabilities. In 2021, India announced a $10 billion chip industry incentive program, promising to provide incentives of up to 50 percent of the project cost to eligible companies. The objective of this program was to attract display and semiconductor manufacturers to set up manufacturing bases in India. In 2022, India introduced an incentive program to promote the manufacturing of chips and display panels. Additionally, the country plans to seek at least $25 billion of investment in cutting-edge digital AI, meta-universes, and other areas of industrialization deployment accelerated. The industrialization of areas such as artificial intelligence, the meta-universe, and other cutting-edge digital deployments has accelerated.

2.2.2 China's digital economy export

In 2022, China's import and export volume of digitally deliverable services is projected to reach 372.71 billion U.S. dollars, representing a year-on-year growth of 3.4 percent. Figure 3-3 is expected to represent a new record high in terms of scale. The export of 210.54 billion U.S. dollars represents a year-on-year growth of 7.6 percent, while imports of 162.17 billion U.S. dollars have declined by 1.6 percent. This has resulted in a surplus of 48.37 billion U.S. dollars, an increase of 17.54 billion U.S. dollars over the previous year. The import and export value of cross-border e-commerce reached

RMB 2.11 trillion, representing a 9.8 percent increase compared to the previous year. Among these figures, exports reached 1.55 trillion RMB, representing an increase of 11.7 percent compared to the previous year (China Global Digital Economy White Paper, 2023, 2024).

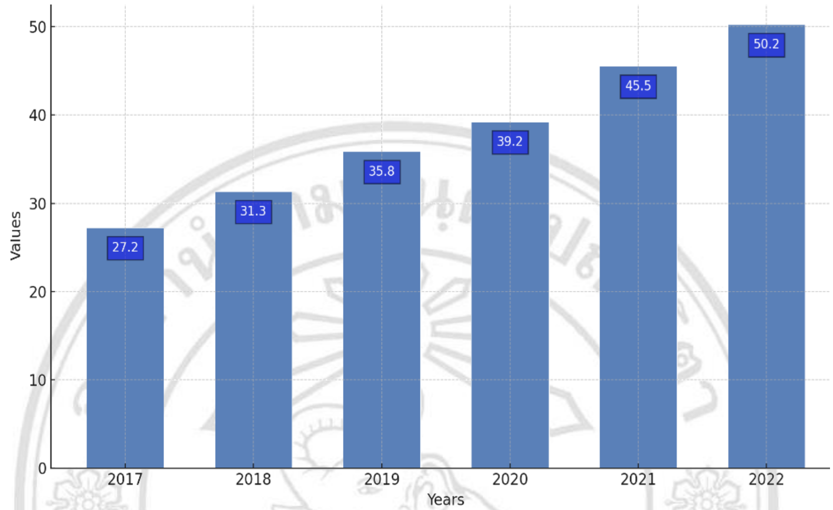

Figure 2.3 Scale of China's digital economy (trillions of RMB)

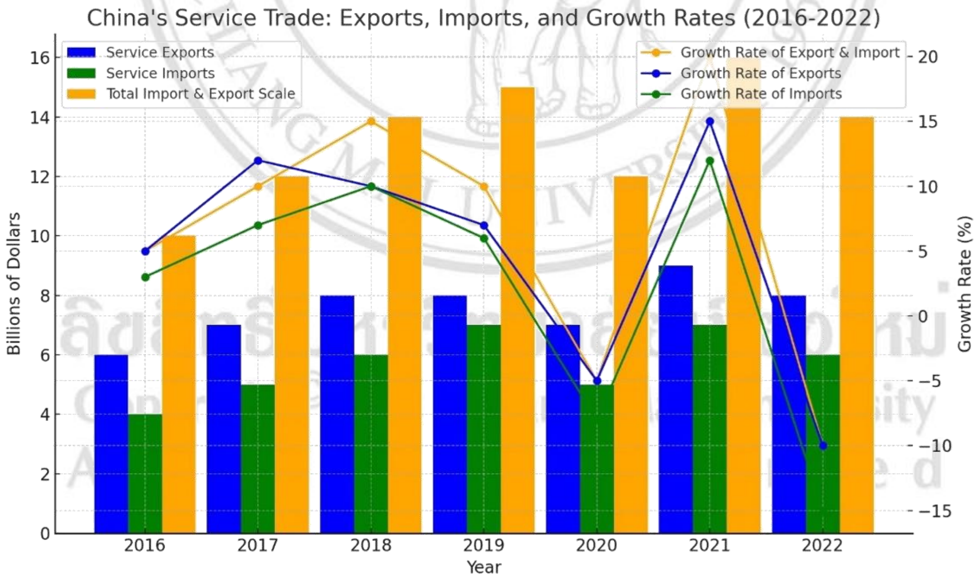

Figure 2.4 China's Services Trade during 2016-2022

According to a joint report by Forbes China and the China Electronic Chamber of Commerce (CECC), the total market capitalization of the “2022 China's Top 100 Digital Economy Enterprises” has reached RMB 16.5 trillion, with a total profit of RMB 732.6 billion and an average profit of RMB 7.325 billion. The top companies are primarily situated in the domains of electronics, computers, household appliances, communications, and e-commerce, encompassing a multitude of industries, including semiconductors, consumer electronics, optical and optoelectronics, software, and computer equipment. By 2022, there will be more than 200 digital trade enterprises with a market capitalization exceeding RMB 7 billion in China. According to the Hurun Research Institute, by the end of 2022, there will be 1, 361 unicorn enterprises globally, with China ranking second with 316 unicorn enterprises, accounting for 23.3 percent. The majority of unicorn enterprises are concentrated in the fields of financial technology, software services, e-commerce, and other related sectors.

Chinese digital platform enterprises are collectively expanding their operations overseas. Digital service platforms are becoming an important hub for connecting international trade and an important carrier for helping enterprises to deeply integrate into the global supply chain. By the end of 2022, there will be more than 200 digital service platforms in China with a market capitalization of more than RMB 7 billion. The advent of short video platforms has ushered in a new era on the global Internet. China's leading short-video enterprises have demonstrated their ability to develop new digital service forms driven by algorithms, user generation, and efficient data utilization based on their experience in the domestic market. These enterprises have also shown strong market competitiveness in the international market (China Global Digital Economy White Paper 2023, 2024).

With regard to China's digital economy policy, the country has issued a number of important documents, including the Opinions of the State Council on Promoting the Innovative Development of Cloud Computing and Cultivating New Industries in the Information Industry, the Circular of the State Council on the Issuance of the Outline of Actions for Promoting the Development of Big Data, the New Generation of Artificial Intelligence Development Plan, and the Three-year Action Plan for the Innovative Development of the Meta-Universe Industry (2023-2025). The country has enhanced its capacity to design and plan the digital economy through the A research institution（The World Economic Forum, 1985) defines export competitiveness as the ability of enterprises to provide goods and services at home and abroad at more advantageous prices and qualities within the context of their economic and social environments. The Forum's core view is that competitiveness is based on the differentiation advantage of quality and price. Export competitiveness is defined as the advantage of a country's products over those of other countries in terms of research and development, production, sales, and service, among other factors (Lall, 1998). Lall notes that export competitiveness can be expressed as the proportion of exports of a given commodity in the total exports in the international market. The higher this proportion, the stronger the export competitiveness. Lu (2014) demonstrated that the productivity improvement of export enterprises effectively contributes to the change of technological complexity of China's exports. This suggests that improving enterprise productivity is the key to realizing product upgrading as well as maintaining the sustainability of China's export competitiveness.

Implementation of a series of measures, including the provision of guidance, the formulation of key core technology research and development strategies, the standardization of systems, the enhancement of security measures, and the promotion of the synergistic development of network construction, the popularization of applications, the innovation of services, and the industrial support necessary to sustain the growth of the digital economy.

The digital economy has developed in a disparate manner across China, with varying degrees of advancement observed in different regions. The eastern region has a clear advantage in the scale of digital trade. In 2022, the scale of import and export of digital delivery services in the eastern region will reach RMB 2, 376.55 billion, accounting for 91.1 percent of the total in the country. Exports will amount to RMB 1, 340.36 billion, while imports will amount to RMB 1, 036.19 billion, resulting in a surplus of RMB 304.17 billion. This advantageous position in the development of digital trade is evident. The provinces and cities with the highest import and export volumes are Shanghai, Guangdong, Beijing, Jiangsu, and Zhejiang. Their respective import and export values are RMB 689.06 billion, RMB 574.35 billion, RMB 508.62 billion, RMB 215.25 billion, and RMB 211.54 billion. The central, western, and northeastern regions are currently undergoing an accelerated phase of catching up. In 2022, the scale of digitally delivered services trade in the aforementioned regions are projected to reach RMB 60.13 billion, RMB 105.96 billion, and RMB 65.31 billion, respectively, accounting for 2.3, 4.1, and 2.5 percent of the national total. The provinces and cities with the highest import and export values are Hunan, Jiangsu, Liaoning, Shanxi, and Henan. Their respective growth rates are 12.6, 12.1, 10.7, 10.5, and 10.4 percent (China Global Digital Economy White Paper 2023, 2024).

In 2022, the digital industry will continue to experience steady growth, and its internal structure will become increasingly stable. In 2022, the added value of digital industrialization reached 9.2 trillion RMB, representing a 10.3 percent increase over the previous year. This marks the second consecutive year of growth exceeding 10 percent. Furthermore, digital industrialization accounted for 7.6 percent of GDP, an improvement of 0.3 percentage points over the previous year. This represents the largest increase since 2018. From a structural perspective, the digital industry's structure appears to be stabilizing, with the service sector accounting for the majority of the value added in the digital industry. The proportion of the software industry continued to grow, while that of the Internet industry declined significantly. Consequently, the overall proportion of the service component increased slightly by 0.3 percentage points (China Global Digital Economy White Paper 2023, 2024, January).

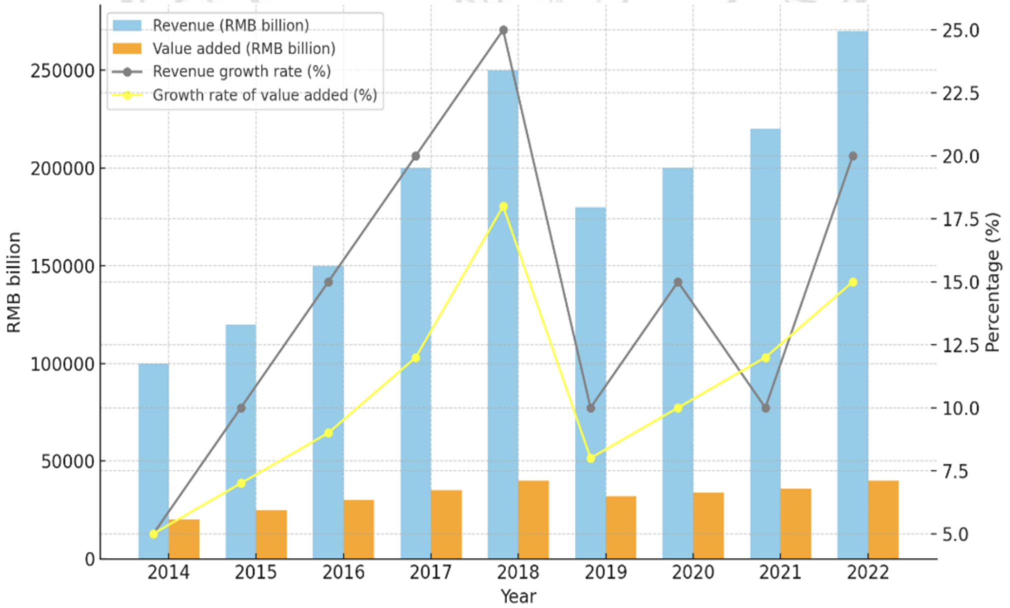

Figure 2-5 Revenue, value-added scale and growth rate of China's digital industrialization, 2014-2022

From the perspective of digital industrialization within the internal sub-sector. The telecommunications industry is stable and experiencing robust growth. New business expansion is particularly noteworthy, with total revenue from telecommunications expected to reach 1.58 trillion RMB in 2022, representing an 8 percent increase over the previous year and a figure that is essentially consistent with that of the previous year. The data center, cloud computing, big data, Internet of Things, and other new businesses have experienced rapid development. In 2022, the total business revenue of these new businesses reached 307.2 billion RMB, representing an increase of 32.4 percent over the previous year. In the telecom business, the revenue accounted for 16.1 percent of the total revenue in the previous year, but increased to 19.4 percent in 2022. The electronic information manufacturing industry demonstrated a consistent growth trajectory, although exports exhibited a slight decline. In 2022, the value-added growth of the above-scale electronic information manufacturing industry was 7.6 percent year-on-year, exceeding that of the industrial and high-tech manufacturing industries by 0.2 and 4 percentage points, respectively. The growth rate of exports from above-scale electronic information manufacturing was 1.8, a significant decline from the previous year's 10.9 percentage point decrease. The income of the software and information technology service industry reached ten trillion RMB. In 2022, the national software and information technology service industry comprised over 35, 000 above-scale enterprises, with a cumulative software business income of 10.8 trillion RMB. This represents an increase of 11.2 percent year-on-year, a growth rate that is 6.5 percentage points lower than that observed in the same period of the previous year. The Internet and related services industry underwent a period of strategic realignment, with a heightened focus on research and development (R&D) investment. In 2022, China's above-scale Internet and related services enterprises achieved an Internet business income of 1.5 trillion RMB, representing a 1.1 percent decline compared to the previous year. R&D investment continued to increase, reaching a total of 77.18 billion RMB, representing a 7.7 percent year-on-year growth. This growth rate was 2.7 percentage points higher than that observed in the previous year (China Global Digital Economy White Paper 2023, 2024).

2.2.3 Industrial digitization

The process of industrial digitization is a crucial element in the development of the digital economy. It has the capacity to catalyze substantial transformations in the tangible economy. Simultaneously, the incorporation of big data, cloud computing, and other developing digital information technologies into many conventional manufacturing firms has introduced a novel variant of economic structure that has significantly influenced society. The process of industrial digitization encompasses the whole extent of the digital economy, and the progressive growth of the digital economy is unavoidable. Digital technology and the real economy are synergistically boosting the transformation and upgrading of China's industries, therefore serving as a significant catalyst for social development and economic expansion.

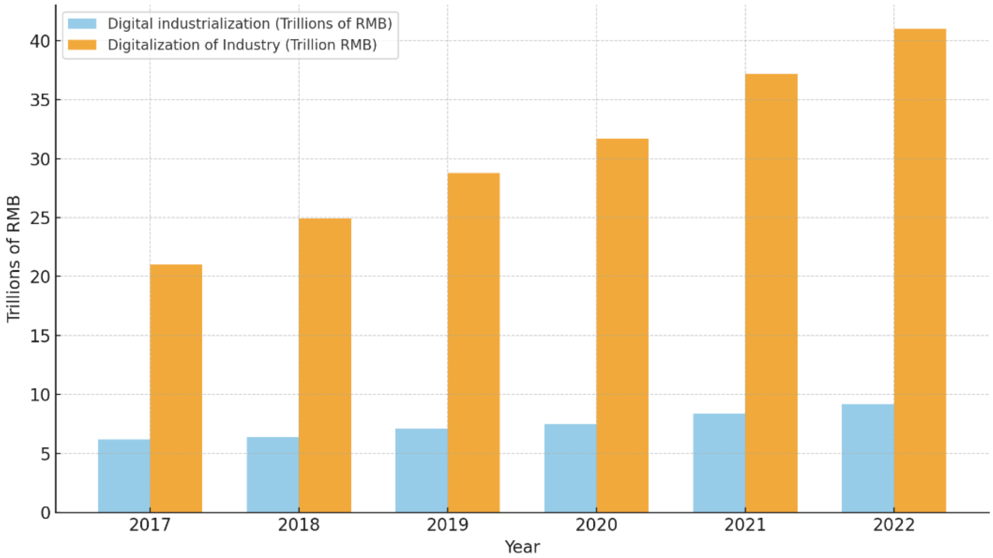

Figure 2-6 Digital industrialization and industrial digitization in China

The industrial digitization penetration in the digital economy varies at 82%, with China's digital industrialization projected to reach 9.2 trillion RMB by 2022. These figures indicate a nominal year-on-year increase of 10.3%, which corresponds to 7.6% of the Gross Domestic Product (GDP) and 18.3% of the digital economy. The process of digital industrialization is currently experiencing a significant change, characterized by a strategic emphasis on enhancing the fundamental aspects and prioritizing innovation. Simultaneously, digital technologies such as the Internet, big data, and artificial intelligence are increasingly playing a significant facilitating role, with a stronger connection with the physical economy. Furthermore, this has resulted in a broadening of research in the domain of industrial digitization and has highlighted the significance of industrial digitization as the primary catalyst for digital economic expansion. The estimated scale of industrial digitization in 2022 is expected to reach 41 trillion RMB, indicating a nominal growth rate of 10.3 percent with respect to the previous year. The figure is projected to represent 33.9 percent of the GDP share and 81.7 percent of the digital economy share. This accounts for 81.7 percent of the GDP share and 81.7 percent of the percentage of the digital economy (China Global Digital Economy White Paper 2023, 2024).

The emergence of the digital economy has triggered a revolution in the administration of the nation. By implementing information and scientific algorithms derived from big data, the country has been able to establish a remarkable and complete governance capacity. This has resulted in the conception of an innovative system of governance. China's digital governance has progressed through three discernible stages: the first incorporation of digital technology into governance, the following management of digital technology, and the continuous overhaul of the governance system. The legislation and operations pertaining to "governance with digital technology" and "governance of digital technology" have been extensively developed and are now undergoing a phase of refinement and enhancement. Digitized governance is facilitating the enhancement and modernization of the governing body. As of 2023, the pertinent laws and regulations concerning the governance of the digital economy have undergone more refinement and perfection. The recently implemented Regulations on the Administration of Deep Synthesis of Internet Information Services establish the specific boundaries of deep synthesis services and provide clear guidelines for the information security responsibilities of all entities involved. The promulgation of the Measures on Standard Contracts for the Exit of Personal Information effectively enhanced the management system for cross-border data flow in China and provided transparency on the necessary standards. The formal publication of the Provisions on Prohibition of Monopoly Agreements, Prohibition of Abuse of Dominant Market Position, and Provisions on Review of Concentration of Operators effectively solidified the regulations pertaining to anti-monopoly legislation and mechanisms. The aforementioned rules adequately address the regulatory requirements of the digital age and offer more accurate control over emerging monopolistic practices in the digital economy. Furthermore, they elucidate the legal limits of market entities.

The monetization of data is a promising catalyst for China's economic expansion and an essential requirement for the advancement of the digital economy. The function of data items depends on the distribution and application of data. Well-defined property rights provide the basis for the efficient transfer of data components. Data trading facilitates the connection between data sources and data applications. Data processing is the systematic gathering, evaluation, categorization, and arrangement of data to convert raw materials into a valued product. The aforementioned commodity is subsequently sold to the demand side, where it is employed to generate additional value. Despite the absence of a data factor market in the country, there are a limited number of data trading platforms, like the Shanghai Data Exchange Center. Simultaneously, improvements are being made to the data trading protocol and standards in order to provide institutional confidence for data trading.

2.3China's digital economy export

According to the main countries, the development of the digital economy continues to accelerate. Overall, according to the World Trade Organization (WTO), international exports of digitally deliverable services in 2022 will reach $4.1 trillion, representing a 3.4 percent increase compared to the previous year. This accounts for 57.1 percent of the total global services exports. The average annual growth rate of global exports of digitally delivered services is projected to be 6.1 percent from 2012 to 2022, surpassing the average annual growth rate of global services exports during the specified time by 1.6 percent. Digital services exports from industrialized economies are projected to reach $3.14 trillion in 2022, representing 77.2 percent of the worldwide market. The digital services exports from industrialized economies are projected to reach $3.14 trillion in 2022, representing 77.2 percent of the worldwide market.

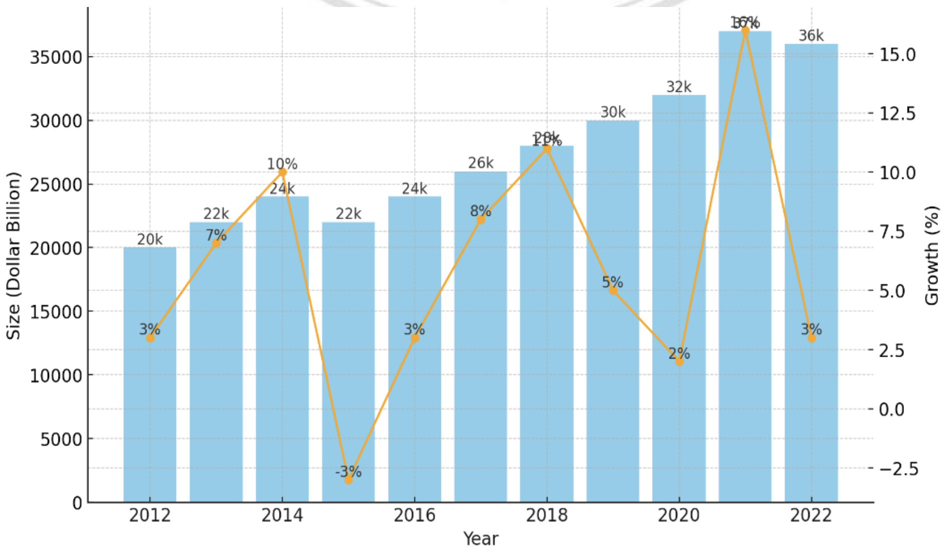

Figure 2-7 Global Digitizable Services Export Size and Growth Rate, 2012-2022

In terms of digital service exports, the United States, the United Kingdom, Ireland, Germany, and Japan accounted for 16.1%, 9.3%, 7.9%, 5.8%, and 2.9% of the global total, respectively, with respective values of $656.1 billion, $378.0 billion, $323.0 billion, $236.8 billion, and $117.1 billion. Emerging economies, namely developing countries, possess the capacity to sustain rapid expansion in the trade of digital services. In 2022, emerging economies generated $927 billion in digital services exports, accounting for 22.8 percent of worldwide exports, reflecting a 14 percent growth compared to the preceding year.

Table 2-1 Size and growth rate of global trade in digitizable services in major economies, 2022

No.	Country	Import & Export (Billion USD)	Growth rate (%)	Export (Billion USD)	Growth rate (%)	Import (Billion USD)	Growth rate (%)
1	USA	10478	5.86	6560	4.93	3917	7.46
2	UK	5630	-1.88	3780	-0.58	1850	-4.44
3	Germany	4598	-2.54	2367	-5.92	2230	1.32
4	China	3727	3.38	2105	7.59	1621	-1.62
5	Netherlands	3489	1.89	1741	3.89	1747	-0.02
6	India	3410	22.56	2354	25.93	1056	15.66
7	France	3154	-0.44	1622	-0.91	1531	0.06
8	Singapore	3104	2.28	1687	4.14	1417	0.15
9	Japan	2684	-3.90	1171	-6.12	1513	-2.10

Digital trade represents the digital economy in international trade and is also the digital form of international trade. This paper divides digital trade into two categories according to the different trade objects and methods. One such category is the digitization of trade modes, which entails the integration of information technology, Internet technology, big data technology, and real economy industry production, manufacturing, and sales. This integration improves the efficiency of traditional enterprises, reduces transaction costs, and simplifies the transaction process. A second category is the digitalization of trade objects, digital technology services, and digital technology products as the object of trade. This represents the realization of the digital economy of foreign trade.

The software industry's revenue reached an impressive ten trillion RMB. In 2022, the number of above-scale enterprises in the national software and information technology service industry exceeded 35, 000, with a cumulative software business income of 108, 126.0 trillion RMB. This represents an increase of 11.2 percent compared to the same period in the previous year, and a growth rate of 6.5 percentage points. Software business exports demonstrated a continued growth trajectory. In 2022, software business exports reached 52.41 billion U.S. dollars, representing a 3.0 percent increase. This growth rate declined by 5.8 percentage points compared to the same period in the previous year. Among the aforementioned sectors, those engaged in software outsourcing services exhibited an increase of 9.2 percent in their exports on a year-on-year basis.

According to the Ministry of Commerce, China's telecommunications, computer, and information services import and export totaled 124.18 billion U.S. dollars in 2022, representing a 3.8 percent increase over the previous year. This growth rate was lower than the overall growth rate of China's import and export of services, which increased by 4.5 percentage points. Among these figures, exports reached 86.15 billion U.S. dollars, representing an 8.4 percent increase compared to the previous year. This growth rate was higher than the growth rate of total exports of services by 0.8 percentage points. Conversely, imports declined by 5.2 percent year-on-year, reaching 38.03 billion U.S. dollars. This decline was greater than the decline in total imports of services, which reached 14.1 percentage points. The trade surplus increased from 39.35 billion U.S. dollars in the previous year to 48.12 billion U.S. dollars in the current year. This represents an 8.76 billion U.S. dollar increase, indicating a promising outlook for future growth (China Global Digital Economy White Paper 2023, 2024).

2.4 Status of cross-border e-commerce exports

Cross-border e-commerce represents a significant manifestation of the digitalization of trade. The Internet platform for the transaction of goods not only reduces the cost of distance-related inquiries and quotations but also renders the trade mode transparent and open, thereby facilitating the management of customs departments. Cross-border e-commerce differs from traditional foreign trade in that it encompasses a broader range of participants. Rather than being limited to transactions between merchants, individuals can also engage in foreign trade. Cross-border e-commerce represents a significant aspect of foreign trade within the context of the digital economy. The advancement of the digital economy is a driving force behind the growth of cross-border e-commerce, and the success of cross-border e-commerce can also facilitate the expansion of the digital economy.

Table 2-2 China's cross-border e-commerce size, year-on-year and share, 2019-2022

Year	**Values (Billion USD)**			**year-on-year (%)**			**Share of trade in goods (%)**		
	Exports	Imports	Total	Exports	Imports	Total	Exports	Imports	Total
2019	1160	710	1870	24.9	6.1	17.0	4.6	3.4	4.1
2020	1570	770	2340	35.5	8.7	25.2	6.1	3.7	5.0
2021	2150	820	2970	37.4	6.1	27	6.4	3.1	4.9
2022	2300	790	3090	6.7	-3.8	3.8	6.4	2.9	4.9
				25.6	3.6	18.2			

As China's cross-border e-commerce sector continues to flourish, China is at the vanguard of the global effort to develop cross-border e-commerce statistics. A comparison of the period preceding and following the epidemic reveals a clear upward trend in terms of both the size and the share of goods exports in China's cross-border e-commerce. China's cross-border e-commerce imports and exports of goods increased from $187 billion in 2019 to $309 billion in 2022, while its share of all goods imports and exports rose from 4.1 percent to 4.9 percent. In terms of compound annual growth rate (CAGR), China's cross-border e-commerce imports and exports, exports and imports will grow at a CAGR of 18.2, 25.6 percent and 3.6, respectively, from 2019 to 2022. In particular, the proportion of China's cross-border e-commerce exports in the total volume of exports is set to increase from 4.6 percent in 2019 to 6.4 percent in 2022. This represents a new growth point that will contribute to the continued expansion of China's export sector.

CHAPTER 3

Panel Data Model

Rather than being incorporated into the literature review chapter, the panel data model selected for analysis in this research warrants its own dedicated chapter, given the depth of its informative content and the significant insights it provides. This allows for a more comprehensive discussion of the model's structure, assumptions, and application, enhancing the clarity and rigor of the empirical analysis.

3.1 Data

Cross-sectional, time series, and panel data are three key data structures in statistical analysis. The explanation and examples of each type are provided in this section. Cross-sectional data captures information from multiple subjects (such as individuals or firms) at a single point in time, enabling researchers to examine differences and relationships among subjects without accounting for time-based changes. This approach is valuable for analyzing variations across subjects at a specific moment. The examples of cross-sectional data are:

- Household Income Survey: Income levels of different households surveyed in a country at a specific year.
- Customer Satisfaction Survey: Satisfaction scores from customers of various companies collected at one particular time.
- Firm Financial Data: Financial performance metrics (e.g., revenue, profit, assets) of various firms for the year 2023; and
- etc.

In contrast, time series data tracks observations of a single subject across multiple time periods, making it ideal for studying trends, cycles, and seasonal patterns, and providing insight into the subject's evolution over time. The examples of time series data are:

- Stock Prices: Daily closing prices of a company's stock over a period of 10 years;
- Unemployment Rates: Monthly unemployment rates in a country over a period of 20 years.
- Weather Data: Daily temperatures recorded in a specific city over the course of a year; and
- etc.

3.2 Models

Panel data models incorporate the heterogeneity or individual variations among data points that may remain constant or change over time. The significance of this trait lies in its ability to mitigate the influence of unobserved variables that may introduce bias into the findings of solely cross-sectional or time series studies. Panel data models can analyze dynamic relationships by explicitly taking into account the impact of previous values of a variable on its present and future values. This capacity is crucial for investigating phenomena such as persistence, adaptation processes, and feedback mechanisms. Following subsections provide descriptions of three widely used panel data models.

3.2.1 Pooled OLS Model

The simplest form of panel data analysis treats the data as a large cross-section by pooling all the observations and running a standard Ordinary Least Squares (OLS) regression. This approach ignores the panel structure and assumes that there are no individual-specific or time-specific effects.

3.2.2 Fixed Effects Model

The fixed effects model controls for unobserved heterogeneity by allowing each entity to have its own intercept (i.e., entity-specific effects). The model assumes that these entity-specific effects are correlated with the independent variables. The fixed effects model is suitable when the interest lies in analyzing the impact of variables that vary over time within an entity while controlling for time-invariant characteristics.

3.2.3 Random Effects Model

The random effects model assumes that the entity-specific effects are random and uncorrelated with the independent variables. This model is more efficient than the fixed effects model when the assumptions hold, as it uses both the within-entity and between-entity variation in the data. The random effects model is appropriate when the entity-specific effects can be considered as random draws from a larger population.

3.3 Model Selection

Due to each specific character, the panel data could be modeled and described differently. The most suitable model could be obtained by several test explained in Figure 3-1

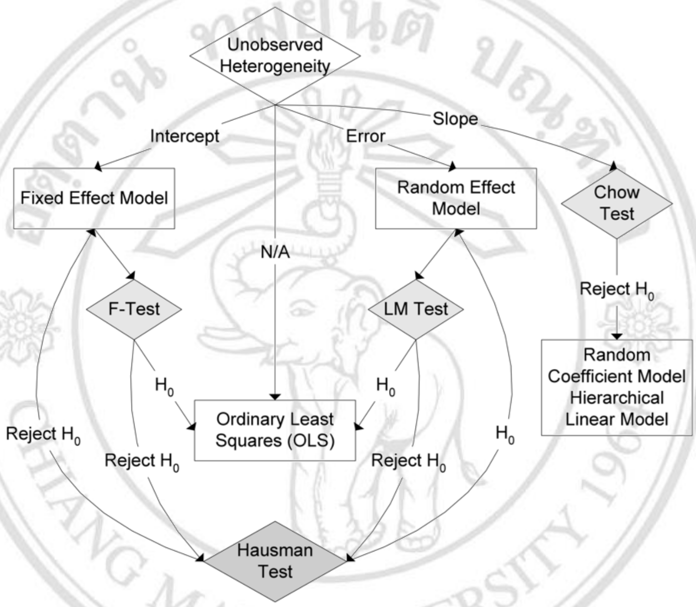

Figure 3-1 Model Selection Process

First, begin the modeling phase by using a pooled Ordinary Least Squares (OLS) model and carefully assess its possible constraints, especially if it fails to consider both observed and unobserved heterogeneity, which includes missing key variables. To ascertain the significance of individual or temporal effects, it is necessary to consider the source of heterogeneity, whether it be cross-sectional or time series variables. A detailed summary of the panel data modeling selection process is presented in Figure 3-1.

Given that the disturbance component accounts for individual variability and the individual effects are not connected with any regressors, a random effects model is suitable. If the heterogeneity can be resolved by using intercepts that are distinct to each individual and if the individual effects may be associated with regressors, then a fixed effects model is the best choice. An optimal fixed effects model is preferred when each individual has their own beginning capacity and shares the same disturbance variance with other people. However, if each individual experiences their own disturbance, a random effects model is better appropriate for representing heteroskedastic disturbances. Then, do suitable formal tests to investigate individual and/or temporal effects. The preference for a random effects model over the pooled ordinary least squares (OLS) model arises when the null hypothesis of the Lagrange Multiplier (LM) test is rejected. Should the null hypothesis of the F-test be rejected, the fixed effects model is preferred over the ordinary least squares (OLS) model. Provided that neither hypothesis is rejected, the combined ordinary least squares (OLS) model is adequate.

When both hypotheses of the F-test and LM test are rejected, perform the Hausman test. If the null hypothesis of uncorrelation between individual effects and regressors is rejected, opt for the robust fixed effects model; otherwise, use the efficient random effects model.

To address the presence of substantial evidence indicating that the heterogeneity encompasses two cross-sectional, two time series, or one cross-sectional and one time series variable, it is advisable to employ two-way effects models. Verify that the panel data exhibit a high level of organization and that the values of $n$$ and $T$$ are adequately large. Refrain from employing two-way models for panels that are poorly distributed, imbalanced, or excessively long/short. To investigate the existence of two-way effects, use suitable F-tests and LM tests. Although Stata does not offer explicit techniques for fitting models with two-way panel data, it is nevertheless feasible to do so. By comparison to two-way random effects models, two-way fixed effects models in Stata are typically more straightforward to implement.

To assess the poolability of the panel data, use a Chow test or its equivalent if the heterogeneity includes divergent slopes (parameter estimates of regressors) among individuals and/or over time. Upon rejection of the null hypothesis of poolable data, it is advisable to choose either a random coefficient model or a hierarchical linear model. Elaborate descriptions of the tests can be found in the subsequent subsections.

3.4 Statistical Tests

The subsequent subsubsections delineate the statistical tests required for the process of selecting the model, as detailed in the previous section. Conducting these tests is essential for verifying the suitability and resilience of the selected model, guaranteeing its alignment with the fundamental data structure and research goals.

3.4.1 F Test

The F-test is used to ascertain the presence of significant fixed effects in a proposed model. More precisely, it examines the null hypothesis that all intercepts (dummy parameters) pertaining to each group are equal to zero, with the exception of one intercept that is excluded. This assessment examines if there is a statistically significant difference between at least one of the group effects and zero, therefore suggesting the existence of fixed effects in the model. Assuming a pooling Ordinary Least Squares (OLS) model is adequate, the null hypothesis (H0) states that all dummy parameters (fixed effects) are equal to zero. The alternative hypothesis (H1) posits that there exists at least one non-zero dummy parameter, thereby suggesting that a fixed effects model is more suitable.

In the context of the F-test for fixed effects, the null hypothesis (H0) and the alternative hypothesis (H1) are defined as follows:

Null Hypothesis (H0):

$$H_0: \alpha_1 = \alpha_2 = \cdots = \alpha_N = 0$$

This implies that all fixed effects are jointly zero or insignificant, suggesting that the pooled OLS model is sufficient.

Alternative Hypothesis (H1):

$$H_1: \text{At least one } \alpha_i \neq 0$$

T These findings indicate the presence of substantial fixed effects in the data, signifying that the fixed effects model offers a superior fit compared to the pooled OLS model. An F-test is performed to ascertain whether the null hypothesis should be rejected in favour of the alternative hypothesis. A significant F-statistic and a low corresponding p-value (usually $p < 0.05$) show that the null hypothesis can be rejected, implying that the fixed effects model is better suitable for the presented data.
A comparative analysis of the goodness-of-fit between two models, namely the fixed effects model (Least Squares Dummy Variables, LSDV) and the pooled OLS model, is conducted using the F-test. This analysis investigates the variation in the sum of squared errors (SSE) or R^2 values among these models. An observed substantial improvement in

goodness-of-fit when employing the fixed effects model indicates that it is more suitable for the given data.

If the F-test yields a rejection of the null hypothesis, particularly a low p-value, it suggests that the fixed effects model offers a far superior fit compared to the pooled ordinary least squares (OLS) model. These findings indicate the presence of significant impacts particular to each group that need to be considered in the study. Provided that the computed F-statistic is statistically significant (e.g., F(5, 81) = 57.73 with a p-value of 0.0000), it indicates that at least one of the intercepts specific to the group is significantly distinct from zero. This finding substantiates the preference for a fixed effects model over a pooled ordinary least squares (OLS) model. Importantly, the F-test presupposes that the errors follow a normal distribution and exhibit homoscedasticity. Failure to meet these assumptions may compromise the reliability of the F-test results. Furthermore, the F-test should not be employed to analyze R^2 values obtained from specific models, such as the original within effect model.

3.4.2 Breusch-Pagan Lagrange Multiplier Test

The Breusch-Pagan Lagrange Multiplier (LM) test is a statistical evaluation method employed to ascertain the suitability of a random effects model over a pooled Ordinary Least Squares (OLS) model for panel data analysis. The main objective of this test is to evaluate the presence of substantial random effects in the data, which would suggest that a random effects model offers a superior fit compared to the pooled overall linear regression (OLS) model.

Null Hypothesis (H0):

$$H_0: \sigma_u^2 = 0$$

The absence of substantial random effects in the panel data indicates that the pooled ordinary least squares (OLS) model is sufficient.

Alternative Hypothesis (H1):

$$H_1: \sigma_u^2 > 0$$

These results reveal the presence of substantial random effects, implying that a random effects model would be more suitable for characterizing the data.

This observation implies that the random effects model is better suitable for the given data, since it takes into consideration the unobserved heterogeneity that impacts the dependent variable. The purpose of the Breusch-Pagan LM test is to ascertain if the null hypothesis should be rejected in favor of the alternative hypothesis. The rejection of the null hypothesis suggests that the random effects model is more effective in handling heterogeneity compared to the pooled OLS model. Therefore, it provides support for the use of random effects in the analysis of panel data.

This study derives the test statistic for the Breusch-Pagan LM test from the residuals of the pooled ordinary least squares (OLS) regression. This analysis compares the variance of the residuals obtained from the pooled model with the variance of the residuals obtained from the random effects model. This comparison is implemented to ascertain the existence of random effects by assessing if there is a statistically significant difference.

If the null hypothesis is rejected, indicated by a low p-value, it implies the presence of a statistically significant random effect in the panel data. In comparison to the pooled OLS model, the random effects model is more effective in capturing the heterogeneity inherent in the data.

Practically, if the Breusch-Pagan LM test produces a test statistic with a p-value below the defined significance level (e.g., 0.05), it suggests that the random effects model is the more favorable choice. If the test results indicate a chi-square value of 0.023 with a p-value, it may be inferred that the random effects are statistically significant. Therefore, the random effects model is suitable for application.

3.4.3 Hausman Test

The Hausman test is a statistical method employed in panel data analysis to determine the suitability of either a fixed effects strategy or a random effects approach. A key objective of the Hausman test is to assess the coherence of estimators in these models. More precisely, it rigorously examines the null hypothesis that there is no correlation between the individual effects and the regressors in the model. If this premise is valid, the random effects model is the favored choice because of its inherent efficiency.

Null Hypothesis (H0):

$$H_0: E[\alpha_i | x_{it}] = E[\alpha_i]$$

These findings suggest that the random effects estimator exhibits consistency and lacks any association between the individual effects and the regressors.

Alternative Hypothesis (H1):

$$H_1: E[\alpha_i|x_{it}] \neq E[\alpha_i]$$

This observation implies that there exists a correlation between the individual effects and at least one regressor, therefore strongly indicating that the fixed effects model is better suitable.

The Hausman test statistic is calculated by subtracting the estimate of random effects from the result of the fixed effects estimator. An analysis is conducted to see if the random effects estimate differs insignificantly from the unbiased fixed effects estimate.

If the null hypothesis is rejected, it suggests that the fixed effects model is preferred due to the correlation between individual effects and regressors. Conversely, if the null hypothesis is not rejected, it indicates that the random effects model may be suitable.

The Hausman test calculates the discrepancy between the estimators of fixed effects and random effects. An analysis is conducted to see if the random effects estimate differs insignificantly from the unbiased fixed effects estimate. The test statistic is computed using this observed difference, and a statistically significant difference suggests that the random effects model is inadequate and suggests the employment of the fixed effects model instead.

If the null hypothesis is rejected (e.g., a low p-value), it suggests that the fixed effects model is preferred because the random effects model would yield biased and inconsistent estimates. Conversely, if the null hypothesis is not rejected, the random effects model may be favored as it is more efficient under the assumption of no correlation.

An inherent constraint of the Hausman test is its assumption of positive definiteness in the covariance matrices. Violating this assumption may result in the test failing to yield definitive findings. Furthermore, it is advisable to apply the Hausman test in conjunction with other tests, such as the Breusch-Pagan LM test, in order to arrive at a thorough determination on the choice of a model.

3.4.4 Chow Test

In panel data analysis, poolability refers to the assumption that the slopes of the regression model remain consistent across several groups or across time. In order to assess this assumption, the Chow test examines whether the coefficients of the regressors are equivalent across groups.

The Chow test is a statistical technique employed to evaluate the poolability of panel data, therefore ascertaining the applicability of a single regression model over several groups or time intervals. The Chow test assesses the homogeneity of regressor slopes among several groups or throughout time. It facilitates the determination of whether the data can be consolidated for analysis or if distinct models are required for various groups.

Null Hypothesis (H0):

$$H_0: \beta_1 = \beta_2 = \cdots = \beta_N$$

This implies that the coefficients of the regressors are the same across all groups or time periods, suggesting that the panel data are poolable.

Alternative Hypothesis (H1):

$$H_1\text{:At least one } \beta_i \neq \beta_j$$

This indicates that the coefficients of the regressors are not the same across all groups or time periods, suggesting that the panel data are not poolable.

The null hypothesis of the Chow test posits that the slope of a regressor remains constant across all individual cases for all regressors simultaneously. These findings indicate that the data can be combined without substantial variations in the modeled connections. The test statistic is derived by summing the squared errors (SSE) obtained from the pooled ordinary least squares (OLS) regression and the SSE for each individual target group. The rejection of the null hypothesis implies that the panel data lack poolability, implying that each individual has distinct slopes for all regressors.

A statistically significant outcome, such as a high-test statistic with a p-value below 0.05, warrants rejecting the null hypothesis, therefore suggesting that the panel data cannot be combined. In such instances, researchers may opt to use random coefficient models or hierarchical regression models to accommodate the variations among groups. The null hypothesis of the Chow test states that the residual slope of a regressor is uniform for all individuals in every group. The rejection of this hypothesis suggests that the panel data lack poolability, implying that each individual may possess distinct slopes for the regressors.

One assumption of the Chow test is that the different components of error variance conform to a normal distribution. Failure to meet this assumption may result in an inaccurate evaluation of the null hypothesis by the test. When errors have varying variances or demonstrate contemporaneous correlation, it is advisable to utilize other approaches like the Seemingly Unrelated Regression (SURE) estimator instead of Ordinary Least Squares (OLS) algorithm. The Chow test computes the total sum of squared errors (SSE) for both the combined ordinary least squares (OLS) model and the models constructed for each individual group. The test statistic is obtained by subtracting the standard error of specification (SSE) between these models. An empirically significant test statistic indicates that the null hypothesis of poolability should be refuted.

A large Chow test statistic along with a p-value below the significance level (e.g., $p < 0.05$) leads to the rejection of the null hypothesis, therefore suggesting that the panel data cannot be pooled. In such instances, researchers may opt to use random coefficient models or hierarchical regression models to accommodate the variations among groups.

CHAPTER 4

Research Methodology

4.1 Scope of Data

This study employs panel data at the regional level and utilizes the ECI as a measure of export competitiveness. The data utilized in this research was sourced from several authoritative databases and platforms. Key sources include the National Bureau of Statistics of China (2023), which provides comprehensive statistical data on China's economy, and the China Knowledge Network's China Economic and Social Big Data Research Platform (China Knowledge Network, 2023). Additionally, the China Economic Network Statistics Database (2023) was consulted for economic analysis. International data were obtained from the World Bank database (World Bank, 2023), the International Monetary Fund (IMF, 2023), and the OECD database (OECD, 2023), all of which offer valuable global economic indicators. Furthermore, micro-level data was drawn from the China Family Tracking Survey (CFPS), accessed via Peking University's open data platform (Peking University, 2023). The scope of data encompasses the various measures of export of 31 provinces and cities during 2012-2022.

The data for this study is primarily derived from official statistics and reports covering the period from 2012 to 2022. The principal sources of data are as follows:

The National Bureau of Statistics of China is the source of the following data. This source provides comprehensive macroeconomic data, including regional gross domestic product (GDP), investment in fixed assets, and other economic indicators pertinent to the digital economy.

The China Statistical Yearbook is a key source of data for this study. This annual publication provides detailed economic, industrial, and regional data, which is instrumental in measuring export competitiveness across different provinces.

Furthermore, the data set includes variables such as provincial export volumes, industrial output, and trade balances.

The Ministry of Commerce of the People's Republic of China: In particular, the Ministry's reports on foreign trade and investment were employed for the purpose of obtaining data pertaining to foreign direct investment (FDI) in the technology and digital sectors. Furthermore, the reports offered insights into China's cross-border e-commerce activity.

The China Academy of Information and Communications Technology (CAICT) provided invaluable insights. The data provided by the CAICT was instrumental in measuring a number of key indicators related to the digital economy, including revenues generated by software businesses, developments in ICT infrastructure, and the scale of the telecommunications industry. Furthermore, the reports provided insights into regional disparities in digital industrialisation.

Provincial Statistical Yearbooks: These regional publications provide supplementary data to the national data set, offering province-specific statistics on export performance, digital economy growth, and infrastructure development. They were particularly useful for analysing regional variations in export competitiveness.

Global Competitiveness Reports (World Economic Forum): To contextualise China's position in global trade, data from the World Economic Forum's Global Competitiveness Reports were used. These reports provide global comparisons of digital infrastructure, ICT adoption, and trade openness, allowing for international benchmarking.

4.2 Research Framework

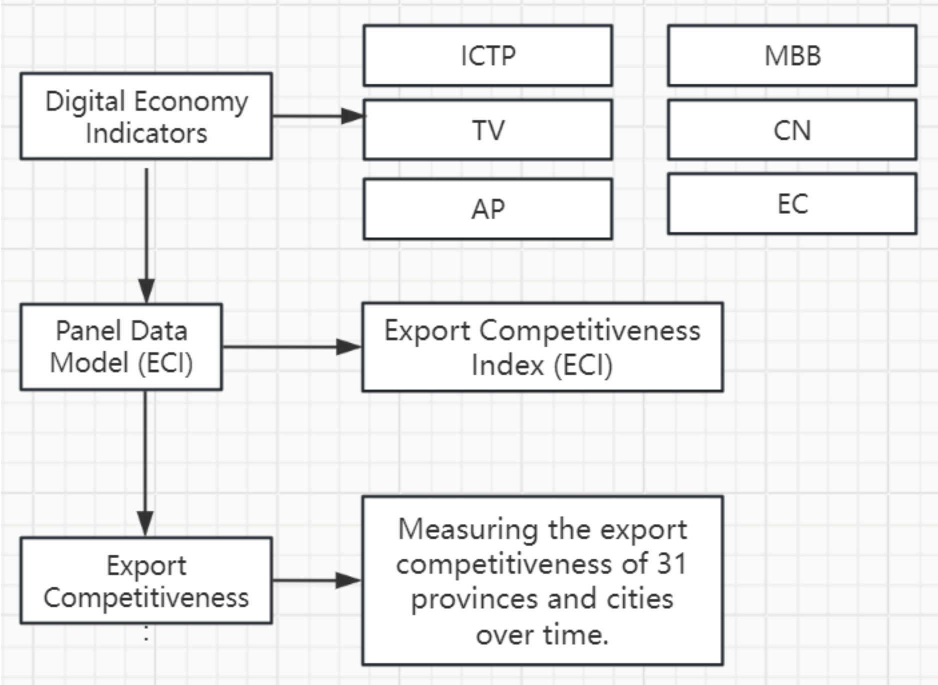

Figure 4-1 Research Framework

4.3 Export Competitiveness Model

Export competitiveness index (ECI) represents a valuable tool for measuring the ability of a country or region to compete in international markets. Currently, the most commonly utilized export competitiveness indicators include the index of revealed comparative advantage (RCA), the index of international market share (MS), and the index of competitive advantage (TC). The Revealed Comparative Advantage Index (RCA) is an indicator that describes a country's export competitive advantage in a particular product or industry. The RCA index is a measure of the proportion of a country's exports in a particular product or industry to the total global exports of that product or industry. A value of the RCA index greater than 1 indicates a competitive advantage for the country in question in the specified product or industry. Conversely, a value less than 1 indicates a relative disadvantage. The international market share index (MS) is a metric that gauges a country's share of exports of a product or industry in the global market. In contrast to the RCA, the MS considers only the market share of a product or industry, without incorporating other factors. Consequently, the MS provides a relative market share rather than a competitive advantage. The Competitive Advantage Index (TC) considers both imports and exports and assesses a country's competitive advantage in a product or industry. The Competitive Advantage Index (TC) assesses a country's competitive advantage in a particular product or industry by comparing the ratio of its product trade balance to its total trade. A country is deemed to have a competitive advantage in a given product or industry if the TC index is greater than 1.

In this paper, in response to the existing literature, and taking into account the availability of data, from the perspective of regional differences, drawing on Yan Bing (2006), we use the ECI index to measure the export competitiveness of China's 31 provinces and cities and conduct an empirical study of the relationship between the digital economy and export competitiveness through this index.

The ECI for this research is represented as follows:

$$ECI_i = \frac{export_i / \sum_{i=1}^{n} export_i}{GDP_i / \sum_{i=1}^{n} GDP_i}.$$

In this context, $export_i$ represents the total export of region i, GDP_i denotes the domestic production of region i, and ECI_i signifies the export competitiveness index of region i. The magnitude of the index reflects the ratio of the proportion of the region's export to the national level and the proportion of the region's GDP to the national level. It is evident that if the ECI index is greater than 1, it signifies that the export development of the region is superior to the economic development, and the export competitive advantage is more pronounced. Conversely, if the index is less than 1, it indicates a relative disadvantage, and the level of export development is not yet commensurate with the economic level. This paper presents a measurement of the ECI index for 31 provinces and cities in China from 2012 to 2022, as shown in the table below.

In this paper, we refer to the literature on the measurement of the digital economy from authoritative organizations at home and abroad, select the indicators, consider the availability of data, and draw on the practice of Chen Xiaohui (2020) and innovate by selecting seven indicators, such as investment in fixed assets of the information and software industry, software business revenue, and telecommunications business volume, from the information and software industry to the information and software industry. This paper conducts an empirical analysis and constructs Equation:

The dimension of information industry development is measured in terms of the proportion of software business revenue to GDP and the proportion of fixed asset investment in ICT industry to social investment. The dimension of telecommunication business is measured in terms of the volume of telecommunication business and the penetration rate of cell phones. The level of development of Internet business is measured by the number of Internet broadband interfaces. Finally, the level of industrial digitization is measured by the sales of e-commerce and the number of domain names. Furthermore, foreign direct investment is incorporated into the model as a control variable, thereby facilitating a more comprehensive assessment of the impact of various aspects of the digital economy on export competitiveness.

The normative analysis method involves a comprehensive reference to domestic and foreign qualitative and quantitative research literature on the digital economy. This paper's understanding of the concepts related to the digital economy is presented, and the export competitiveness of China's regions is analyzed with reference to scholars' research results on export competitiveness measurement indexes. A model of the impact of the digital economy on export competitiveness is constructed, and relevant suggestions are put forward.

The comparative analysis method was employed to assess the export competitiveness of China's provinces. The ECI index was utilized to gauge the export competitiveness at the regional level, with a focus on identifying and comparing the disparities between different regions and between different years. The ECI index offers a straightforward means of quantifying the extent to which a region's local economy contributes to exports.

The empirical analysis method involved the construction of a regression model to analyze the export competitiveness index as the dependent variable, based on the description of the development of the digital economy. The relevant data on China's digital economy development and export competitiveness are collected and organized. Thereafter, empirical tests are carried out using Stata software, and in-depth analysis is carried out based on the empirical results.

When analyzing panel data, which combines both cross-sectional and time series dimensions, several key concepts and methodologies are crucial to understand. This chapter provides a detailed overview of the necessary concepts, tests, and models involved.

In this research, we refer to the literature on the measurement of the digital economy from authoritative organizations at home and abroad, select the indicators, consider the availability of data, and draw on the practice of Chen Xiaohui (2020) and innovate by selecting seven indicators, such as investment in fixed assets of the information and software industry, software business revenue, and telecommunications business volume, from the information and software industry to the information and software industry.

The model is mathematically written as:

$$ECI_{it} = \beta_0 + \beta_1 SI_{it} + \beta_2 ICTP_{it} + \beta_3 TV_{it} + \beta_4 MBB_{it} + \beta_5 AP_{it} + \beta_6 CN_{it} + \beta_7 EC_{it} + \beta_8 FDI_{it} + \mu_i + \mu_t + \varepsilon_{it}$$

where the descriptions of random variables are shown in Table 4-1:

Table 4-1 Description of random variable in the panel data model

Random Variable	Description	Unit
$\boldsymbol{i}$	Index of area that include 31 provinces and cities in China	No unit (Index)
$\boldsymbol{t}$	Index of time in year between 2012- 2022	Year
$\boldsymbol{ECI}$	Export Competitiveness Index in four industries i.e. Information industry, telecommunication business, Internet business, and industrial digitization	No unit (Index)
$\boldsymbol{ICTP}$	Share of fixed asset investment in the ICT industry	Percentage (%)
$\boldsymbol{TV}$	Volume of telecommunication service	Billion CNY
$\boldsymbol{AP}$	Number of broadband access ports	Units (count)
MBB	Cell phone penetration rate	Percentage (%)
$\boldsymbol{CN}$	Number of domain names	Units (count)
$\boldsymbol{EC}$	E-commerce sales	Billion CNY
$\boldsymbol{FDI}$	Volume of foreign direct investment	Billion CNY
$\boldsymbol{\mu_i}$	Fixed effects of province	No unit
$\boldsymbol{\mu_t}$	Fixed effects of time	No unit
$\boldsymbol{\varepsilon_{it}}$	Residual term	No unit

CHAPTER 5

Results

The objective of this chapter is to empirically analyze the relationship between the digital economy and export competitiveness by constructing a model.

5.1 Model Selection

Table 5-1 Results of Model selection by Statistical Tests

	Method			
	LM test	F test	Hausman test	Chow Test
Parameter	Chi^2	F (30, 302)	Chi^2	F (10, 292)
	313.26	17.36	20.16	8.75
P-value	0.0000	0.0000	0.0097	0.0000
Results	The use of mixed models is not recommended, and alternative approaches, such as fixed effects or random effects models, should be considered.	Random effects models are superior to mixed models	Fixed effects models are superior to random effects models	It is recommended that two-way fixed effects models be employed. should be used

In F-test, the F-statistic (F (30, 302) = 17.36) measures the ratio of variances. In this case, 17.36 is the calculated F-value, reflecting the overall explanatory power of the independent variables on the dependent variable in the regression model. The P-value (P = 0.0000) is much smaller than the usual significance levels (such as 0.05 or 0.01), indicating that the test results are highly significant. Given the very small P-value, the null hypothesis is strongly rejected. The null hypothesis generally states that all regression coefficients are zero, meaning that the independent variables have no significant impact on the dependent variable. The F-test results suggest that the 30 independent variables in your regression model (as inferred from the degrees of freedom) jointly explain a significant portion of the variation in the dependent variable. Therefore, the model is statistically significant overall. A random effects model is preferable to a mixed model.

In LM test, The P-value is 0.0000, which is significantly lower than the commonly used significance levels (such as 0.05 or 0.01). This indicates that the test results are highly significant, allowing us to reject the null hypothesis. Given the very small P-value, the null hypothesis is rejected. The test results suggest that there is significant heteroscedasticity in your model, meaning that the variance of the error terms is not constant and may vary with the independent variables. A mixed model may not be appropriate; instead, a fixed effects or random effects model should be considered.

In Hausman test, The Chi^2 statistic (20.16) is used to measure the difference between the fixed effects and random effects models. The larger the value, the greater the difference between the two models. The P-value (0.0097) indicates the statistical significance of this difference. A P-value of 0.0097 is significantly lower than the commonly used significance level (such as 0.05). Since the P-value is less than 0.05, the null hypothesis can be rejected. The null hypothesis assumes that the random effects model is appropriate and that the independent variables are uncorrelated with the individual effects. The results suggest that the fixed effects model is a more suitable choice. Based on the Hausman test results ($Chi^2 = 20.16$, $p = 0.0097$), the assumption of the random effects model is rejected, and the fixed effects model is chosen for further analysis. The fixed effects model is preferable to the random effects model.

In Chow test, The F-statistic (8.75) is used to test the overall significance of the model. Specifically, it tests whether the combined influence of multiple independent variables on the dependent variable is significantly greater than that of a model with only a constant term (i.e., no independent variables). A higher F-value indicates that the independent variables have a stronger explanatory power over the dependent variable. The P-value (0.0000) is statistically highly significant, far below the usual significance levels (such as 0.05 or 0.01). This suggests that there is strong evidence that at least one independent variable has a significant impact on the dependent variable. The F-test results ($F(10, 292) = 8.75$, $p = 0.0000$) indicate that the combination of independent variables in the model significantly explains the dependent variable, demonstrating that the model is statistically significant. A two-way fixed effects model should be used.

Table 5-2 presents the results of the LM, F, Hausman, and final model tests, which are critical for determining whether to use a mixed-effects model or a fixed-effects model in the analysis. The LM test assesses the presence of significant individual effects, helping to decide the most appropriate data model type. The F test results are used to compare the suitability of the mixed-effects model versus the random-effects model. The Hausman test results guide the selection between the fixed-effects and random-effects models. The statistical values and p-values in the table indicate whether the fixed-effects or random-effects model should be retained. The final model test results further assist in deciding between these two models. By comparing the differences among the four models, the results in the table guide the selection of the most appropriate model for panel data analysis. This step also includes testing whether to incorporate time fixed effects to develop a two-way fixed-effects model, thereby enhancing the accuracy of the analysis.

Table 5-2 presents the Export Competitiveness Index (ECI) for 31 provinces and cities in China from 2012 to 2022. The ECI measures regional export performance relative to economic development. Analyzing the ECI trends over this period provides critical insights into the shifts in export competitiveness across different regions, highlighting economic disparities and competitive dynamics.

$$ECI_i = \frac{export_i / \sum_{i=1}^{n} export_i}{GDP_i / \sum_{i=1}^{n} GDP_i} \quad \{1\}$$

Table 5-2 China's Export Competitiveness Index by Region, 2012-2022

#	Province	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
1	Shanghai	2.52	1.70	2.64	2.48	1.82	2.45	2.02	1.50	1.74	1.54	2.04
2	Yunnan	0.26	1.00	0.58	0.41	0.29	0.58	0.23	1.00	0.33	0.32	0.57
3	Inner Mongolia	0.07	0.06	0.12	0.23	0.09	0.25	0.12	0.18	0.08	0.12	0.30
4	Beijing	0.86	0.92	1.00	0.76	0.35	0.85	0.77	1.03	0.65	0.74	0.71
5	Jilin	0.17	0.09	0.13	0.24	0.09	0.23	0.13	0.13	0.13	1.00	0.19
6	Sichuan	0.41	0.44	1.21	1.03	0.29	0.98	0.46	0.68	0.48	0.54	1.11
7	Tianjin	1.08	0.97	0.86	1.81	0.93	1.82	0.84	0.91	1.12	1.21	1.19
8	Ningxia	0.22	0.12	0.44	0.96	0.21	1.00	0.31	0.26	0.08	0.15	0.25
9	Anhui	0.46	0.38	0.43	0.52	0.44	0.40	0.47	0.49	0.42	0.44	1.12
10	Shandong	0.75	0.73	0.71	0.77	0.46	1.46	0.72	1.23	0.82	0.90	1.15
11	Shanxi	0.16	0.19	1.00	0.23	0.19	0.24	0.26	0.31	0.24	0.26	0.25
12	Guangdong	2.29	1.16	2.48	2.51	1.05	2.75	2.24	2.23	1.00	1.59	1.98
13	Guangxi	0.45	0.19	0.42	1.18	0.46	0.54	0.53	1.00	0.66	0.53	0.69
14	Xinjiang	0.65	0.32	0.68	1.36	0.61	1.29	0.51	0.78	0.24	0.33	0.93
15	Jiangsu	1.61	1.58	1.35	1.42	1.51	1.45	1.00	1.77	1.34	1.14	1.39

Table 5-2 China's Export Competitiveness Index by Region, 2012-2022 (continued)

#	Province	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
16	Jiangxi	0.45	0.55	0.54	0.62	0.56	1.05	0.65	0.73	0.62	0.51	1.00
17	Hebei	0.31	0.22	0.47	0.83	0.29	0.39	0.42	0.53	0.30	0.35	0.40
18	Henan	0.44	0.34	0.41	0.36	0.39	0.40	0.42	0.39	0.34	0.41	0.46
19	Zhejiang	1.64	1.92	2.05	2.03	2.07	2.03	2.15	2.55	1.56	1.73	2.17
20	Hainan	0.30	0.15	0.36	0.82	1.00	0.40	0.33	0.55	0.25	0.23	0.74
21	Hubei	0.28	0.20	0.27	0.30	0.32	0.88	0.26	0.39	0.33	0.32	0.41
22	Hunan	0.15	0.12	0.25	0.53	0.17	0.28	0.35	0.46	0.30	0.45	0.59
23	Gansu	0.17	0.18	0.24	0.26	0.13	0.09	0.12	0.12	0.05	0.04	0.10
24	Fujian	1.00	0.77	1.65	2.52	1.30	1.18	1.12	1.25	1.00	1.23	1.14
25	Tibet	1.35	1.07	0.84	0.19	0.15	0.34	0.10	0.16	0.04	0.06	0.14
26	Guizhou	0.20	0.19	0.27	0.31	0.16	0.35	0.15	0.14	0.13	0.11	0.11
27	Liaoning	0.57	0.75	1.28	0.58	0.74	0.68	0.68	0.92	0.59	0.63	0.72
28	Chongqing	0.87	1.05	1.31	2.43	0.59	1.72	0.87	1.16	0.93	0.82	0.96
29	Shaanxi	0.22	0.20	0.29	0.26	0.30	0.87	0.57	0.61	0.38	0.45	0.45
30	Qinghai	0.10	0.06	0.31	1.00	0.08	0.13	0.05	0.06	0.02	0.03	0.03
31	Heilongjiang	0.29	0.30	0.30	0.17	0.09	0.31	0.13	0.18	0.07	0.13	0.19

The results demonstrate that the ECI index of different provinces exhibits considerable fluctuations in terms of the overall national trend. This reflects inter-regional variability and the combined influence of various factors. In general, different regions are affected by different policies, and the export competitiveness shows different development trends. However, most regions exhibit a trend of export growth and competitiveness improvement. Regions with ECI indexes greater than 1 are indicated in the table. Specifically, Shanghai has a higher ECI index between 2012 and 2014, indicating that its export competitiveness is stronger. Nevertheless, the ECI index exhibited a gradual decline between 2015 and 2019, which may have been influenced by various factors, including market competition, policy changes, and the global economic environment. In 2020 and 2021, the ECI index exhibited a resurgence, which may have been influenced by factors such as the recovery of market demand and policy support. From 2012 to 2014, Guangdong Province exhibited a high ECI index, indicative of robust export competitiveness. Nevertheless, the ECI index fluctuates between 2015 and 2019, which may be influenced by factors such as competition in the international market and industrial restructuring. In 2020 and 2021, the ECI index declines slightly but remains at a high level, indicating the resilience of Guangdong's export competitiveness. In recent years, provinces such as Sichuan, Jiangsu, and Zhejiang have demonstrated export competitiveness, evidenced by relatively stable or slightly increasing ECI indexes. This may be influenced by a number of factors, including the advantages of regional economic structure and policy support. The ECI indexes for provinces such as Inner Mongolia, Jilin, Shanxi, Ningxia, and Gansu are relatively low, indicating that their export competitiveness is relatively weak. This may be constrained by a number of factors, including the regional resource endowment, the relatively homogenous industrial structure, and the insufficient market demand.

Cross-Section Analysis (Comparison with Other Provinces). In 2012, Sichuan's Export Competitiveness Index (ECI) was 0.41, which placed it behind more economically developed regions like Shanghai (2.52) and Guangdong (2.29). Compared to other provinces, Sichuan started at a relatively moderate level of export competitiveness. By 2022, Sichuan's ECI increased to 1.11, suggesting that its competitiveness improved over time, but still lagged behind top regions like Zhejiang (2.17).

Time-Series Analysis (Sichuan's Performance Over Time). Sichuan's export competitiveness fluctuated between 2012 and 2022, with noticeable changes in several years. In 2012, its ECI was 0.41, and by 2014, it had jumped to 1.21, indicating a significant improvement. This may suggest that during this period, Sichuan experienced favorable economic conditions or policies that boosted its export capacity. By 2022, its ECI had risen again to 1.11, showing a positive trend toward recovery and growth in competitiveness.

In the cross-section analysis, Sichuan has moderate export competitiveness compared to provinces like Shanghai, Guangdong, and Zhejiang, which have consistently higher ECIs. Over time, Sichuan's competitiveness shows a fluctuating but overall upward trend, suggesting that its export capacity has improved despite some challenges.

$$ECI_{it} = \beta_0 + \beta_1 SI_{it} + \beta_2 ICTP_{it} + \beta_3 TV_{it} + \beta_4 MBB_{it} + \beta_5 AP_{it} + \beta_6 CN_{it} + \beta_7 EC_{it} + \beta_8 FDI_{it} + \mu_i + \mu_t + \varepsilon_{it} \{2\}$$

Table 5-3 Descriptive statistics for key variables

Variable	Obs	Mean	Std. Dev.	Min	Max
ECI	341	0.697	0.607	0.022	2.749
SI	341	0.048	0.069	0.000	0.541
ICTP	341	0.029	0.027	0.008	0.207
Tv	341	6.552	1.146	3.495	9.617
MBB	341	120.760	27.949	71.700	228.090
AP	341	7.416	1.021	3.715	9.341
CN	341	3.687	1.551	-0.734	6.783
EC	341	7.480	1.538	1.920	10.767
FDI	341	8.699	1.598	4.240	12.852

As evidenced by the data presented in the table, the average value of China's ECI is 0.697, which is considerably below the level of 1. This indicates that the overall export competitiveness of China's regions has not yet reached a level commensurate with the size of the economy. Additionally, there is a significant disparity between the maximum and minimum values, suggesting that export competitiveness in various regions is subject to unbalanced development. In terms of the average value of inputs and outputs in the information industry, investment in fixed assets accounts for only 2.9 percent of the total investment in fixed assets across the entire society. However, income generated by the software business accounts for 4.8 percent of the GDP. This indicates that the digital industry has a substantial profit margin and an optimal input and output structure, yet it also implies that fixed asset investment has a relatively low proportion in the information industry. With regard to the development of the Internet, it can be observed that the number of broadband access ports varies considerably, which indicates that the construction of digital economy infrastructure varies considerably between regions. Furthermore, the development of the Internet also exhibits an uneven phenomenon.

5.2 Empirical studies

$$ECI_{it} = \beta_0 + \beta_1 SI_{it} + \beta_2 ICTP_{it} + \beta_3 TV_{it} + \beta_4 MBB_{it} + \beta_5 AP_{it} + \beta_6 CN_{it} + \beta_7 EC_{it} + \beta_8 FDI_{it} + \mu_i + \mu_t + \varepsilon_{it} \{2\}$$

Table 5-4 presents the pairwise correlations among the key variables, including the Export Competitiveness Index (ECI) and various indicators of digital and economic development.

Table 5-4 Pairwise correlations

Variables	ECI	SI	ICTP	TV	MBB	AP	CN	EC	FDI
ECI	1.000								
SI	0.440*	1.000							
ICTP	0.328*	0.918*	1.000						
TV	0.281*	0.252*	0.195*	1.000					
MBB	0.493*	0.764*	0.783*	0.248*	1.000				
AP	0.405*	0.322*	0.262*	0.769*	0.299*	1.000			
CN	0.466*	0.524*	0.454*	0.755*	0.445*	0.849*	1.000		
EC	0.543*	0.585*	0.521*	0.652*	0.499*	0.845*	0.856*	1.000	
FDI	0.558*	0.559*	0.489*	0.614*	0.532*	0.817*	0.826*	0.872*	1.000

* $p<0.01$, $p<0.05$, * $p<0.1$

The preceding empirical results demonstrate the correlation between the indicators. Specifically, the following conclusions can be drawn: The Export Competitiveness Index (ECI) is found to be positively correlated with all other indicators, with correlation coefficients generally being high. This indicates a significant positive correlation between export competitiveness and software business income (SI), fixed asset investment in the ICT industry (ICTP), telecom business volume (Tv), cell phone penetration (MBB), number of broadband access ports (AP), number of domain names (CN), e-commerce sales (EC), and foreign direct investment volume (FDI). In particular, the enhancement of these indicators may facilitate export competitiveness. At the 0.01 level of significance, the indicators with the highest correlation with ECI are, in descending order, foreign direct investment (FDI), e-commerce sales (EC), domain names (CN), and mobile phone penetration (MBB). This indicates that these factors may have the most significant impact on the improvement of export competitiveness. Furthermore, the correlation between software business income (SI), ICT industry fixed asset investment (ICTP), and telecommunication service volume (Tv) and ECI is also more significant, although to a slightly lesser extent than the previous indicators.

Table 5-5 reports the Variance Inflation Factor (VIF) analysis, which is used to assess the degree of multicollinearity among the independent variables in the model.

Table 5-5 Multi-collinearity check

Variable	SI	ICTP	AP	EC	CN	FDI	MBB	Tv	Mean VIF
VIF	7.57	7.27	7	6.98	6.11	5.49	2.89	2.86	5.77
1/VIF	0.1321	0.1375	0.1428	0.1433	0.1636	0.1823	0.3456	0.3490	

This study evaluates the presence of multicollinearity using Variance Inflation Factor (VIF) analysis, which quantifies the degree of correlation between each independent variable and the remaining independent variables in the model. A high VIF value suggests potential multicollinearity issues. In this analysis, the average VIF value is calculated as 5.77, indicating that the model passes the multicollinearity test. As a general rule, VIF values exceeding 10 are considered indicative of serious multicollinearity concerns.

Table 5-6 presents the benchmark regression results, assessing the impact of the digital economy on export competitiveness. Four model specifications are employed: Ordinary Least Squares (OLS), Fixed Effects (FE) with individual controls, FE with both individual and time controls, and Random Effects (RE). These models investigate the relationship between digital economy indicators—such as software business income (SI), ICT industry fixed asset investment (ICTP), mobile phone penetration (MBB), broadband access ports (AP), e-commerce sales (EC), and foreign direct investment (FDI)—and the Export Competitiveness Index (ECI).

Table 5-6 Benchmark regression results

	ECI			
	OLS	FE	FE	RE
SI	3.749*	1.704*	1.603*	1.831
	(0.988)	(0.964)	(0.868)	(0.848)
ICTP	-15.241*	-7.786*	-6.202	-5.148
	(2.449)	(2.737)	(2.716)	(2.332)
Tv	-0.060	-0.019	0.086	0.104
	(0.036)	(0.025)	(0.137)	(0.118)
MBB	0.009*	-0.000	0.003	0.005*
	(0.002)	(0.002)	(0.002)	(0.002)
AP	-0.109*	-0.216	-0.312	-0.156
	(0.064)	(0.090)	(0.134)	(0.111)
CN	0.020	0.031	-0.018	-0.008
	(0.039)	(0.037)	(0.038)	(0.036)
EC	0.157*	0.129*	0.081	0.118*
	(0.042)	(0.040)	(0.041)	(0.037)
FDI	0.097*	0.038	0.085	0.110*
	(0.036)	(0.037)	(0.036)	(0.034)
_cons	-1.052*	1.175*	0.941	-0.964
	(0.300)	(0.328)	(1.042)	(0.452)
Individual fixation	uncontrolled	containment	containment	uncontrolled
Year fixed	uncontrolled	uncontrolled	containment	containment
s	341	341	341	341
r2	0.451	0.799	0.845	0.538

Standard errors in parentheses
* $p < 0.1$, $p < 0.05$, * $p < 0.01$

This paper employs a comprehensive sample to investigate the influence of the digital economy on export competitiveness. The estimation results are presented in the table above. Column (1) of Table X presents the OLS (ordinary least squares) regression results of the digital economy on export competitiveness, with a series of control variables included. Column (2) shows the regression results with individual fixed effects added on top of that. Column (3) presents the regression results with year fixed effects added on top of that. Finally, column (4) shows the regression results with only year fixed effects added on top of that.

The results in column (1) indicate that there is a significant and positive relationship between software business income (SI) and the export competitiveness index (ECI) at the 1 percent level in the OLS model. The software industry is typically characterized by high levels of innovation and technological intensity. An increase in the share of software business income in GDP may be indicative of the country's investment and achievement in technological innovation and R&D. Such technological innovations can enhance the quality and competitiveness of products and services, thereby contributing to the growth of exports. However, after the inclusion of various fixed effects, the regression results indicate that software business income (SI) is significantly and positively related to the export competitiveness index (ECI) at the 10 percent level. The regression coefficient, which decreased from 3.749 in column (1) to less than 2 in (2)- (4), suggests a positive association between the two variables. This may be attributed to the influence of inherent individual characteristics on the relationship between software industry revenue and export competitiveness. For instance, there may be certain individual characteristics, such as geographic location, industrial structure, and level of economic development, that are correlated with the relationship between software industry revenue and export competitiveness. After the introduction of fixed effects, the influence of these individual characteristics is controlled, thereby rendering the relationship between software industry revenue and export competitiveness purer. Consequently, the regression coefficient of SI may become smaller.

In all four models, there is a statistically significant negative correlation between ICT industry fixed asset investment (ICTP) and the export competitiveness index (ECI) at the 5 percent level. A higher level of ICT industry fixed asset investment may be indicative of a more developed ICT sector within the region. However, a relatively low level of ICT technology may limit the international competitiveness of the region's products and services, thereby reducing export competitiveness. Some regions may encounter difficulties due to an overreliance on the ICT industry. While increased investment in the ICT industry may lead to economic growth, overdependence on this industry may lead to the decline of other traditional industries, affecting the stability of the overall economy and the diversity of export products, thus reducing export competitiveness.

The coefficients of cell phone penetration (MBB) on the export competitiveness index (ECI) in the regression results of (1) and (4) are both positive and significant at the 1 percent level. This may be attributed to the fact that a higher cell phone penetration rate typically indicates a more robust communication infrastructure within a given region. This suggests that firms may have greater access to stable and efficient communication services in the region, which enhances the efficiency of their communication and transactions with domestic and foreign customers and facilitates export business. Concurrently, the high penetration of cell phones enables a greater number of individuals to utilize them for information access. Enterprises can leverage this information-acquisition ability to gain a timelier understanding of market dynamics, customer needs, and competitor positioning, thereby enabling more agile product and service adjustments and enhanced export competitiveness.

The regression results of (1)- (3) indicate a significant negative correlation between the number of broadband access ports (AP) and the export competitiveness index (ECI) at the 10 percent level. This may be attributed to the fact that a lower number of broadband access ports may indicate a relatively weak Internet infrastructure in a region. A lack of sufficient broadband access ports may impede the ability of firms to conduct online communication, data transmission, and information sharing, thereby reducing the efficiency and competitiveness of their export operations. A low number of broadband access ports may indicate slower network speeds or unstable network connections, which could result in increased delays and uncertainty in information transfer. This can impede the ability of firms to obtain timely market information, communicate with customers, and process orders and deliveries, which in turn affects the operation and competitiveness of their export business. The insufficient number of broadband access ports may impede the ability of enterprises to enter the Internet market. In the context of globalization, the Internet has emerged as a crucial conduit for enterprises to engage in international trade and export business. A lack of broadband access ports in a region may result in entry barriers for enterprises, thereby affecting their export competitiveness in that region.

The results of the regression analysis (1)- (4) indicate a significant and positive correlation between e-commerce sales (EC) and the export competitiveness index (ECI) at the 5 percent level. Furthermore, the regression coefficients exhibit a slight decrease with the inclusion of fixed effects. The observed increase in e-commerce sales may be indicative of an enhanced level of activity and influence exerted by firms operating within the international market. The e-commerce platform enables enterprises to reach global customers with greater ease, expand their overseas market share, and boost the sales and market share of exported products, thereby enhancing their export competitiveness. Concurrently, the expansion of e-commerce sales may diminish the expenditure incurred by enterprises, encompassing traditional logistics costs and sales channel costs. The e-commerce platform enables enterprises to undertake the entire digital operation, including online sales, online payment, and online logistics. This improves the efficiency and convenience of transactions, while also allowing enterprises to engage in online marketing, brand promotion, and other activities to enhance brand awareness and influence. As a consequence of enhanced brand influence, the competitive position of enterprises in the international market will be reinforced, which will in turn result in an expansion of market share and competitiveness of export products.

The results of the regression analysis indicate that the volume of foreign direct investment (FDI) is significantly and positively correlated with the Export Competitiveness Index (ECI) at the 5 percent level. This suggests that FDI may contribute to enhanced levels of production technology and product quality in the enterprise. The transfer of technology, management experience, and innovation resources from foreign investors to domestic enterprises may be a key factor in this relationship. This technology transfer and innovation capacity enhancement facilitates the development of more competitive products and reinforces the competitive position of export products in the international market. Concurrently, foreign direct investment is typically associated with internationally renowned enterprises or multinational corporations, which possess a considerable degree of brand influence and market recognition on the international stage. By entering into a cooperative or acquisition agreement with these enterprises, enterprises can leverage their brand influence and market channels to enhance the popularity and market position of their products and strengthen their competitiveness in the international market.

Table 5-7 presents the heterogeneous regression results examining the impact of digital economy indicators on export competitiveness across different regions in China: the Eastern, Central, and Western regions. Given the significant economic disparities across these regions, the analysis controls for individual and time effects to isolate the regional variations in export competitiveness (ECI).

Table5-7 Heterogeneous results

		ECI	
	Eastern Region	Central Region	Western Region
SI	2.341	8.770*	-0.956
	(1.136)	(4.916)	(3.498)
ICTP	-10.468	-9.156	11.069
	(4.199)	(7.241)	(6.916)
TV	0.116	0.293	0.120
	(0.355)	(0.264)	(0.204)
MBB	-0.002	-0.003	0.006
	(0.004)	(0.006)	(0.005)
AP	-0.055	-0.197	-0.353
	(0.278)	(0.301)	(0.249)
CN	-0.140*	0.009	0.137*
	(0.076)	(0.052)	(0.077)
EC	0.171	-0.013	0.178*
	(0.130)	(0.055)	(0.061)
FDI	0.063	0.114	0.109
	(0.062)	(0.074)	(0.075)
_cons	-0.111	-0.611	-1.008
	(2.704)	(2.197)	(2.211)
Individual fixation	containment	containment	containment
Year fixed	containment	containment	containment
N	121	99	121
r^2	0.845	0.614	0.705

Standard errors in parentheses
* $p < 0.1$, $p < 0.05$, * $p < 0.01$

Given the considerable variation in the economic development status of different regions in China, it is evident that the export competitiveness of these regions also exhibits considerable disparity. Consequently, this paper estimates the export competitiveness of the eastern, central, and western regions separately, and the regression results after controlling for individual effects and time effects are presented in table.

The results indicate that, with the exception of the western region, the share of software industry revenue in GDP (SI) is significantly and positively correlated with the export competitiveness index (ECI) at the 10 percent level. Moreover, the regression coefficient for the central region is considerably larger than that for the eastern region. This may be attributed to the fact that the regression coefficient of the central region is considerably larger than that of the eastern region. This could be due to the economic structure of the central region being more reliant on the software industry, or the central region having a relatively higher level of software industry development, which is crucial for export competitiveness. The software industry in the central region has developed to a relatively high level, and its contribution to export competitiveness is therefore more significant. Furthermore, it is possible that other industries in the eastern region contribute to export competitiveness, resulting in a relatively minor impact of the software industry on export competitiveness.

In the eastern region, there is a significant negative correlation between ICTP and the export competitiveness index (ECI) at the 5 percent level. However, this is not the case in the central and western regions. This may be attributed to the fact that in the eastern region, the negative correlation between fixed asset investment in the ICT industry and export competitiveness may be due to the possibility that excessive fixed asset investment in the ICT industry in these regions may result in the misallocation of resources, which subsequently affects the export competitiveness. In the central and western regions, the relationship between fixed asset investment in the ICT industry and export competitiveness is not statistically significant, likely due to the influence of economic structure and other factors.

In the eastern region, there is a statistically significant negative correlation between the number of domain names (CN) and the export competitiveness index (ECI) at the 10 percent level. In contrast, in the western region, there is a statistically significant positive correlation between the number of domain names (CN) and the export competitiveness index (ECI) at the 10 percent level. This may be attributed to the fact that in the eastern region, the inverse correlation between the number of domain names and export competitiveness may be due to the fact that the number of domain names in these regions is higher, but there may be instances of fake domain names or low-quality domain names, which results in an increase in the number of domain names that does not imply an increase in export competitiveness. In the western region, the positive correlation between the number of domain names and export competitiveness may be attributed to the fact that the number of domain names in these regions is closely related to the development of export business. An increase in the number of domain names may therefore be indicative of an increase in export business activities, which in turn improves export competitiveness.

In the western region, there is a significant and positive correlation between e-commerce sales (EC) and the export competitiveness index (ECI) at the 1 percent level. This may be attributed to the fact that in the western region, the positive correlation between e-commerce sales and export competitiveness may be due to the low level of e-commerce develop ent in the western region. The development of e-commerce can expand sales channels and enhance product awareness, thus promoting export competitiveness.

Table 5-8 presents the results of robustness tests conducted using a shrinking tail treatment, where the Export Competitiveness Index (ECI) has been winsorized at the top and bottom 1percent to mitigate the influence of outliers.

Table5-8 Robustness Tests - Shrinking Tail Treatment

	ECI_W			
	(1) OLS	(2) FE	(3) FE	(4) RE
SI	3.759*	1.675*	1.573*	1.809
	(0.981)	(0.955)	(0.861)	(0.842)
ICTP	-15.218*	-7.631*	-6.076	-5.062
	(2.432)	(2.712)	(2.694)	(2.314)
Tv	-0.060*	-0.019	0.077	0.097
	(0.036)	(0.025)	(0.136)	(0.117)
MBB	0.009*	-0.000	0.003	0.005*
	(0.001)	(0.002)	(0.002)	(0.002)
AP	-0.107*	-0.214	-0.306	-0.150
	(0.063)	(0.089)	(0.133)	(0.110)

Table5-8 Robustness Tests - Shrinking Tail Treatment (continued)

	ECI_W			
	(1)	(2)	(3)	(4)
	OLS	FE	FE	RE
CN	0.020	0.032	-0.016	-0.007
	(0.039)	(0.037)	(0.037)	(0.035)
EC	0.156^{*}	0.128^{*}	0.080	0.117^{*}
	(0.042)	(0.040)	(0.040)	(0.037)
FDI	0.097^{*}	0.036	0.082	0.107^{*}
	(0.036)	(0.037)	(0.036)	(0.034)
_cons	-1.041^{*}	1.176^{*}	0.973	-0.940
	(0.298)	(0.325)	(1.033)	(0.449)
Individual fixation	uncontrolled	containment	containment	uncontrolled
Year fixed	uncontrolled	uncontrolled	containment	containment
N	341	341	341	341
r^2	0.452	0.800	0.846	0.538

Standard errors in parentheses
* $p < 0.1$, $p < 0.05$, * $p < 0.01$

The robustness test of this paper primarily entails shrinking the export competitiveness index (ECI) by 1 percent through data reduction and the elimination of extreme values. The regression results indicate that, when considering the total sample, the software business income (SI) continues to exert a significant positive influence on the export competitiveness index (ECI). Conversely, the ICT industry fixed asset investment (ICTP) remains significantly negatively correlated with the export competitiveness index (ECI) at the 5 percent level. The coefficients of all other variables on the Export Competitiveness Index (ECI) remain unchanged, suggesting that the previous conclusions are robust.

CHAPTER 6

Conclusions

A comprehensive analysis is conducted on the progress of the digital economy in China's 31 provinces and municipalities between 2010 and 2019. The study specifically concentrates on the information industry, telecommunications, Internet business, and industrial digitalization. Furthermore, it examines the regional export competitiveness and uncovers that China's cumulative export competitiveness is not commensurate with its economic magnitude. The key findings suggest that the digital economy greatly improves export competitiveness, especially in the eastern region. Based on these findings, this chapter provides policy suggestions to give priority to the development of the digital economy, enhance infrastructure, guarantee equitable regional growth, encourage foreign investment, and broaden trade openness. The objective of these initiatives is to narrow the disparity between China and industrialized economies, therefore promoting long-lasting economic expansion.

6.1 Main conclusion

This study provides an examination of the extent of digital economy advancement in the 31 provinces and municipalities of China between 2010 and 2019. The analysis specifically concentrates on four main sectors: information industry, telecommunication service, Internet business, and industrial digitization. Moreover, the study utilizes currently available literature on export competitiveness testing to examine China's export competitiveness on a regional scale. The results suggest that China's overall export competitiveness has not achieved a level that is proportional to the growth of its economic size. Conclusions derived from statistical and empirical analysis are as follows:

(1) The advancement of the digital information sector will enhance the ability to compete in international trade.

(2) The progress of the Internet business industry will improve the ability to compete in exports.

(3) There exists a notable unequal distribution in the advancement of export competitiveness among different regions in China.

(4) The Eastern area of China experiences the most significant influence of the digital economy on export competitiveness.

6.2 Policy recommendations

Based on the empirical findings of this study, several key policy recommendations are proposed to enhance China's export competitiveness through the development of its digital economy. The research results provide concrete examples of how specific policy measures can drive improvements.

6.2.1 Prioritize the Development of the Digital Economy

The findings demonstrate that provinces with higher digital industrialization and ICT investments have experienced significant gains in export competitiveness. For example, regions with stronger software business revenues and higher levels of ICT usage showed marked improvements in production efficiency, cost reduction, and innovation. This reinforces the need for policies that prioritize the growth of the digital economy by fostering digital industrialization and encouraging ICT investment at both the national and provincial levels. Targeted support for regions lagging in digital economy development could further optimize the export landscape.

6.2.2 Strengthen Digital Infrastructure

The empirical analysis revealed that improvements in telecommunications services and internet penetration are strongly associated with higher export performance. Specifically, regions with advanced telecommunications infrastructure, such as Guangdong and Zhejiang, displayed superior export competitiveness compared to less digitally connected provinces. This underscores the importance of strengthening digital infrastructure across the country. Policies should aim to expand high-speed internet access and modernize telecommunication systems, particularly in underdeveloped areas, to ensure that all regions can benefit from digital economy growth.

6.2.3 Pursue Balanced Regional Growth

The research highlighted significant regional disparities in how the digital economy influences export competitiveness. Eastern provinces, such as Shanghai and Beijing, which have well-developed digital economies, vastly outperformed central and western regions. To address this imbalance, policies aimed at achieving balanced regional growth are crucial. The government should provide targeted investment and incentives to help less-developed regions, such as those in the central and western parts of China, to catch up. These policies would ensure that the benefits of the digital economy are more evenly distributed, thereby enhancing national export competitiveness.

6.2.4 Promote Foreign Investment

The study found that regions with higher levels of foreign direct investment (FDI) in digital industries enjoyed enhanced export competitiveness, particularly in non-state-owned enterprises. For instance, the empirical results indicate that provinces receiving significant FDI in technology and innovation sectors, such as Jiangsu and Shandong, saw substantial growth in their export capacities. Promoting FDI in the digital economy, particularly in high-tech industries, can further boost exports by facilitating technology transfers and fostering innovation.

6.2.5 Expand Openness to Trade

Lastly, the results showed that increased openness to trade, facilitated by the digital economy, has had a positive impact on export competitiveness. For example, regions with robust cross-border e-commerce activities, such as Shenzhen, benefited greatly from enhanced trade efficiencies and lower transaction costs. Expanding trade openness through policies that reduce trade barriers, simplify customs procedures, and promote digital trade platforms will further strengthen China’s position in the global market.

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