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ABSTRACT

The objectives of this study are to generate an improved digital economy development index (DEDI), to examine the impact of digital economy development on the urban-rural income gap (URIG) from both aggregate and disaggregate perspectives, and to test the mediating effect of industrial structure in this relationship. Data from 30 provincial-level regions in Mainland China are collected from 2013 to 2022. The study employs the entropy method for index construction, system-GMM for dynamic panel estimation, heterogeneity testing to identify regional differences, and the mediating effect test. The findings show, the improved index (DEDI) effectively measures digital economy development across China. The system-GMM results documented a positive and significant first-order coefficient for DEDI, with a negative and significant second-order coefficient. The results of Heterogeneity test indicate significant regional variation in the relationship between DEDI and URIG, and the findings of the third analysis provides indication that industrial structure upgrading significantly mediates the relationship between digital economy development and the income gap, while industrial structure optimization does not. Additionally, the impact of DEDI on URIG follows an inverted U-shape at the aggregate level, with significant regional heterogeneity at the disaggregate level. Based on the findings obtained, we may conclude there is a complex, regionally differentiated relationship between digital economy development and income distribution in China. However, in term of policy implications, it is highly recommended the policy makers to focused on the roles of different secondary indicators within DEDI, for the purpose of improving DEDI's acceleration in reducing of the urban-rural income gap. Other than that, policymakers should also implement region-specific digital economy strategies, particularly in regions where its impact is most pronounced, prioritize industrial structure upgrading, and reconsider the role of industrial structure optimization in policies aimed at improving income equality.

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KESAN PEMBANGUNAN EKONOMI DIGITAL SERTA KESAN PERANTARAAN STRUKTUR INDUSTRI TERHADAP JURANG PENDAPATAN BANDAR-DESA DI TANAH BESAR CHINA

ABSTRAK

Objektif kajian ini adalah untuk membangunkan indeks pembangunan ekonomi digital yang ditambahbaik (DEDI), mengkaji kesan pembangunan ekonomi digital ke atas jurang pendapatan bandar-luar bandar (URIG) dari perspektif agregat dan disagregat, dan menguji kesan pengantaraan struktur perindustrian dalam hubungan ini. Data daripada 30 wilayah di Tanah Besar China dikumpul dari 2013 hingga 2022. Kajian ini menggunakan kaedah entropi untuk pembinaan indeks, sistem-GMM untuk anggaran panel dinamik, ujian heterogeniti untuk mengenal pasti perbezaan wilayah dan ujian kesan pengantaraan. Penemuan menunjukkan, indeks yang ditambahbaik (DEDI) mengukur pembangunan ekonomi digital di seluruh China dengan lebih berkesan. Keputusan Sistem-GMM merekodkan koefisien tertib pertama yang positif dan signifikan untuk DEDI, dengan nilai koefisien tertib kedua yang negatif dan signifikan. Keputusan ujian Heterogeniti menunjukkan keputusan yang pelbagai dalam hubungan antara DEDI dan URIG, dan penemuan analisis ketiga memberikan petunjuk bahawa hanya faktor peningkatan struktur perindustrian merekodkan keptuusan signifikan manakala faktor pengoptimuman struktur adalah tidak signifikan. Selain itu, kesan DEDI ke atas URIG mengikut bentuk U terbalik bagi analisis agregat, dengan keputusan signifikan yang pelbagai bagi analisis yang sama dalam analisis disagregat. Berdasarkan penemuan yang diperoleh, kami membuat kesimpulan terdapat hubungan yang kompleks dan dibezakan secara serantau antara pembangunan ekonomi digital dan pengagihan pendapatan di China. Walau bagaimanapun, dari segi implikasi dasar, penggubal dasar amat disyorkan untuk memberi tumpuan kepada peranan penunjuk sekunder yang berbeza dalam DEDI, bagi tujuan menambah baik pecutan DEDI dalam mengurangkan jurang pendapatan bandar-luar bandar. Selain itu, penggubal dasar juga harus melaksanakan strategi ekonomi digital khusus wilayah, terutamanya di wilayah yang kesannya paling ketara, mengutamakan peningkatan struktur perindustrian, dan mempertimbangkan semula peranan pengoptimuman struktur industri dalam dasar yang bertujuan untuk meningkatkan kesaksamaan pendapatan.

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LIST OF ABBREVIATIONS

BIC	Bayesian Information Criterion
BP Test	Breusch-Pagan Lagrange Multiplier test
DEDI	Digital Economy Development Index
DED	Digital Economy Development Index
EA	Educational Attainment
ED	Economic Development
EO	Economic Openness
F Test	Fisher Test
FE	Fiscal Expenditures
FE Model	Fixed Effect Model
GDP	Gross Domestic Product
GMM	Generalized Methods of Moments
HT	Harris–Tzavalis
IPS	Im, Pesaran and Shin Impulse
LNGDP	Level of Economic Development
OIS	Optimization of Industrial Structure
RE Model	Random Effect Model
UIS	Upgrading of Industrial Structure
UR	Urbanization Rate
URIG	Urban-rural Income Gap Index

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CHAPTER 1

INTRODUCTION

1.0 Introduction

Many developing countries around the world face challenges such as underdeveloped rural economies and an imbalance between urban and rural development. Moreover, an increasingly important criterion for distinguishing between developing and developed countries is the size of the urban-rural income gap (Zhong et al., 2022). At the same time, the digital economy has emerged as a key driver of economic development with the rapid development of digital technology. It also has profound implications for reshaping urban-rural relations, promoting equitable regional development and changing income distribution patterns. Hence, the impact of the digital economy development on urban-rural income gap (URIG) should be taken seriously, as the decision-making process could affect the future urban-rural income gap or even the economic performance either positively or negatively. For a further detailed discussion, this chapter provides the background research in section 1.1. Section 1.2, 1.3 and 1.4 provides the discussions on problem statements, research questions and research objectives, respectively. Then, followed by the research

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hypothesis in section 1.5. Section 1.6 and 1.7 discuss significance of the study and limitations of the study, respectively. The theoretical framework of the study is in section 1.8 and the operational definition is in section 1.9. At last, section 1.10 provides a summary of this chapter.

1.1 Background research

Economic development and income distribution are eternal themes in economy research (Kuznets, 2019; Nijman & Wei, 2020). On one hand, although the income inequality in the developing world is lower than 30 years ago, the decline in inequality between developing countries has been the main contributor, and the average inequality within developing countries has been slowly increasing (Ravallion, 2014). One of the most obvious indicators of economic inequality in China is the significant urban-rural income gap (Jiang et al., 2022; Jiang & Jin,2024). Additionally, one of the key factors separating the developing and developed countries is the gap in income between urban and rural areas (Jiang et al., 2022; Peng & Zheng, 2022). On the other hand, the digital economy recently years, has emerged as a novel economic paradigm characterized by creativity, revolution, and scalability. It can shorten the gap between time and location, boost regional trade, and increase production effectiveness（Jurayevich & Bulturbayevich, 2020). It is, therefore, essential to explore whether the rapid development of the digital economy can alleviate income inequality and, more specifically, its impact on the urban-rural income gap. This forms the primary focus of this research.

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Along with the development of digital technology in recent year, the digital economy is growing rapidly worldwide. The digital economy is a broad concept, referring to the collective term for economic activities based on digital technologies. The digital economy encompasses all economic activities conducted through digital technologies and internet platforms, including electronic commerce, digital finance, digital advertising, and a wide range of services and products related to information technology. According to the International Monetary Fund (2021), the digital economy includes both traditional internet industries and the digital transformation of traditional sectors. The Organisation for Economic Co-operation and Development (2021) further describes it as utilizing digital technologies to facilitate economic activities, creating new business models and altering traditional economic operations. Additionally, the World Bank (2016) highlights its impact on economic growth, innovation, and job creation, emphasizing its broad scope and influence. Understanding these definitions is critical for framing the role of the digital economy in influencing income distribution and the mechanisms driving the urban-rural income gap.

With the rapid development and widespread adoption of digital technologies, the digital economy has become a significant driver of global economic growth. Data from CAICT(CAICT, 2023; CAICT, 2022) shows that the value added by the digital economy in 47 countries around the world grew by around 37 per cent between 2018 and 2022, indicating the global digital economy is expanding. The digital economy's contribution to the global economy increased by 5.8 percentage points over this four-year period, highlighting its growing importance to GDP. This demonstrates a

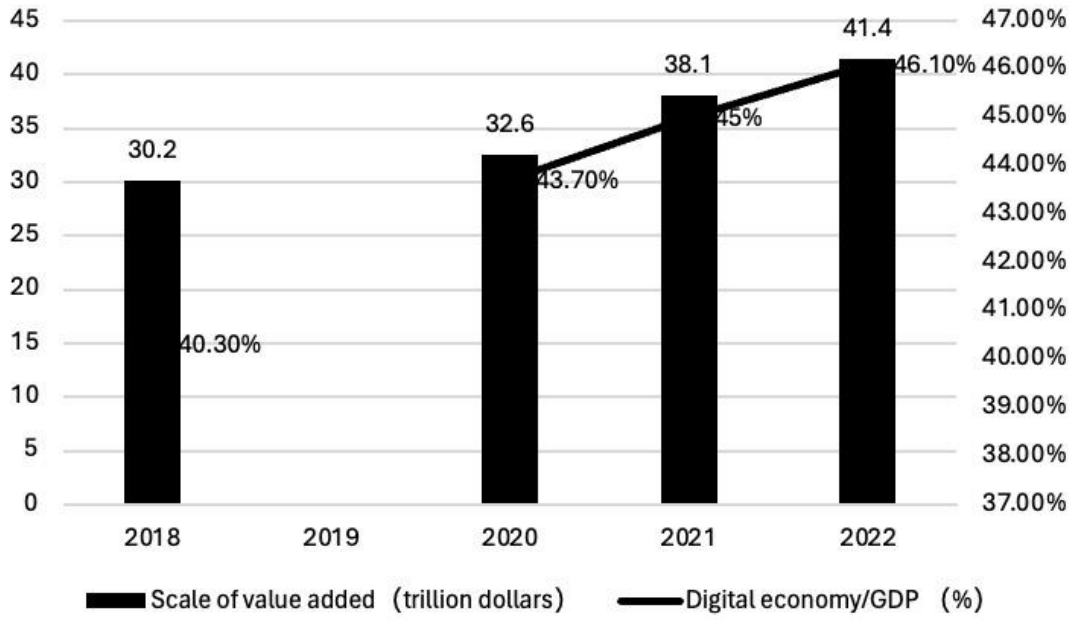
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steady growth trend both in absolute size and as a share of GDP, reflecting significant progress in digital transformation across countries. With advancements in technology and the increasing accessibility of the Internet, the digital economy's contribution to global economic growth is rising. The trend is expected to continue in the coming years, further boosting global economies.

Figure 1.1

Size of the Digital Economy (47 Countries) and Share of GDP



Note: Data are from the *White Paper on Global Digital Economy Development* (2019, 2021, 2022, 2023) by the China Academy of Information and Communication Research (CAICR). The 2020 report was not published. Figures for 2019 are based on digital economy statistics from 47 countries. By 2022, the number of countries increased to 51 with the inclusion of Laos, South Africa, the Philippines, and Israel

In 2022, the estimated value added by the digital economy across 51 countries reached 41.4 trillion USD, marking a nominal increase of 7.4% year-on-year and accounting for 46.1% of global GDP (CAICT, 2024). In terms of scale, the United States ranks first, with a digital economy valued at 17.2 trillion USD, while China

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ranks second at 7.5 trillion USD. In terms of proportion, the digital economy accounts for more than 65% of GDP in the UK, Germany, and the United States. Saudi Arabia, Norway, and Russia, with growth rates exceeding 20%, rank among the top three countries in terms of digital economy growth.

The rapid development of the digital economy has garnered global attention for its critical role and wide-reaching impact. As a result, many countries have made it a strategic priority (Sorescu & Schreier, 2021; Heng et al., 2020; Hui & Lin, 2019). By 2022, nearly all United Nations member states had formulated digital economy strategies at various stages of development (Xu & Li, 2022). Japan, for instance, began its digital economy efforts early. In 1997, Japan's Ministry of International Trade and Industry coined the term digital economy and introduced a series of policies to bolster the digital information industry (Abbos et al., 2021; Peng, 2021). Similarly, in 1998, the U.S. Department of Commerce published its inaugural report, The Emerging Digital Economy, which underscored the pivotal role of digital resources in both macro and microeconomics (Peng, 2021). In 2009, the UK launched its Digital Britain initiative, aiming to accelerate the digital economy with the aid of information technology. Germany followed with its Industry 4.0 and Digital Germany 2015 plans, designed to foster digital transformation in businesses and boost economic growth. Russia also introduced a Digital Economy Development Plan, highlighting its commitment to unlocking the potential of the digital economy. The G20 further spotlighted this shift, adopting the G20 Digital Economy Development

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and Cooperation Initiative at the 2016 Hangzhou Summit, providing fresh momentum for global innovation and growth. In 2021, the United States Agency for International Development (USAID) released its 2020-2024 Digital Strategy, outlining 30 objectives to be achieved within the specified period.

The digital economy is widely acknowledged as a key driver of contemporary economic growth (Hu et al., 2021; Li et al., 2020; Myovella et al., 2020). The integration of digital technologies across various industries has led to profound transformations in operational frameworks and business models, reshaping traditional sectors. In finance, the adoption of big data analytics and blockchain technology is revolutionizing service delivery, fostering financial innovation, and promoting the development of inclusive finance. In manufacturing, the industrial internet and smart manufacturing technologies are driving the digitalization and automation of production processes, improving both efficiency and product quality. Similarly, in the service sector, technologies like artificial intelligence and big data analytics are enhancing service delivery and operational efficiency. Furthermore, in agriculture, digital innovations are catalyzing the modernization of the sector, boosting productivity and ensuring higher-quality agricultural outputs. These advancements across industries underscore the transformative impact of the digital economy on global economic structures.

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In addition to its widespread application in the economic sphere, the digital economy has also exerted profound impacts on social development. The emergence of digital technologies represented by computers, the internet, intelligent manufacturing, 5G, and blockchain is the most significant change in human society since the industrial revolution, changing the traditional relationship between individuals, companies, and society (Fu et al., 2022; Voronkova et al., 2020). It provides entrepreneurs and innovators with more opportunities and platforms, fostering innovation and entrepreneurship activities. The development of the digital economy has also created a large number of job opportunities, particularly in high-tech fields and emerging industries, providing new impetus for the development of the labor market. However, the digital economy development also presents challenges, such as the widening digital divide between developed and developing regions, which can exacerbate economic inequalities. Moreover, issues related to data privacy and cybersecurity are increasingly prominent as more economic activities move online. Besides, the digital economy also has significant implications for urban-rural development inequality, industrial restructuring, talent cultivation, and other aspects, requiring governments and enterprises to formulate corresponding policies and strategies to address them. Therefore, gaining a deep understanding of the background and definition of the digital economy, as well as its impact on economic and social development, is of great significance for formulating future development strategies and policies.

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While the digital economy is growing globally, China's unique trajectory offers valuable insights into its role in addressing income disparities, particularly between urban and rural areas. The Chinese government has played a crucial role in shaping the digital economy by formulating and implementing a range of policies aimed at facilitating its growth. Since the 18th National Congress of the Communist Party of China, the government has placed great importance on the development of the digital economy, recognizing it as a strategic priority for the country's long-term growth. In line with this, a series of supportive measures, including the National Big Data Strategy, have been introduced and consistently implemented since 2015 (Belozyorov et al., 2022) . The emphasis on the deep integration of the internet, big data, artificial intelligence, and the real economy has been a key policy recommendation from the Communist Party of China's 19th National Congress. Furthermore, the government has prioritized investments in digital infrastructure, talent cultivation, and innovation, all of which have helped strengthen the foundation for the growth of the digital economy in China.

China's digital economy is one of the most dynamic and rapidly evolving sectors globally, garnering widespread attention both domestically and internationally. Since being officially included in China's government work report in 2017, the digital economy has been recognized as a primary driver of innovation and a crucial component for sustaining economic growth. This recognition has been accompanied by consistent and remarkable growth in the scale of China's digital economy (Hu et

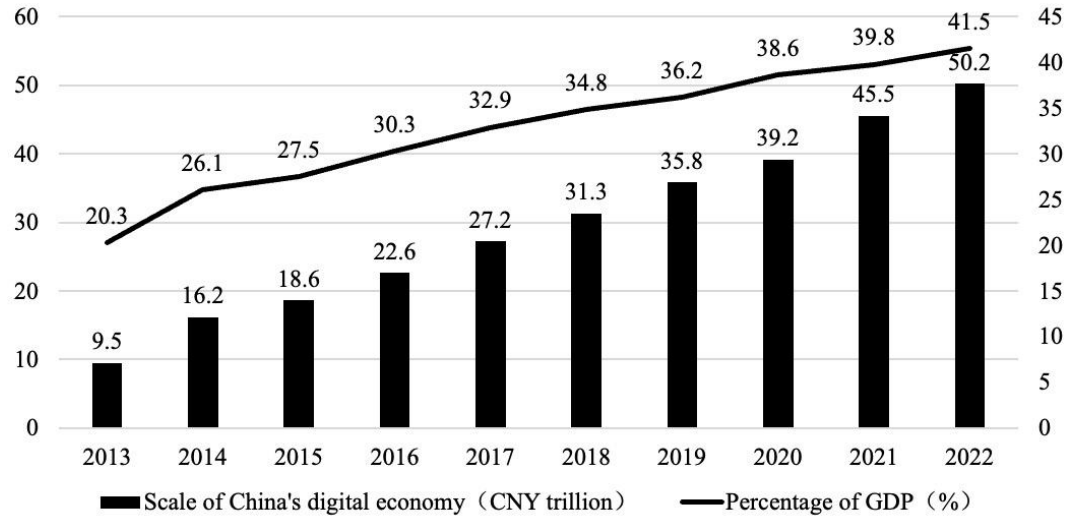
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al., 2021; Li et al., 2020; Myovella et al., 2020). According to the *China Digital Economy Development Report* (2023), the digital economy in China reached a remarkable size of CNY 50.2 trillion in 2023, marking a growth rate of 10.3% compared to the previous year. This growth outpaced China's GDP expansion for over a decade, positioning China as the second-largest digital economy in the world. Its contribution to the GDP stands at 41.5%, highlighting the importance of this sector, on par with the traditional secondary industries in the national economy. The rapid penetration of digital technologies into various sectors continues to propel China's economic progress, revealing the vast potential of the digital economy.

Figure 1.2

China's Digital Economy Scale from 2013 to 2022 Sources: China's Digital Economy Development Report from 2014-2023



As the world's largest digital market, China has demonstrated both strong momentum and immense potential in the digital economy. Several factors have

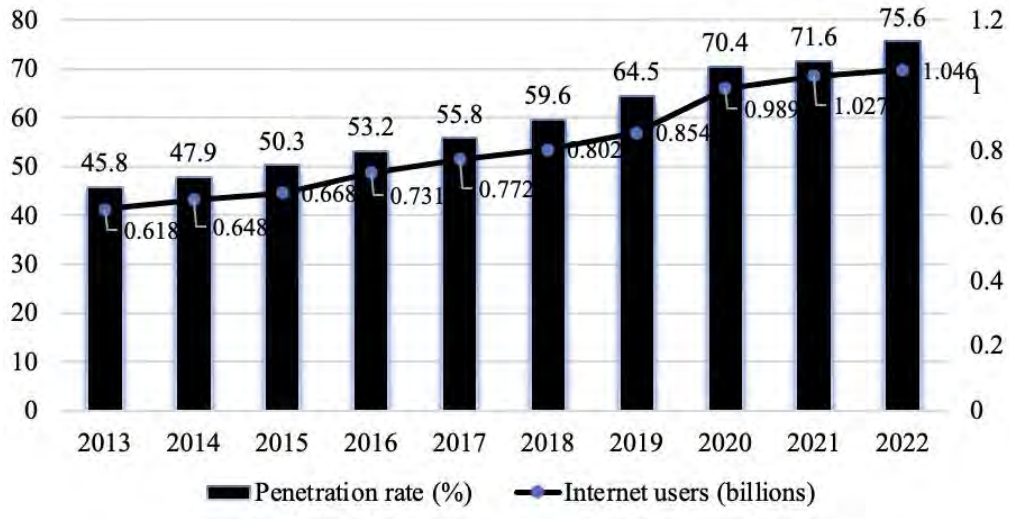
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contributed to the rapid growth of the sector. Firstly, the internet penetration is really high. With China having the largest internet user base globally, internet penetration reached 75.6% by December 2022, with 1.067 billion internet users (CNNIC, 2023). This widespread adoption of the internet, coupled with the growing ubiquity of smartphones and mobile internet, has transformed the way people consume goods and services, produce content, and socialize. Digital platforms are becoming increasingly central to everyday life, and their impact continues to expand, further driving the development of the digital economy. The digital economy now encompasses an ever-growing range of industries, from e-commerce to digital entertainment and beyond.

Figure 1.3

The Number of China's Netizens from 2013 to 2022



Sources: Statistical Report on the Development Status of China's Internet from 2014-2023

Secondly, e-commerce has provided substantial support for the growth of the digital economy. According to the China E-Commerce Report (2022), the country's

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national e-commerce turnover reached CNY 43.83 trillion in 2022. Of this, rural online retail sales amounted to CNY 2.17 trillion, reflecting the expanding reach of e-commerce into rural areas. The rapid development of e-commerce has not only boosted economic activity but also created significant employment opportunities, with the number of e-commerce-related employees reaching 69.37 million in 2022. Therefore, the digital economy has opened new entrepreneurial opportunities for farmers, helping bridge the employment gap between urban and rural regions.

Furthermore, the rapid development of China's digital economy is driving a profound transformation in the nation's industrial structure. In 2022, China's digital industrialization reached CNY 9.2 trillion, with the scale of industrial digitalization totaling CNY 41 trillion, representing 18.3% and 81.7% of the digital economy, respectively. These figures highlight the significant and growing digital penetration across the primary, secondary, and tertiary sectors. The advancement of digital technologies, including cloud computing, big data, artificial intelligence, and 5G, is accelerating the integration of these technologies into industries, thereby reshaping production processes, business models, and industry organization (Bahrini & Qaffas, 2019; Luo et al., 2023). As a result, the digital economy not only facilitates the transformation of traditional industries but also introduces new business models, creating opportunities for industrial upgrading.

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In particular, the digital economy has played a key role in optimizing industrial structures by improving economic efficiency and promoting technological innovation (Murthy et al., 2021; Ping & Yi, 2022). It encourages companies to adopt data-driven business strategies and promotes internal corporate reforms, which leads to better resource utilization and more efficient production processes (Guo & Miao, 2023; Reuschke & Mason, 2022). Furthermore, the rapid technological advancements within the digital economy have reshaped industrial competition, as firms leverage these innovations to create new products, services, and business models, thus accelerating industrial restructuring (Zang, 2019; Xiao & Zhou, 2021). This dynamic interplay of technology and industry is contributing to the overall optimization and upgrading of China's industrial structure, fostering the continued growth of the digital economy while enhancing industrial integration and competitiveness. These transformations in industrial structure directly impact employment and income distribution, making it crucial to analyze their role in narrowing or widening the urban-rural income gap.

While the digital economy has significantly reshaped China's economic landscape, its influence on income distribution, particularly on the urban-rural income gap, remains under explored.

Amidst the transformative forces of digitalization, the persistent urban-rural income gap remains a critical challenge for China's socioeconomic development. The

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significant urban-rural income gap has long been a crucial issue in China's social development (Lagakos, 2020; Sicular et al., 2008). The high-quality development of an economic society is not only reflected in the continuous growth of the economy, but also in the sharing of the fruits of development by the majority of residents (Rodrik, 2000). In China, the economy has grown rapidly after the reform and opening up. The GDP has grown from USD 149.5 billion in 1978 to USD 18 trillion in 2022, and the GDP per capita has grown from USD 156 in 1978 to USD 12,741 in 2022, which has significantly raised the income level of residents. However, from 2003 to 2020, the Gini coefficient of per capita disposable income of Chinese residents has always been above 0.46, which is at a relatively high level, and there is no obvious shrinking trend in recent years (Li, et al., 2021b; Sicular et al., 2008; Wen & Ying, 2021). And in 2020, the income ratio between urban and rural residents in China was 2.56, significantly higher than the levels observed in OECD countries (Guo et al., 2022). Compared to major developed economies, China's urban-rural income gap is the result of the intertwined effects of multiple imbalances in economic development, with significant differences between regions (Huang & Mao,2023).

In recent years, the rapid development of the digital economy has reshaped economic structures globally, creating both opportunities and challenges for income distribution. While urban and rural areas alike have benefited from technological advancements, significant income disparities between these regions persist, particularly in China. Before examining the impact of digital economy development

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on the urban-rural income gap, it is crucial to highlight the key role that this disparity plays in shaping China's economic and social landscape.

Many scholars agree that the widening income disparity between urban and rural areas is a major contributor to the rising inequality in China (Molero-Simarro, 2017). Chen et al. (2015), for instance, estimated that the urban-rural income gap accounted for about 58% of the total income inequality in China from 2005 to 2012, using the Gini coefficient. On average, urban residents in China earned more than three times the income of those in rural areas, making the urban-rural income ratio one of the highest in the world (Sicular et al., 2008), with the trend expected to continue. This gap is even more pronounced when considering differences in welfare between urban and rural populations. Li (2021) emphasized that the excessive urban-rural income gap has become a defining feature of China’s economy and society, posing significant challenges to sustainable economic development. This widening disparity not only exacerbates social inequality but also hampers the country’s efforts towards high-quality economic development (Manduca, 2019; Nijman & Wei, 2020). As a result, numerous studies have focused on identifying the causes behind the urban-rural income gap and exploring potential solutions (Bowen & Morris, 2019; Couture et al., 2016; Li, Sun, et al., 2021b; Li , 2018; Tang & Sun, 2022; Yuan et al., 2020).

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Building on this, it is also important to explore the drivers of the urban-rural income gap, which can be grouped into two broad categories. The first includes factors that contribute to the expansion of the gap. The shift in industrial structures has been a key driver of the urban-rural income divide (Dong et al., 2020; Huang & Mao,2023). Initially, industrialization, marked by the growth of capital-intensive sectors, resulted in a reduction of agriculture's contribution to national income, thereby widening the gap between urban and rural areas. However, with the development of the service sector and the transition to a post-industrial economy, this disparity began to narrow. This progression aligns with the general "inverted U-shaped" pattern observed in income inequality during economic development. Institutional factors, notably the urban-rural dual structure, have also contributed to income disparities (Kuang, 2018; Zhang, 2020; Huang & Mao, 2023). The urban-centered resource allocation policies of the planned economy era left rural areas disadvantaged in terms of industrial policies, infrastructure, and public services. Although recent policies, such as the rural revitalization strategy, aim to address these imbalances, the legacy of past institutional arrangements continues to sustain urban-rural income differences. Regional disparities further compound the urban-rural income gap (Huang & Mao, 2023). In the eastern regions, where economic development is more advanced, the income ratio between urban and rural areas is relatively low, approaching 2. However, in the central and western regions, where economic growth has been slower, this ratio remains above 2.5. These regional

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differences reflect variations in economic growth rates, industrial development, and resource allocation, further exacerbating the overall income inequality in the country.

The second category of studies addresses factors that help to reduce the income gap between urban and rural regions. The narrowing of the urban-rural income gap in China is driven by a combination of government policies, industrial transformation, regional development, human capital improvements, and the advancement of the digital economy. Government initiatives, such as rural revitalization and targeted poverty alleviation efforts, have been crucial in boosting rural incomes. Yin and Wang (2020) suggest that expanding financial services has the potential to narrow the income gap in the short term. The restructuring and upgrading of China's industrial structure and urban-rural integration have played a pivotal role in reducing the urban-rural income gap. Industrialization and urbanization have historically been drivers of income inequality, but the shift toward modernizing rural industries and improving agricultural productivity has gradually mitigated the gap. Wu et al. (2023) concluded that the integrated development of rural industries significantly decreased the urban-rural income gap, possibly by boosting rural economic growth or accelerating urbanization. In a study of small and medium-sized towns across China, Tang (2023) found that rising urbanization levels contributed to a reduction in the income disparity between urban and rural areas.

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Additionally, several studies (Li, 2019; Liu, 2020; Wang et al., 2021) have highlighted the non-linear relationships between various factors and the urban-rural income gap. For example, Li (2019) identified a U-shaped effect in the relationship between market potential, industrial structure upgrading, and the urban-rural income gap. Wang et al. (2021) argued that in the early stages of the digital economy, the benefits were widely distributed across the population, thus narrowing the urban-rural income gap. However, as the digital economy matured, the barriers to access increased, potentially exacerbating the gap. Liu (2020) through a dynamic spatial panel model, found that industrial intelligence led to a widening gap overall, with variations observed across different regions of China. In the eastern region, it narrowed the gap, while in the western region, it had the opposite effect, and no significant impact was found in the central region. Song (2017) also suggested that improving financial inclusion could play a role in reducing the urban-rural income gap, providing digital dividends in the context of the growing digital economy

Moreover, disparities in public services such as education, healthcare, and social security contribute significantly to the urban-rural income gap. Due to limited public service access in rural areas, rural residents often face lower levels of human capital investment and weaker social security coverage compared to their urban counterparts. Institutional factors, including the household registration system (hukou) and the land tenure system, also contribute to shaping the income disparity between urban and rural areas.

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To address these challenges, the Chinese government has implemented various policies aimed at reducing the urban-rural income gap. These include poverty alleviation initiatives, increased investment in rural infrastructure, and efforts to promote rural economic development. In addition, the government has focused on enhancing public services such as education and healthcare in rural areas, fostering human capital development among rural populations. Moreover, promoting integrated urban-rural development and facilitating the mobility of labor and other resources between the two areas are seen as essential steps in narrowing the income gap.

Despite some successes, challenges remain in addressing the urban-rural income gap. For instance, public services in rural areas are still underdeveloped, and there is significant room for improvement in human capital investment among rural populations. Economic structural differences between urban and rural regions also persist, with rural economies lagging behind. To overcome these challenges, it is essential for the government to continue enhancing policy support for rural areas and promote more balanced, coordinated development between urban and rural regions in the future.

The rapid growth of the digital economy offers transformative opportunities to address the structural, institutional, and regional factors driving the urban-rural income gap. Digital platforms have the potential to optimize resource distribution, enhance public service delivery, and create new economic opportunities. By improving access to employment, healthcare, and education in rural areas, digital

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technologies can help bridge the urban-rural divide. Moreover, the integration of digital tools into traditional industries has the potential to reshape industrial structures, creating more equitable opportunities for economic development.

Increasing focus has been placed on how the growth of the digital economy influences both economic expansion and income inequality. (Jurayevich & Bulturbayevich, 2020; Olamide et al., 2022; Yalmaev et al., 2020). Some scholars have argued that developing and emerging countries are not benefiting from investments in ICT to the same extent as developed economies; however, significant regional heterogeneities exist within the same country (Appiah-Otoo & Song, 2021; Bahrini & Qaffas, 2019; Zhang, & Chen, 2021). Others believe that ICT generally increases economic growth in both countries, but poor countries tend to gain more from the ICT revolution (Appiah-Otoo & Song, 2021). Some studies have also shown that the impact of the digital economy development on income inequality exists widely and differs between countries, urban and rural areas, and individuals (Barata, 2019; Ning & Leming, 2022).

Research exploring the relationship between the digital economy and income inequality largely originates from discussions surrounding the dual implications of digital technology development, specifically the concepts of the digital divide and the digital dividend. On one hand, the extensive implementation and advancement of digital infrastructure and related industries under the digital economy framework have

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enabled digital empowerment at the micro, meso, and macro levels, fostering both economic progress and social development (Peng & Zheng, 2022). The connectivity facilitated by internet capital and the narrowing of access disparities have significantly expanded opportunities for individuals to benefit from internet-based platforms (Qiu et al., 2016). For example, the rapid expansion of the Internet economy has enhanced access to employment information and job prospects. According to data from the China Academy of Information and Communications Technology, the digital economy generated 191 million jobs in 2018, representing 24.6% of total national employment for that year. Digital tools such as communication technologies, the Internet, and other information systems play a vital role in improving access to essential resources and uncovering opportunities. Through various channels, including job portals, recruitment applications, and public accounts, farmers can quickly gather information on employment opportunities. This enhanced accessibility allows them to monitor industry trends, adapt to market fluctuations, increase their income, and ultimately enhance their quality of life (Deng et al., 2023).

On the other hand, while the digital economy has presented significant opportunities for growth, it has also led to economic and social differentiation. This issue is particularly concerning as the progression of the digital divide has evolved from disparities in access opportunities to disparities in internet usage, ultimately resulting in significant digital inequalities（Furuholt & Kristiansen, 2007). Users with higher levels of education, higher income, and higher scores on cognitive tests are

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more inclined to utilize the internet to accumulate capital and obtain economic benefits. The differences in information and communication technology across regions, industries, ownership types, and company sizes have caused or widened the income level and inequality between different groups. Büchi et al. (2016) refer that the digital divide exists not only between prefecture-level cities, but also between urban and rural areas. The digital divide exists not only between prefectures but also between urban and rural areas. According to the 50th Statistical Report on the Development Status of the Internet in China published by the China Internet Network Information Center (CNNIC), there were 1.032 billion Internet users in China as of the end of December 2021, representing a 73.0% Internet penetration rate, while there were 284 million Internet users in rural areas, representing a 57.6% Internet penetration rate (China Internet Network Information Center, 2020). Although China's rural digital infrastructure has accelerated and network conditions have improved, the primary digital divide is remains significant. In addition, at this stage, the overall education level of China's rural residents is low, they face limited opportunities to systematically learn about computers, smartphones, and other digital tools, and a large number of groups have barriers in applying digital devices, which exacerbates the secondary digital divide between urban and rural areas.

However, many scholars agree that the combined effects of digital dividends and the digital divide determine the structure of income inequality (Mora-Rivera & García-Mora, 2021). The digital economy could bring digital dividends through

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economies of scale, technology spillover effects, optimal labor allocation, easing financial constraints and lowering barriers to financial services (Du, 2022). It can also promote the revitalization of rural industries by expanding the production possibility boundary of rural industries, alleviating information asymmetry, saving production and transaction costs, stabilizing production expectations and smoothing sales channels (Guo & Miao, 2023). While, the divides could come from the access divide, application divide and income divide (Philip & Williams, 2019).

In this context, it is crucial to recognize that the impact of DEDI on the URIG can be observed directly through employment opportunities and income levels. Moreover, it can also manifest indirectly through factors such as changes in human capital investment among urban and rural residents, as well as improvements in the efficiency and transparency of the labor market. For instance, the development of the digital economy has facilitated the emergence of new business models such as rural e-commerce, online education, and remote work, thereby enhancing the income levels of rural residents. Moreover, the widespread application of digital technology can also improve access to education and healthcare services. However, existing studies rarely explore the mediating role of industrial structure in this relationship, which this research aims to address.

The impact of industrial structure on the urban-rural income gap is a significant research topic in the field of economics. Early studies are primarily based

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on human capital theory and income inequality theory, suggesting that differences in industrial structure would affect the income levels of urban and rural residents (Chen & Ma, 2022). With the progress of urbanization and industrialization, researchers have increasingly focused on the mechanisms through which industrial restructuring affects the URIG. Current research indicates that changes in industrial structure not only directly influence the employment opportunities and income levels of urban and rural residents but also indirectly affect the formation and evolution of the URIG through their impact on the labor market, education, and skills training (Hong & Zhang, 2020).

China's urban rural industrial structure has been continuously upgrading and optimizing over time. With the advancement of urbanization and industrial upgrading, the share of the secondary and tertiary sectors in urban areas has increased significantly (Wan et al., 2024). In contrast, rural areas remain primarily reliant on the primary sector, though its proportion has gradually declined (Long et al., 2016). At the same time, the secondary and tertiary sectors in rural regions have also experienced some development; however, their overall scale and growth rate remain considerably lower than those in urban areas (Long et al., 2016).. This trend has led to the differentiation of urban rural industrial structures and further widened the URIG. Additionally, in recent years, the Chinese government has intensified efforts to adjust the industrial structure. Through the implementation of various policy measures, it has promoted the development of advanced manufacturing, high-tech industries, and the

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service sector, among other emerging industries. However, to some extent, these policies have also exacerbated the differentiation of urban rural industrial structures.

The impact mechanism of industrial structure on the URIG can be analyzed from two primary aspects. Firstly, changes in the industrial structure directly influence the employment opportunities and income levels of both urban and rural residents. As the proportion of secondary and tertiary industries increases, urban areas tend to experience a rise in job opportunities, whereas rural areas face challenges such as increased employment pressure and lower income levels (Chen & Ma,2022). Secondly, adjustments in the industrial structure also affect the provision and quality of public services, including education and skills training, which in turn impacts the investment in human capital and the employability of urban and rural residents. Studies, such as those by Diao et al (2019) highlight that the essence of industrial structural adjustment lies in changing the allocation across different industries. In the context of China, a developing country, significant inequality exists in the economic structure between rural and urban areas (Lagakos, 2020).The primary industry, primarily focused on agricultural production, is largely concentrated in rural areas, while secondary and tertiary industries, which emphasize non-agricultural production, are predominantly found in urban centers (Yu & Lu, 2021). The modernization and transformation of industries during economic development inevitably alter the flow of production elements (Liang et al., 2021). Consequently, this leads to changes in the distribution of resources between urban and rural areas, which affects residents' income and contributes to the URIG (Manduca, 2019).

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In sum, despite the progress made since the beginning of the reform and opening up, the URIG in China remains significant, highlighting persistent constraints and challenges (Che, 2022). The barriers of the urban rural dual system have yet to be fully broken, and the process of urban rural integration faces numerous obstacles (Lu, 2013). The journey towards common prosperity is still arduous. However, the development of the digital economy has brought new opportunities and ways of developing. It can drive rural economic growth and provide new opportunities to narrow the URIG by employment effect, financing effect, market participation effect in China. While many types of studies have previously explored the scope of the impact of the DEDI and the factors influencing the urban rural income divide, there are fewer comprehensive empirical studies on the impact of the DEDI on the urban rural income divide (Hossain, 2020) and a lack of studies that explore how the DEDI affects the urban rural income divide. Therefore, this study aims to systematically examine the impact of the DEDI on the URIG and how the DEDI affects the URIG.

In China, how to take advantage of the DEDI in narrowing the URIG and accelerating economic growth has raised widespread government concern. At present, the rural revitalization strategy is being comprehensively promoted in China. In order to support the rapid growth of the digital economy in rural areas, policies such as network speed reduction, fee reduction, and full coverage of urban rural broadband have been consistently deepened and implemented (Ji, 2023). The Fourteenth Five-Year Plan for National Economic and Social Development and Outline of

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Long-term Goals for 2035 also further pointed out that digital transformation should be used to drive the transformation of production methods, lifestyles and governance methods as a whole, so as to further consolidate the common prosperity of the people. In this context, it is of great practical significance to deeply explore the impact of the DEDI on the URIG (Li et al., 2021; Peng, 2021).

1.2 Problem statement

The income gap has long been a focal point in economic research (Ma et al., 2018), particularly in developing countries, with China serving as a notable example due to its pronounced urban-rural divide (Molero-Simarro, 2017; Jiang , Li, & Si, 2022; Ma et al., 2022). Although the ratio of the urban-rural income gap in Mainland China narrowed from 2.80 in 2013 to 2.45 in 2022, it remains considerably higher than the international average level, which typically falls below 1.6 (Sicular 2010; Yuan et al., 2020; Wang et al., 2024). Moreover, the absolute income difference between urban and rural residents widened, underscoring a growing disparity (Li, 2018). This widening gap poses significant risks to both social stability and economic development, as an excessive income inequality can lead to social polarization, reduced consumption, and hindered economic growth (Sicular et al., 2007; Stewart et al. , 2020; Wang et al., 2024).

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In recent years, the accelerated advancement of information technology and its widespread integration into economic systems have established the digital economy as a new engine of economic growth (Heng et al., 2020). Since 2003, China's digital economy has undergone rapid expansion, promoting the deep integration of digital technologies with the traditional real economy (Ping & Yi, 2022; Wu & Yang, 2022). The digital economy development plays a critical role in reducing the urban-rural income gap, significantly transforming urban-rural dynamics and fostering more balanced development (Ji, 2023; Xiong et al., 2022). This transformation has also affected income inequality between urban and rural regions, contributing to a more equitable distribution of wealth (Leng, 2022; Zhang,2022). Nevertheless, disparities in the development of digital infrastructure, coupled with differing levels of digital literacy among various demographic groups, have resulted in a pronounced digital divide, further intensifying social inequality (Hong et al., 2024; Liao et al., 2022; Robinson et al., 2020).

The role of industrial structure is also critical in this context. Changes in industrial structure, such as shifts in the economy's sectoral composition, can significantly affect wage distribution and job opportunities (Wang & Li, 2024). Yu and Wang (2021) argue that the digital economy's impact on the urban-rural income gap is not direct but mediated through these structural changes. The transition from traditional to more technology-driven industries could lead to improved productivity (Zheng et al., 2023; Chang et al., 2024) and income levels (Ghosh et al., 2023),

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particularly in rural areas, thus narrowing the income gap. However, this process is complex and may also result in new forms of inequality if the benefits of industrial upgrading are not evenly distributed across regions.

Given the emerging significance of digital economy development, scholars have started to explore its impact on the urban-rural income gap, focusing on aspects such as ICT (Appiah-Otoo & Song, 2021; Niebel, 2018), Internet development (Cheng & Zhang, 2019; Mora-Rivera & García-Mora, 2021), and digital financial inclusion (Li, 2022). However, existing studies present conflicting results regarding whether the digital economy effectively narrows this income gap (Chen et al. 2021; Wen & Ying, 2021). Additionally, limited empirical research has examined the mediating role of industrial structure in this relationship (Guo, 2022; Wang et al., 2022).

Another challenge lies in the measurement of digital economy development (Bánhidi & Dobos, 2023; Wang et al., 2021). Current methods include calculating the added value of the digital economy, constructing indicator systems, and developing digital economy satellite accounts (Barefoot et al., 2018; Duc et al., 2024). Compared to the added value calculation, digital economy indices and indicator systems offer a more comprehensive capture of information across various aspects of digital economy development. Furthermore, in comparison to digital economy satellite accounts, digital economy indices provide more concise and intuitive measurement results

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(Mirolyubova et al., 2020； Zhang, & Xu, 2024). However, up to now, significant differences exist among the results of various digital economy-related indices due to the different perspectives of scholars and institutions regarding the digital economy (Duc, 2024; Leng & Zhong, 2024； Wang., 2024). Studies using the index method often focus on only some aspects of the digital economy but do not reflect the digital economy as a whole (Duc, 2024). Moreover, these indicators only allow evaluation of some features of the digital economy but do not help determine its monetary contribution to total economic product output, and authoritative digital economy indices have not yet been compiled by the Chinese government (Leng & Zhong 2024; Tao et al., 2024). These weaknesses in existing digital economy indices make it crucial to improve them to provide a more precise and comprehensive understanding of the digital economy development's role in addressing the urban-rural income gap.

Given these complexities, it is essential to conduct in-depth research on the impact of digital economy development on the urban-rural income gap in Mainland China. This study aims to provide empirical evidence by analyzing data from 30 provinces in Mainland China from 2013 to 2022. First, it generate an improved and comprehensive Digital Economy Development Index (DEDI) that captures the multidimensional characteristics of digital economy development across Chinese provinces. Second, using the improved index, the study examines the relationship between digital economy development and the urban-rural income gap, both at the aggregate level, reflecting national trends, and at the disaggregate level, focusing on

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province-level heterogeneity. Special emphasis is placed on testing the existence of an inverted U-shaped relationship. Third, the study tests the mediating role of industrial structure, with a focus on how the optimization and upgrading of industrial structure influence the transmission mechanism between digitalization and income inequality.

Methodologically, the research employs dynamic panel data model, with the System GMM approach used to address potential issues of endogeneity, unobserved heterogeneity, and temporal dynamics. The theoretical foundation of this study integrates Kuznets' inverted U-shaped hypothesis, which explains the inverted U shape relationship between development and inequality; inclusive growth theory, which highlights the importance of equitable access to digital opportunities; and digital divide theory, which emphasizes structural barriers in digital accessibility and participation. Additionally, the industrial convergence theory provides a theoretical basis for understanding the mediating role of industrial structure. It posits that the integration of digital technologies into traditional industries can reshape economic structures, improve productivity, and facilitate income redistribution. The findings from this research could offer valuable insights for policymakers, public and private sector organizations, and scholars, aiding in the formulation of effective strategies to leverage digital economy development for reducing the urban-rural income gap in Mainland China.

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1.3 Research questions

Building upon the identified statement of the problem, this study aims to address three specific research questions as outlined below:

i. How to generate a comprehensive digital economy development index that captures the nuanced impacts on the urban-rural income gap?

ii. What is the impact of digital economy development on the urban-rural income gap from aggregate and disaggregate perspectives?

iii. Do the optimization and upgrading of industrial structure play a mediating effect on the relationship between digital economy development and urban-rural income gap?

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1.4 Research objectives

Based on the research questions and problem statement, the three research objectives are addressed as follows:

i. To generate an improved and comprehensive digital economy development index identified as DEDI.

ii. To examine the impact of DEDI on the urban-rural income gap from aggregate and disaggregate perspectives.

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iii. To test the mediating effect of industrial structure optimization and upgrading in the relationship between the digital economy development and the urban-rural income gap.

1.5 Research hypothesis

In this section, research hypotheses are proposed regarding the relationships among the independent, dependent, and mediating variables. To achieve research objective 2, two hypotheses (H1 and H2) are formulated. Similarly, to achieve research objective 3, two additional hypotheses (H3 and H4) are proposed.

1.5.1 Impact of the digital economy development on urban-rural income gap

Based on an extensive review of prior literature, as summarized in Chapter 2, the development of the digital economy impacts the urban-rural income gap through a variety of interconnected mechanisms (Jin & Shao, 2016; Cheng & Zhang, 2019; Pazarbasioglu et al., 2020). On the one hand, numerous studies have demonstrated that the digital economy promotes rural income growth by enabling effects such as enhanced employment opportunities (Yin et al., 2019; Abdurakhmanova et al., 2020), improved financial inclusion and accessibility (Pazarbasioglu et al., 2020; Yu & Wang, 2021), increased participation in broader markets (Mekonnen, 2009; Yang, 2022), and the optimization of industrial structures (Babkin et al., 2020; Han & Li, 2022; Ge et al., 2022). These positive influences are widely considered to contribute to the

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narrowing of the urban-rural income gap. On the other hand, opposing views also exist, with studies like those conducted by Wu et al. (2023) arguing that structural transformations driven by the digital economy may, under certain conditions, aggravate the income gap between urban and rural areas. Furthermore, the persistent digital divide, which includes disparities in both access to and utilization of digital technologies, has been identified by scholars such as Fuchs and Horak (2008) and Zhang et al. (2020) as a critical factor contributing to the widening income gap between rural and urban regions.

Additionally, several studies have explored the potential non-linear effects of digital economy development on the urban-rural income gap. For instance, Chen and Lin (2013) argue that the relationship between economic development and the urban-rural income gap in China demonstrates a U-shaped trend. They observe that the gap first narrows during the initial stages of economic growth but widens again as development progresses, ultimately challenging the applicability of Kuznets' inverted U-shaped curve to the Chinese context. In contrast, Jin and Shao (2016) suggest that the income gap in China exhibits a more robust inverted U-shaped pattern, driven by the dual processes of modernization and the transition from a planned to a market-oriented economy. Further, Cheng and Zhang (2019) provide both theoretical and empirical insights into the non-linear dynamics between Internet penetration, a key component of the digital economy, and the urban-rural income gap. Using provincial panel data spanning from 2003 to 2016, they reveal that the relationship

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follows an inverted U-shaped trajectory. Specifically, they find that Internet penetration initially amplifies the urban-rural income gap, but once a critical inflection point, identified as occurring around 2009, is reached, this trend reverses, and the gap begins to narrow. Their findings underscore the transformative potential of Internet technologies in mitigating income disparities between urban and rural areas, particularly when digital tools and platforms become more widely accessible.

This study posits that the early stages of digital economy development in China were characterized by pronounced disparities in digital infrastructure and technological capabilities between urban and rural regions. These disparities resulted in a primary digital divide, reflected in unequal access to physical infrastructure, such as broadband and mobile networks, and a secondary digital divide, involving differences in individuals' capacities to process, interpret, and leverage digital information effectively. Together, these divides contributed to the gradual widening of the urban-rural income gap during the initial phase of digital economy development. However, as digital technologies became more widespread and affordable, rural residents began to derive significant benefits from the digital economy. For example, the proliferation of e-commerce platforms, mobile payment systems, and other digital innovations has enabled rural households to access broader markets, reduce production costs by bypassing traditional intermediaries, and allocate resources more efficiently. Moreover, these advancements have created new employment opportunities outside of agriculture and fostered entrepreneurial activities, further supporting rural income growth and narrowing the income gap.

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From a theoretical perspective, the principle of diminishing marginal returns provides a useful framework for understanding the evolving relationship between digital economy development and the urban-rural income gap. This principle suggests that as the digital economy progresses, its incremental impact on reducing the income gap tends to decline. To capture this non-linear dynamic, the inclusion of a squared term for the digital economy development index ($DEDI^2$) in empirical models is essential. Such an approach allows for the identification of critical thresholds, where the marginal benefits of digital economy development begin to diminish or even reverse. This theoretical insight aligns with the findings of numerous empirical studies, which collectively suggest that while the digital economy initially exacerbates income disparities, its longer-term effects are more complex and context-dependent.

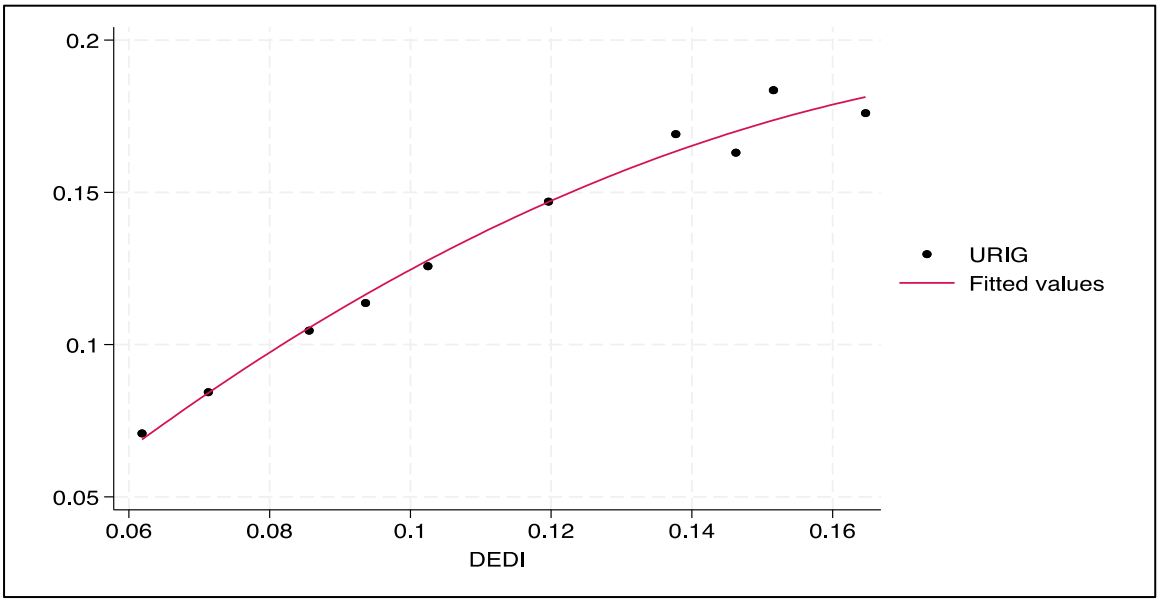
Lastly, Figure 1.4 provides empirical support for the inverted U-shape relationship between DEDI and URIG. The scatterplot, which examines the relationship between the URIG and the DEDI across China from 2013 to 2022, reveals a clear inverted U-shaped trend. Specifically, the analysis shows that in the initial stages of digital economy development, increases in the DEDI are associated with a widening income gap. However, once the DEDI surpasses a certain threshold, further increases are correlated with a narrowing of the gap, illustrating the dual impact of DEDI on URIG.

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Figure 1.4

Relationship between DEDI and URIG in China (2013–2022)



Therefore, this research proposes the first research hypothesis in line with research objective two, from aggregate perspective:

H1: The impact of digital economy development on the urban-rural income gap in China follows an inverted U-shape from an aggregate perspective.

1.5.2 Regional heterogeneity

In examining the regional heterogeneity of the impact of digital economy development on the urban-rural income gap in China, this study draws upon Regional Economics Theory, which highlights spatial disparities as critical factors in economic development. This theory examines the distribution of economic activities across regions, accounting for disparities in resources, infrastructure, and policy

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environments. Key concepts such as location theory and industrial clusters highlight how geographic and policy factors contribute to varied development trajectories across regions. Additionally, Regional Economics Theory underscores the role of regional innovation systems, wherein interactions among local governments, enterprises, and research institutions significantly influence the effectiveness of digital economy initiatives. By incorporating these principles, the study recognizes that the impact of digital economy development is not uniform across regions but varies according to distinct regional characteristics, supporting the hypothesis that regional heterogeneity plays a crucial role in shaping the urban-rural income gap.

China's vast territory and diverse regional characteristics have led to significant economic disparities across the country, which have been formalized into four distinct economic regions under the Eleventh Five-Year Plan for National Economic and Social Development (2006–2010): Eastern, Central, Western, and Northeastern regions[1]. These categories are based on variations in economic development, infrastructure capacity, and historical as well as geographic conditions.

China's four major economic regions, which are named the Eastern, Central, Western, and Northeastern regions, exhibit significant disparities in terms of economic development, infrastructure, and digital economy readiness, which

[1] The Eastern region encompasses Beijing, Tianjin, Hebei, Shandong, Jiangsu, Zhejiang, Shanghai, Fujian, Guangdong, and Hainan. The Central region includes Henan, Shanxi, Hubei, Hunan, Anhui, and Jiangxi. The Western region comprises Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang. The Northeastern region consists of Heilongjiang, Jilin, and Liaoning.

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influence the effects of digital economy development on the urban-rural income gap. The Eastern region leads with its advanced infrastructure, robust innovation ecosystem, and open institutional environment, enabling it to reap substantial benefits from digital economy advancements (Fan & Sun, 2013; He et al., 2019; Wei, 2015). In contrast, the Central and Western regions, characterized by slower economic growth, limited resources, and less openness, face greater obstacles in leveraging the digital economy to narrow the income gap (Wei, 2015). Meanwhile, the Northeastern region, though historically an industrial powerhouse, struggles with outdated industrial structures and institutional challenges, which hinder its ability to fully capitalize on digital transformation (Zhang et al., 2024). These regional differences highlight the need for tailored strategies to address the unique challenges and opportunities across China's diverse economic landscape.

These regional differences suggest that the impact of digital economy development on the urban-rural income gap varies significantly across China. In more developed regions, where digital economy growth may have already reached a saturation point, its marginal effect on narrowing the urban-rural income gap could be diminishing. In contrast, in less developed regions where the digital economy is still in its early stages of development, the potential for reducing income disparities may be more significant, as these areas have greater room for growth and innovation. Therefore, the impact of digital economy development on income disparities is likely to differ depending on the level of development and the specific challenges faced by

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each region. Based on the above analysis, this research proposes the second hypothesis in line with research objective two, , from disaggregate perspective:

H2: Regional heterogeneity exists in the impact of digital economy development on the urban-rural income gap across China's four major regions.

1.5.3 Mediating effect of industrial structure

The development of the digital economy has a transformative impact on various facets of economic activity, particularly in the upgrading and optimization of industrial structures (Liu & Chen, 2021; Mason et al., 2021). As digital technologies become more integrated into the economy, they drive significant changes in how industries operate, often leading to more efficient, innovative, and higher-value-added sectors (Jiang, 2017; Zhou et al., 2022). This process of industrial evolution can significantly impact income disparities between urban and rural areas. The industrial structure refers to the composition of different sectors within an economy and their relative importance (Peneder, 2003). A well-optimized and upgraded industrial structure can lead to more equitable income disparities by enhancing productivity, creating better employment opportunities, and fostering regional economic development. Conversely, a lack of such optimization might exacerbate income inequality.

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The benefits of digital economy development are channeled through the process of optimizing the industrial structure (Qi & Chu, 2021; Ge et al., 2022). As digital technologies facilitate the restructuring of industries toward higher productivity and efficiency, the resultant economic benefits could lead to a more balanced income disparities between urban and rural areas. Industrial structure optimization, characterized by a shift toward more advanced and diversified industries, may help in bridging the income gap by providing better employment opportunities and enhancing regional economic integration. Digital economy development impacts the urban-rural income gap by driving the upgrading of the industrial structure. Industrial structure upgrading involves transitioning from traditional, lower-value-added industries to more advanced, higher-value-added sectors. This shift can enhance economic growth and income generation in both urban and rural areas, potentially reducing disparities. The upgrading process, facilitated by digital innovations, may lead to a more dynamic and inclusive economic environment, thereby influencing the disparities of income between urban and rural regions. Based on the analysis of previous studies as discussed in section 2.5.2, the current study proposes the following hypotheses in line with research objective three**:**

H3: Digital economy development affects urban-rural income gap through industrial structure optimization.

H4: Digital economy development affects urban-rural income gap through industrial structure upgrading.

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1.6 Significance of the study

This study aims to provide in-depth insights into the pressing issue of how the development of the digital economy influences the urban-rural income gap. Its significance lies in its ability to contribute both theoretically and practically. On the theoretical front, the study seeks to establish a comprehensive framework that delineates the pathways through which digital economy development affects the urban-rural income gap, with particular emphasis on the role of industrial structure as a mediating factor. On the practical front, it endeavors to offer actionable recommendations to policymakers, aiding the formulation of targeted strategies to reduce the urban-rural income gap in China while supporting sustainable economic transformation.

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1.6.1 Theoretical contributions

The accelerated expansion of China's digital economy is profoundly transforming various domains of society and the economy. While existing research has explored the urban-rural income gap, there remains a notable scarcity of studies that integrate the perspective of digital economy development into this issue. In particular, limited attention has been given to investigating the role of industrial structure as a mediating factor within this context. This study addresses these gaps by establishing a comprehensive framework to elucidate the mechanisms through which digital economy development influences the urban-rural income gap, explicitly incorporating industrial structure as a mediator.

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Furthermore, the theoretical pathways underlying the relationship between digital economy development and income disparities are systematically analyzed. A regression model is constructed to empirically validate the effects of digital economy development on the urban-rural income gap in China. By bridging theoretical analysis with empirical testing, this research offers a deeper understanding of these dynamics.

The findings contribute to advancing the academic discourse on the interplay between digital economy development, industrial transformation, and income distribution. They also provide new insights into the mechanisms shaping urban-rural income disparities in the Chinese context, thereby enriching the literature on this increasingly important topic.

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1.6.2 Practical contribution

This study makes substantial practical contributions by serving as a reference for the formulation and implementation of targeted policies by local governments in China. Specifically, it provides a nuanced understanding of how digital economy development impacts the urban-rural income gap, with a special emphasis on the mediating role of industrial structure. By systematically exploring these relationships, the study establishes a comprehensive analytical framework that elucidates the pathways through which industrial structure moderates and amplifies the effects of digital economy development on income disparities between urban and rural areas.

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The findings are particularly valuable for policymakers seeking to design evidence-based interventions aimed at reducing income inequality. By revealing the mechanisms through which digital economy development influences the urban-rural income gap, this research offers practical recommendations to promote more inclusive and equitable economic growth. For instance, the insights gained from this study highlight the need to optimize industrial structure, foster regional innovation systems, and leverage digital technologies to create employment opportunities and enhance income levels for rural populations.

In addition, the study aligns with the strategic objectives of the Chinese government to achieve high-quality economic transformation and narrow the urban-rural development gap in the context of rapid digitalization. It sheds light on effective strategies to harness digital technology as a driving force for balanced regional development. These include promoting digital infrastructure in rural areas, encouraging digital entrepreneurship, and facilitating cross-regional collaboration to reduce resource imbalances. Moreover, this research enriches the practical understanding of digital economy dynamics by addressing the broader implications of digital transformation. It provides actionable insights into how digital tools can be utilized to improve resource allocation, increase access to education and healthcare, and reduce transaction costs, all of which are critical for alleviating urban-rural disparities.

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Beyond its policy relevance, this study also contributes to methodological advancements by validating and refining measurement tools used to evaluate the impact of digital economy development. The robust methodological approach adopted in this research ensures that the findings are both reliable and applicable to other contexts, thereby offering a replicable model for future studies examining the socioeconomic impacts of digitalization.

In conclusion, this study not only deepens the understanding of the role of digital economy development in shaping the urban-rural income gap but also provides a practical foundation for addressing one of China's most pressing socioeconomic challenges. The insights derived from this research can guide policymakers in designing targeted strategies to maximize the benefits of digital economy development while minimizing its potential drawbacks, thereby contributing to the realization of more equitable and sustainable growth.

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1.7 Limitations of the study

This study has identified several limitations that can be improved in further research. Firstly, this study only generates the digital economy development index from the four dimensions namely, digital economy development carrier, digital industrialization, industrial digitization, and digital economy development environment. Regarding the measurement of the regional digital economy development level, there is not yet a unified and mature index system. Due to the availability of data and the limitations of

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my academic ability, the index system constructed in this study cannot fully reflect the status quo of the level of the digital economy development in different regions of China. It is hoped that there will be more in-depth research in the future.

Second, this study limits its sample size to 30 provinces of in Mainland China. Additionally, this study limits the data period and only utilizes annual-based datasets, spanning from 2013 to 2022, due to data availability constraints. Nonetheless, the findings of this study achieve the research objectives and provide appropriate results for the research questions. However, future research could consider extending the time horizon by utilizing data spanning a longer period to better observe the long-term effects of digital economy development on the urban-rural income gap. Such an extended temporal scope would provide a more comprehensive understanding of how advancements in the digital economy affect income disparities over time. Additionally, incorporating municipal-level data in future studies could enable a more detailed analysis, revealing more specific regional differences and trends. This approach would offer deeper insights into the variability of digital economy effects across smaller geographic units, thereby enhancing the robustness and nuance of the findings regarding the relationship between digital economy development and urban-rural income gap.

The third limitation concerns the selection of the variables. This study's regression analysis included only a limited number of macroeconomic variables,

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which may not fully capture the complex factors that influence the urban-rural income gap in China. The indirect impact of digital economy development on this income disparity are likely mediated by a broader range of factors. By focusing on a subset of explanatory variables, this research may have overlooked other potential mediating factors. Consequently, the findings might not be comprehensive or fully representative of the multifaceted nature of the issue. Future research should aim to incorporate additional variables to explore their roles in the mechanisms at play, thereby providing a more nuanced understanding of the relationship between digital economy development and the urban-rural income gap.

1.8 Theoretical framework

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The framework in Figure 1.5 shows the main relationships among the key variables of this study, and the related theory is comprehensively introduced in Chapter 2.

Figure 1.5 illustrates the theoretical framework of this study, which investigates the impact of digital economy development (DEDI) on the urban-rural income gap (URIG) in Mainland China. The framework posits both direct and indirect pathways through which the digital economy affects income disparity.

The independent variable is digital economy development (DEDI), which is hypothesized to influence the dependent variable, the urban-rural income gap (URIG).

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The direct effect captures how improvements in digital infrastructure, accessibility, and usage may either widen or reduce income disparities between urban and rural regions.

The indirect effect is modeled through mediating variables, specifically components of industrial structure transformation: the optimization of industrial structure (OIS) and the upgrading of industrial structure (UIS). These dimensions reflect the structural changes in the economy induced by digitalization, in line with industrial convergence theory, which suggests that digital technology facilitates industrial integration and evolution, particularly benefiting less developed rural areas.

The framework also includes five control variables. They are economic development level, openness, fiscal expenditure, educational attainment, and urbanization rate, which accounting for other socioeconomic factors potentially influencing the urban-rural income gap.

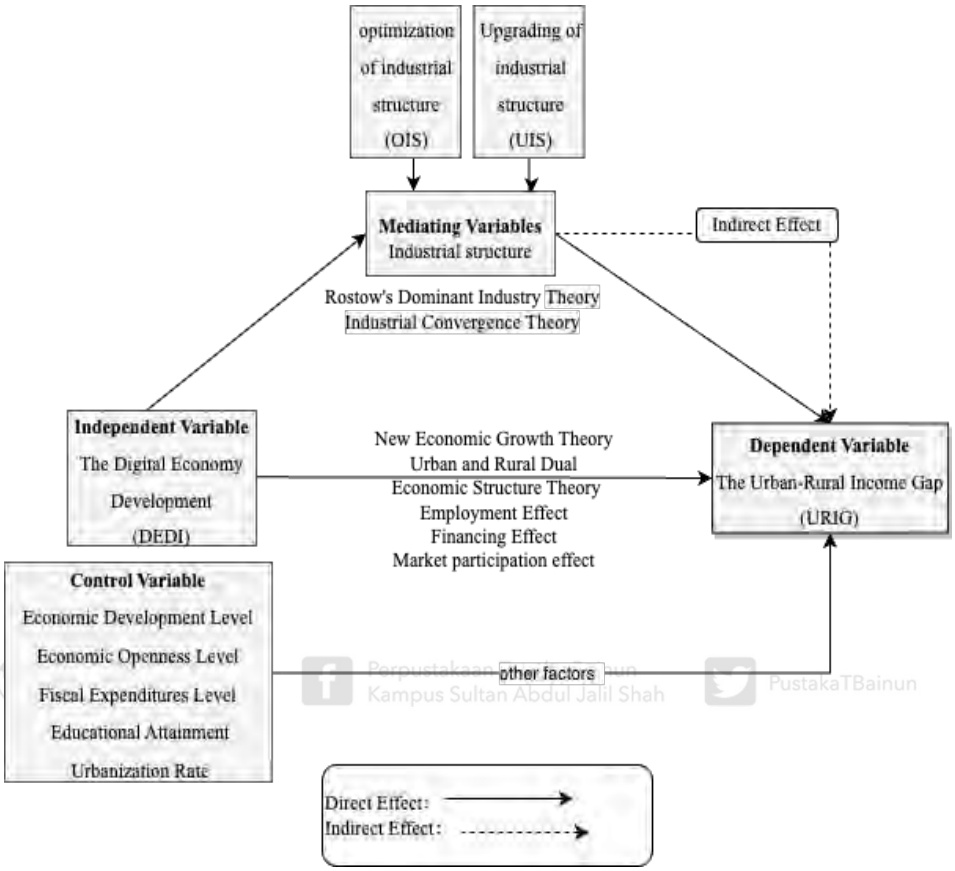
This theoretical framework provides the basis for empirical testing using a mediation analysis within a dynamic panel modeling approach, aimed at disentangling the pathways through which digital development impacts inequality in China.

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Figure 1.5

The Theoretical Framework



1.9 Operational definition

The following terms and definitions are included in this research mainly primarily focusing on digital economy, digital economy development, urban-rural income gap, optimization and the upgrading of industrial structure, economic openness, fiscal expenditures, educational attainment and urbanization rate.

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i. Digital Economy

The concept of digital economy, in the context of this study, is specifically aligned with the official definition established by Chinese authorities. The most recent version of the Classification of Digital Economy and Its Core Industries (2021), published by the National Bureau of Statistics of China, provides a framework for understanding the digital economy in China. According to this official classification, the digital economy is viewed as a comprehensive set of economic activities that depend heavily on data as a fundamental resource for production, with modern information networks acting as critical enablers. Furthermore, it highlights the importance of information and communication technology (ICT) as a driving force for improving operational efficiency and optimizing the overall economic structure. Key elements of the digital economy include the development of infrastructure, the openness and inclusiveness of the Internet economy, the focus on cyber security and privacy, consumer empowerment, and the fostering of innovation and sustainability.

In this study, the operational definition of digital economy development refers to the level or degree to which the digital economy has advanced in China. To measure this, we employ the Digital Economy Development Index (DEDI), which captures four critical dimensions: the digital economy development carrier, digital industrialization, industrial digitization, and the development environment for the digital economy.

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ii. Urban-rural Income Gap

The urban-rural income gap (URIG) refers to the disparity in average income levels between urban and rural populations within a given geographical region (Kumar, 2014). This gap is typically quantified by calculating the ratio of the average income of urban households to that of rural households. A higher ratio indicates a greater disparity in income, and therefore, a wider urban-rural income gap (Sicular et al., 2007). An alternative approach to measuring this gap involves analyzing the distribution of income within each area and comparing the proportion of households with higher or lower income levels between urban and rural settings (Sicular et al., 2007). A more pronounced income gap generally suggests that a substantial segment of rural households struggles to reach a standard of living comparable to urban households. In this research, the Theil index are used to quantify the urban-rural income gap, as it offers a precise measure of income inequality and regional disparities.

iii. Optimization and Upgrading of Industrial Structure

From a dynamic economic perspective, the adjustment and development of an economic system's industrial structure can be viewed through two main processes: the optimization and upgrading of industrial structure (Gan et al., 2011). The optimization of industrial structure (OIS) refers to the extent to which industries align with one another, ensuring efficient resource allocation and improving coordination. This

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involves examining the balance and interaction between input and output structures, which ultimately indicates the degree of economic aggregation within a region or nation (Zhang, Tang, & Yan, 2024). On the other hand, the upgrading of industrial structure (UIS) entails the gradual shift of a country's economic focus from the primary sector (such as agriculture) to the secondary (industry) and tertiary sectors (services). This shift often signifies the nation's level of economic development and determines the direction of future growth (Guan et al., 2022). Together, these processes are essential for understanding the evolving dynamics of a country's industrial landscape and its ability to meet new developmental challenges.

iv. Economic Development

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Economic development (ED) refers to the scope, pace, and depth of a nation's economic progress. It plays a pivotal role in examining the disparities and growth trajectories of different regions within a country, particularly between urban and rural areas. In this study, per capita Gross Domestic Product (GDP) is adopted as the key indicator of economic development. Per capita GDP measures the total economic output of a region or nation divided by its population size, offering a comprehensive reflection of the average economic wellbeing and standard of living of individuals in the area (Li & Li, 2022).

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v. Economic Openness

Economic openness (EO) refers to the extent to which a country or region actively engages in international economic exchanges. This concept is critical for understanding how a nation's integration into the global economy can influence domestic economic conditions, including income disparity. To measure economic openness, this study uses the ratio of total imports and exports relative to the Gross Domestic Product (GDP) of the region where the enterprise is located, which provides a clear indication of the region’s involvement in global trade (Li & Li, 2022).

vi. Fiscal Expenditures

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Fiscal expenditure (FE) refers to the total amount of government spending during a specific period, covering areas such as public services, infrastructure, social welfare, education, healthcare, and more. The level of fiscal expenditure often serves as an indicator of government involvement and intervention in the economy, reflecting priorities in public spending (Qin, 2022). This variable is crucial for this study as it helps measure the government's role in mitigating the urban-rural income gap through public policies and investments. Specifically, the study used general government expenditure as a percentage of GDP, which helps control for the potential impacts of government spending on the economy and its influence on income distribution.

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vii. Educational Attainment

Educational attainment (EA) refers to the highest level of education an individual has completed. This measure is typically expressed in terms of years of formal education or academic qualifications. In the context of this study, educational attainment is measured by the average number of years of education per capita, which serves as a key indicator of human capital development and the capacity for skill acquisition (Li & Li, 2022). The level of education directly influences an individual's potential for economic mobility, thus affecting income levels in both urban and rural areas.

viii. Urbanization Rate

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Urbanization refers to the process by which a population shifts from rural to urban areas, leading to the expansion of urban regions and a reduction in rural populations. This process includes various facets such as demographic, regional, social, and spatial urbanization (Wang et al., 2012). The urbanization rate (UR) is typically quantified by calculating the proportion of the urban population relative to the total population (including both agricultural and non-agricultural sectors) within a region (Arif, 2013). This measure is important for understanding the scale and pace at which urbanization occurs, as well as its potential effects on income distribution and regional economic disparities.

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1.10 Summary

This chapter outlines the background and problem statement of the study. In recent years, the digital economy has experienced rapid growth globally, with China emerging as the second-largest globally. Despite this advancement, China continues to face one of the widest urban-rural income gaps, a persistent issue that has drawn significant attention from the government. The government is actively seeking to leverage digital economy development to reduce this income disparity and promote the goal of achieving common prosperity. This study investigates not only the direct impact of digital economy development on the urban-rural income gap, but also the mediating role of industrial structure adjustments. Additionally, it examines the related challenges and opportunities in government policies and practical applications. The next chapter provides a theoretical and empirical review of previous literature on the key theories and variables relevant to this study.

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CHAPTER 2

LITERATURE REVIEW

2.0 Introduction

This research aims to explore the impact of digital economy development on the urban-rural income gap and examine the mediating role of industrial structure optimization and upgrading in this process, from both theoretical and empirical perspectives. While significant studies have been conducted in the fields of digital economy development (Barata, 2019; Lechman, 2022; Li et al., 2020; Mulaydinov, 2021; Park et al., 2019), income disparity (Jiang, Li, & Si, 2022; Myovella et al., 2020; Wang et al., 2021) and industrial structure adjustment (Han & Li, 2022; Li, 2021; Yang & Zhao, 2014; Zhao et al., 2022), the interrelationships between these constructs have received limited attention in existing literature. Furthermore, there is a gap in research addressing the innovative interactions between these factors, specifically the mediating effect of industrial structure, in a single empirical study.

This study seeks to bridge these gaps by investigating the intertwined effects of digital economy development, industrial structure optimization, and the

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urban-rural income gap. Scholars and policymakers have increasingly turned their attention to the impact of digital economy development on income disparity, particularly in China (Peng & Zheng, 2022). The digital economy, characterized by technological advancements and innovation, is often viewed as a catalyst for economic growth (Dimaggio & Bonikowski, 2008; Jurayevich & Bulturbayevich, 2020). However, its effects on income inequality, specifically the urban-rural income gap, remain contentious (Liu, 2021; Myovella et al., 2020). Much of the existing research on digital economy development has primarily focused on its role in driving economic growth (Jurayevich & Bulturbayevich, 2020) or or industrial structure adjustments (Wu & Shao, 2022).

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Therefore, the main objective of this chapter is to provide a comprehensive review of both theoretical and empirical literature on the relationships between digital economy development, the urban-rural income gap, and the optimization and upgrading of industrial structure. The following sections of this chapter outlines the relevant theoretical frameworks, review previous studies on digital economy development, the urban-rural income gap, and industrial structure optimization, and explore the mechanisms through which these factors interact. Additionally, a review of the pertinent literature examining the interconnections between these elements are presented, followed by a summary of identified research gaps in the existing body of work.

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2.1 Related theories

In order to establish the theoretical framework of this study, several theories can be utilized. The following section explains these theories.

2.1.1 New economic growth theory

The new economic growth theory builds upon the foundations of neoclassical economic growth theory (Coccia, 2019; Lucas, 1988; Solow, 1988). Neoclassical theory incorporates technological progress as an external factor in economic growth models. However, because it does not address the source of technological progress, it falls short of explaining sustained economic growth and variations in growth rates across regions. In the 1980s, Romer, Lucas, and others advanced a new economic growth theory to address these limitations (Lucas, 1988). Romer emphasized the role of knowledge, positing that knowledge can be reused without additional cost, thereby enhancing the value of both capital and labor and generating positive externalities (Romer, 1990). By incorporating knowledge and technology into the production factor system, production efficiency can be significantly improved. Lucas, on the other hand, highlighted the crucial role of human capital, replacing labor with human capital as a factor of production in his growth model (Lucas, 1988). Human capital encompasses not only the quantity of labor but also includes individuals' education level, labor skills, and literacy, which collectively contribute to economic growth (Lucas, 1988).

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The new economic growth theory emphasizes that economic growth is fundamentally linked to two key factors: technology and human capital. In the context of urban and rural areas, economic development in urban regions typically outpaces that of rural areas due to the advanced technologies available in cities and the superior quality of the urban labor force compared to the rural population. Urban areas are generally better equipped with cutting-edge technologies and benefit from a higher concentration of skilled workers, creating a significant gap between urban and rural economies. However, the emergence of the digital economy has begun to address these disparities by bridging the technological and human capital gaps between urban and rural regions. By leveraging digital technologies, the rigid dual economic structure that once existed between urban and rural areas has been weakened, contributing to a gradual reduction in the income gap between these two regions.

In particular, digital technology, as a representation of the current advanced technological level, plays a central role in driving the digital economy. The rapid advancement of digital technologies has significantly accelerated the speed at which information circulates, thereby facilitating the faster dissemination of knowledge. This increased flow of information has helped narrow the technological and human capital gaps between urban and rural populations. Knowledge externalities, which refer to the beneficial spillover effects of information and expertise, have played a

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key role in enabling rural residents to access new technologies and improve their skills, thereby closing the developmental divide between rural and urban areas. As rural economies continue to absorb and apply these technological advancements, the income levels of rural residents have started to rise, gradually aligning with those of their urban counterparts.

Thus, from the perspective of new economic growth theory, the development of the digital economy has the potential to reduce the income gap between urban and rural areas by fostering technological innovation and enhancing human capital. This process ultimately facilitates the economic catch-up of rural areas and promotes a more balanced income distribution across regions.

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The classic CES (Constant Elasticity of Substitution) function, which assumes a constant elasticity of substitution between production factors as opposed to the unit elasticity in the Cobb-Douglas production function, has been widely adopted. Drawing from Feng (2017) study on the impact of biased technological progress on the marginal output of capital and labor, we can explore the direction of digital technological progress and its implications for the urban-rural income gap. Assuming the production function is the classic CES production function:

$$Y_t = A_t\left[\alpha K_t^{\frac{\sigma-1}{\sigma}} + (1-\alpha)N_t^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{2.1}$$

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Where A_t represents the Hicks-neutral technological progress parameter, Y_t, K_t and N_t denote total output, capital input, and labor input, respectively. The parameter α signifies the factor inequality parameter, and σ indicates the elasticity of substitution between factors. With the theoretical advancement and expanding application of the CES function, the assumption of Hicks-neutral technological progress has been questioned (Acemoglu, 2002). The direction of technological progress varies with the relative scarcity of factors. To reflect the direction of technological progress in the CES production function, it is common to introduce factor-augmenting coefficients Γ_t^K and Γ_t^N, setting the generalized technological progress parameter to 1. This results in a CES production function with biased technological progress, as shown below:

$$Y_t = A_t\left[\alpha(\Gamma_t^K K_t)^{\frac{\sigma-1}{\sigma}} + (1-\alpha)(\Gamma_t^N N_t)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{2.2}$$

Derivative both sides with respect to K and N, then

$$\frac{\partial Y_t}{\partial K_t} = \alpha\left(\frac{Y_t}{K_t}\right)^{\frac{1}{\sigma}}(\Gamma_t^K)^{\frac{\sigma-1}{\sigma}} \tag{2.3}$$

$$\frac{\partial Y_t}{\partial N_t} = (1-\alpha)\left(\frac{Y_t}{N_t}\right)^{\frac{1}{\sigma}}(\Gamma_t^N)^{\frac{\sigma-1}{\sigma}} \tag{2.4}$$

Marginal product of capital to labor ratio is as follows:

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$$\Delta_t = \frac{\partial Y_t / \partial K_t}{\partial Y_t / \partial N_t} = \frac{\alpha}{1-\alpha}\left(\frac{\Gamma_t^K}{\Gamma_t^N}\right)^{\frac{\sigma-1}{\sigma}}\left(\frac{N_t}{K_t}\right)^{\frac{1}{\sigma}} \tag{2.5}$$

When $\frac{dln(\Gamma_t^K)}{dt} > \frac{dln(\Gamma_t^N)}{dt}$, the relative marginal output of capital to labor increases, indicating a greater enhancement of capital's marginal output compared to labor's. This suggests a capital-augmenting or labor-saving technological progress direction. Conversely, when $\frac{dln(\Gamma_t^K)}{dt} < \frac{dln(\Gamma_t^N)}{dt}$, the technological progress is labor-augmenting or capital-saving. When technological progress favors capital, causing the marginal output of capital to grow faster than that of labor, wealth tends to flow towards those who possess significant capital, leading to a widening income gap. On the other hand, when technological progress favors labor, it endows labor with higher productivity, resulting in wealth flowing towards labor providers (workers) and narrowing the income gap.

The digital economy, derived from advancements in digital technology, continuously expands its scope as digital technology develops. Digital technology affects the marginal output ratio of capital to labor, thereby impacting the income disparities within society. In the early stages of digital technology development, it is predominantly applied in capital-intensive industries such as finance and high-end manufacturing, which are mainly concentrated in urban areas and develop alongside urban agglomeration. The enabling effect of digital technology accelerates the

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marginal output of capital relative to labor, indicating a capital-augmenting or labor-saving technological progress direction, thus widening the urban-rural income gap. As digital technology further advances, the economies of scale and scope become prominent, reducing the application costs of digital technology and extending its reach to rural areas. At this stage, the relative diminishing returns to capital and the increasing returns to labor shift the direction of digital technological progress to capital-saving or labor-augmenting. Consequently, labor-intensive industries in rural areas experience relatively faster development, narrowing the urban-rural income gap. Therefore, the progress of digital technology and the urban-rural income gap exhibit an inverted U-shaped relationship.

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2.1.2 Urban and rural dual economic structure theory

The theory of urban-rural dual economic structure originated in the 1950s and was first proposed by the British economist Lewis (Du et al., 2023). Later, LaniYs, Jorgensen and others revised it.

In 1954, Lewis proposed the famous dual economy theory, which pointed out that in developing countries, there coexist the traditional agricultural sector with low productivity and the modern non-agricultural sector with relatively high productivity. The rural economy has the characteristic of small-scale production, while the urban economy has the characteristic of socialized production. The workers' income in the

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urban economy is higher, and labor shift from the low-income traditional sector to the high-income modern sector. In the early stages of urbanization, this widen the income gap. With the transfer of rural labor, the rural productivity is liberated, and the marginal productivity rises, which leads to an increase in wages. In theory, Lewis stated that the production sectors of developing countries are divided into two types, namely modern industrial sectors and traditional agricultural sectors (Gollin, 2014). Manufacturing is the center of modern industry, while agriculture is the center of the traditional agricultural sector. The productivity of the industrial sector is higher than that of agriculture, and its profits are used to invest in reproduction. The industrial sector is characterized by a small labor force that can be accommodated and a high wage level. However, the labor productivity in the agricultural sector is low. Its labor income can only maintain a living, and there is a large amount of hidden unemployment. That is, there is a labor surplus (Gollin, 2014).

Ranis–Fei model. John Feiand and Gustav Ranis find that Lewis' dual economic structure theory ignored the important role of agriculture. Feiand and Ranis improve it and emphasized the importance of agriculture to economic growth. They believe that the surplus of agricultural products caused by the increase of agricultural labor productivity is the prerequisite for the transfer of agricultural surplus labor force, and the outflow of surplus labor force from the agricultural

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sector form agricultural accumulation at the same time (Ranis & Fei, 1963). They believe that labor transfer in the agricultural sector go through three stages: the first stage is the outflow of labor from agriculture with zero labor productivity; In the second stage, the labor force whose labor productivity is greater than zero but lower than the average output of the agricultural sector flows out of agriculture, leading to a decrease in the output of agricultural products and a shortage of supply; The third stage is that after the surplus labor force in the previous two stages flows into the industrial sector, the labor transfer between the agricultural sector and the urban sector forms a dynamic balance (Ranis & Fei, 1963).

According to the urban-rural dual economic structure theory, the main reason for the urban-rural income gap is the difference in production efficiency between the two sectors of agriculture and industry. In order to break the dual economic structure, the efficiency of agricultural production must be improved (Timmer, 1988). Farmers' low level of knowledge, backward technical conditions, and lack of funds are all important reasons for agricultural production efficiency (Timmer, 1988). By accelerating the movement of urban knowledge, technology, and capital to rural areas, the digital economy's development can increase agriculture's productivity (Jiang, Li, Si, et al., 2022). The improvement of agricultural production efficiency further increase the rural surplus labor force, and the non-agricultural employment of the rural surplus labor force become crucial.

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The digital economy development could improve the employment efficiency of rural surplus labor and increase the employment channels of rural surplus labor. On the one hand, the digital economy makes information circulation more efficient, and the channels for rural residents to obtain employment information and knowledge are more diversified, which not only reduces the occupational income cost of rural residents, but also improves the human capital of rural residents, enabling them to work in non-agricultural employment. Increased job search efficiency in the marketplace. On the other hand, the digital economy development has spawned many new economic forms such as e-commerce, sharing economy, live broadcasting, etc., creating a large number of emerging jobs, and the entry threshold for these jobs is relatively low, expanding the employment options for rural surplus labor. At the same time, with the development of information technology, rural areas are no longer closed, high-quality agricultural products no longer need to be sold through word of mouth, but through the Internet can increase popularity, expand sales, and increase farmers' income. Therefore, the theory of urban-rural dual economic structure is an important theoretical basis of this research.

2.1.3 Information asymmetry theory

The Information Asymmetry Theory, a foundational concept in information economics, explores how unequal access to information influences economic

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behaviors and outcomes. Unlike the classical economic assumption of perfect information, where all individuals are presumed to have equal and comprehensive knowledge, this theory acknowledges the reality of information imbalances. In economic activities, some individuals or entities possess superior information, granting them advantages in decision-making and negotiations, while others with limited access to information face challenges and may experience unfavorable outcomes (Balakrishnan & Koza, 1993). The theory suggests that disparities in information access often result in market inefficiencies, particularly in areas such as labor markets, financial services, and product markets (Alogoskoufis et al., 2023). In these scenarios, those with more information can optimize their choices, whereas others are constrained by incomplete or inaccurate knowledge. This dynamic is especially relevant in contexts characterized by significant regional or socioeconomic disparities, such as the urban-rural divide in China.

With the rapid development of the digital economy, the ways in which information is accessed and disseminated have undergone transformative changes. Digital technologies have the potential to mitigate information asymmetry by making knowledge more readily available and reducing barriers to participation in economic activities (Deichmann et al., 2016). Platforms such as e-commerce, online education, and digital finance enable broader access to information, theoretically empowering rural populations to engage more effectively in markets and economic

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opportunities (Li & Zhang, 2024). As a result, the digital economy is often viewed as a means to bridge the urban-rural income gap by reducing the informational disadvantages traditionally faced by rural residents.

However, the reality is more complex. While digital tools can enhance access to information, disparities in digital infrastructure and literacy between urban and rural areas create a persistent digital divide (Abdullahi & Muhammad, 2024). Urban regions generally benefit from superior internet connectivity, higher penetration of digital services, and better digital literacy among residents (Wang, et al., 2021). In contrast, rural areas often lack adequate infrastructure and face higher costs of accessing information, further widening the gap (Wang, et al., 2021). This divide manifests in several ways that limit the potential of the digital economy to alleviate rural disadvantages. First, rural residents often incur higher search costs when seeking job opportunities, market prices, or educational resources due to limited digital access and skills. For instance, older generations and individuals with lower educational attainment may find it challenging to navigate digital platforms effectively, reducing their ability to leverage online resources for economic gain. Second, the inadequate availability of high-speed internet and advanced digital tools in rural areas restricts participation in online markets, training programs, and digital financial services. This disadvantage reinforces existing inequalities in income and economic mobility.

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Furthermore, the quality of information available to rural populations can differ significantly from that in urban areas. Urban residents often access more timely, accurate, and diverse information, while rural communities may rely on outdated or less relevant sources (Abdullahi & Muhammad, 2024). This discrepancy can perpetuate imbalances in decision-making, such as job selection or market participation, thereby maintaining or even exacerbating the income gap. For example, urban workers are more likely to benefit from job postings and training opportunities shared through advanced digital networks, whereas rural workers may struggle to access similar information, resulting in fewer opportunities for upward mobility (Au, 2023).

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Given these challenges, the role of digital economy in addressing information asymmetry and income ineaquality depends heavily on reducing structural barriers in rural areas. Expanding digital infrastructure, promoting digital literacy, and lowering the costs of accessing information are critical steps toward ensuring that rural populations can benefit more equitably from digital advancements. This study incorporates Information Asymmetry Theory as a key theoretical framework to analyze how the digital economy influences the urban-rural income gap in mainland China. It explores the interplay between digital economy development, regional disparities in information access, and structural challenges that hinder the narrowing of income inequality. By examining the mediating role of

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industrial structure, this research aims to provide deeper insights into how digital tools can reshape economic participation and opportunities in rural areas, ultimately contributing to reducing the income gap.

In summary, Information Asymmetry Theory highlights the crucial role of information distribution in determining economic outcomes. While the digital economy offers significant potential for reducing information-related disadvantages and fostering economic equity, the persistent digital divide between urban and rural areas underscores the need for targeted interventions. Addressing these disparities is essential to ensure that the benefits of digital economy development are shared equitably and contribute meaningfully to narrowing the urban-rural income gap in China.

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2.1.4 Inclusive growth theory

The concept of inclusive growth, initially introduced by the Asian Development Bank in 2007, emphasizes the importance of fostering economic growth that is accessible to all segments of society. This model advocates for broad participation in economic activities, where every individual, regardless of their social or economic background, can share the benefits of growth (Ali & Son, 2007). Inclusive growth goes beyond simply reducing poverty. It aims to integrate all social groups into the economic fabric, ensuring that the disadvantaged and marginalized populations are

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included in the development process. As such, it seeks to address inequalities by creating more equitable opportunities for people across different regions, particularly rural and urban areas.

Inclusive growth also aligns with the concept of pro-poor growth, which specifically emphasizes that economic development should result in measurable benefits for the poor. This concept was formalized in the early 2000s by development economists such as Ravallion and Chen (2003), who proposed that growth can be considered pro-poor only if it leads to a reduction in poverty. They introduced the growth incidence curve (GIC) as a tool to evaluate whether the benefits of growth are disproportionately accruing to poorer segments of the population. In contrast to earlier models, such as Kuznets' inverted U-shaped hypothesis, which suggested that income inequality would naturally decrease as economies mature, empirical evidence from the rapid growth periods of the 1980s in many developing countries revealed that economic expansion can, in fact, exacerbate income disparities. This realization highlighted the need for growth strategies that are not only robust but also deliberately inclusive and equity-oriented. This discrepancy led to skepticism about the Kuznets curve, especially as developing economies witnessed simultaneous economic growth and rising inequality (Bahmani-Oskooee & Gelan, 2008). In response to this, scholars began proposing more inclusive approaches, arguing that economic growth must be

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designed to benefit everyone, especially the poor, by ensuring they can equally participate in economic activities and share in the benefits of development.

The concept of inclusive growth broadens the focus of pro-poor growth by suggesting that economic development should not solely target the poor but should encompass all social classes, ensuring that everyone has access to the benefits of progress (Niekerk, 2020). This framework emphasizes the need for policies that reduce inequalities and promote sustainable, equitable growth across all sectors of society. One critical component of inclusive growth is reducing the urban-rural income gap, which has long been a significant issue in many developing countries, including China.

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In China, the rural population continues to face significant socio-economic disadvantages compared to their urban counterparts. These disparities manifest in various forms, including unequal access to employment opportunities (Zhu et al.,2020), healthcare (Ma et al., 2021), education (Wu, 2024), and other basic services. The digital economy, however, offers significant potential for bridging this gap. Technologies, particularly the internet, have made it easier for rural residents to access information and economic opportunities that were previously unavailable (Ma et al., 2020). For instance, digital platforms have enabled rural workers to find employment opportunities in different sectors, offering them income opportunities beyond traditional agricultural work. Moreover, the development of e-commerce

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platforms has allowed rural residents to participate in the broader economy by selling agricultural products to a global market, reducing reliance on local intermediaries and improving their income (Li & Zhang, 2024).

The advancement of digital technologies has also facilitated access to education and healthcare in rural areas. Online education platforms and telemedicine services have become powerful tools in addressing the educational and healthcare inequality between urban and rural regions (Wang et al., 2021; Gao et al., 2022). This digital transformation enables rural residents to access high-quality resources and services, contributing to a reduction in the urban-rural income gap by improving their living standards and providing them with more equal opportunities.

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The role of digital technologies in promoting inclusive growth has gained significant attention in the context of China's efforts to reduce the urban-rural income gap. Government policies aimed at expanding internet coverage and promoting digital literacy are central to these efforts. These policies, which often focus on rural areas, are designed to provide the rural population with the tools and knowledge needed to participate fully in the digital economy. The Digital Rural Development initiatives, for instance, aim to connect rural areas with high-speed internet and provide digital skills training to local residents. By doing so, these policies help to foster economic inclusion, reduce regional disparities, and promote balanced development.

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In summary, the theory of inclusive growth emphasizes the importance of equitable participation in economic development, with a focus on reducing the urban-rural income gap. The rapid development of the digital economy provides a pathway for achieving more inclusive growth, as it offers rural populations access to economic opportunities, educational resources, and healthcare services that were previously out of reach. The integration of digital technologies into the rural economy is therefore a key factor in addressing income inequality between urban and rural areas and promoting the goal of shared prosperity for all.

2.1.5 Petty—clark theorem

William Petty, an early British economist who examined the laws of industrial structural evolution, identified differences in industrial structures as key factors influencing national income levels and stages of economic development (Luo, 2019). In Political Arithmetic*,* he argued that industry generates higher value-added than agriculture, and services generate higher value-added than industry, a concept now known as Petty's Law. Later, Colin Clark expanded on this by analyzing labor shifts across the primary, secondary, and tertiary sectors based on a three-sector classification. Clark observed that, with economic development and rising national income, labor initially moves from the primary to the secondary sector; as per capita income further increases, labor then shifts toward the tertiary sector (Fan et al., 2003).

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According to the Petty-Clark Law, the trend in industrial structural change involves a gradual decline in the share of the primary industry, accompanied by increases in the shares of the secondary and tertiary industries. This law offers fundamental guidance for understanding the evolution of industrial structure and economic development, explaining how income disparities among industries drive the distribution of labor across these sectors. As a result, labor shifts away from the primary industry, while employment in the secondary and tertiary industries progressively grows. This theory provides a basis for studying industrial upgrading and the structural shifts in output and income among the three sectors.

The Petty-Clark theorem provides a valuable framework for understanding the structural evolution of economies, particularly in the context of the digital economy development in China. With the rapid proliferation of digital technologies, the tertiary sector, which includes industries such as finance, education, and e-commerce, has experienced unprecedented growth, surpassing traditional sectors in both value creation and labor absorption (Shi &Wei, 2024). This trend aligns with the Petty-Clark prediction that economic development leads to a shift toward the tertiary sector. However, the dynamics of this transition in the digital era are more nuanced, as they interact with urban-rural inequality in infrastructure, technology adoption, and labor market accessibility.

In rural China, the primary industry (agriculture) still employs a significant proportion of the labor force, but its contribution to GDP has been declining steadily (Baležentis et al., 2021). The digital economy introduces opportunities for

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value-added activities in agriculture, such as precision farming, e-commerce platforms for agricultural products, and digital supply chains (Baležentis et al., 2021). However, the extent to which rural areas can benefit from these advancements depends heavily on access to digital infrastructure and digital literacy. This creates a dual challenge: enabling the primary industry to integrate with the digital economy while facilitating labor mobility toward higher-value-added sectors in the secondary and tertiary industries. Meanwhile, in the early stage of development urban areas, with their superior access to digital infrastructure and human capital, have seen rapid growth in the tertiary sector (Du & Wang, 2024). This divergence highlights the role of the industrial structure as a mediator in the relationship between digital economy development and the urban-rural income gap. Specifically, urban areas' accelerated transition into tertiary industries intensifies income inequality if rural regions fail to achieve comparable structural upgrading.

2.1.6 Rostow's theory of dominant industries

Rostow's theory of economic growth stages provides a foundational perspective on how economies progress over time. By categorizing economic and social development into six distinct stages, namely, the traditional society stage, the take-off prerequisite stage, the take-off stage, the maturity advancement stage, the high public consumption stage, and the pursuit of quality of life stage, Rostow (1990)

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highlights the critical role of industrial transformation in driving economic growth. A key insight of this theory is the emergence of Dominant Industries at each stage, which serve as the driving forces behind economic and social development.

Each dominant industry reflects the technological, economic, and institutional priorities of a particular stage of development. For example, in the traditional society stage, agriculture dominates due to its foundational role in sustaining livelihoods. In contrast, the take-off stage often sees the rise of manufacturing industries, as economies begin to industrialize and urbanize. These dominant industries not only define the stage-specific economic activities but also influence the transition to subsequent stages. As Rostow (1990) and Lin (2011) note, the growth and turnover of these sectors create the conditions for industrial structure upgrading, making them indispensable for sustained economic progress. The input-output relationships within these industries amplify their economic significance. For instance, a thriving manufacturing sector generates demand for upstream industries, such as raw materials, and downstream industries, such as logistics and retail. This interconnectedness enhances productivity across the economy and drives industrial evolution. However, Rostow emphasizes that these transitions must follow a logical sequence. Skipping stages or attempting to accelerate transitions prematurely often leads to inefficiencies or systemic challenges (Stough et al.,2005).

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In the contemporary era of digital transformation, Rostow's theory of dominant industries remains highly relevant. The digital economy, characterized by technologies such as big data, artificial intelligence (AI), and the Internet of Things (IoT), has emerged as a new dominant sector, reshaping traditional industries and creating unprecedented opportunities (Kumar et al., 2024). For instance, traditional manufacturing has evolved into smart manufacturing, where digital tools optimize production processes, enhance resource efficiency, and improve quality.

Moreover, the influence of the digital economy extends beyond its immediate applications. It creates a ripple effect by stimulating ancillary sectors, such as logistics, e-commerce, and financial technology (Yang et al., 2024). This interconnectedness amplifies the economic impact of the digital economy, making it a pivotal force for industrial upgrading. In China, the digital economy is not only a growth engine but also a key driver of structural transformation, particularly in underdeveloped regions (Zhang et al., 2022). Strategic industries like green technology, blockchain, and digital finance are helping to address regional disparities and enhance global competitiveness.

Rostow's emphasis on stage-appropriate development provides a framework for understanding these dynamics. In the context of China's regional heterogeneity, this theory suggests that different regions may experience distinct trajectories of digital economic growth based on their existing industrial base, infrastructure, and

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labor market conditions. For example, coastal regions, which are more advanced, may focus on high-end digital services, while inland regions could prioritize the digitalization of agriculture and manufacturing to drive development.

A particularly relevant application of Rostow's theory is in examining the relationship between dominant industries and income distribution, specifically the urban-rural income gap (Zhong et al., 2022). Dominant industries play a critical role in shaping income patterns by influencing employment, productivity, and resource allocation (Bidwell et al., 2013). In the digital economy, emerging industries like precision agriculture and e-commerce platforms have the potential to integrate rural economies into broader markets, thereby narrowing the urban-rural divide. For instance, digital tools enable rural producers to access urban markets more effectively, reducing transaction costs and increasing income opportunities (Abate et al., 2023). Similarly, the application of AI and IoT in agriculture enhances productivity, enabling rural areas to compete more effectively in national and international markets (Javaid et al., 2023). These developments align with Rostow's principle that dominant industries drive structural changes, ultimately benefiting broader segments of the population.

Drawing from Rostow's theory, fostering the digital economy as a dominant industry in China requires a balanced approach that considers the country's stage-specific development characteristics. Policymakers must identify and nurture

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strategic sectors that align with the nation's broader economic goals. For instance, investments in green technology, digital healthcare, and smart cities can address both economic and social priorities, such as environmental sustainability and public welfare.

Additionally, the integration of digital tools into traditional sectors offers a pathway for achieving industrial upgrading and narrowing income disparities. The development of rural e-commerce platforms, for example, can bridge the urban-rural divide by connecting rural producers to broader markets. Similarly, promoting digital education and skill development can enhance labor market outcomes, ensuring that more individuals benefit from the growth of dominant industries.

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2.1.7 Industrial convergence theory

Rosenberg, an American scholar, first proposed the concept of industrial convergence in 1963, pointing out that technological innovation has blurred industrial boundaries and promoted industrial convergence (Sick et al., 2019). In 1978, Negrouponte used a famous diagram to describe the technological boundaries of three different industries. He considered the intersection of the three circles to be the most innovative and promising. He pointed out that with the development of network technology, digital convergence is gradually driving the convergence of related industries (He, 2021).

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With the theory of industrial integration research, so far the definition of industrial integration has also formed a more unified view: Industrial integration is a process of gradual expansion, penetration and fusion between different industries or different sub-sectors within the same industry, thus forming new industries. External factors such as technological innovation promote industrial integration and improve industrial production efficiency and competitiveness (Greenstein & Khanna, 2010).

With the rapid advancement of the digital economy, industrial integration has emerged as a critical driver of both industrial development and economic growth (Wang et al., 2024). Through fostering technological integration across various industries, the digital economy stimulates the creation of new demand markets, encourages the relaxation of external regulatory constraints, and facilitates the widespread occurrence of industrial convergence (Sun et al., 2023). By bridging the gap between the digital economy and the real economy, it effectively blurs the boundaries between traditional industries and fosters the growth of strategic emerging industries, thereby transforming the industrial landscape (Sun et al., 2024). The integration of digital technologies with the manufacturing sector represents a significant breakthrough in industrial development. This fusion enhances the efficiency of resource allocation within traditional manufacturing processes, enabling the precise and effective execution of production and operational activities (Sun et al., 2024). Consequently, it accelerates the digital transformation of the manufacturing industry, driving its shift toward high-quality development.

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Moreover, the incorporation of digital technology into the manufacturing sector enables enterprises to streamline their operations, optimize production chains, and adopt innovative practices that enhance overall competitiveness (Attaran, 2020). Simultaneously, the deep integration of digital technology with the service industry generates a wealth of opportunities for innovation. This convergence leads to the emergence of novel models, products, services, and business frameworks that redefine industry standards. Furthermore, it promotes the "servitization" of the economy, marked by an increasing emphasis on service-oriented economic activities (Zaki, 2019). This trend not only diversifies industrial offerings but also contributes to the upgrading and optimization of the industrial structure. By driving such comprehensive transformations, the digital economy serves as a catalyst for sustainable economic development and industrial modernization.

2.2 Digital economy

In this section, relevant literature on the digital economy is presented, encompassing four main dimensions: definition, measurement methods, the impact of digital economy development, and the influencing factors.

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2.2.1 Definition of digital economy

A clear understanding of the concept of the digital economy is essential for accurately grasping its fundamental functions and specific characteristics Don Tapscott originally introduced the concept of the digital economy in 1996 (Abbos et al., 2021). With the continuous advancement of information technology, internet technology, and new generations of digital technology, the connotation of the digital economy has evolved from narrow to broad. In 1998, the U.S. Department of Commerce (BEA) released a report called The Emerging Digital Economy, pointing out that the phenomenon of high economic growth, high employment rate, and low inflation rate coexisting for 118 months in the 1990s, known as the New Economy, was due to the widespread application of information technology (U.S. Department of Commerce, 1998). At this stage, the digital economy, as denoted by research institutions and scholars, essentially pertained to the ICT industry, specifically adhering to the narrow definition of the digital economy.

Later, observing the application of Internet technology in the economic and social spheres, BEA released the series of reports Emerging Digital Economy II (U.S. Department of Commerce, 1999) and Digital Economy 2000 (U.S. Department of Commerce, 2000) in 1999 and 2000, respectively. They explicitly stated that the digital economy is a combination of the information technology production industry, usage industry, and e-commerce. The Bureau of Economic Analysis (2022)

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interprets the digital economy from the perspective of commercial operations and its economic, delineating it into three dimensions: first, the digitized infrastructure associated with computer network operations; second, the electronic commerce transactions facilitated through networks; and third, the digital media generated and utilized by users of the digital economy. The BEA primarily defines the digital economy from the standpoint of the Internet and related information and communication technologies (ICT).

The Organization for Economic Cooperation and Development (OECD) switched from Information Technology Outlook to Internet Economy Outlook in 2012. It provided a detailed explanation of the socio-economic changes triggered by the Internet. Since 2014, the OECD has replaced its Internet Economy Outlook report with the Digital Economy Outlook series, which views the digital economy as the information society and emphasises its pervasive impact (OECD,2014). The Organisation for Economic Co-operation and Development views the digital economy as a broad cluster of digital technologies and defines its scope from an ecosystem perspective. According to the OECD (2015), the digital economy constitutes an ecosystem driven by digital technologies, undergoing continuous digital transformation in the economic and social domains. This ecosystem encompasses at least big data, the Internet of Things (IoT), artificial intelligence, and blockchain technologies. At that time, the definition of the digital economy was still focused on the rapid development of the information technology industry, internet,

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and e-commerce, and did not yet cover topics such as technology empowerment of traditional industries and data becoming a production factor.

With the development of new digital technologies, such as the Internet of Things (IoT) and Artificial Intelligence (AI), and their deep integration into agriculture, manufacturing, and services industries, the boundaries of the digital economy have expanded significantly. Currently, most scholars no longer limit the definition of the digital economy to the narrow ICT industry or e-commerce but consider it as a new type of economic activity or economic form based on digital technology. BEA (2019) also explicitly points out that the digital economy is constantly evolving, and its content and scope should be updated with the application of innovative technologies (Limna et al., 2022). When defining the digital economy, different researchers have different perspectives, which can be summarized into the following three categories:

The first perspective begins by describing the phenomenon, focusing on the transformative changes in economic activities brought about by the advancement of digital technology. Kling and Lamb (1999) define the digital economy as an economic framework where the production, sales, and delivery of goods and services rely heavily on digital technology. Similarly, the European Commission (2013), the British Computer Society (2014), and Rouse (2016) conceptualize the digital economy as a novel economic model driven by the application of digital

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technologies (Bukht & Heeks, 2019). In line with this, Nathan and Rosso (2012) and Knickrehm et al. (2016) emphasize that the economic outputs derived from the integration of digital technology and digital communication devices constitute an integral part of the digital economy (Zhang & Chen, 2021). Furthermore, the UK House of Commons (2016) characterizes the digital economy as an ecosystem where goods and services are transacted through digital platforms (Bukht & Heeks, 2017). Zhang (2019) further expands this definition by describing the digital economy as a platform-based organization powered by information and communication technology, encompassing transaction platforms, data platforms, and systems that emerge through the optimized allocation of resources.

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The second perspective examines the characteristics of the digital economy, highlighting its distinctions from traditional economies in terms of driving forces, key production factors, and operational dynamics. A notable definition, formulated at the G20 Hangzhou Summit, describes the digital economy as a series of economic activities underpinned by digitized knowledge and information as core production factors, modern information networks as critical carriers, and the strategic application of information and communication technology as key drivers for improving efficiency and optimizing economic structures. Similarly, the China Academy of Information and Communications Technology (2020) defines the digital economy as a new economic form that leverages digitalized knowledge and

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information as foundational production factors, digital technology as its core driver, and modern information networks as essential carriers. This definition emphasizes the continuous progression of digitalization, networking, and intelligence through the deep integration of digital technologies.

The digital economy can be categorized into four interconnected domains. First, digital industrialization refers to the creation of industries directly based on digital technology, offering foundational technologies, products, services, and solutions that drive the broader digital economy. This encompasses sectors such as electronic information manufacturing, telecommunications, software and information technology services, and the internet industry. Second, industrial digitization involves the transformation of traditional industries through the adoption of digital technologies, which enhances productivity and optimizes production processes. Examples include the industrial internet, intelligent manufacturing, and the platform economy, which foster new business models and economic structures. Third, digital governance pertains to the application of digital technologies in the management and governance of societal systems, including multi-stakeholder governance models and digital public services. Lastly, data valorization focuses on the processes of data collection, standardization, rights confirmation, annotation, pricing, trading, circulation, and protection. These facets collectively encapsulate the foundational elements, technological attributes, and development trajectories of the

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digital economy, forming a comprehensive framework utilized by scholars (Li & Li, 2022; Tao et al., 2020; Zheng et al., 2023).

The third perspective adopts a structural decomposition approach, emphasizing the accounting scope of the digital economy. The UK Office for National Statistics (2015) conceptualizes the digital economy as an integration of hardware, software, telecommunications infrastructure, and e-commerce (UK Office for National Statistics, 2015). Bukht and Heeks (2019), alongside the United Nations Conference on Trade and Development (UNCTAD) (2019), categorize the digital economy into three layers: the digital sector, the digital economy, and the digitized economy (Murthy et al., 2021). The Bureau of Economic Analysis (BEA) (2019) provides a similar perspective, identifying digital infrastructure, e-commerce, and digital services as the core components of the digital economy (Strassner & Nicholson, 2020). Additionally, the China Academy of Information and Communications Technology (2017) aligns with this framework, dividing the digital economy into digital industrialization, industrial digitization, digital governance, and data valorization (Dong et al., 2022). Meanwhile, the National Bureau of Statistics of China (2021) narrows the scope by defining the digital economy through two primary dimensions: digital industrialization and industrial digitization (Liu & Hong, 2022).

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In conclusion, while countries and organizations worldwide have conducted extensive research into the connotation of the digital economy, varying levels of digital economic development across nations have resulted in the absence of an internationally unified definition. Scholars generally interpret the concept of the digital economy from three perspectives: core, narrow, and broad (Bukht & Heeks, 2017). At its core, the digital economy encompasses the IC/ICT sectors, which produce foundational digital goods and services, such as hardware manufacturing and information services. In a narrower sense, it includes business models built around digital goods and services, such as e-business and the platform economy. From a broader perspective, the digital economy spans the application of information and communication technologies across all economic sectors, integrating developments such as Industry 4.0 and the algorithmic economy.

As the digital economy evolves, scholars have increasingly highlighted the critical role of external environments, including governance frameworks and innovation ecosystems, as essential components of digital economic growth (Zhang & Jiao, 2017; Wang et al., 2021). In essence, the digital economy represents a dynamic stage concept whose definition and scope continues to expand. Considering the rapid development of the digital economy in China, this study identifies three distinguishing characteristics: (1) its reliance on the internet as a core carrier, which is indispensable for its growth; (2) the central role of data as a production factor,

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differentiating it from traditional economies and imbuing conventional production factors with a digital connotation; and (3) its capacity to drive innovation, foster industrial transformation, and promote high-quality economic development. These defining traits provide a foundation for constructing an indicator evaluation system to measure the level of digital economic development.

2.2.2 Development of digital economy in China

Drawing insights from the existing literature and government reports, it is evident that the development of China's digital economy can be divided into three distinct stages (China People's Daily, 2018; Shi, 2022):

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The initial stage, spanning from 1994 to 2002, marked the embryonic phase of China's digital economy. During this period, the internet industry in China was in its infancy, and numerous startups imitated successful foreign business models rather than focusing on independent technological innovation. Consequently, the industry primarily concentrated on acquiring user traffic and building a user base, with limited attention paid to fostering innovation. However, the collapse of the NASDAQ stock market in 2000, which symbolized the bursting of the dot-com bubble, triggered a global downturn in the internet industry. This economic setback affected China as well, leading to a 2-3 year period of stagnation that reshaped the digital economy landscape and paved the way for more sustainable growth.

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Following this brief downturn, the digital economy in China experienced rapid growth from 2003 to 2012. This phase was driven by the high-speed expansion of internet users, who consistently exhibited double-digit growth rates, and the emergence of innovative business models. Key developments during this time included the rise of e-commerce platforms like Taobao, which significantly boosted consumer-to-consumer trade and catalyzed the transition of the digital economy from its embryonic stage to a new level of development. By the end of 2012, the number of mobile internet users in China had surged to 420 million, surpassing desktop users for the first time. This milestone marked a shift from reliance on traditional internet services to the widespread adoption of mobile-based digital platforms, signaling a critical turning point for the digital economy.

Since 2013, China's digital economy has entered a phase of maturity, characterized by the widespread adoption of mobile internet technology and its seamless integration into everyday life. Digital services, including online shopping, remote work, distance education, and smart healthcare, have become deeply embedded in daily routines, transforming traditional industries and making significant contributions to social and economic growth. Unlike developed Western nations, which generally achieve industrialization, urbanization, and agricultural modernization before transitioning to a digital economy, China's unique developmental trajectory involves embracing digitalization alongside these

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processes. While this simultaneous progression creates complex challenges, it also presents unprecedented opportunities, underscoring the importance of strategic policy support to ensure sustainable growth.

The development of China's digital economy has been heavily influenced by policies at the national level, which have provided crucial support throughout its evolution. The digital economy policies in China have gone through the following developmental stages, which can be categorized into three phases:

The first phase of policy development focused on the construction of infrastructure to support informatization. For instance, in 1999, the State Council Office issued notices to accelerate the development of the mobile communication industry (Chen, 2024), while in 2001, it promoted the construction and application of the national spatial information infrastructure (Chen et al., 2024). These initiatives laid the groundwork for subsequent advancements in communication technologies and the transformation of related industries.

With the gradual improvement of information infrastructure, the second phase of policy development emphasized the exploration of new applications through initiatives like Internet Plus. Reduced costs for communication devices and broader accessibility to digital services spurred the growth of the internet economy, with e-commerce emerging as a dominant force. Policy initiatives during this time

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included the Notice on Revitalizing the Software Industry in 2002 (Ma et al., 2021) and the Opinions on Accelerating the Development of E-commerce in 2005 (Shi, 2024). These measures, coupled with later documents like the Guiding Opinions of the State Council on Actively Promoting the Internet Action issued in 2015 (Li & Yan, 2023), demonstrated the government's commitment to fostering digital innovation across sectors.

The third phase of policy evolution signaled a deeper integration of the internet into traditional industries, moving beyond the earlier focus on Internet Plus. This transformation began with General Secretary Xi Jinping's keynote speech at the Second World Internet Conference in December 2015, where he emphasized the construction of Digital China. Subsequent policies shifted towards leveraging the internet as a transformative force across various sectors. Major initiatives included the Guiding Opinions of the State Council on Deepening the Integration of Manufacturing and the Internet Development and the Guiding Opinions of the State Council on Accelerating the Promotion of Internet Plus Government Services in 2016 (Qi & Zhang, 2023).

Building on these developments, the 2017 Government Work Report mentioned the digital economy for the first time, highlighting its growing significance in national development strategies. In 2022, the State Council released the 14th Five-Year Plan for the Development of the Digital Economy, which

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outlined a comprehensive framework for advancing the digital economy during the 14th Five-Year Plan period. This plan detailed guiding principles, developmental objectives, and key tasks to ensure the healthy and sustainable growth of the digital economy. As a result, China's digital economy is poised to achieve even greater heights, solidifying its role as a driving force for the country's overall development.

2.2.3 Measurement methods of digital economy development

There has been an extensive discussion on the quantification of the digital economy development, which can be categorized into two primary approaches, one is absolute scale of the digital economy measurement, and the other is relative level of digital economy development measurement：

The first approach to measuring the absolute scale of the digital economy involves methods developed by both national and international organizations, as well as scholars and research institutions. Two prominent approaches are the value-added measurement method, spearheaded by organizations like the U.S. Bureau of Economic Analysis (BEA) and the China Academy of Information and Communications Technology, and the Digital Economy Satellite Account (DESA) framework, promoted by the Organisation for Economic Co-operation and Development (OECD). Additionally, scholars and research institutions have contributed to refining these methodologies.

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Methods developed by both national and international organizations comprehensively analyze the digital economy level of a certain entity through the construction of a systematic indicator system, defining the measurement scope, and integrating measurement indicators (Xu & Wang, 2024). The OECD calculates the value added of the ICT industry in its member countries using the international standard industrial classification, which encompasses seven categories of digital production activities and five categories of digital service activities (OECD, 2018; Chinoracky & Corejova, 2021). Xiang and Wu (2019) refer to the OECD classification method and combine it with the actual situation in China to measure the scale of China's digital economy using the four-digit national economic industry classification standard. The U.S. Bureau of Economic Analysis (BEA) consistently released value-added data for U.S. infrastructure, e-commerce, and fee-based digital services from 2018 to 2021. By clearly defining the scope of the digital economy and excluding partially digitized products and services, the BEA utilized a supply-use framework to measure key digital goods and services in terms of output, value-added, employment, and compensation, thereby assessing the overall scale of the U.S. digital economy. In June 2021, the BEA expanded the digital economy indicators into three categories by broadening the data sources. This expansion, calculated at purchaser prices, not only refined the scope of the analysis but also accounted for the additional costs and profits generated by digital technologies during transactions, resulting in a more scientifically grounded measurement

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approach (Nicholson et al., 2023; Strassner & Nicholson, 2020). Since 2017, the China Academy of Information and Communications Technology (CAICT) has been releasing estimates of the overall digital economy scale for various provinces across China. The indicator system focuses on digital industrialization and industrial digitization, excluding digital governance and the valuation of data. Starting in 2017, CAICT began publishing the White Paper on China's Digital Economy Development by defining the concept of the digital economy. Its most notable contribution lies in dividing the digital economy into two main modules: digital industrialization and industrial digitization. The former measures the conditions of digital technology infrastructure, including sectors such as electronic information manufacturing, basic telecommunications, software services, and the internet industry, while the latter assesses the integration and development of industries with digital technologies (Jin et al., 2020).

Alternative methodologies gauge the magnitude of the digital economy by utilizing the DESA In 2017, the Organisation for Economic Co-operation and Development (OECD) introduced a basic framework for the Digital Economy Satellite Account (DESA). This framework was used to create supply-use tables and to assess and measure the digital economy in the United States. This provided a crucial theoretical and practical foundation for the U.S. Department of Commerce to later construct satellite accounts for evaluating the level of the U.S. digital economy

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(Xu & Wang, 2024). In 2017 and 2020, the OECD used the satellite account methodology to measure the digital economy development levels of its member countries, covering aspects such as digital connectivity, digital usage, digital innovation, digital work, digital society, digital trust, and digital market openness. Satellite accounts are auxiliary accounting systems based on the central framework of the System of National Accounts (SNA), adapted to incorporate the concept of the digital economy. Compared to the value-added measurement and index compilation methods, the digital economy satellite account methodology offers timely and accurate feedback on the depth and breadth of integration between various sectors of the national economy and the digital economy. It is an effective approach for systematically measuring the scale of the digital economy. However, challenges arise from the extensive workload involved in data collection and screening, as well as limitations in data availability during the practical compilation process.

Broadly speaking, the calculation of the digital economy's scope encompasses not only industries directly linked to digital technology but also the added value generated through the integration of digital technology with traditional industries. The latter, which involves the measurement of the integration between digital technology and traditional sectors, has emerged as a challenging focal point in contemporary research. Efforts to quantify this integration have led to the development of diverse methodologies. Among these, the calculation of the

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integration part is currently the focus and difficulty faced by research. Chen and Kong (2021), drawing on Machlup's calculation framework and utilizing input-output table data, divided the digital economy into two main components: the digital industry sector and digital auxiliary activities. By separating these elements, They provided one of the earliest systematic assessments of China's digital economy size. Building on this foundation, Cai and Niu (2020) introduced an innovative two-step calculation approach to address the substitution and synergy effects of digital technology on the traditional economy. Their method, which progresses from incremental changes to total value and from contributions to scale, offers a refined perspective on the dynamic interplay between digital technology and traditional economic structures. Using this framework, the size of China's digital economy in 2017 was estimated to reach USD 1.386 trillion (Cai, 2018; Cai & Niu, 2020).

In 2020, the China Academy of Information and Communications Technology (CAICT) provided another significant contribution to this field. They redefined the scope of the digital economy by categorizing it into two distinct components: digital industrialization and industrial digitization. By employing the growth accounting framework, CAICT quantified the contribution of digital technology to the value added of each industry within the national economy. Their findings revealed that the scale of China's digital economy in 2017 amounted to an impressive USD 3.95 trillion. This method highlighted the diverse ways in which

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digital technology permeates traditional industries, further emphasizing the multidimensional nature of the digital economy.

Similarly, Xu and Zhang (2020) proposed a novel definition for the digital economy that incorporates four key dimensions: digital empowerment infrastructure, digital transactions, digital economic transaction products, and digital media. Their methodological approach captured a broader spectrum of digital economic activities, culminating in an estimated digital economy size of approximately USD 821.153 billion in 2017. The distinctiveness of this approach lies in its emphasis on digital infrastructure as a fundamental enabler of digital economic growth, alongside the inclusion of digital media as a critical component of economic activity. Han et al. (2021) adopted a more comprehensive lens by analyzing the digital economy through four interconnected dimensions: production, circulation, exchange, and consumption. This multidimensional framework offers a holistic view of the digital economy's role within the national economy, showcasing its impact across different stages of economic activity. Their analysis estimated the size of China's digital economy in 2017 at USD 770.82 billion, further contributing to the growing body of evidence regarding the substantial scale of China's digital economy during this period. Xian and Wang (2022), leveraging the statistical classification standards for digital economy industries developed by the National Bureau of Statistics, focused specifically on the core digital economy industries. Their research, which provides a narrower yet highly detailed perspective, estimated the size of China's core digital

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economy industry at USD 853.92 billion in 2017. By honing in on core industries, this study underscores the foundational role these sectors play in driving the overall development and growth of the digital economy.

In summary, regarding DESA, it stands as an advantageous instrument for observing Digital Industrialization and Industrial Digitalization Brynjolfsson et al. (2019). However, the current state of research on DESA is still in its nascent phase of theoretical exploration. Discrepancies among scholars emerge, particularly concerning the suitable definition of boundaries in consumption and production, methodologies for assessing the value of free products, and the pricing of assets. While these methods effectively measure the digital economy, their limitations become evident when attempting to establish Value Added and DESA. The all-encompassing influence of the digital economy on diverse aspects of our lives makes traditional statistical calibers impractical. Consequently, discrepancies in estimating the digital economy's size arise among researchers due to differing definitions of its scope.

The second dimension entails assessing the relative level of digital economy development. This necessitates the construction of a multidimensional indicator system, employing diverse evaluation methods to measure the level of digital economy development. Numerous international organizations and nations are dedicated to gauging the level of digital economy development at the national level,

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with the primary focus on the following four key indicators：

The International Telecommunication Union (ITU), a specialized agency within the United Nations, measured the ICT Development Index (IDI) from three dimensions: ICT access, ICT usage, and ICT skills (ITU, 2018). This composite index is distinguished by its minimalist design and the transparency of its methodology, which avoids dependence on expert opinions and subjective assessments as empirical foundations. However, certain source data employed in the IDI are marginally pertinent to the ICT development of regions, exemplified by elements within the ICT skills subindex such as adult literacy rate, secondary gross enrolment ratio, and tertiary gross enrolment ratio. Additionally, the ICT access and use subindices incorporate source data that presently lack direct relevance to the concept, such as the number of telephone subscriptions. It is noteworthy that the IDI constitutes a frequently cited benchmark in international research endeavors (Arkhipova & Sirotin, 2019; David, 2019).

The Networked Readiness Index (NRI) is collaboratively released by the World Economic Forum and the European Institute of Business Administration (INSEAD). It gauges the preparedness of individual countries in utilizing information and communication technology (ICT) to drive societal and economic development. Founded on 54 indicators, these metrics are categorized into 10 pillars, which are further subdivided into 4 sub-indices (World Economic Forum, 2016).

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Methodological drawbacks include the adoption of a rather subjective non-dimensionalized approach to source data, implying a lack of transparency in the scoring allocation mechanism. Numerous singular indicators exhibit only indirect relevance to ICT issues. Certain pillar indicators distinctly emphasize information and communication technology, mirroring metrics employed in international development indices that reflect population skills, encompassing general literacy rather than information and communication technology proficiency. Examples include the quality of the education system, the gross enrollment rate in secondary education, and adult literacy rate (Sidorov & Senchenko, 2020).

The Economic Growth and Development Index (EGDI) is published by the United Nations Department of Economic and Social Affairs (UN DESA). This index comprises three sub-indices, each based on 13 indicators that delineate the status of information and communication technology infrastructure, human capital, and online public services. Simultaneously, akin to the indices designed to assess knowledge and skills, the Human Capital Index neglects the distinctive facets of information and communication technology proficiency. Instead, it relies on indicators describing overall education, encompassing adult literacy rate, gross enrollment rate, expected years of education, and average years of education.

Digital Economy and Society Index (DESI) is a comprehensive index that consolidates indicators reflecting the effectiveness of digital technologies in Europe,

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aiming to monitor the evolution of digital competitiveness among EU member states. The compilation of this index encompasses key dimensions: Connectivity, assessing the development of the EU broadband market; Human Capital, examining digital inclusivity and skills; Utilization of Internet services; Integration of digital technologies; and Digital public services. Structurally, DESI does not function as a universal metric (European Commission, 2020). Its continuous evolution is manifested through the incorporation of novel indicators. This not only signifies the ongoing development of this assessment tool but also underscores challenges in achieving comparability across different periods (Jovanović et al., 2018). Stavytskyy et al. (2019) stated that 98% of the DESI values are, in fact, determined by its preceding trends.

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Many international scholars are dedicated to the evaluation and development of these indices, such as Barefoot et al. (2018), Sidorov and Senchenko (2020) and so on. In addition, Chinese scholars and research institutions predominantly focus on exploring how to establish digital economic development indices from the perspective of provincial and even municipal levels. Typical examples include: Caixin Insight (2017) analyzed China's digital economy from dimensions such as digital economy industry index, convergence index, spillover index, and infrastructure index. Tencent Research Institute (2017) conducted measurement research on the digital industry, digital culture, digital life, and digital government. In October 2023, China's Ministry of Industry and Information Technology (MIIT),

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through its Electronics Fifth Research Institute, issued its inaugural comprehensive delineation of statistical classifications pertaining to the digital economy and its core industries. This publication included a detailed exposition and the disclosure of methodologies employed in index computation. Nevertheless, owing to the continuous enrichment of the connotations and extensions within the digital economy, the process of quantitatively assessing the regional digital economy development remains an ongoing and evolving endeavor. Many Chinese scholars have used the Digital Inclusive Finance Index of Peking University to represent the digital economy index (He & Song, 2020) or used individual indicators (Ping & Yi, 2022) to conduct research.

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In contrast to the rapid growth of the digital economy, the construction and measurement of the digital economy development indicator system appear relatively lagging, failing to keep pace with the advancements in the digital economy. Presently, the construction and measurement of digital economy development indicators in China are primarily based on interpretations of the digital economy development from reports on digital economy development by entities such as the United Nations or China. The current methodologies for constructing and measuring digital economy development indicators vary based on different emphases. This study summarizes the construction of measurement indicator systems for the digital economy development by Chinese scholars, as shown in Table 2.1.

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Overall, these indicators primarily focus on four aspects: (a) investment in smart infrastructure; (b) societal empowerment; (c) fostering creativity and innovation; (d) promoting growth and employment. The covered topics range from the availability of infrastructure to the openness and participation in the internet economy, cybersecurity and privacy, protection and empowerment of consumers and citizens, and innovation and sustainability. The common consensus in the relevant literature is that the digital economy index encompasses four essential factors: infrastructure, platforms, industries, and innovation.

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Table 2.1

Summary Table of Measurement Indicators for the Digital Economy Development Level

Author	Primary indicators	Publish Time
Zhang and Jiao	Information and communication infrastructure, Primary and advanced ICT applications, Number of enterprises, Development of the information and communication technology industry	2017
Dong and Mi	Institutional and innovation environment, Infrastructure construction, Information technology application	2019
Wen et al.	Infrastructure, Penetration level	2019
Liu et al.	Development of information technology, Internet development, Digital transaction development	2020
Fan	Environment, Readiness, Applications	2020
Qi et al	Internet and telecommunications industry, Software industry, E-commerce and retail industry, Scientific and technological industry	2020
Ning	Digital infrastructure, Digital life applications, Digital industrial development	2020
Wu and Zhang	Mobile networks and talent training, Communication technology carrying capacity, Economic and technological foundation	2020
Zhang et al	Digital inclusive finance index	2021
Yang and Jiang	Digitization of industries, Industrialization of digitization.	2021
Ge and Wu	Development environment, Digital industrialization, Industrial digitalization, Digital governance.	2021
Wang et al.	Digital economy development carriers,Digital industrialization, Industrial digitalization, Digital economy development environment	2021

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Author	Primary indicators	Publish Time
Liu and Chen	Digital infrastructure, Digital industrialization, Industrial digitalization	2022
Sheng and Liu	Digital infrastructure, Digital industry, Digital governance	2022
He et al.	Digital infrastructure, Digital industry development, Digital economic environment	2023
Wang	Digitalization of infrastructure, Industrialization of digital technology, Digitalization of industry, Sustainable development capability	2023
Li et al.	Digital infrastructure, Digital industry, Digital integration, Digital innovation	2023

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The measurement of the digital economy remains a critical yet unresolved issue due to the absence of a standardized and universally accepted accounting framework. This challenge is likely to persist as an essential focus for countries seeking to accurately quantify and understand the scope of their digital economies.

In the United States, efforts to measure the absolute size of the digital economy typically encompass components such as digital infrastructure, e-commerce, and digital media. However, this methodology overlooks the broader integration and application of digital information technology in various other industries. Such exclusions may result in an underestimation of the total size of the digital economy, as these technologies significantly influence economic activities beyond the directly accounted-for sectors (Tong & Zhang, 2022). This limitation underscores the need for more comprehensive frameworks capable of capturing the extensive contributions of digital technology across diverse economic domains.

In contrast, the measurement of China's digital economy presents the risk of overestimation. Data provided by institutions such as the China Academy of Information and Communications Technology (CAICT) often suggest a relatively high valuation of the digital economy and its contribution to GDP. For instance, Kang (2008) highlights that CAICT's estimates are significantly higher compared to those derived from other methodologies. This disparity can be attributed not only to the adoption of different measurement methods but also to varying interpretations of the

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concept and scope of the digital economy. Such inconsistencies, whether stemming from overestimation or underestimation, inevitably impact the precision of GDP data and may influence policy decisions.

One prominent alternative methodology is the satellite accounts method. However, as Xu and Zhang (2020) argue, this approach is not without its limitations. The absence of a clear and universally recognized definition of the digital economy industry introduces significant ambiguity into the accounting process. Moreover, the inherent complexity of the satellite accounts method, coupled with the challenges of collecting and estimating large volumes of data, further complicates efforts to generate accurate and reliable measurements. These limitations highlight the importance of refining both the conceptual framework and data collection mechanisms to enhance the precision of digital economy estimates. Another critical consideration is the contextual adaptability of the satellite accounts method. As Wang (2021) emphasizes, constructing a measurement framework for digital economy satellite accounts requires careful alignment with the specific conditions and realities of individual countries. This necessitates significant adjustments when compiling supply-side data to ensure consistency with the unique characteristics of each national economy. Failure to tailor the framework appropriately risks producing results that may not accurately reflect local economic structures and dynamics. Furthermore, before the satellite accounts method can be fully adopted as a standard measurement approach, several unresolved challenges must be addressed. For example, the

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compatibility of the accounting framework with existing national accounting systems and practices needs thorough evaluation. Additionally, the system's relevance and applicability to the dynamic and multifaceted nature of the digital economy must be rigorously tested to ensure its efficacy in practical scenarios. These considerations underscore the need for ongoing refinement and empirical validation of the satellite accounts method to enhance its credibility and usability.

In summary, the measurement of the digital economy is a complex and evolving process fraught with methodological challenges and contextual variations. The absence of a unified accounting framework, coupled with the inherent limitations of existing methodologies, has resulted in significant discrepancies in the estimation of the digital economy's size and contribution to GDP. As countries strive to develop more accurate and reliable measurement systems, it is crucial to balance methodological rigor with adaptability to local conditions. By addressing these challenges, policymakers and researchers can work towards a more comprehensive understanding of the digital economy's role in global and national economic development.

Regarding the digital economy development indicator system, research institutions exhibit varying focuses and approaches, leading to differences in selected indicators. For instance, the digital economy accounting system of EU countries emphasizes the Digital Society Index and the Digital Livelihood Index (Afonasova et

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al., 2019), while the United States prioritizes metrics related to industries connected with the digital economy (Barefoot et al., 2018; Mesenbourg, 2001). In contrast, China's digital economy development index reflects distinctive priorities and methodological frameworks aligned with local characteristics (Feng, J. 2023; Wang, 2021). Despite these efforts, a universally accepted standard for assessing the digital economy has yet to emerge, whether from international organizations or independent researchers. This variation arises partly because the development stage of the digital economy differs across regions, resulting in unique features that make indicator systems region-specific and challenging to transfer across countries. Furthermore, whether using index-based ranking, value-added measures for absolute levels, or satellite accounting to gauge the digital economy's scale, all approaches encounter consistent challenges in terms of data selection and methodological alignment.

Measurement indicators from macro to micro levels urgently need improvement. While macro-level research can reveal the overall development trends of the digital economy at the national and regional levels, micro-level measurement is equally crucial for understanding its specific impacts on different regions, industries, and enterprises. Such micro-level analysis not only helps to more accurately identify the heterogeneous development characteristics of the digital economy within a country but also provides policymakers with more targeted decision-making tools. In recent years, an increasing number of studies have focused on the micro-measurement of the digital economy within countries, arguing that neglecting this aspect leads to a

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partial understanding of the digital economy's development. Therefore, future research must address both macro and micro levels to form a comprehensive understanding of digital economy development.

2.2.4 Impact of digital economy development

When discussing the impact of digital economy development on the urban-rural income gap, it is important to delve into its effects across various dimensions. Specifically, in this section, the impacts of digital economy development on industrial structure, income inequality, and other aspects are introduced, respectively.

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2.2.4.1 On industrial structure

Scholars have long been intrigued by the relationship between the digital economy and industrial structure, recognizing its transformative potential in reshaping economic systems. The digital economy facilitates industrial structure optimization and upgrading through two interconnected pathways: digital industrialization and industrial digitization. Both mechanisms play a critical role in fostering the emergence of new industries while simultaneously promoting the transformation of traditional industries, thereby driving structural evolution (Liu & Chen, 2021).

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Digital industrialization represents the creation of industries driven by advancements in digital technologies. This process leads to the formation of innovative sectors such as electronic information manufacturing, information and communication technology, and software services, which serve as the foundation of the digital economy. Jaakkola et al. (1991) argue that information technology acts as a transformative force for industrial restructuring, enabling the development of high-tech industries and accelerating industrial upgrading. Heo and Lee (2019) further assert that digital industrialization facilitates industrial structure optimization by fostering new formats and business models, driven by cutting-edge technologies such as 5G, big data, artificial intelligence, and blockchain. These innovations not only push traditional manufacturing toward high-end and intelligent production but also promote the deep integration of manufacturing and services, thereby enhancing overall industrial efficiency.

In parallel, industrial digitization empowers traditional industries to achieve transformation and upgrading by embedding digital technologies across production, distribution, and management processes. This pathway emphasizes data as a critical driver, leveraging technologies such as the Internet, the Internet of Things (IoT), and big data to optimize resource allocation and improve operational efficiency. Mason et al. (2021) highlight the growing importance of information and communication technologies in the marketing and organizational structure of traditional sectors, noting their pivotal role in driving industrial adjustments. Similarly, Stiroh (2002)

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observes productivity improvements in ICT-related industries, underscoring the capacity of digital technologies to enhance output and efficiency. O'Mahony and Vecchi (2005), through a comparative analysis of panel data from the United States and the United Kingdom, demonstrate that information and communication technologies significantly contribute to industry output growth. Von Krogh (2012) further emphasizes that digital tools enable knowledge sharing and management, fostering enterprise-level development and advancing industrial evolution.

In the context of China, existing research has explored the role of the digital economy in promoting industrial structure optimization, although much of the literature remains theoretical. Xie et al. (2012) argue that the integration of informatization and industrialization reduces the dominance of the primary industry while facilitating the expansion of secondary and tertiary industries, thereby promoting industrial structure rationalization. Chen and Kong (2008) underscores the pervasive influence of China's digital economy, describing the digital economy industry as a fundamental driver of economic transformation. His findings suggest that digital technologies not only permeate traditional sectors but also contribute to structural adjustments by fostering innovation and efficiency. Jiang (2017) explores the impact of Internet technology on the service industry, noting its role as a critical factor in reshaping industrial structures. Zhou et al. (2022) extend this perspective, emphasizing that the integration of digital technologies across industries optimizes production, distribution, and sales processes. This integration enhances industrial

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efficiency and drives the transformation of traditional sectors, providing a continuous impetus for structural optimization and upgrading. Moreover, Zhou et al. (2018) highlight how digital technologies enable industries to achieve higher levels of productivity and innovation, further supporting structural advancement.

In summary, the digital economy exerts a profound influence on industrial structure by fostering the emergence of new industries through digital industrialization and enabling the transformation of traditional industries through industrial digitization. These dual pathways not only enhance industrial efficiency but also serve as a crucial mechanism for structural upgrading. In China, the digital economy's deep integration into various sectors continues to accelerate structural optimization, contributing to sustainable economic development and laying a solid foundation for addressing broader socio-economic challenges.

2.2.4.2 On income inequality and urban-rural income gap

The impact of the digital economy development on income inequality has been a focal topic in academia in recent years. However, the impact of the digital economy on income inequality is currently in the exploratory stage (Ning & Leming, 2022). The advent of digital technology and its advancemen of the digital economy as a distinct technological advancement and economic form have significantly influenced the pattern of income inequality (Carlsson, 2004; Guellec & Paunov, 2017).

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In the era of the digital economy, digital technology exhibits new characteristics in income inequality, unlike historical technological advancements. Firstly, data emerges as a pivotal production factor, with its low marginal cost and evident economies of scale (Nekhvyadovich et al., 2020). Secondly, the digital economy entails network externalities, where users' benefits are influenced by the number of other users on the same network (Koch & Windsperger, 2017). This characteristic of a two-sided market prompts mutual attraction between supply and demand sides to converge on the same platform. These novel features alter the relationship between the digital economy and income inequality. Galbraith (1977) pointed out that with societal development, the relative importance of production factors undergoes change. Labor remains a pivotal factor of production, while the relative importance of other factors has shifted over time, from land in agrarian societies, to capital in industrial economies, and more recently to data in the digital economy. These characteristics collectively induce new dynamics in the relationship between the digital economy and income inequality.

The operation mechanism of the digital economy is complex, and there are differences in observation perspectives and research methods on the digital economy, leading to divergent conclusions. From the perspective of the digital divide between developing and developed countries, Fuchs and Horak (2008) argued that the digital divide was challenging to narrow, while Fink and Kenny (2003) disagreed with this

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notion. Examining within developed countries, Guellec and Paunov (2017) suggested that digital economy led to an increase in income inequality. Zhang (2013) research indicated a negative correlation between the Gini coefficient and the slope of the internet diffusion curve, with developed countries often exhibiting higher slopes. Looking at the situation within developing countries, using China's digital financial development as an example, Zhang et al. (2020) proposed that digital financial development inhibits the widening of the digital divide and its adverse effects.. While the global digital divide generated by the new round of technological revolution generally exacerbates social wealth disparity, the impact of the digital divide issue in China, its mitigation, and overcoming it possess distinct characteristics under the socialist system. Similarly, Wang and Zhao (2020) argued that there has been a clear Matthew effect in the development of digital finance between impoverished and non-impoverished households. This effect reflects the imbalance and inadequacy in China's financial development process, constraining the integrated development of urban and rural areas and the construction of a socialist harmonious society.

The literature emphasizes the positive effects of the digital dividend on reducing income inequality. Goldfarb and Tucker (2019) outline five distinct advantages the digital economy offers over traditional economic models: reduced search costs, lower replication costs, decreased transportation expenses, minimized tracking costs, and lower verification costs. Building on this, research has examined how the digital dividend directly supports globalization, accelerates urban-rural

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integration, creates jobs and income in emerging sectors, and enhances individual capabilities. Hjort and Poulsen (2019), by mapping land-based cable networks and analyzing shifts in employment rates and average income in Africa as undersea internet cables connected coastal regions, empirically demonstrated the substantial positive impact of internet access on employment rates and income growth in Africa. This increase in employment is largely localized, leading to significant income gains for individuals with lower educational attainment. However, the study also notes that much of the employment growth arises in high-skilled occupations, with relatively fewer gains in employment for low-skilled workers.

Meanwhile, the development of the digital economy may also have adverse impact on income inequality, potentially exacerbating the urban-rural income gap. Salemink et al. (2017) conducted a comprehensive analysis of 157 studies investigating the impact of the digital economy on rural development in developed countries. Their research focused on two critical dimensions: connectivity and inclusivity. In terms of connectivity, they identified a widening disparity in data infrastructure between urban and rural areas, partly due to the lagging response of public policies compared to the rapidly evolving market. Regarding inclusivity, which concerns whether technological diffusion is equitable, researchers have found that individuals with lower levels of education and technological skills, who are typically expected to benefit from improved digital connectivity in remote areas, often fail to actively participate in the development of the digital economy.

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In China, scholars have examined the relationship between the digital economy and the urban-rural income gap from multiple perspectives, including digital infrastructure, internet usage, and e-commerce, leading to diverse and sometimes conflicting conclusions. Some researchers contend that the digital economy amplifies income disparities. For example, Tan et al. (2017) observed that the returns on internet usage for urban residents significantly exceed those for rural residents. Similarly, Zhang and Han (2017) highlighted that although e-commerce improves the income levels of both urban and rural populations, its impact on urban residents is more pronounced, thus widening the urban-rural income gap. Other studies indicate that economically advanced regions benefit disproportionately from investments in digital infrastructure, while less-developed areas experience limited effects (Lam & Shiu, 2010; Ward & Zheng, 2016). Building on this, Wei (2020) argued that information infrastructure development only significantly affects income gaps within localized regions, with minimal impact on surrounding areas. Li and Ke (2021) found that while the digital economy promotes overall income growth among farmers, it also intensifies income inequality. He and Xu (2019) pointed out that as internet coverage expands, significant differences emerge in how urban and rural residents utilize online platforms for employment opportunities, thereby exacerbating the income gap. Furthermore, Liu (2020) noted that industrial intelligence increases the substitutability of agricultural migrant workers, diminishing their bargaining power and employment stability, which further widens the income divide. Conversely, some scholars

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emphasize the positive effects of digital finance and inclusive financial services. For instance, Zhang et al. (2021) and Zhang and Wan (2021) found that the expansion of inclusive finance significantly boosts rural residents' income levels and fosters entrepreneurship, particularly among families with limited material or social capital, thereby helping to narrow the urban-rural income gap.

Several studies have presented opposing conclusions. Lin and Liu (2003) argued that income inequality remains the primary driver of urban-rural disparities in China. The digital economy, by lowering search costs and enhancing communication between regions, helps to eliminate information asymmetries, thereby increasing financial accessibility and reducing barriers to entry, which narrows the income gap (Zhou et al., 2020). Similarly, Zhang (2019) attributed the reduction in urban-rural income inequality to internet trade, which, through the penetration and diffusion of digital technologies, expands the scale and scope of trade services (Lan et al., 2020). Zhang et al. (2021) observed that the income growth effects of the digital economy are stronger for rural households than for urban ones. Moreover, the development of agricultural e-commerce has effectively shortened the sales cycle of agricultural products, overcoming geographical limitations and expanding market channels, which significantly boosts farmers' income and narrows the urban-rural income gap.

Some other scholars have proposed that the relationship between the digital economy and the urban-rural income gap is non-linear. For instance, Cheng et al.

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(2019) and Luo et al. (2021) found evidence of an inverted U-shaped relationship, while Chen et al. (2021) reported a U-shaped relationship. These studies suggest that the impact of the digital economy on income inequality may vary depending on its stage of development. Additionally, other scholars argue that factors such as urbanization, technological innovation, and regional economic development further influence this relationship. Liu et al. (2021) noted that higher levels of urbanization might inhibit the ability of the digital economy to reduce income inequality. In contrast, regions characterized by advanced economic development and robust research capabilities are better positioned to leverage the digital economy to reduce income disparities among residents.

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2.2.4.3 Others

i. High-quality economic development

The digital economy is often considered a key driver for achieving high-quality economic development. Scholars have extensively debated whether and how the digital economy can foster such development, resulting in a variety of perspectives on the topic. Global evidence suggests that promoting the development of the digital economy positively impacts economic growth, while also enhancing the overall quality of economic progress (Mardonakulovich & Bulturbayevich, 2020; Myovella et al., 2020). Additionally, digital economy development not only boosts the resilience of economies but also plays a critical role in promoting high-quality growth (Choi & Hoon Yi, 2009).

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From both macro and micro perspectives, researchers such as Ren (2022) and Zhang et al. (2021) have identified several levels of impact. At the micro-level, the digital economy reduces both production and transaction costs for enterprises, thereby enabling economies of scale and scope. On the medium level, digital technologies spur industrial innovation and the digitization of industries, which together create new models and formats. At the macro level, digital economy development enhances high-quality economic growth by optimizing capital utilization, improving efficiency, and driving total factor productivity.

From the perspective of the supply system, Song (2020) argued that digital economy development helps reduce risks, maintain stable economic performance, and improve the efficiency of resource allocation. Furthermore, scholars like Kuang and Peng (2020), as well as Shi (2020), emphasized that the digital economy fosters industrial growth through digital industrialization, while simultaneously empowering the real economy via industrial digitization, further contributing to high-quality economic development.

Finally, Bai and Song (2021) explored the effects of the digital economy from the standpoint of political economy, analyzing its influence across the stages of production, distribution, exchange, and consumption.

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ii. Impact on the employment

The relationship between the development of the digital economy and employment has been widely studied by scholars, with research focusing on three main areas: the impact on the scale, structure, and quality of employment.

From the perspective of employment scale, many scholars agree that digital technology and the digital economy significantly contribute to expanding the employment market. Yang and Zhang (2019) argued that the flexibility and diversity of employment opportunities in the digital economy help counterbalance the job losses resulting from market competition, capacity reduction, and structural adjustments in traditional industries. Similarly, Hu et al. (2016) highlighted that the development of internet technologies in China has created numerous employment opportunities, with digital technology playing an increasingly crucial role in optimizing employment structures. However, some scholars point out that the digital economy's impact on employment is not entirely positive, as the enhanced productivity brought by digital technologies can have a short-term negative effect on employment levels.

When examining employment structure, the integration of digital technologies with traditional industries has caused significant shifts in labor markets. Mo and Ma (2019) observed that while the digital economy creates new job opportunities, it also leads to the displacement of many traditional jobs. Furthermore, the demand for

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high-skilled labor in technology-driven industries has expanded, while the need for low-skilled labor in traditional sectors is also growing, leading to polarization in the job market. Liang and Liu (2023), through an analysis based on digital infrastructure, transactions, and carriers, found that the development of the digital economy influences employment structures across industries and sectors. Overall, the digital economy drives a shift toward higher-end and more intelligent job types, with early stages of digital integration resulting in reduced demand for technicians in secondary industries, followed by an eventual increase in high-end employment opportunities as integration deepens.

In terms of employment quality, the digital economy has significantly transformed the real economy, leading to improvements in total factor productivity and corporate profitability. This, in turn, enhances welfare benefits and working conditions, thereby contributing to higher-quality employment. Qi et al. (2020) emphasized that technologies like the internet and artificial intelligence can substantially improve labor compensation and protection, while also motivating workers to enhance their skills through self-directed learning. Additionally, He and Song (2020) argued that digital economy development reduces borrowing constraints for entrepreneurs and alleviates the decision-making limitations faced by employed individuals due to their social connections.

In summary, the technological revolution, driven by the internet, artificial intelligence, and automation, has facilitated the integration of the digital economy

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across various sectors of society. While this integration creates a large number of job opportunities, optimizes employment structures, and improves the quality of employment, it may also lead to the replacement of some low-tech jobs, particularly in manufacturing. Moreover, the digital economy's promotion of platform-based enterprises has resulted in the disorderly expansion of capital, contributing to wealth imbalances that contradict the goal of achieving common prosperity. Thus, it is crucial to study the mechanisms through which the digital economy affects employment, refine policies that prioritize employment, and harness the positive impacts of digital economy development to foster more inclusive and high-quality employment outcomes.

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2.2.5 Factors influencing digital economy development

The development of the digital economy is influenced by a variety of factors, which can be broadly categorized into four key dimensions: Digital Economy Development Carrier, Digital Industrialization, Industrial Digitization, and the Digital Economy Development Environment. These four dimensions are interconnected and collectively contribute to the growth and success of the digital economy. In this section, we explore these four dimensions in detail, highlighting their significance and impact on the digital economy’s development.

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i. Digital economy development carriers

The development of the digital economy is inherently tied to the availability and quality of infrastructure supporting digital activities. These infrastructures form the carriers that enable digital transformation and economic growth. Key factors influencing the digital economy's development include the density of internet broadband access ports, the proportion of internet users to the resident population, the number of domain names per capita, mobile base station density, cell phone penetration rates, and fiber optic cable density. These indicators collectively represent the foundation upon which digital innovation and adoption are built.

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Pradhan et al. (2019) explored the relationship between venture capital, ICT infrastructure, and economic growth in 25 European countries from 1989 to 2016, highlighting how infrastructure advancements catalyze digital economy development. Similarly, Choi and Hoon Yi (2009) emphasized the transformative role of information technology adoption, which fosters economic development and enhances total factor productivity in industries leveraging ICT (Basu & Fernald, 2007; Jorgenson et al., 2016).

Broadband access port density is a critical indicator of a region's digital readiness. High-density broadband infrastructure enables faster and more reliable internet access, which is essential for digital economy activities such as e-commerce,

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remote work, and online education. Yi et al. (2019) demonstrated that regions with a higher density of broadband access ports tend to experience accelerated digital economy growth, a conclusion further supported by Liu et al. (2020). Moreover, the development of broadband networks facilitates the diffusion of digital technologies, enabling businesses and individuals to leverage digital tools more effectively ((Jing & Sun, 2019).

The percentage of internet users within a population reflects the level of digital inclusivity and connectivity in a region. Scott et al. (2022) argued that internet penetration not only measures the extent of digital adoption but also serves as a driver for economic activities that rely on digital platforms. Regions with higher internet user ratios tend to exhibit greater e-commerce activity, digital content creation, and innovation, contributing significantly to the digital economy.

The number of domain names per capita is an indicator of digital entrepreneurial activity and online presence. High domain name density signifies a robust digital ecosystem where businesses and individuals actively participate in the online economy. Regions with a high per capita number of domain names often showcase greater levels of innovation, digital services, and market accessibility (Kim et al., 2002).

Mobile base stations form the backbone of wireless communication networks, which are vital for the proliferation of mobile internet services. High-density mobile

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base station networks ensure widespread and reliable connectivity, facilitating digital economy activities such as mobile banking, app-based services, and IoT applications. The importance of mobile base station density has been underscored by its impact on bridging urban-rural digital divides and enhancing regional connectivity.

Cell phone penetration serves as a proxy for digital device accessibility and usage. High penetration rates indicate widespread adoption of mobile technologies, which are pivotal for accessing digital platforms and services. As noted by Chinoracky and Corejova (2021), regions with high cell phone penetration rates often experience enhanced digital economic activities, as individuals can easily engage in e-commerce, mobile payments, and digital communication.

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Fiber optic networks provide the high-speed, high-capacity infrastructure required for modern digital economy operations. The density of fiber optic cable lines in a region determines the quality of internet services available, influencing the efficiency of digital transactions and the reliability of cloud-based services. Ma et al. (2022) emphasized that robust fiber optic networks are essential for supporting the data-intensive applications of the digital economy, such as big data analytics and AI-powered tools.

Infrastructure indicators such as broadband access port density, internet user proportion, domain name density, mobile base station density, cell phone penetration, and fiber optic line density collectively form the foundational carriers of digital

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economy development. These infrastructures not only enable digital transformation but also drive economic growth by enhancing connectivity, accessibility, and innovation. Expanding and optimizing these infrastructures are critical for ensuring the sustained development of the digital economy.

ii Digital industrialization

Digital industrialization plays a foundational role in the development of the digital economy by promoting the integration of digital technologies across various industries. This integration drives the transformation of production, management, and service processes, enhancing innovation, reducing costs, and improving efficiency (Shi et al., 2022). As a critical component of the digital economy, digital industrialization lays the groundwork for sustainable economic growth and efficiency improvements, particularly in regions with more developed digital infrastructure and ecosystems.

The evaluation of digital industrialization often focuses on specific metrics that measure its contribution to the economy. One key indicator is the proportion of software business revenue to GDP, which reflects the scale and significance of the software industry in supporting digital transformation. The development of the software sector not only facilitates technological innovation but also accelerates the application of advanced technologies such as big data, artificial intelligence, and

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cloud computing (Li et al., 2020). Zhang (2023) emphasizes that regions with strong software industries typically experience faster economic digitalization and enhanced industrial efficiency.

Another important metric is the proportion of information technology services revenue to GDP. This indicator reflects the reliance of various industries on IT services to optimize operations and improve decision-making. IT services, encompassing cloud computing, data analytics, and digital infrastructure management, are instrumental in fostering collaborative innovation and strengthening industrial ecosystems. Ma & Li (2022) highlight that a well-developed IT service sector supports knowledge-sharing and enhances the digitalization of traditional industries, thereby contributing to economic growth.

The telecommunications sector also plays a pivotal role in digital industrialization. The proportion of total telecommunications business revenue to GDP indicates the significance of telecommunications infrastructure in facilitating connectivity and digital adoption. A robust telecommunications network enables the development and application of emerging technologies such as 5G, the Internet of Things (IoT), and autonomous systems, which drive industrial digitization and innovation (Li,2021; Sun et al., 2021). Investments in telecommunications infrastructure are critical to ensuring the seamless operation of digital platforms and enhancing accessibility to digital services, which, in turn, accelerates the digital transformation of industries (Jorgenson et al., 2016).

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The adoption of e-commerce is another key aspect of digital industrialization. The proportion of enterprises engaged in e-commerce activities serves as an indicator of how extensively businesses are leveraging digital platforms for transactions, supply chain management, and customer engagement. Zhou et al. (2022) suggest that greater e-commerce participation by enterprises contributes to economic efficiency and inclusivity, enabling small and medium-sized enterprises (SMEs) to compete in both domestic and international markets. Additionally, the proportion of e-commerce revenue to GDP highlights the economic impact of digital trade, reflecting the extent to which e-commerce has reshaped traditional business models and created new value chains (Zhang & Li, 2023).

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Efforts to enhance digital industrialization focus on addressing gaps in infrastructure, workforce skills, and supportive policies. Governments and organizations can facilitate the digital transformation of industries by investing in broadband networks, promoting the adoption of advanced digital tools, and implementing targeted policies to encourage private sector participation. Moreover, fostering a skilled digital workforce through education and training programs is essential for sustaining innovation and competitiveness in a rapidly evolving digital economy.

Digital industrialization not only reflects the current level of digital economy development but also serves as a vital determinant of future economic performance.

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Metrics such as the proportion of software business revenue to GDP, IT service revenue to GDP, and e-commerce participation rates provide crucial insights for measuring and enhancing the progress of digital industrialization. These indicators form an essential foundation for constructing a comprehensive framework to assess and guide digital economy development effectively.

iii. Industry digitization

Industry digitization involves the application of cutting-edge digital technologies, such as artificial intelligence, big data, and the Internet of Things, across various industries to optimize production processes, enhance service quality, and promote efficient management practices (Matt et al., 2023). The degree of industry digitization reflects the maturity and adoption level of these technologies, which enables industries to respond effectively to the demands of the digital era. It also plays a critical role in enhancing industrial competitiveness and driving economic growth by fostering innovation and productivity improvements.

Indicators of industry digitization highlight the integration of digital infrastructure, data-driven decision-making, and the development of digital talent within enterprises. Key metrics include the number of computers used per 100 employees in enterprises, the number of websites per 100 enterprises, and the Digital Inclusive Finance Index, which measures access to and the use of digital financial

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services (Guo & Zhu, 2021). These indicators provide insights into the depth of digital technology adoption and its transformative impact on industrial activities.

The number of computers used per 100 employees in enterprises and the number of websites per 100 enterprises demonstrate the technological readiness of enterprises to integrate digital tools into their operations and customer engagement strategies (Kim et al., 2002). High values in these metrics indicate robust infrastructure for digital transformation and a proactive approach to leveraging online platforms for business growth.

The Digital Inclusive Finance Index serves as a crucial measure of the accessibility and usage of digital financial services across industries. It reflects the extent to which enterprises and individuals utilize digital finance platforms to facilitate transactions, manage investments, and access credit. Research has shown that industries with higher levels of digital financial inclusion experience enhanced efficiency and reduced transaction costs, further supporting economic growth (Chen et al., 2020; Sun et al., 2022). In addition, the application of digital technologies fosters data-driven management and decision-making processes, enabling enterprises to analyze market trends, consumer behavior, and operational efficiency with greater accuracy. This integration supports dynamic business strategies and enhances the competitiveness of industries in a rapidly evolving digital economy (Wang & Luo, 2022).

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Industry digitization also emphasizes the cultivation and utilization of digital talent, as a skilled workforce is essential for implementing and maintaining advanced technologies. Enterprises that invest in employee training programs and adopt digital tools to enhance workforce productivity are better positioned to achieve sustainable growth in the digital economy (Zhou et al., 2021). The integration of these elements underscores the significance of industry digitization in shaping the digital economy. By adopting digital technologies, industries can adapt to the changing economic landscape, enhance productivity, and contribute to the overall development of the digital economy.

v. Development environment

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The development environment of the digital economy is a critical foundation for fostering and assessing the level of digital economic development, as it encompasses infrastructure investment, industrial innovation, and digital workforce support (Chinoracky & Corejova, 2021). Among the key factors, per capita fixed asset investment in the information transmission, computer services, and software industries serves as a barometer of infrastructure readiness and technological advancement. Regions with higher per capita investment in these areas tend to exhibit stronger capabilities to support digital infrastructure and innovation (Basu & Fernald, 2007; Zhou et al., 2022). Such investments facilitate the development of robust communication networks, data centers, and software ecosystems, which are essential for promoting the digital economy's growth.

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Another pivotal component is the R&D expenditure of large-scale industrial enterprises, which signifies industrial innovation and the adoption of new technologies. As Yi et al. (2019) highlight, sustained R&D investment accelerates technological breakthroughs and fosters the integration of digital tools such as big data analytics, artificial intelligence, and the Internet of Things (IoT) into traditional industries. This drives the transformation and upgrading of industrial structures, enhancing efficiency and competitiveness. Furthermore, Zhang et al. (2024) emphasize that higher R&D expenditures not only stimulate innovation but also create a conducive environment for the commercialization of digital products and services.

The proportion of employees in information transmission, software, and information technology service industries relative to the total urban employment population is another essential indicator of the digital economy's development environment. A larger share of employment in these sectors reflects a stronger digital talent base and higher labor participation in digital economic activities (Kim et al., 2002; Guo & Zhu, 2021). This workforce plays a key role in promoting the adoption and diffusion of digital technologies across industries, enabling the digital economy to thrive. Moreover, as digital skills become a core competency in modern economies, cultivating and retaining digital talent is vital for sustaining long-term digital economic growth (Matt et al., 2023).

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In addition to the above factors, the development environment of the digital economy has been shaped by significant shifts in economic activities, particularly the rise of digital transactions and mobile payment systems (Yi et al., 2019). Digital goods and services, as well as platforms enabling seamless transactions, have become integral to economic operations, transforming market mechanisms and organizational structures. Data, as a new production factor, has redefined property rights systems, credit relationships, and economic incentives, creating a dynamic environment conducive to digital economy expansion (Kim et al., 2002).

Overall, the development environment for the digital economy reflects the synergy between infrastructure investment, industrial innovation capabilities, and human capital readiness. These factors collectively establish a solid foundation for enabling sustainable growth, technological progress, and industrial transformation in the digital age.

2.3 Urban-rural income gap

Samuelson believes that income refers to all the revenue and cash received by a person or a family within a certain period and income can be divided into two levels: macro and micro (Fatuła, 2018). Household income belongs to the micro level of income, which can be further divided into national income and personal income. National income is the sum of all individuals' income and is formed by the initial and

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subsequent distribution of national income. Personal income includes wages, salaries, other labor income, owner's income, interest, dividends, rent, transfer payments from enterprises and governments to individuals, and individual payments for social insurance. The income that individuals can use for consumption and savings is called disposable income. The urban-rural income gap refers to the difference in income levels between urban and rural areas within a country or region.

2.3.1 Measurement methods of urban-rural income gap

Overall, there are two methods for measuring income inequality, which are represented by absolute or relative values. However, absolute values is difficult to compare and cannot reflect the relative proportion of income inequality, so relative values are often used to represent income inequality. Currently, there are three main methods for measuring the relative value of urban-rural income inequality： the ratio of urban residents' disposable income to rural residents' per capita net income; the Theil index; and the Gini coefficient index (Fan et al., 2022;Jiang, Li, & Si, 2022; Wen & Ying, 2021).

i. Ratio of Urban Residents' Disposable Income to Rural Residents' Per Capita Net Income

The use of the ratio of urban residents' disposable income to rural residents' per capita net income is more widely used (Wang & Ouyang, 2001). It compares the disposable

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income of urban and rural residents to obtain the proportion of urban-rural income inequality. Disposable income refers to the income that individuals or households have left after deducting taxes and necessary living expenses. The smaller the ratio of disposable income between urban and rural residents, the greater the income inequality between urban and rural areas. Its advantages are as follows: (i) it can reflect the difference in living standards between urban and rural residents with simple calculation, and has more practical significance. (ii) it can reflect the specific reasons for urban-rural income inequality, such as the occupational structure, education level, and wage level of urban and rural residents. (iii) it can reflect the population size of different regions and groups, and is more universal. However, it does not take into account the proportion of urban and rural populations, nor does it consider the distribution structure and dynamic changes of urban and rural residents' income levels (Luo et al., 2021).

ii. Gini Coefficient

The Gini coefficient divides the population into different income groups and ranks them from low to high. It constructs the Lorenz curve using the percentage of population and the percentage of income, and defines two regions based on this curve: the unequal region and the perfectly equal region. The Gini coefficient represents the ratio of the areas of these two regions. It measures the overall income gap, and the

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closer the Gini coefficient is to 1, the more unequal the income distribution. Its advantages are simplicity and ease of understanding, but it has two disadvantages in measuring the urban-rural income gap. Firstly, this method cannot separate urban and rural areas from the Gini coefficient, leading to an inability to measure the urban-rural income gap. Secondly, if there are changes in the middle income group, the Gini coefficient is easily affected, making it sensitive to such changes (Ma et al., 2022; Wen & Ying, 2021). Since the income ratio does not take into account population proportions, it is difficult to measure the urban-rural income gap accurately using the Gini coefficient.

iii. Theil Index

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The Theil index is another indicator that reflects the degree of income inequality. It is calculated by sorting individual incomes by size and dividing them into several equal groups, and then calculating the proportion of total income contributed by each group. The closer the Theil index is to 1, the more unequal the income distribution. Changes in high and low income groups can be reflected more quickly in the Theil index, and changes in the income gap between urban and rural areas mainly come from changes in the income of the two extreme groups. Therefore, many scholars use the Theil index to measure the income gap between urban and rural areas (Luo & Peng, 2016; Wu & Liu, 2014;). In 1967, Theil applied the concept of average information quantity from information theory to economics. He used entropy to study income distribution

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and believed that measuring income inequality could be expressed as the expected amount of information contained in the transformation from population share to income share.

2.3.2 Evolution of the urban-rural income in China

In the international arena, the urban-rural income gap is not viewed as crucial as income inequality and poverty in measuring socio-economic development. This is because, for most countries, the urban-rural income gap is primarily attributed to natural factors (Zhong, et al., 2022). However, in China, the urban-rural income gap is more a result of institutional divisions (Li. et al., 2021a; Wang & Zhuo, 2018). This has led to constraints on the free movement of factors such as labor, land, and capital between urban and rural areas, hindering the balanced development of towns and villages.

To better understand the evolution of China's urban-rural income gap, the definitions of urban and rural areas should be known. From the establishment of the People's Republic of China to the present, the criteria for distinguishing between urban and rural areas have transitioned from using population density to using actual urban construction connections to the territory. Currently, the criteria for urban-rural classification come from the Regulations on Statistical Division of Urban and Rural Areas issued in 2008, which defines urban areas as including cities and towns. Cities

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refer to actual construction connected to residents' committees and other areas within municipal districts and districts of cities without districts; towns refer to country government seats and other towns outside urban areas, where actual construction is connected to residents' committees and other areas (National Bureau of Statistics of China, 2023). Independent industrial and mining areas, development zones, research units, colleges, and universities with a resident population of over 3,000, as well as special areas such as farms and forestry areas, are considered towns if they are not connected to the actual construction of government seats. Rural areas refer to regions outside the defined urban areas. In current population statistics, urban population refers to all permanent residents living within urban areas, while rural population refers to all residents not included in the urban population (National Bureau of Statistics, 2023b). In the seventh national population census, urban population refers to those who have resided in urban areas for more than six months, regardless of their household registration status.

The urban-rural income gap in China has evolved in a phased manner, reflecting key historical and policy shifts. From the founding of the People's Republic of China until the pre-reform period, the country operated under a planned economic system, which aimed to foster industrialization (Su et al., 2015; Sicular et al., 2008). This was primarily achieved through mechanisms such as the unified purchase and sale system for agricultural products, the people's commune system, and the household registration system, which collectively facilitated the capital accumulation

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necessary for industrial development. This system also resulted in a situation where rural areas subsidized urban growth, but income distribution was centrally controlled by the state, meaning the income gap between urban and rural areas did not significantly widen. However, this arrangement has contributed to the deep-rooted structural challenges behind the urban-rural income gap in China today (Cai & Yang, 2000).

With the onset of the reform and opening-up policy in 1978, the urban-rural income gap experienced significant fluctuations. As illustrated in Figure 2.1, which tracks the changes in this gap since 1978, the income disparity is commonly measured by comparing the per capita disposable income of urban residents to that of rural residents. From 1978 to 1985, the gap steadily narrowed due to early reforms aimed at boosting agricultural productivity and improving rural incomes. However, from 1986 onward, urban development became a more prominent focus of the government, driven by various reform measures and preferential local policies that encouraged rapid urban growth. Despite these developments, the household registration system continued to restrict the free movement of rural labor to cities, thereby limiting opportunities for rural income growth. This institutional constraint caused the urban-rural income gap to widen significantly until 1993, as urban areas surged ahead while rural regions lagged.

In response to the growing inequality, the government implemented a series of regional balance adjustment policies starting in 1993, which temporarily reduced the

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urban-rural income gap. Nevertheless, as China transitioned to a socialist market economy and adopted further economic liberalization measures, the nation's economy grew at a rapid pace. While this growth benefited urban areas, institutional limitations continued to restrict rural workers' mobility, perpetuating a widening urban-rural income gap. This trend persisted until 2009, when a shift occurred, signaling a gradual decline in the gap. However, despite this narrowing, the income disparity remained substantial, reflecting ongoing systemic challenges (Li & Zhu, 2018).

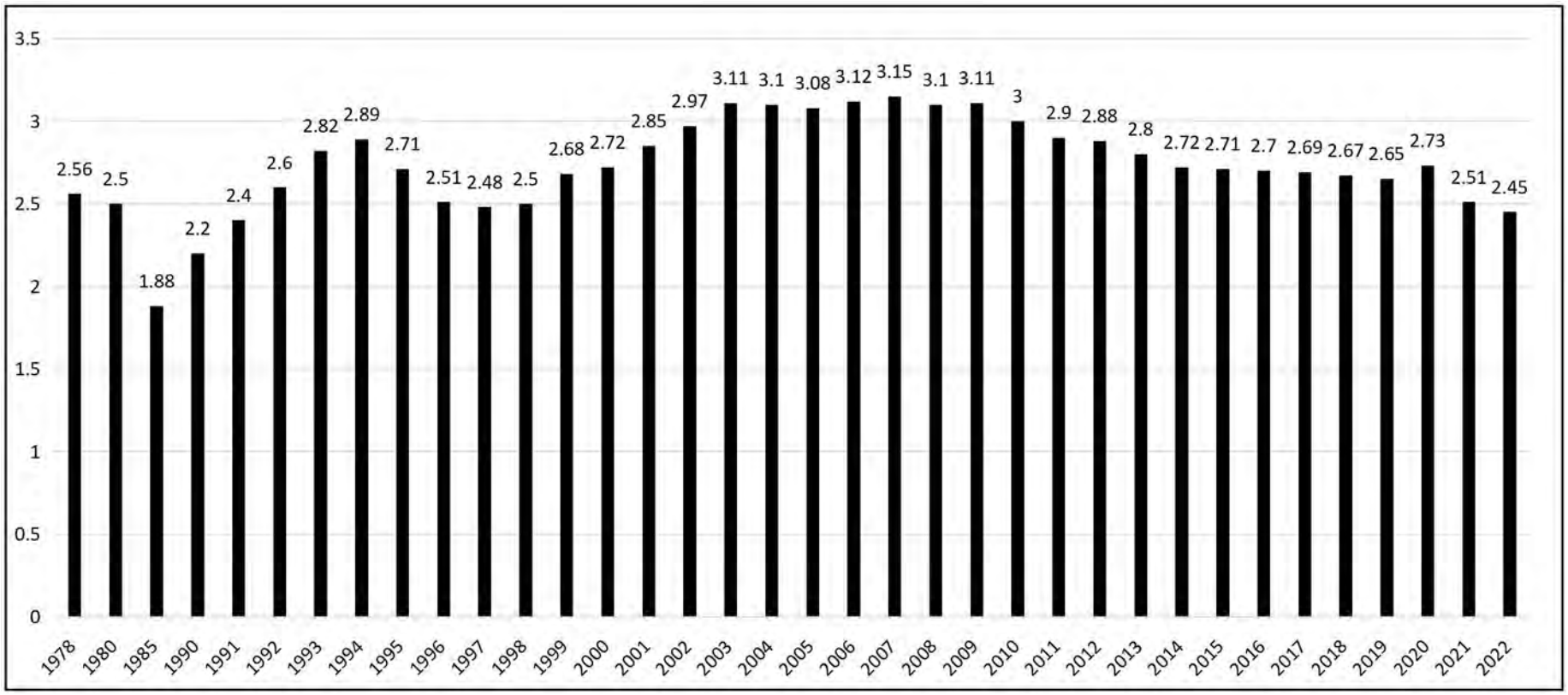
Further studies have suggested that the urban-rural income gap in China followed an inverted U-shaped pattern over a more extended period, from 1978 onwards (Lin & Chen, 2011; Shao & Jin, 2016). This inverted U-shaped trajectory suggests that the gap initially increased as urbanization and industrialization advanced, before gradually narrowing due to subsequent policy shifts and structural changes in the economy. These findings highlight the dynamic and complex nature of the urban-rural income gap, influenced by both economic reforms and institutional constraints.

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Figure 2.1

Ratio of Urban Residents' Disposable Income to Rural Residents' Per Capita Net Income in China Since 1978



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2.3.3 Factors influencing the urban-rural income

Compared to other countries, China's urban-rural income gap is primarily caused by the dualistic segmentation system between urban and rural areas. This section mainly analyzes the impact of the dual structure, urban bias system, urbanization, human capital, digital technology, industrial structure and other factors on the urban-rural income gap.

2.3.3.1 Economy development

Scholars have extensively discussed the urban-rural income gap issue, with a focus on the impact of economic development. Kuznets (1955) conducted statistical analysis on historical data from countries such as England, the United States, and Germany, proposing the famous hypothesis known as the Kuznets curve. It suggests that income inequality undergoes a process of widening and then narrowing with economic development, depicting an inverted U-shaped relationship between economic development and income inequality. Subsequent studies have further explored this idea, aiming to confirm the existence of the Kuznets curve or identify the specific stage of the inverted U-shaped curve. For instance, Montek et al. (1976) empirically confirmed the existence of the inverted U-shaped curve. Moreover, Deininger and Squire (1996) found that continued widening of income inequality leads to social inequality, thereby impeding economic growth. Allowing income inequality to widen

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naturally with economic growth may create a vicious cycle of low economic growth and high income inequality. Hence, it is crucial to address urban-rural income gap by improving other conditions.

2.3.3.2 Dual structure and urban-biased institutional system

China exhibits common characteristics of developing countries, characterized by the coexistence of traditional sectors with surplus labor, primarily in small-scale agricultural economies, alongside modern sectors focused on industrial production with a shortage of labor. This duality is referred to as the dual structure in development economics. However, the most notable feature of China's urban-rural dual structure is the deep-seated institutional division between urban and rural areas due to long-standing historical issues. This division is prominently manifested in systems such as household registration, statistical surveys, employment, social security, and welfare, leading to a bias in income distribution favoring urban areas. The urban-rural division is a prominent feature of China, not only reflecting an economic division between agriculture and non-agriculture but also an artificial division resulting from institutional barriers that hinder the free flow of factors between urban and rural areas. Urban-biased policies contribute significantly to the long-standing urban-rural divide and the significant income gap, driven by the prioritization of heavy industrial development at the expense of agriculture, with the

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surplus from agriculture transferred to urban capital accumulation and urban subsidies (Yang, 1999). Estimates by the Research Office of the CPC Central Committee and the Development Research Center of the State Council Agricultural Investment General Project Group (1996) suggest that between 1950 and 1978, the income from the price difference between industrial and agricultural products amounted to approximately CNY 510 billion, with agricultural tax revenue reaching 97.8 billion yuan. After deducting agricultural support expenditures of CNY 157.7 billion, the government extracted a net surplus from agriculture of CNY 450 billion. From 1979 to 1994, the government gained approximately CNY 1.5 trillion from the price difference between industrial and agricultural products, while agricultural tax revenue amounted to CNY 175.5 billion. After deducting agricultural support expenditures of CNY 376.9 billion, the government extracted a net surplus from agriculture of CNY 1.3 trillion (Fei,2017).

The urban bias system mainly manifests in the household registration system, employment system, social security, and welfare system in the urban-ruraldivision. The household registration system forms the foundation of this series of urban bias systems, and the urban-rural division's employment, social security, and welfare systems are established based on the division of agricultural and non-agricultural household registrations in China. The urban-rural division's household registration system not only brings political, social, and economic rights differences to different

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social groups but also brings unfair treatment to farmers and migrant workers, resulting in segmented labor markets between urban and rural areas and within urban areas, reducing labor allocation efficiency, and widening the urban-rural income gap (Song & Li, 2013). The establishment of the household registration system is not only for population statistics and individual identification but also serves other important government objectives. In the early days of the People's Republic of China, the government took on the responsibility of providing jobs and welfare to all urban residents, while rural populations largely lacked government support. To maintain this dual structure, the household registration system emerged. In the 1950s, the Chinese government issued a series of policies to restrict the free movement of rural labor. Finally, in 1958, the Regulations on Household Registration of the People's Republic of China was promulgated, officially establishing the dual household registration system. The establishment of the urban-rural dual household registration system has far-reaching impacts on all aspects of Chinese society. Even though the dual household registration system, abolished in 2014, its influence continues to this day. Nowadays, although rural migrant workers can freely search for jobs in cities, their treatment often remains lower than that of urban workers, and they find it difficult to enter high-paying industries.

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2.3.3.3 Urbanization

The rapid pace of urbanization has been another significant feature since the reform and opening-up policy, and its impact on the urban-rural income gap remains inconclusive. Studies by (Lu, et al., 2005), Xiang and Xu (2016) suggest that urbanization helps narrow the urban-rural income gap. During urbanization, factors of production such as labor and capital shift from rural areas with lower returns to urban areas with higher returns, reducing the disparity in labor productivity between sectors and thus narrowing the urban-rural income gap (Zhang et al., 2013). Furthermore, urbanization leads to an increase in urban population and the expansion of urban areas, enabling cities to exert a greater radiation effect and driving the development of rural areas (Ouyang et al., 2014).

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However, urbanization also plays a role in widening the urban-rural income gap. Zhou (2009) pointed out that during the process of economic development, the initial influx into urban sectors consists of a small group of rural individuals with certain skills and capital, who tend to have higher incomes. Therefore, in the early stages of urbanization, the urban-rural income gap tends to widen. The transfer of rural labor force prompts urban expansion, leading to more pronounced urban economies of scale and agglomeration effects, enhanced production efficiency, increased urban resident income levels, and ultimately, the widening of the urban-rural income gap (Ouyang, 2014).

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2.3.3.4 Human capital

Human capital is also an important factor contributing to the urban-rural income gap. Human capital refers to the knowledge, skills, education, experience, health, and other attributes possessed by laborers. According to human capital theory, the main determinant of income inequality among individuals is the difference in their levels of education (Kapheck & Zillberberg, 2007). The role of human capital includes: first, increasing income by enhancing laborers' productive skills; second, improving the efficiency of resource allocation; third, expanding laborers' employment opportunities; and fourth, increasing the output of physical capital and its marginal returns through the improvement of laborers' operational skills (Guo, 2005).

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A substantial body of research indicates that educational inequality between urban and rural areas is a significant factor contributing to the widening urban-rural income gap in China. Empirical findings by Xue et al. (2008) suggested that unequal education between urban and rural areas significantly affects income gap, and with the deepening of market-oriented reforms, the role of education becomes increasingly crucial. Chen et al. (2010), based on CHIP2002 data, employed the Oaxaca-Blinder decomposition to analyze the factors influencing the urban-rural income gap and found that the contribution of differences in educational levels accounted for 34.69% of the gap.

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Education, often measured by average years of schooling, is widely used as a proxy variable for human capital in empirical studies. For instance, Gregorioand Lee 2002) analyzed the contribution of human capital to income inequality and concluded that extending average years of schooling among rural populations can significantly narrow the income gap. Similarly, LaRose et al. (2007) emphasized the role of continuous education investment in bridging urban and rural divides, suggesting targeted policies to reduce discrepancies in educational access and quality. Despite its significance, the effects of human capital are not uniform. Variations in educational returns between urban and rural areas further exacerbate inequality. Empirical evidence by Zhang et al. (2015) demonstrates that the returns to education in urban areas are significantly higher than those in rural regions due to inequality in industrial structures, labor market conditions, and resource endowments . This inequality underscores the need for more inclusive education policies tailored to the needs of rural labor markets.

Additionally, health, which is another critical component of human capital, impacts labor productivity and income levels. Studies by Bor et al. (2017) indicate that poor healthcare infrastructure in rural areas limits productivity growth, contributing indirectly to income inequality. Integrating health-focused interventions alongside education policies could provide a more comprehensive approach to addressing income inequality.

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In summary, human capital plays a central role in shaping urban-rural income gap, with educational inequality being a significant factor. Most studies adopt average years of schooling as a proxy for human capital due to its measurability and strong correlation with income levels. Addressing the urban-rural income gap requires multi-dimensional strategies, including improving educational access and returns in rural areas and addressing health-related challenges to fully leverage human capital's potential.

2.3.3.5 Digital technology

The digital economy development mainly relies on the combination of digital technology and the physical economy to function. More relatively mature digital technologies include internet technology. And the development of digital technology affects the urban-rural income gap through income. Forman et al., (2012) studied the relationship between internet technology and regional wage inequality. The study found that although internet application is widespread, its economic benefits are not high, and only 6% of the regions have a relationship between internet technology and income increase. These regions are relatively prosperous, with well-educated people and a dense internet industry. Other regions with advanced internet technology have no relation to wage growth. Overall, the application of internet technology can explain more than half of the regional income differences. In the same year, Forman and Van

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Zeebroeck (2012) published another article explaining the problem of internet benefits and specifically pointed out that the internet has exacerbated regional wage inequality.

Some Chinese scholars have shown in their research that the widespread use of internet technology has exacerbated the imbalance in urban-rural development and increased income inequality. Qiu et al. (2016) believed that although the application of internet technology can theoretically provide equal opportunities for income, in reality, the benefits obtained from the internet dividend between urban and rural areas differ, and there are also differences between regions, with more developed economic regions such as the Southeast coastal areas benefiting more. However, some scholars have also shown that the popularization of internet technology can reduce the urban-rural income gap. Li and Xie (2017) found that the internet use has a negative impact on wage income gap. The research results of Cheng and Zhang (2019) showed that the impact of internet technology on the urban-rural income gap has been shrinking since 2009. Wang (2021) stated that the development of mobile internet in the eastern and central regions can significantly reduce the urban-rural income gap.

2.3.3.6 Industrial structure

The transformation of industrial structure plays a crucial role in shaping the urban-rural income gap by influencing employment opportunities, value creation, and regional economic balance. However, the relationship between industrial structure and

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income inequality is complex, with various scholars offering different perspectives on how industrial adjustments affect income gap between urban and rural areas.

One viewpoint posits that industrial structural adjustment exacerbates the urban-rural income gap. Jiang（2007) and Luo (2009) have contended, through an analysis of the employment structure and value-added structure within the three sectors of the economy, that the fundamental cause of the urban-rural income gap expansion lies in the unequal employment structure among industries. Based on time-series data from China spanning the years 1952 to 2008, Gao (2011) identified a positive correlation between the increasing share of secondary and tertiary sectors and the widening income gap, emphasizing that industrial transformation often benefits urban regions more substantially than rural areas.

In contrast, another perspective argues that industrial structural adjustments can mitigate the urban-rural income gap by fostering inclusive growth. Chen and Ravallion (2007) conducted an empirical analysis using data spanning the years 1980 to 2004 in China to investigate the influence of different industries on income inequality. The results of the study reveal that the expansion of value-added output in the primary sector plays a favorable role in mitigating rural poverty and, consequently, in reducing the urban-rural income gap. Liu and Lv (2011), based on provincial-level panel data in China from 1978 to 2006, contended that the development of both the primary and secondary sectors effectively narrows the urban-rural income gap. Zhou

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and Li (2021), using panel data from 29 provinces (2000–2018), concluded that improving industrial structures at the national level contributes to narrowing the income gap, with industrial upgrading benefiting both urban and rural areas when inclusivity is prioritized.

Some scholars focus on the shift from traditional agricultural sectors to modern non-agricultural sectors. Robinson (1976) argued that, in economies with two distinct sectors, the income gap between them inevitably leads to increased income inequality during early stages of development. This phenomenon follows a U-shape pattern, where income inequality rises as labor moves from the agricultural to the industrial sector, but the gap narrows over time as industrial productivity increases and more people migrate to higher-productivity sectors. Lee (1996) also developed a framework, referred to as the Push-Pull theory, to explain population migration driven by industrialization. Pull factors, such as urban job opportunities in emerging industries, and push factors, such as mechanization in agriculture, both contribute to rural-to-urban migration (Al-Maruf et al., 2022).

The role of technological progress in industrial transformation is another critical factor affecting income inequality. Li and Yang (2021) argued that the adjustment and upgrading of industrial structures are crucial for income distribution, with technological advancements driving differences in labor productivity across sectors. These productivity differences contribute to the persistence of income

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inequality between urban and rural areas. When technological advancements are uneven, sectors that adopt advanced technologies may see faster growth, but the benefits may be limited to urban areas, thereby exacerbating income inequality (Wang & He, 2005). If technological development overly favors capital-intensive industries rather than labor-intensive ones, it can lead to higher unemployment in rural areas, thereby widening the income gap.

Finally, the impact of industrialization on the urban-rural income gap remains a debated issue. Tian et al. (2009) and Mu and Wu (2012) found that industrialization initially exacerbates income inequality by concentrating wealth in urban areas but, over time, this negative effect diminishes, and industrialization can eventually help reduce the income gap. Studies focusing on the role of different industries in income disparity also support this argument. For instance, research on Anhui Province by Wang and Dong (2010) highlighted the significant contribution of the primary sector to rural income, while the tertiary sector had a more substantial impact on urban income levels. Similarly, studies by Wang et al. (2015) and Hu (2023) showed that the development of the secondary and tertiary sectors can significantly increase urban income, but the impact on rural areas is less pronounced, at least in the short term.

In conclusion, while some scholars argue that industrial structural transformation exacerbates the urban-rural income gap, others suggest that with the right policy emphasis on inclusivity, such transformation can reduce gap. The key lies in ensuring that industrial growth and technological progress benefit both urban and

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rural areas, with a focus on promoting industries that are labor-intensive and capable of absorbing rural surplus labor.

2.3.3.7 Other factors

The urban-rural income gap is a complex socio-economic phenomenon influenced by multiple factors. In this section, we focus on five key control variables: education level, urbanization rate, fiscal expenditure, economic openness, and economic development level. These factors not only serve as important determinants of the income gap but also interact with each other, further complicating the underlying mechanisms.

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Education plays a pivotal role in determining income levels, as it directly impacts labor productivity and employability. Chen et al. (2010) demonstrated that gap in education between urban and rural populations significantly contribute to the widening of the income gap. Furthermore, Li and Pei (2019) pointed out that public education funding, while aimed at improving overall education quality, may inadvertently widen the urban-rural divide if the allocation disproportionately favors urban areas. The distribution of educational resources, the quality of schooling, and access to higher education remain critical in bridging the gap, emphasizing the importance of equitable educational policies.

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Urbanization serves as a double-edged sword in influencing the income gap. Wu (2011) highlighted that urbanization has a narrowing effect on the income gap in the long term by creating employment opportunities and improving infrastructure in rural areas. However, in the short term, urbanization can exacerbate income inequality as rural migrants struggle to integrate into urban labor markets. Research by Wu and Liu (2014). Peng et al. (2020) suggests that urbanization combined with tertiary industry development can help reduce the income gap, though the effects may vary based on regional contexts and policy implementations.

Government fiscal policies, particularly in areas such as social security, healthcare, and education, have a profound impact on income distribution. Hu et al.(2011) found that social security expenditure could reduce the income gap, while Gao (2016) reported contrasting results in specific regional contexts, such as Shandong Province. This divergence highlights the importance of the structure and targeting of fiscal spending. Similarly, Yu and Wang (2021) argued that increasing the share of guaranteed expenditures in government budgets can help narrow the urban-rural income gap. In contrast, Li et al. (2021) emphasized the urban bias in fiscal expenditure allocation, which can widen the income gap by favoring urban residents over rural populations.

The role of economic openness in shaping the urban-rural income gap is multifaceted. Foreign direct investment (FDI), for example, can stimulate economic

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growth but may disproportionately benefit urban areas where industries and infrastructure are concentrated. Wang and Pang (2019) demonstrated that greater economic openness could negatively impact the income gap, particularly when rural areas lack the capacity to attract investment or compete in global markets. Policies aimed at fostering inclusive growth, such as rural-friendly trade agreements and investment incentives, are therefore crucial in mitigating these effects.

The impact of government fiscal expenditure on the urban-rural income gap likewise fails to reach a consensus. Some scholars believe that expanding government fiscal spending can reduce the urban-rural income gap (Dodge, 2010). Specifically, if the government increased the guaranteed portion of budgetary expenditure, then it would have a negative effect on the income gap between urban and rural residents (Yu & Wang, 2021). Li et al. (2021) believed that due to the urban bias of fiscal expenditure and the unreasonable allocation of labor resources by the factor market, the income gap between urban and rural areas has widened.

Economic development level exhibits a nuanced relationship with the urban-rural income gap, often following a U-shaped trajectory. Chen and Lin (2013) described this pattern as an initial decrease in the income gap during early development stages, followed by an increase as economies transition to higher stages of industrialization. The benefits of economic growth are not always evenly distributed, with urban areas typically reaping more substantial rewards due to better

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access to infrastructure, technology, and markets. Yao and Deng (2020) emphasized that middle-to-high levels of rural human capital are essential for narrowing the income gap, suggesting that targeted interventions to enhance rural capabilities can play a significant role in achieving equitable development.

2.4 Optimization and upgrading of industrial structure

This section is arranged as follows: 2.4.1 is the definition of optimization and upgrading of industrial structure. 2.4.2 is the measurement methods for optimization and upgrading of industrial structure. 2.4.3 is the impact of optimization and upgrading of industrial structure on the urban-rural income gap and 2.4.4 is the factors influencing the optimization and upgrading of industrial structure.

2.4.1 Definition of optimization and upgrading of industrial structure

The industrial structure refers to the composition of various industries and the connections and proportions among them. It is a concept proposed in development economics, also known as the industrial system, and is a major component of the socio-economic system (Carree & Thurik ,1999). In economic research and management, the three-sector classification method is one of the commonly used classification methods (Xu, 2004). The three-sector classification method divides the industrial structure according to the historical development sequence of social

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production activities. The sectors that directly extract products from nature are called the primary industry, those that process primary products are called the secondary industry, and the sectors that provide various services for production and consumption are called the tertiary industry. This classification method has become a widely used method for classifying industrial structures worldwide.

According to the classification by the National Bureau of Statistics of China (2023b), the structure of China's three industrial sectors is outlined as follows: The primary industry encompasses agriculture, forestry, animal husbandry, and fisheries, excluding related specialized and auxiliary activities. The secondary industry covers mining (excluding specialized mining activities and auxiliary operations), manufacturing (with the exception of metal products, machinery, and equipment repairs), electricity generation, heat production, gas and water supply, as well as construction. The tertiary industry, also known as the service sector, consists of all industries not included in the primary or secondary categories. This sector comprises a wide range of activities, including wholesale and retail trade, transportation, warehousing, and postal services, accommodation and catering, information transmission, software and information technology services, financial services, real estate, leasing and business services, scientific research and technical services, water conservancy, environmental protection, and public facility management, as well as services such as education, healthcare, social work, culture, sports, and entertainment.

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It also includes public administration, social security, and social organizations, as well as specific activities in agriculture, forestry, animal husbandry, and fisheries, mining, and manufacturing industries, such as auxiliary activities in primary and secondary sectors and repairs in manufacturing.

Scholars believe that the industrial structure adjustment refers to improving the efficiency of resource utilisation and innovation, effectively utilising existing resources, optimising the proportion of the three industries, and achieving the optimal allocation of resources (Li et al., 2020). The process of achieving industrial structure adjustment involves, firstly, adjusting factors that are incompatible with industrial structure upgrading, such as outdated production methods, inefficient production factors and unreasonable resource allocation (Zhou, 1990). Second, the optimisation of supply and demand structure involves the optimisation of production factors of different industrial sectors, such as human capital, physical capital and capital input, as well as the optimisation of product supply quantities, profit distribution methods and other demand-side factors based on consumer needs (Yang & Chen, 2000). Then, optimizing the technological structure involves upgrading enterprise production processes and production equipment technology, improving enterprise technical and innovation capabilities (Shi & Zhao, 2011). Finally, optimizing the international trade structure involves the free flow of resources due to differences in resource endowments among countries, which leads to reduced costs of factor mobility between countries in the context of economic globalization (Zuo et al., 2020).

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From the perspective of production factors, Garret et al. (2001) argued that advanced industrial structure refers to the process of transferring production factors from labour-intensive industries to capital and technology-intensive industries. According to Oztemel and Gursev (2020) the advanced industrial structure refers to the leading industry of a country or region that gives priority to improving the level of technology and efficiency within the industry through innovation, which in turn drives the development of related industries, optimises the overall industrial structure and promotes the improvement of the overall efficiency of industrial cooperation. The specific manifestations of this are: first, innovation achievements and high technology gradually penetrate into various industries. The products of a country or region can always be seen in the production process, more or less the shadow of innovative achievements, high technology, technology into the added value of the product, to improve the overall value of the product Second, to achieve the allocation-Clark's theorem, that is, a country or region's labour force, the proportion of capital in the transfer between the three industries, gradually from the primary industry to the transition of secondary and tertiary industries. Thirdly, the division of labor between industries becomes more refined, fostering an increased degree of inter-industry cooperation. There is a rise in the number of integrated industries across different sectors, with the development of industrial structure being more significantly influenced by international factors. This dynamic environment leads to a faster pace of industrial upgrading (Zhong et al., 2020).

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Overall, industrial structure adjustment includes two aspects: industrial structure rationalization and advancement (Fan et al., 2003; Li & Hu, 2008; Luo, 2019; Sui, 2022). Industrial structure rationalization refers to the mutual coordination among industries, with strong ability to transform industrial structures and good adaptability to changes in market demand, resulting in the optimal industrial structure that brings the best benefits. This is specifically manifested in the process where the quantity proportion relationship, economic and technological connections, and interaction among industries tend to be balanced and coordinated.

2.4.2 Evolution of Chinese industrial structure

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Since 1978, China's industrial structure has undergone profound changes (Wang,2019). Between 1978 and 2020, the proportion of the primary industry has continued to decrease, the proportion of the secondary industry has fluctuated downward, and the proportion of the tertiary industry has continued to rise, decreasing (increasing) from 27.7%, 47.7%, and 24.6% in 1978 to 7.6%, 37.8%, and 54.5% in 2020, respectively (Tencent Research Institute, 2021). The development process of China's industrial structure exhibits significant stage characteristics (Wang, 2019): In terms of industrial value-added, the first stage was from 1978 to 1984, showing a two-one-three structure with industry as the mainstay, followed by agriculture, and services at the lowest level. The second stage was from 1985 to 2012, showing a

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two-three-one structure with industry as the mainstay, followed by services, and agriculture at the lowest level. The third stage, from 2013 to the present, formed a three-two-one structure with services as the mainstay, followed by industry, and agriculture at the lowest level. In fact, not only in terms of value-added structure but also in terms of employment structure, growth rate structure, contribution rate structure, and the role of GDP traction, all have synchronously transitioned to a "three-two-one" structure around 2013 (Hui & Liu, 2019). In 2022, the proportion of value-added of the primary industry to GDP was 7.3%, the proportion of the secondary industry was 39.9%, and the proportion of the tertiary industry was 52.8% (National Bureau of Statistics of China, 2023c). In terms of the proportion of the value-added of China's three industries to the global economy, the proportions of the three industries in global GDP have shown a continuous upward trend, increasing from 18.40%, 4.40%, and 1.82% in 1994 to 24.35%, 22.13%, and 9.52% in 2019, respectively (Tencent Research Institute, 2021). Their positions in the world economy demonstrate the characteristic of the primary industry having the largest proportion, the secondary industry ranking in the middle, and the tertiary industry having the smallest proportion.

Over the years, a stable three-two-one pattern of industrial structure development has emerged globally, wherein the proportion of the tertiary industry in Gross Domestic Product (GDP) exceeds that of the secondary industry, which in turn

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exceeds that of the primary industry. Additionally, the proportions of value-added by the primary and secondary industries in GDP have both exhibited a declining trend. Data from the World Bank indicates that these proportions decreased from 7.60% and 31.94% in 1995 to 3.27% and 25.61% in 2018, respectively. Meanwhile, the proportion of the tertiary industry has continued to rise, increasing from 60.46% in 1995 to 71.12% in 2018. Upon comparison, it is evident that China's industrial structural development process exhibits a significant asynchronous phenomenon. While the industrial structure domestically had already taken on the characteristics of a three-two-one pattern by 2013, it has been slow to break free from the constraints of a one-two-three pattern internationally. The gap in industrial structure between domestic and international spheres are pronounced, with their evolution progressing at different paces. This is visually manifested by the relatively high proportion of China's primary industry in the global economy, indicating a relatively weak industrial foundation. Although the proportion of the secondary industry has been increasing rapidly, it has yet to fundamentally reverse the situation of being large but not strong. Meanwhile, the proportion of the tertiary industry in the global economy remains relatively low, and the pace of internal optimization and upgrading within the industry sector is slow (Han et al., 2023).

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2.4.3 Measurement methods for optimization and upgrading of industrial structure

When studying the impact of industrial structure on economic growth, the multi-country model developed by Syrquin and Chenery (1989) or the Shift-Share Method proposed by Fabricant (1942) are generally used for analysis (Timmer & de Vries, 2009). The selection of control variables in the multi-country model is ambiguous, which can lead to omitted variable problems and inaccurate analysis. Additionally, the measurement of industrial structure in the model is also a challenge (Gan et al., 2011). The Shift-Share Method is an effective method for analyzing structural problems, but it may underestimate structural effects (Lyu, 2002). Furthermore, when using this method for analysis, the analysis of changes in industrial structure is not detailed enough.

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i. Measurement Methods for Upgrading of the Industrial Structure

Currently, there are some differences in the research on the measurement of high-level development of industrial structure, which can be broadly divided into two categories.

One is from the perspective of output value. For example, Gao et al. (2015) believed that the upgrading of industrial structure mainly targets the transformation and upgrading of the non-agricultural sector, so he proposed to measure it using the proportion of secondary and tertiary industries in GDP. However, Jia and Yin (2015) believed that the essence of industrial structure is the optimisation of resource allocation, so GDP should not be included in the calculation. Instead, the proportion

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of value added in tertiary and secondary industries should be used for measurement.

Another is to measure the level of industrial structural upgrading from the perspective of advanced industrial structure. For example, Fu et al. (2013) believed that advanced industrial structure means extracting the essence and removing the dross of the original industry, and propose to measure the level of industrial structural upgrading by using the output value of new products. Fu (2010) suggested that the difference in output value is the main manifestation of industrial structural upgrading from the perspective of the Patten-Clark theorem. As the industrial structure becomes more advanced, the proportion of value added in the tertiary sector increases. Therefore, the angle formed by the proportion space vector of different industrial output values and the space vector of industrial ranking from low to high is used to measure it. The higher the value measured by this angle, the higher the level of industrial structural upgrading. Tian and Han (2012) believed that industrial structural upgrading represents the level and direction of economic development, and the goal of industrial structural upgrading can only be achieved when the main production factor gradually shifts to technology.

Although the increase in the proportion of non-agricultural production in the economy is an important trend, the information technology revolution that took place in major industrialised countries after the 1970s has had a major impact on their industrial structure, leading to a trend towards economic servitisation. As

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socio-economic development continues, this trend towards economic servitisation has become more apparent, especially during the COVID-19 pandemic in 2020-2021, where the development of the online economy has led to a more significant consumption pattern in offline entities. Economic servitisation is an important feature of the process of industrial structural upgrading. However, traditional measurement methods cannot reflect this trend in the economic structure. Given that a typical fact in the process of economic servitization is that the growth rate of the tertiary industry is faster than that of the secondary industry (Jia & Yin, 2015; Wu, 2008), this study adopts the ratio of the output value of the tertiary industry to that of the secondary industry as a measure of the degree of industrial structural upgrading, based on the reference of Gan et al. (2011). This measure could clearly reflect the trend of servitisation in the economic structure and indicate whether the industrial structure is developing towards servitisation, making it a better measure. If the it value is in an upward trend, it means that the economy is moving towards servitisation and the industrial structure is upgrading.

ii. Measurement Methods for Optimization of the Industrial Structure

The optimization of industrial structure generally means the degree of integration between industries, which reflects the speed of adjustment between industries and the efficiency of resource allocation. In other words, the optimization of industrial structure refers to the degree of match between production factors and industrial

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structure. With the development of research by different scholars, indicators for measuring the degree of industrial structure optimization have been continuously optimized, including indicators such as structural perspective (Li & Hu, 2008), industrial structure deviation, the Theil index, and the index of industrial structure optimization (Gan et al., 2011). Using the structural angle value measure the upgrading of industrial structure has the advantage of being easy to use and highly operable. However, it has the following disadvantages: it cannot reflect the internal structural changes of each industry, such as the influence of technological progress and productivity improvements (Gan et al., 2011). It is sensitive to extreme values and may be less stable and reliable as an industry may account for a smaller proportion of the data but a larger proportion of the results. It cannot capture multi-dimensional industrial optimization and can only measure industrial optimization from an aggregate perspective, which may ignore differences between industries.

The calculation formula for the industrial structure deviation coefficient is shown as formula 2.6:

$$E = \left(\frac{Y_1/Y}{L_1/L} - 1\right) + \left(\frac{Y_2/Y}{L_2/L} - 1\right) + \left(\frac{Y_3/Y}{L_3/L} - 1\right) \quad (2.6)$$

In the formula 2.1, Y represents the GDP of a country or region, Y_1, Y_2, and Y_3 represent the value added of the first, second, and third industries respectively, L represents the number of employed people in the country, and L_1, L_2, and L_3 represent

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the number of employed people in the primary, secondary and tertiary industries respectively. It is generally believed that when E=0, the economy of a country or region has reached an equilibrium state, and when E is different from 0, it indicates that there is still room for improvement towards an equilibrium state in the industrial structure. However, the industrial structure deviation coefficient lacks consideration of the impact of the connections between industries on the overall economy. Therefore, Gan et al. (2011) proposed the Theil index, as shown in formula 2.7:

$$T = \left[\frac{Y_1}{Y}\right] \ln \frac{Y_1/L_1}{Y/L} + \left[\frac{Y_2}{Y}\right] \ln \frac{Y_2/L_2}{Y/L} + \left[\frac{Y_3}{Y}\right] \ln \frac{Y_3/L_3}{Y/L} \qquad (2.7)$$

As can be seen in formula 2.2, the Theil coefficient takes into account the impact of inter-industry linkages on the economy as a whole, while avoiding the calculation of absolute values. Therefore this study adopts it as a measure of the degree of industrial structure optimization.

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2.4.4 Impact of optimization and upgrading of industrial structure on urban-rural income gap

The role of industrial structure in economic development has been a subject of extensive research, providing a strong theoretical foundation for understanding the dynamics of national economies. Iam Petty, one of the earliest classical economists, was among the first to offer an explanation for the disparities in economic

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development and national income across countries (Goodacre, 2018). Petty argued that the industrial structures in different nations account for significant differences in their levels of economic development, positing that industrial advancement plays a central role in driving economic growth (Kurz & Salvadori, 2003). His ideas laid the groundwork for later economists to explore how shifts in industrial structure impact income inequality, especially between urban and rural areas.

Following Petty's work, David Ricardo further expanded on these concepts in his seminal book *Principles of Political Economy and Taxation*. Ricardo delved into the underlying causes of the urban-rural income gap, explaining that the divergence between the industrial and agricultural sectors in terms of production methods, technologies, and demand for products contributed substantially to the widening income gap between urban and rural regions. Ricardo's arguments highlighted that industrialization, through its complex interactions with agriculture, deepened income disparities by favoring urban areas, where industries were concentrated, over rural ones, which remained dependent on agriculture (Zhong et al., 2022).

In the 20th century, Colin Grant Clark, drawing on empirical studies from various countries, proposed a theory of industrial structure development. Clark's work emphasized the evolution of industrial sectors as economies advanced. He noted that, with economic growth, the secondary and tertiary sectors tend to experience higher relative income growth compared to the primary sector, especially agriculture. This shift leads to a reallocation of labor from rural, agricultural areas to urbanized,

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industrial sectors. Over time, as agricultural labor declines and output per worker in agriculture decreases at a faster rate than the decline in agricultural employment, the urban-rural income gap becomes more pronounced (North, 1955). Clark's theory underscored the critical relationship between industrial structure and income distribution, providing a framework to understand how structural shifts could either mitigate or exacerbate regional income disparities.

Building on these theoretical foundations, scholars have integrated classical economic theories with the specific conditions of China's economic transformation, especially regarding the urban-rural income gap. The impact of industrial structure adjustment in China has been the subject of extensive study, with scholars taking two distinct approaches to analyzing its effects：

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i. Widening Urban-Rural Income Gap

A significant body of research argues that changes in industrial structure in China have contributed to the widening urban-rural income gap. Bi and Jian (2002) explored the effects of China's economic structural transformations on income distribution and concluded that the country's industrial structure has become increasingly distorted, exacerbating income inequality. According to their findings, the concentration of industrial development in urban areas has hindered efforts to bridge the urban-rural income gap, as rural areas remained underdeveloped due to a lack of industrial

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diversification. Su (2002) further examined how the pace of industrial development in different sectors influenced income disparities between urban and rural populations. His analysis suggested that uneven industrial development was a major driving factor behind the growing income gap. Fan (2008) expanded on this idea using data from 28 provinces in China and found a positive correlation between the expansion of the secondary industry and increasing regional income disparities. Pan (2010) added another layer of insight, arguing that although industrialization has increased the income levels of urban residents, it has simultaneously contributed to a deepening of the income divide between urban and rural populations. Pan's research highlighted that industrialization, while elevating urban living standards, did little to improve conditions in rural areas, thus exacerbating the urban-rural income gap.

Additionally, the concept of industrial agglomeration has emerged as an important factor in understanding income disparities. Cai and Chen (2012) constructed a spatial panel model to study the relationship between industrial agglomeration and the urban-rural income gap. Their study revealed that while industrial agglomeration in urban areas has led to greater economic efficiency and growth, the benefits of this agglomeration were unevenly distributed. Rural areas, due to their limited industrialization, did not experience the same economic benefits, which in turn deepened the income divide between urban and rural regions.

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ii. Narrow the Urban-Rural Income Gap

Contrasting with the above view, other scholars argue that industrial restructuring holds significant potential for reducing the urban-rural income gap. Ma (2008) suggested that regional industrial upgrading, particularly through the relocation of industries from more developed coastal regions to less-developed inland areas, could help mitigate income inequality. By promoting industrial growth in rural areas, this strategy could reduce the income gap between urban and rural regions by improving local economic opportunities and employment prospects. Liu and Lyu (2011), using provincial panel data spanning from 1978 to 2006, found that the expansion of primary and secondary industries in rural areas contributed to real income growth, particularly for low-income groups. This income growth, in turn, helped to reduce the urban-rural income gap. Similarly, Zheng and Li (2012) focusing on central China, concluded that the increasing share of secondary and tertiary industries in regional economies helped narrow the urban-rural income divide. Their study indicated that a balanced industrial development approach could bridge the income gap by promoting growth in both urban and rural areas.

Yang and Zhao (2014) provided additional evidence of industrial restructuring's potential to reduce the income gap. Their study, which analyzed data from 30 provinces between 1998 and 2012, used a simultaneous equation model and an endogenous distribution lag model to explore the effects of industrial restructuring.

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Their results suggested that while industrial restructuring had a negative short-term impact on income inequality, it played a significant role in reducing the urban-rural income gap in the long term. The study highlighted that, in the long run, the development of secondary and tertiary industries in rural areas could contribute to more equitable income distribution.

A more nuanced perspective has emerged, with some scholars focusing on the optimization and upgrading of industrial structures to address income distribution issues. Li and Hu (2008) emphasized that improving the dual economic structure and optimizing the industrial framework could reduce the urban-rural income gap by enhancing productivity and increasing the income of rural workers. Their argument suggests that a strategic shift towards higher-value industries in rural areas could bring economic benefits and reduce inequalities. However, Cheng (2014) offered a more complex view, asserting that while upgrading the industrial structure could improve income distribution in certain contexts, it could also exacerbate the urban-rural income gap. In his research indicated that the pace and nature of industrial upgrading were critical factors in determining its impact on income inequality. If industrial upgrading occurs too rapidly in urban areas without sufficient support for rural industries, it could lead to even greater disparities in income.

In conclusion, the literature on industrial structure adjustment and its impact on the urban-rural income gap presents a diverse range of perspectives. Some studies

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suggest that industrial restructuring exacerbates income inequality, particularly by concentrating economic benefits in urban areas. Other scholars argue that strategic industrial restructuring, including upgrading and relocating industries, can help reduce the urban-rural income gap. Despite these varying viewpoints, a consensus has not been reached, and much of the research to date has focused on national-level data, often overlooking regional differences that may influence the effects of industrial changes on income distribution.

2.4.5 Factors influencing optimization and upgrading of industrial structure

The optimization and upgrading of industrial structure are key to driving economic transformation and improving national competitiveness. Numerous factors influence this process, which can be grouped into six primary categories: human capital, capital deepening, technological innovation, financial development, foreign direct investment (FDI), and government policies. These factors collectively play a critical role in shaping the industrial structure and facilitating its evolution.

i. Human capital and its spillover effect

Human capital plays a crucial role in enhancing technological capabilities within regions, thus indirectly influencing industrial structural adjustments (Glaeser, 1999). As China's human capital continues to improve, this enhancement accelerates the

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pace of industrial structural changes. The distribution of human capital in China exhibits a non-linear, U-shaped pattern in its effect on industrial structure adjustments. Li et al. (2017) argue that as human capital becomes more efficiently allocated across regions, the rate of industrial restructuring increases. Acemoglu and Guerrier (2008) found that the impact of human capital on industrial structure adjustments is crucial as it fosters the development of a more diversified, technologically advanced industrial base. Improved human capital distribution helps shift labor from low-productivity sectors to higher-value-added industries, contributing to overall industrial upgrading.

ii. Capital deepening and its role in structural adjustment

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Capital deepening refers to the increased accumulation of capital, which has a direct effect on the relative prices of capital and labor, impacting industrial composition. According to Li et al. (2017), capital deepening has been a significant driver of industrial adjustments in China, particularly by promoting a shift from labor-intensive industries to capital-intensive sectors. Yu and Xu (2014) further assert that capital accumulation, including inter-industry capital deepening, enhances the overall industrial structure by boosting productivity and fostering innovation. The increased availability of capital allows for more efficient production processes and better positioning within global value chains, thus driving structural upgrading (Guo et al., 2020).

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iii. Technological innovation and industrial upgrading

Technological innovation is pivotal in optimizing and upgrading industrial structures, as it influences production inputs, demand structures, and overall productivity. Henderson and Wilson (2002) argue that technological progress promotes industrial upgrading and economic benefits by transitioning industries from low-value-added to high-value-added sectors, thereby driving economic growth. Furthermore, Humphrey and Schmitz (2002) emphasize that technological innovations enhance product competitiveness, thus supporting industrial structure upgrading. Reeve (2006) noted that technological advances lead to the flow of resources from inefficient sectors to more productive ones, facilitating structural shifts. However, some scholars caution that while technological innovation drives industrial upgrading in the short term, its long-term effects may experience diminishing returns. As Zuo et al. (2020) observe, the development of an information-based society and the rapid advancement of internet technologies are critical factors in the continued optimization and upgrading of China's industrial structure. Li et al. (2020) used panel regression analysis to demonstrate that both technological and institutional innovations have a positive impact on industrial upgrading, though their effects on optimization may vary depending on broader institutional and economic contexts.

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iv. Financial development and structural adjustment

The development of financial markets is another important factor influencing industrial structure optimization and upgrading. Fisman and Love (2003) argue that efficient financial markets help promote industrial upgrading by improving capital allocation, which allows resources to flow from less productive sectors to more efficient ones. Beck et al. (2005) suggest that financial development, by lowering financing costs for small and medium-sized enterprises (SMEs), supports their expansion into more innovative and high-growth sectors, thus contributing to industrial restructuring. Alfaro et al. (2010) believed that the financial market provides financial support for the development of emerging industries through efficient resource allocation, thus promoting the upgrading of industrial structure.

Financial deepening, achieved through improved access to capital, more sophisticated financial instruments, and enhanced banking systems, has a positive impact on industrial optimization. Financial development could improve the level of technological innovation and optimize the structure of technological innovation, which is conducive to the adjustment of industrial structure (Wang & Wang, 2021). Xu and Tan (2020) highlight that financial deepening aids technological innovation, which in turn supports the adjustment of industrial structures. Additionally, Li and Li (2022) argue that inclusive finance, by improving access to capital for underdeveloped regions and sectors, plays a key role in supporting the optimization and upgrading of industrial structures in China.

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v. FDI and its impact on industrial transformation

Foreign direct investment (FDI) plays a critical role in shaping the industrial structure of recipient countries. Based on Kojima (1978) marginal industry expansion theory, FDI not only affects the industrial structure of the host country but also promotes industrial development in the sectors receiving investment. FDI brings advanced technologies, managerial expertise, and global market access to local industries, thereby promoting their upgrading. Li, Lin, et al., (2021) and Wang (2014) note that FDI has been a crucial driver in the development of China's industrial sectors, especially in high-tech and manufacturing industries, contributing to the acceleration of industrial restructuring.

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FDI helps bridge gaps in technology, capital, and management skills, which enhances local firms' ability to compete globally. This infusion of capital and technology is particularly important for developing economies, as it enables industrial sectors to leapfrog traditional stages of development and enter high-value-added industries more rapidly

vi. Government policies and their role in structural optimization

Government policies, particularly fiscal and taxation policies, have a significant impact on industrial structure optimization and upgrading. Peters et al. (2012) argue

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that industrial policies can guide technological innovation, optimize resource allocation, and ultimately drive industrial restructuring. An and Song (2016) contend that adjusting fiscal expenditure structures across sectors can influence the development direction of industries, helping direct resources to more strategic and growth-oriented sectors.

In addition, government subsidies play a major role in promoting industrial upgrading. Peng et al. (2020) found that government subsidies have an inverted U-shape relationship with industrial upgrading, meaning that their impact is most significant at moderate levels. Gan et al. (2022) emphasize that improving the efficiency of fiscal expenditures is crucial for promoting sustainable industrial development. By prioritizing investments in technology, infrastructure, and strategic industries, the government can significantly enhance the industrial structure.

In conclusion, the optimization and upgrading of industrial structure are influenced by various interrelated factors. Human capital, capital deepening, technological innovation, financial development, foreign direct investment, and government policies all play vital roles in shaping the industrial landscape. A balanced approach that integrates these factors is essential for achieving sustainable industrial development and fostering long-term economic growth.

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2.5 Impact mechanism of digital economy development on urban-rural income gap

Based on the existing literature studies the mechanism of digital economy development on urban-rural income could be divided into direct impact and indirect impact.

2.5.1 Direct impact

The current research on the direct impact of digital economy development on the urban-rural income gap presents two divergent perspectives. One viewpoint asserts that digital economy development can yield a digital dividend, primarily manifested through employment effects, financial effects, and market participation effects. This is seen as beneficial for rural development and narrowing the urban-rural income gap. In contrast, another perspective contends that digital economy development would bring about a digital divide, mainly characterized by access gaps, application gaps, and income gaps, thereby exacerbating the urban-rural income gap.

Firstly, Employment effect. The development of the digital economy has significantly diminished the gap in human capital and career search costs between urban and rural residents, thereby improving employment opportunities for rural individuals (Abdurakhmanova et al., 2020). This improvement, in turn, has contributed to a reduction in income inequality among residents. In the pre-digital era,

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the dissemination of knowledge and technology relied predominantly on books and teachers, which posed challenges for spreading these resources to rural areas. Consequently, rural residents had limited access to high-quality educational resources, advanced medical treatments, and innovative ideas, leading to a significant gap in human capital between urban and rural populations (Dede, 1996). The development of the digital economy has effectively overcome barriers to information dissemination, facilitating the sharing of knowledge, experiences, and technologies with rural communities. This advancement has resulted in a more efficient distribution of resources, thereby narrowing the human capital gap between urban and rural residents and improving the disadvantaged position of farmers in the job market (Yin et al., 2019). In rapidly urbanizing regions, numerous employment opportunities arise (Agrawal et al., 2015). In contrast to rural residents, urban inhabitants can swiftly access employment information and secure jobs that align with their skills. While rural residents primarily engage in agriculture, the agricultural sector cannot absorb the majority of the labor force, prompting a substantial influx of rural workers into urban areas. The unfamiliar urban environment hinders these individuals from quickly obtaining jobs that suit their qualifications, resulting in higher career search costs. However, with the advent of the internet and cloud computing, rural dwellers can now access employment-related information, gain insights into potential working environments, and reduce the expenses associated with their job searches (Velte et al., 2009). Thus, the internet-driven digital economy has mitigated the unfairness in

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knowledge acquisition and career search between urban and rural residents, contributing to the reduction of the urban-rural income gap.

Secondly, Financing effect. Rural areas are located in remote areas, with backward production and few financial institutions (Saxena, 2012). Compared with urban residents, rural residents have difficulty in obtaining financing. The combination of digital technology and financial services has changed the backwardness of the rural financial industry (Yu & Wang, 2021). The internet and electronic payment platforms have expanded the reach of financial services to rural residents, irrespective of their physical location (Pazarbasioglu et al., 2020). This effectively reduces the gap in financial service coverage between urban and rural areas (Pazarbasioglu et al., 2020). In addition, through digital means, the collection of customer information can be made more efficient and comprehensive, and the identification and judgment of risks can be more accurate (Demirkan & Delen, 2013). Investors who invest in local industries can boost the income levels of rural residents.

Last but not least is the Market participation effect. The digital economy development increases rural residents' market participation (Mekonnen, 2009). Transactions in the real economy market are often based on shops, while the rural commodity economy is backward and located in remote areas (Mekonnen, 2009). For instance, in rural areas, it is inconvenient to buy and sell goods, resulting in low participation rates of residents in the market. As a result, rural residents have

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significantly lower operating incomes than their urban counterparts. Moreover, the fixed capital of rural residents is much lower than urban residents, further widening the income gap between urban and rural areas (Osti, 2010). By utilizing e-commerce platforms and social media such as Taobao, TikTok, and WeChat, agricultural product sales channels can be expanded, rural resources can be revitalized, and the efficiency of matching supply and demand for agricultural production services can be improved (Yang, 2022). This enables rural areas to operate in a larger "seller's market," offering goods and labor, while also having access to a larger "buyer's market" to purchase goods and raw materials (Yang, 2022). This increased market participation helps make the market positions of urban and rural residents more equitable, reducing the urban-rural income gap.

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However, there are also divide Firstly, in rural areas, the lower level of internet access, slower internet speeds, and unstable connections diminish the effectiveness of digital technology as a tool, potentially giving rise to an Access Divide (Jiang, Li, & Si, 2022a). Secondly, rural residents, influenced by factors such as age, education, and occupation, lack the skills that align with the application of digital technology. This may result in their marginalization or even exclusion from the labor market, suggesting a possible Application Divide (Yudina, 2020). Thirdly, the heterogeneity prevalent in households in terms of human capital, social capital, material capital, and others, after transforming into varying levels of Internet Capital, contributes to more

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pronounced differences in digital dividends among households, potentially leading to an Income Divide as driven by the scale of the network market (Stromquist, 2019).

2.5.2 Indirect impact

Digital economy development promotes the upgrading and optimization of industrial structure, which significantly affects urban-rural income distribution. Therefore, the digital economy development can affect the income distribution structure through the upgrading and optimization of the industrial structure.

i. Impact of digital economy development on optimization and upgrading of industrial structure

The change of industrial structure can be measured from two dimensions: optimization of industrial structure and upgrading of industrial structure (Fan et al., 2003; Li & Hu, 2008; Luo, 2019; Sui, 2022). The optimization of industrial structure refers to the coordinated development of different industries and the efficient use of resources. The upgrading industrial structure refers to the gradual transfer of economic centers in the order of primary, secondary, and tertiary industries (Gan et al., 2011). The proportion of production factors such as technological progress and technological innovation has increased, and more and more high-value-added high-tech industries have gradually replaced labor-intensive industries. The

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emergence of digital technology and the subsequent development of new economies, formats, and models have presented fresh opportunities for optimizing and upgrading industrial structures (Gardan, 2017). This advancement supports enhancements in the internal production efficiency of industries, the rational allocation of resources, and the progress of industries towards higher-end levels, which can impact the income gap between urban and rural areas. The digital economy's growth can enhance resource allocation efficiency in various industries. With data sharing and low-cost reproducibility, economic entities can leverage the Internet for frequent exchanges, faster information dissemination, broader technology and knowledge sharing, increased resource utilization efficiency, and optimized industrial structure upgrades (Babkin et al., 2020; Zang, 2019). Utilizing network technology and platforms can also effectively pool resources such as funds, talents, and elements from society, reduce resource underutilization and waste, and promote the optimization and upgrading of industrial structures (Babkin et al., 2020; Guan et al., 2022; Liu, 2022; Qin et al., 2022; Iams, 2021; Zang, 2019; Zhao et al., 2022).

Industrial integration can advance with the expansion of the digital economy (Babkin et al., 2020; Han & Li, 2022; Kuang & Jiang, 2021; Li et al., 2021). By fusing numerous conventional cultural industries with the tourism sector with the aid of digital technologies like VR and CR, for instance, the development of digital technology encourages the deep integration of the cultural and tourism industries.

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Additionally, the digital economy development has aided in the close integration of agricultural and tourism-related activities. Digital technology has made it easier for different industries to communicate with one another, encouraged industry integration and growth, and aided in optimizing and modernizing the internal organization of industries.

ii. Impact of Industrial Structure on Urban-rural Income Gap

The optimization of industrial structure promotes the movement of labor from low-productivity sectors to high-productivity sectors and increases industrial productivity (Fan et al., 2003). In this process, on the one hand, a large amount of surplus rural labor flows to the more productive industrial and service sectors for higher labor remuneration. On the other hand, the increased productivity of rural labor raises the remuneration of residents who continue to work in agriculture, thus narrowing the urban-rural income gap. The optimization of industrial structure promotes the integration of industries (Ge et al., 2022).

Meanwhile, country industrial upgrading has become a key driver of economic growth. The dividend of industrial structure accounts for 4% of country GDP and contributes 24% to GDP growth (Wang et al., 2018). Industrial upgrading continues to extend urban secondary and tertiary industries to rural areas (Kuznets, 1949; Li, 2021; Yang & Zhao, 2014; Yuan, 2018). Digital technology has promoted the integration of

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the whole industry in rural areas (Zhang et al., 2023). New forms of business such as tourist agriculture and rural tourism are constantly emerging. Industrial upgrading has also provided more non-agricultural employment opportunities for farmers and increased the source of income for people living in rural areas (Zhang et al., 2023; Reardon et al., 2000). With the integration of rural primary, secondary and tertiary industries, the source of income of rural residents is no longer the simple production of primary agricultural products, but the development of agricultural products processing and agricultural tourism can improve the income of rural residents.

2.6 Summary

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This chapter has provided an in-depth discussion on the conceptualization of the digital economy, the urban-rural income gap, and the relationship between these two concepts. A comprehensive review of relevant literature has followed, focusing on these variables and their interconnections.

Given the significant urban-rural income disparity in mainland China, investigating how the development of the digital economy influences this gap can contribute to achieving sustainable development goals. The novelty of this study can be substantiated by three main points. First, the existing research lacks a unified conclusion, and theoretical mechanisms behind these relationships remain underexplored. Much of the current literature primarily addresses the impact of digital

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economy development on the urban-rural income gap through lenses such as the Internet, inclusive finance, e-commerce, and digital infrastructure. Second, there is no standardized approach to measuring digital economy development at the provincial level within China, and the methods in use are still in the exploratory phase. Third, no empirical research has investigated the mediating role of industrial structure in the relationship between digital economy development and the urban-rural income gap.

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CHAPTER 3

METHODOLOGY

3.0 Introduction

This chapter focuses on the methodology adopted to answer the research questions and to attain the objectives of the study. It starts with Data (an overview of the dataset, data sources, and sample size utilized in the study), followed by Model specification, method of analysing data and a summary.

To be specific, the model specification in the study are as follows: for the Objective 1, which is to generate an improved and comprehensive digital economy development index, this study develops an improved digital economy development level index (DEDI). Then introducing the Correlation Coefficient Test, Multi-collinearity Test, Panel Unit Root Tests, and Panel Cointegration Test to test the correlation, multicollinearity, stability, and long-term cointegration relationships among the variables. Based on the static panel model test, a static panel model suitable for this study was selected for testing the necessity and scientific validity of the inclusion of the control variables and the quadratic terms of the independent

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variables and the lagged terms of the dependent variables in the model. Based on these tests, dynamic panel model estimated using the system GMM approach for the Objective 2. Since the dynamic panel model is similar to regression analysis and correlation analysis, it evaluates the relationship between variables. However, it goes further to understand the causal relationship between variables, not just whether they move together. To further explore the impact of independent variables on dependent variables, the study employs a mediating effect model, followed by variable measurement and data analysis.

3.1 Data

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This section provides an overview of the dataset, data sources, and sample size utilized in the study. Panel data analysis offers significant advantages, particularly when applied to unbalanced panels, making it a powerful tool for this research.

Firstly, it addresses the issue of omitted variable bias, which arises from unobserved factors that could influence the outcome variables (Kumar, 2024). In this study, unobserved individual-specific effects, such as regional factors in different provinces of Mainland China, can be controlled for, particularly when these factors are time-invariant. This is a critical advantage because it helps in isolating the impact of variables like digital economy development and industrial structure.

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Secondly, capturing dynamic individual behavior: Panel data combines both cross-sectional and time-series dimensions, providing richer information about individual behavior over time (Chen, 2014). This is particularly valuable in analyzing income gap, as it allows the study to track changes over time while simultaneously controlling for regional differences. For instance, in the context of analyzing the urban-rural income gap, panel data allows for observing both short-term fluctuations and long-term trends, providing a more nuanced understanding of how digital economy development impacts income distribution.

Lastly, larger sample size and improved estimation precision (Chen, 2014). The combination of cross-sectional and time dimensions generally results in a larger sample size compared to pure cross-sectional or time-series data. This larger sample size improves the precision of estimates and allows for the inclusion of additional control variables and interaction effects, enhancing the robustness of the analysis.

The secondary data employed in this research have been collected and are readily available from the Bureau of Statistics. Since this study is conducted across the provinces in China mainland, the sample comprises 30 provinces (municipalities, autonomous regions, collectively referred to as provinces) in mainland China, including Beijing Municipality Shanghai Municipality, Tianjin Municipality, Chongqing Municipality, Guangdong Province, Jiangsu Province, Zhejiang Province, Shandong Province, Fujian Province, Hainan Province, Hebei Province, Henan

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Province, Shanxi Province, Shaanxi Province, Gansu Province, Qinghai Province, Liaoning Province, Jilin Province, Heilongjiang Province, Anhui Province, Jiangxi Province, Hubei Province, Hunan Province, Sichuan Province, Guizhou Province, Yunnan Province, Xinjiang Uygur Autonomous Region, Inner Mongolia Autonomous Region, Guangxi Zhuang Autonomous Region, and Ningxia Hui Autonomous Region. The inclusion of these provinces in the study serves as a foundation to examine the impact of digital economy development on the urban-rural income gap in China mainland. It is essential to note that these 30 provincial-level administrative regions collectively constitute China mainland. The selection of these provinces is based on considerations of data availability, reliability, and previous research findings. Panel data are samples of data that are created by simultaneously choosing sample observations from several time series sections.

The data collection is conducted on an annual basis, spanning from the year 2013 to 2022. The term per capita rural disposable income was substituted by the National Bureau of Statistics in 2013 for per capita net income in rural areas. This study select annual data from 2013 to 2022 to assure data comparability. The urban-rural income gap measured by theil index is used for 30 provinces. The digital economy development is measured by an index, and the indicator data used for this index are sourced from statistical yearbooks. In addition, data for control variables and mediator variables were obtained exclusively from statistical yearbooks. To be specific, data related to informatization foundation and influence of informatization

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be collected from China Statistical Yearbook, China Information Industry Yearbook and China Population and Employment Statistical Yearbook. Fixed Internet Basics and Mobile Internet Basics be found from China Statistical Yearbook. For digital transaction impact, the data can be found from the China E-Commerce Report. Please refer to Table 3.1, Table 3.2 and Table 3.3 for specific information.

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Table 3.1

Indicator System for the Level of Digital Economy Development

Primary indicators	Secondary indicators	Data Sources
Digital Economic Development Carrier	Internet broadband access port density	China Statistical Yearbook
	Proportion of Internet users to resident population	China Information Industry Yearbook
	Number of domain names per capita	China Population and Employment Statistical Yearbook
	Density of mobile base stations	China Statistical Yearbook
	Cell phone penetration rate	China Statistical Yearbook
	Density of fiber optic cable lines	China Statistical Yearbook
Digital Industrialization	Proportion of software business revenue to GDP.	China Statistical Yearbook
	Proportion of information technology services revenue to GDP	China's Internet Development Statistical Report
	Proportion of total telecom business to GDP	China Statistical Yearbook
	Proportion of enterprises with e-commerce trading activities	China Statistical Yearbook
	Proportion of enterprise e-commerce to GDP	China Information Industry Yearbook
Industrial Digitization	Number of computers used by enterprises per 100 people	China Population and Employment Statistical Yearbook
	Number of websites per 100 enterprises	China Statistical Yearbook
	Digital Inclusive Finance Index	China Statistical Yearbook

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Primary indicators	Secondary indicators	Data Sources
Digital Economic Development Environment	Fixed asset investment in information transmission, computer services and software industry per capita	China Statistical Yearbook
	R&D Expenditure of Industrial Enterprises Above Scale	China Statistical Yearbook
	Proportion of information transmission, software and information technology service industry employed persons to total urban employment population.	China's Internet Development Statistical Report

Note：all the Statistical Yearbooks and reports were published from 2014-2023

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Table 3.2

Index for Optimization and Upgrading of Industry Structure and Data Sources

Index	Data sources
Number of persons employed in the primary industry (10,000)	China Statistical Yearbook published from 2014-2023
Number of persons employed in the secondary industry (10,000)	China Statistical Yearbook published from 2014-2023
Number of persons employed in the tertiary industry (10,000)	China Statistical Yearbook published from 2014-2023
Number of employed persons (10,000)	China Statistical Yearbook published from 2014-2023
Added value of primary industry	National Bureau of Statistics published from 2014-2023
Added value of Secondary industry	National Bureau of Statistics published from 2014-2023
Added value of tertiary industry	National Bureau of Statistics published from 2014-2023
Gross regional product	Bureau of Statistics published from 2014-2023

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Table 3.3

Index for Control Variables and Data Sources

Control Variables	Measurement	Data sources
Economic development (ED)	the logarithm of per capita GDP	China Statistical Yearbook published from 2014-2023
Economic openness (EO)	the ratio of the total quantity of imports and exports of the location of the business unit to its GDP	China Statistical Yearbook published from 2014-2023
Fiscal expenditures (FE)	the proportion of urban government fiscal expenditure to GDP	China Statistical Yearbook published from 2014-2023
Educational attainment (EA)	the average number of years of education per capita	National Bureau of Statistics of China published from 2014-2023
Urbanization rate (UR)	Urban resident population / total population	National Bureau of Statistics of China published from 2014-2023

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3.2 Model specification

This section includes the improved digital economy development index (DEDI), the urban-rural income gap index, measurement method of mediating variables, measurement method of control variables, explanation of dynamic panel model and mediating effect model.

3.2.1 Improved digital economy development index (DEDI)

As highlighted in Chapter 2, the considerable variations in absolute scale measurements among different countries prompt the selection of the digital economy development index as a measurement of digital economy development level in this study to fulfill research objective 1. Currently, research on the relative scale of the digital economy predominantly relies on a series of index systems. However, across various levels (national, regional, provincial, and municipal levels), researchers often resort to distinct index systems due to divergent definitions of the digital economy, variations in data reporting methodologies, and challenges related to data accessibility. As of now, there is no universally standardized index system in place (Chinoracky & Corejova, 2021). It is noteworthy that the concepts and scopes introduced by the International Monetary Fund (IMF) and the Bureau of Economic Analysis (BEA) collectively constitute the primary digital economic industries proposed by the Organisation for Economic Co-operation and Development (OECD) (Chen, et al.,

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2022). These industries are categorized into six groups: digital empowerment infrastructure, digital intermediary platforms, e-commerce industry, digital content industry, industries primarily reliant on digital intermediary platforms, and other industries. While Liu et al. (2020)'s original digital economy development index (DED) incorporates the content of digital industries. What is more, the comprehensive digital economy development index established by Liu et al. (2020) places significant emphasis on in-depth analyses of the temporal evolution and spatial correlations in the development of the digital economy, whose emphasis aligns cohesively with the research objectives of this study. And this index (DED) could be seen in Table 3.4. In the indicator system for measuring provincial-level digital economy development in China, Liu et al. (2020)'s digital economy development index (DED) covers content from these six aspects, which has been cited by many scholars. However, there are still the following shortcomings:

Firstly, the most salient issue lies in the omission of coverage, particularly the exclusion of the digital finance sector, overlooking its contribution to employment and the significance of the developmental environment in appraising the advancement of the digital economy. The latest Classification of Digital Economy and Its Core Industries released by the National Bureau of Statistics of China on May 4, 2021, explicitly categorizes digital finance as a core industry within the digital economy framework. Despite its importance, this crucial aspect is notably absent from Table

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3.4. Furthermore, the employment contribution of the digital economy and the essential financial and intellectual support for its growth are inadequately considered. Essential elements imperative for fostering the sustained development of the digital economy encompass fostering innovation, supporting startup ecosystems such as business incubators, venture capital funds, and technology hubs, along with cultivating the requisite skills and knowledge base. Consequently, the lack of integration of these pivotal factors may result in an incomplete assessment of the current status of digital economy development.

Secondly, the allocation of weights is not entirely rational. Weight distribution can reflect the decision-makers' emphasis on various aspects of the digital economy. In Table 3.4, assigning equal weights to all primary indicators overlooks the actual differences in importance among these indicators, potentially limiting the comprehensiveness and objectivity of the comprehensive assessment (Xu & Ding, 2019).

Finally, the lack of clarity regarding the units of measurement for tertiary indicators poses an issue. For instance, discrepancies in units such as Total Telecom Business and Software Business Revenue may lead to variations in measurement outcomes. This ambiguity could undermine the reliability and consistency of the assessment results.

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Based on the identified shortcomings and the digital economy development indices summarized in Chapter 2, which mainly revolves around the four elements of infrastructure, platforms, industries, and innovation, this study draws on relevant literature and research findings to establish an indicator system from four dimensions: Digital Economy Development Carrier, Digital Industrialization, Industrial Digitization, and Digital Economy Development Environment. The details of the improved digital economy development index (DEDI) are shown in Table 3.5. Specific improvements include:

Firstly, the addition of the primary indicator Digital Economy Development Environment was proposed in the development of the improved digital economy development index (DEDI). Specifically, it comprises three secondary indicators: the Digital Inclusive Finance Index, the per capita Fixed Asset Investment in Information Transmission, Computer Services, and the Software Industry, the R&D Expenditure of Industrial Enterprises Above Scale, and the Proportion of Information Transmission, Software, and Information Technology Service Industry Employed Persons to the Total Urban Employment Population. The Digital Inclusive Finance Index reflects the development of the core industry of digital finance (Lee et al., 2023). This index is released by the Institute of Digital Finance (IDF) at Peking University, which is one of the leading research institutions in digital finance in China, known for its high academic reputation and professional background. Therefore, the indicators released

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by this institution possess a certain degree of authority. The transparency of data sources and methodologies, along with validation and review by academia or professionals, lends credibility to the index. Widely utilized in academia, the index is considered highly reliable. The indicator of Fixed Asset Investment in Information Transmission, Computer Services, and the Software Industry per capita reflects the level of investment by a region or country in digital infrastructure and technology (Liu et al., 2022). A high level of fixed asset investment signifies significant expenditure on the construction and improvement of digital infrastructure and services, laying a solid foundation for the development of the digital economy (Dahlman et al., 2016). The indicator of R&D Expenditure of Industrial Enterprises Above Scale indicates the level of investment by industrial enterprises in technological innovation and digital transformation (Li et al., 2022). A high level of R&D expenditure suggests that enterprises have a stronger capability in technological innovation and digital development, enabling them to drive continuous progress and upgrade in the digital economy.

Secondly, the indicators are weighted using the entropy weighting method. Entropy weighting, as a multi-indicator comprehensive evaluation approach, offers advantages such as consideration of indicator correlation, elimination of subjective weight setting, strong adaptability, simplicity in calculation, and robust interpretability of results (Wang et al., 2021). Through entropy value calculation, this method

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objectively determines the weight of each indicator, thus avoiding subjective interference. Moreover, it is applicable to various types of indicators and evaluation objects, making it easy to implement and operate. The results are also intuitive, providing clear insights into the contribution of each indicator to the evaluation object, which facilitates a deeper understanding of the evaluation outcomes.

Lastly, each indicator in Table 3.5 is accompanied by a unit, such as Unit/km^2, Unit/person, etc., to make it more precise and explicit. In contrast, the indicators in Table 3.4 lack units, which may lead to difficulties in understanding for readers. The indicators in Table 3.5 are more specific and actionable as a result.

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Table 3.4

The Weighting of Digital Economy Development Evaluation Indicators (DED)

First-class indicators	Weight	Secondary indicators	Weight	Third-level indicators	Weight	Index attribute
Informatization Development	0.3333	Informatization Basics	0.1667	Fiber Optic Cable Density	0.0556	+
				Mobile phone base station density	0.0556	+
				Proportion of information practitioners	0.0556	+
		Informatization Impact	0.1667	Total Telecom Business	0.0834	+
				Software Business Revenue	0.0834	+
Internet Development	0.3333	Fixed Internet Basics	0.0834	Internet Access Port Density	0.0834	+
		Mobile Internet Basics	0.0834	Mobile Internet Penetration Rate	0.0834	+
		Fixed Internet Impact	0.0834	Proportion of Broadband Internet Users	0.0834	+
		Mobile Internet Impact	0.0834	Proportion of Mobile Internet Users	0.0834	+
Digital Transaction Development	0.3333	Digital Transactions Basics	0.1667	The number of websites per 100 enterprise	0.0556	+
				Business use of computers	0.0556	+
				Proportion of e-commerce enterprises	0.0556	+
		Digital Transaction Impact	0.1667	E-commerce sales	0.0834	+
				Online retail sales	0.0834	+

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Table 3.5

Indicator System for the Level of Digital Economy Development Among Chinese Provinces (DEDI)

Primary indicators	Secondary indicators	Unit	Index attribute
Digital Economy Development Carrier	Internet broadband access port density	Unit/km^2	+
	Proportion of Internet users to resident population	%	+
	Number of domain names per capita	Unit/person	+
	Density of mobile base stations	Unit/km^2	+
	Cell phone penetration rate	Unit/person	+
	Density of fiber optic cable lines	km/km^2	+
Digital Industrialization	Proportion of software business revenue to GDP.	%	+
	Proportion of information technology services revenue to GDP	%	+
	Proportion of total telecom business to GDP	%	+
Industrial Digitization	Proportion of enterprises with e-commerce trading activities	%	+
	Proportion of enterprise e-commerce to GDP	%	+
	Number of computers used by enterprises per 100 people	Unit	+
	Number of websites per 100 enterprises	Unit	+
Digital Economy Development Environment	Digital Inclusive Finance Index	/	+
	Fixed asset investment in information transmission, computer services and software industry per capita	Yuan/person	+
	R&D Expenditure of Industrial Enterprises Above Scale	Ten Billion Yuan	+
	Proportion of information transmission, software and information technology service industry employed persons to total urban employment population.	%	+

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Broadly, existing weighting methods can be categorized into subjective and objective approaches. Subjective weighting methods rely on subjective judgments of the relative importance among indicators to assign corresponding weights. Examples include Principal Component Analysis (Bharadiya, 2023 ; Lyu & Cui, 2020; Wang & Zhang, 2018) and methods such as Delphi and Analytic Hierarchy Process (AHP) (Ghavi, 2024). On the other hand, objective weighting methods use the original information of indicators for weighting and include approaches like cluster analysis, standard deviation method, entropy method, and range method. Xu and Ding (2019) argued that subjective weighting methods might be susceptible to subjective biases, leading to imbalances in the assignment of weights to indicators and consequently failing to accurately reflect composite indices. Consequently, considering the comprehensive perspective to mitigate potential inaccuracies resulting from subjective weighting, the entropy weighting method, an objective weighting approach, was employed for the assignment of weights to indicators. To ensure accuracy and avoid subjective weighting errors in the entropy method, an objective approach was used to assign weights to the indicators (Wang et al., 2021). The first step involves standardizing these diverse indicators, thereby guaranteeing the precision of the final index estimation. The formula for processing the indicators is as follows:

$$x_{ij} = \frac{x_{ij} - min\{\mathrm{x_j}\}}{\max\{\mathrm{x_j}\} - \min\{\mathrm{x_j}\}} \tag{3.1}$$

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Where $\max\{x_j\}$ represents the maximum value of the indicators across all years, $\min\{x_j\}$ is the minimum value among the indicators across all years, and x_{ij} represents the dimensionless result. Following the normalization of the indicators, the objective weights for each indicator are determined using the entropy method. To calculate the proportion of the j-th indicator in the i-th year, it is expressed using ω_{ij} :

$$\omega_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{3.2}$$

To compute the information entropy e_{ij} of the indicators, the formula is as follows:

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$$e_j = -\frac{1}{ln\,\mathrm{m}} \sum_{i=1}^{m} \omega_{ij} \times ln\omega_{ij} \tag{3.3}$$

To calculate the redundancy d_j of information entropy：

$$d_j = 1 - e_j \tag{3.4}$$

Where m is the assessment year, and the indicator weight φ_j is calculated based on information entropy redundancy:

$$\varphi_j = \frac{d_j}{\sum_{j=1}^{m} d_j} \tag{3.5}$$

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Based on the standardized indicator x_{ij} and the calculated indicator weight φ_j, the improved digital economy development index (DEDI) is obtained through the weighted summation using a multiple linear function. By calculating the comprehensive improved digital economy development index through the formula 3.6:

$$DEDI_{ij} = \sum_{j=1}^{m} \varphi_j \times \omega_{ij} \tag{3.6}$$

Where $DEDI_j$ represents the comprehensive improved digital economy development index of province i, ranging between 0 and 1. A larger $DEDI_j$ indicates a higher level of digital economy development, whereas a smaller $DEDI_j$ ndicates a lower level.

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3.2.2 Urban-rural income gap index

As mentioned in the section 2.3.1, the ratio of urban to rural per capita disposable income, the Gini coefficient, and the Theil index are three commonly used methods in existing research to measure the urban-rural income gap. The population split between urban and rural areas is not taken into consideration in the ratio of per capita disposable income between the two. It is a static indicator and cannot capture how people move between the two places. The Gini coefficient, which gauges the entire income gap, is more responsive to changes in middle-class income. The Gini

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coefficient, however, cannot accurately depict the urban-rural income divide because the majority of the urban-rural income gap lies at both ends. Therefore, the Theil index is a superior option for measuring the urban-rural income gap in China since it is more sensitive to changes in income in both high and low income groups at both ends. Theil's index is used in this research to calculate the urban-rural income gap.

Following the approach of Wang and Ouyang (2001), the calculation formula for the Theil index is:

$$\mathrm{URIG}_{it} = \sum_{i=1}^{2} \left(\frac{I_{it}}{I_t}\right) ln \frac{I_{it}/P_{it}}{I_t/P_t} = \left(\frac{I_{1t}}{I_t}\right) ln \frac{I_{1t}/P_{1t}}{I_t/P_t} + \left(\frac{I_{2t}}{I_t}\right) ln \frac{I_{2t}/P_{2t}}{I_t/P_t} \qquad (3.7)$$

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Where i=1 and 2 represent urban and rural areas, respectively; P_{it} denotes urban/rural t year-end resident population (million). P_t indicates an urban and rural population in the year of t. I_{it} represents per capita disposable income of urban or rural residents respectively; I_t indicates disposable income per capita for all inhabitants.

3.2.3 Measurement method of mediating variables

The digital economy development is intimately related to the shift in industrial structure. According to a dynamic approach, there are two perspectives to the change in the industrial structure: optimization of the industrial structure (OIS) and upgrading

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of the industrial structure (UIS) (Wu et al., 2023; Gan et al., 2011). Therefore, the industrial structure's optimization and upgrading were chosen as path variables for the digital economy's impact on the urban-rural income gap.

i. Metrics of the optimization of industrial structure

Researchers frequently use structural deviations and Theil index to gauge the industrial structures' degree of optimization. The structural deviation indicator, on the other hand, treats all industries equally, disregarding the significance of each industry in the economy, and the calculation of absolute values makes it challenging to analyze. Therefore, this study follows the approach of Gan et al. (2011), using the Theil index to calculate industrial structure optimization. The calculation formula is:

$$OIS = \sum_{i=1}^{n} \left(\frac{Y_i}{Y}\right) \ln\left(\frac{Y_i}{L_i} \Big/ \frac{Y}{L}\right) \tag{3.8}$$

Where value of output is indicated by the letters Y, the number of employee by L, primary, secondary and tertiary industry by i=1,2,3 respectively, and the number of industrial sectors by n. A non-zero Theil index indicates a deviation from equilibrium and an irrational industrial structure.

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ii. Measurement of the upgrading of industrial structure

The advanced industrial structure is a measure of upgrading the industrial structure. In general literature, the non-agricultural output ratio is used as a measure of industrial structure upgrading based on Clark's law. Although the increase in the proportion of non-agricultural output is an important rule, the information technology revolution since the 1970s has had a great impact on the industrial structure of major industrialized countries, resulting in a trend of economic servitization. This traditional measurement method cannot reflect this trend in the economic structure. The servitization of the economic structure driven by information technology is an important characteristic of industrial structure upgrading. Given the fact that in the process of economic servitization, the growth rate of the tertiary industry is faster than that of the secondary industry (Ran et al., 2023; Wu, 2008; Yu, 2015), this study uses the ratio of the output value of the tertiary industry to that of the secondary industry (referred to as UIS in this study) as a measure of upgrading industrial structure upgrading.

$$UIS = \frac{Y_3}{Y_2} \tag{3.9}$$

Where Y_3 represents the output value of the tertiary industry; Y_2 represents the output value of the secondary industry. This measurement method can clearly reflect the tendency of economic structure towards servitization and clearly indicate

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whether the industrial structure is developing towards servitization, making it a better measure. If the UIS value is increasing, it means that the economy is moving towards servitization, and the industrial structure is upgrading.

3.2.4 Measurement method of control variables

Chen (2014) mentioned that due to the difficulty in obtaining certain data, the phenomenon of omitted variables is almost unavoidable. One of the primary methods to address omitted variable bias is to include as many control variables as possible (deHaan et al., 2023). In this study, the following variables are primarily chosen as the set of control variables by reference to the widespread practice in the existing literature. The descriptions for control variables are as shown in Table 3.6.

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Table 3.6

Description of Control Variables

Control variables	Calculation method
Economic development (ED)	The natural logarithm of the annual per capita GDP
Economic openness (EO)	The total amount of imports and exports of the location of the business unit / its GDP
Fiscal expenditures (FE)	Government general fiscal expenditure /GDP
Educational attainment (EA)	Average years of education
Urbanization rate (UR)	Urban resident population / total population by region

Note： Source from DOI:10.27283/d.cnki.gsxcc.2022.000258.

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i. Economic development (ED)

Some scholars have found that the level of economic development can influence income distribution, thereby affecting the urban-rural income gap (Kuznets, 2019; Chen and Lin, 2013). A region with a developed economy implies that the government has more fiscal resources, which can be used for rural development and agricultural production through fiscal transfers and other means. This can improve agricultural productivity and subsequently narrow the urban-rural income gap. Regions with relatively developed economic conditions offer more employment opportunities, allowing rural residents to engage in non-agricultural industries and earn higher wages, thus improving the urban-rural income gap. Economic development levels vary among the 30 provinces, municipalities, and autonomous regions in China. Therefore, the logarithm of per capita GDP, abbreviated as ED, is chosen to represent the level of economic development as a control variable, and introduce its quadratic term as one of the explanatory variables (Li &Li, 2022).

ii. Economic Openness (EO)

Greater trade and intellectual interchange with the outside world occurs in more open regions, allowing rural individuals to learn more and engage in the market economy more effectively, narrowing the urban-rural income gap (Okafor et al., 2023). The ratio of the total quantity of imports and exports of the location of the business unit to

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its GDP serves as a measure of the degree of economic openness, which substantially impacts the urban-rural income gap (Suleman et al., 2023). Moreover, opening up to the outside world alters the demand for skilled and unskilled labor through changes in the export structure, further affecting the urban-rural income gap (He & Zhang,2024).

iii. Fiscal expenditures (FE)

Government general fiscal expenditure, to a certain extent, reflects the extent of government investment and intervention in the economy and society. When studying the impact of the digital economy development on the urban-rural income gap, government expenditure may serve as a crucial control variable. This is because it reflects the government's level of attention to aspects such as infrastructure development and social security, factors that may be associated with the urban-rural income gap. Therefore, in this study , fiscal expenditures are expressed by the proportion of general fiscal expenditure to GDP (Arawatari et al., 2023).

iv. Educational attainment (EA)

Education could effectively alleviate poverty and improve human capital (Ji et al., 2021). Development economics suggests that the development of education can provide equal employment opportunities for low-income groups, which is beneficial for narrowing the urban-rural income gap (Ananian & Dellaferrera, 2024). Due to

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China's long-standing dualistic economic structure, educational resources in rural areas lag behind those in urban areas. The average level of education per capita in urban areas is much higher than in rural areas. As a result, residents with higher educational levels in rural areas gradually become urban residents. Therefore, the improvement in educational attainment may lead to a polarization of economic income among residents. This study use the average number of years of education per capita as an indicator of educational attainment (Égert et al., 2024). Calculated as follows:

$$EA = \frac{\left(\begin{array}{c} Number\ of\ Individuals\ with\ Primary\ Education \times 6 \\ +Number\ of\ Individuals\ with\ Junior\ High\ School\ Education \times 9 \\ +Number of Individuals with Senior High School and \\ Technical\ Secondary\ Education \times 12 \\ +Number\ of\ Individuals\ with\ College\ and \\ Bachelo'sDegree sor Above \times 16 \end{array}\right)}{Total\ Population\ Aged\ 6\ and\ Above} \quad (3.10)$$

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v. Urbanization rate (UR)

The development of urbanization provides rural residents with more employment opportunities in cities, leading to a continuous influx of population towards urban areas (Auwalu & Bello, 2023). On one hand, the labor force migrating to urban areas can earn higher income, thereby narrowing the income gap among residents. On the other hand, the decrease in rural labor force raises the marginal productivity value of agricultural labor, resulting in an increase in the value of agricultural products. The

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urban-rural income gap continues to close as more people choose to stay in their rural communities rather than go to the cities to work (Wang et al, 2024). This can be represented as follows: UR= Urban resident population / total population (Wang et al., 2023)

3.2.5 Static panel model

In order to validate research hypotheses 1 and 2, it is necessary to identify the most suitable research model for this study. Based on relevant theories, this study begins by establishing a static panel model. This study uses the inclusive growth theory, specifically Kuznets Curve Hypothesis. The Kuznets Curve Hypothesis, proposed by Simon Kuznets in the 1950s, originally aimed to explain the changes in income inequality observed during the process of economic development. Through historical data analysis of industrialized nations, Kuznets introduced a classic inverted U-shaped curve, suggesting that income inequality tends to increase in the early stages of economic growth but eventually decreases as the economy matures. In the initial phase of economic growth, resources and wealth tend to concentrate in urban areas and industrial sectors. These regions and sectors benefit more from economic growth, leading to a widening income gap. Rural areas, often characterized by outdated technology, insufficient capital, and lower educational levels, struggle to keep pace, resulting in an increasing urban-rural income disparity. As economic growth continues,

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technological advancements begin to spread to the agricultural and rural sectors. The technological spillover from the industrial sector stimulates overall economic progress. Additionally, government redistribution policies, such as social security and tax reforms, begin to take effect, gradually narrowing the urban-rural income gap and leading to a more balanced income distribution.

In this study, the Kuznets Curve Hypothesis can be utilized to explain the relationship between digital economy development and the urban-rural income gap. Specifically, the digital economy, as an integral part of economic development, may have varying effects on the urban-rural income gap at different stages of its development. During the early phase of digital economy development, digital infrastructure and technology are likely to be concentrated in urban areas, especially in major cities. This allows urban areas to benefit more rapidly from the digital economy development, while rural areas, due to a lack of infrastructure and technological support, may become further marginalized, thereby widening the urban-rural income gap. As the digital economy becomes more widespread and deepens, digital technologies begin to penetrate rural areas. The proliferation of digital finance, e-commerce, and other platforms helps reduce the divide between urban and rural areas. At this stage, the urban-rural income gap may begin to narrow, potentially leading to a more equal income distribution. This non-linear relationship can be captured by the coefficient of the squared term of the improved digital economy

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development index ($DEDI^2$) in relation to the urban-rural income gap. A negative coefficient ($\alpha_{12}<0$) would suggest an inverted U-shaped relationship between digital economy development and the urban-rural income gap, consistent with the logic of the Kuznets Curve Hypothesis.

In addition, the production function theory and the new economic growth theory provide theoretical support for the control variables in this research model. The core of the new economic growth theory is the role of technological progress and innovation in promoting long-term economic growth. The development of the digital economy is essentially a reflection of technological progress and innovation. Therefore, the improved digital economy development index (DEDI) as the core explanatory variable (independent variable) of the model has a theoretical basis. The new economic growth theory also emphasizes the importance of knowledge accumulation and human capital in economic growth. In the model setting, adding human capital-related control variables (such as education level, etc.) can better capture the impact of the digital economy on the urban-rural income gap. The theory also mentions the impact of government policies and institutional environment on economic growth. Effective government policies can promote technology diffusion and knowledge dissemination, and promote the development of the digital economy. Therefore, the model can consider introducing control variables that reflect policy support and institutional quality. Based on this, this study established a static panel model 3.11 to preliminarily verify the inverted U-shaped relationship.

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$$URIG_{j,t} = a_j + DEDI_{j,t} + \alpha_{12} DEDI_{j,t}^2 + \beta_j X_{j,t} + \varepsilon_{j,t} \quad (3.11)$$

Where $DEDI_{j,t}$ denotes the digital economy development index, which is the core explanatory variable. $X_{j,t}$ is a group of control variables; $\varepsilon_{j,t}$ is the random error item. j indicates the province, t indicates the year, a_j is a constant item. If $\alpha_{12}<0$, the digital economy development and the urban-rural income gap have an inverted U-shaped relationship; If $\alpha_{12}>0$, the digital economy development and the urban-rural income gap have a positive U-shaped relationship; if $\alpha_{11}>0$, $\alpha_{12}=0$, the digital economy development has widened the urban-rural income gap; if $\alpha_{11}<0$, $\alpha_{12}=0$, the digital economy development has narrowed the urban-rural income gap.

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3.2.6 Dynamic panel model

In real life, the income of urban and rural residents, as well as the income disparity between these groups, is a dynamic process. This means it depends not only on current factors but also on past factors, indicating a certain path dependency. Therefore, considering its dynamic changes is essential (Han & Zhang, 2017), and the inclusion of lagged terms of the dependent variable among the explanatory variables is necessary. Therefore, this study incorporates the lagged dependent variable and sets up a dynamic panel model to achieve research objective 1 and ensure a more accurate analysis of the relationship between digital economy development and the urban-rural income gap.

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In cross-sectional data, determining causality mainly depends on logical relationships and theoretical assumptions, but both of them have a lot of uncertainty. Panel data could establish the time sequence of variables, eliminate the problem of reverse causality, and reveal the dynamic trends of things over time. It could also reveal reciprocal processes and panel data can also eliminate interference from other factors. The choice of which model to use for analyzing panel data is essentially a consideration of the trade-off between bias and efficiency. Dynamic panel model was introduced by Hansen in 1982, which was a generalized approach for estimating the parameters of a model. This model allowed the number of moment conditions to exceed the number of parameters, which allowed the instrumental variables in the model to exceed the number of parameters making the estimatoers more efficient (Labra & Torrecillas, 2018). This approach to panel data modeling is widely used in empirical studies and finance, where in addition to controlling for endogeneity it is also been shown to be robust to heteroscedasticity and serial correlation (Bond, 2002). Therefore introducing lagged term of the dependent variable ($URIG_{j,t-1}$) as an independent variable into the model and turning it into a dynamic panel model can avoid the possible result deviation caused by the ordinary panel model and can also overcome the endogenous problem of the model (Li & Li, J.2022). To achieve the second research objective and to validate H1, the following dynamic panel model (3.12) for the impact of digital economy development on the urban-rural income gap is constructed.

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$$\mathrm{URIG}_{j,t} = \mathrm{a_j} + \gamma_j \mathrm{URIG}_{j,t-1} + \alpha_{11} DEDI_{j,t} + \alpha_{12} DEDI_{j,t}^2 + \beta_j X_{j,t} + \varepsilon_{j,t} \quad (3.12)$$

Where $\mathrm{URIG}_{j,t}$ is the explained variable, which denotes the urban-rural income gap. $\mathrm{DEDI}_{j,t}$ denotes the improved digital economy development index, which is the core explanatory variable. $X_{j,t}$ is a group of control variables; $\varepsilon_{j,t}$ is the random error item. j indicates the province, t indicates the year, a_j is a constant item. If $\alpha_{12}<0$, the digital economy development and the urban-rural income gap have an inverted U-shaped relationship; If $\alpha_{12}>0$, the digital economy development and the urban-rural income gap have a positive U-shaped relationship; if $\alpha_{11}>0$, $\alpha_{12}=0$, the digital economy development has widened the urban-rural income gap; if $\alpha_{11}<0$, $\alpha_{12}=0$, the digital economy development has narrowed the urban-rural income gap.

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3.2.7 Mediating effect model

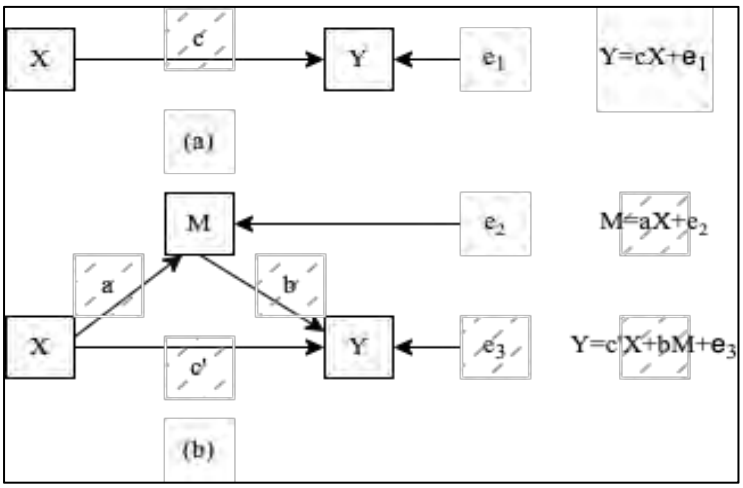
Mediating effect analysis explains how the independent variable X influences the dependent variable Y through the mediating variable M, and has become a critical statistical method in multivariate research (Chen et al., 2014). In this research, in order to achieve research objective 3, three kinds of methods for the mediating effect model were employed.

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Figure 3.1

Mediating Effect Model



When considering the impact of the independent variable X on the dependent variable Y, if X not only directly affects Y but also affects Y through an intermediary variable M, then M is referred to as a mediator variable. Assuming that the variables have been centered or standardized, the relationships between variables can be explained using the path diagram and corresponding equations shown in Figure 3 1. In this equation, the independent variable X's overall impact on the dependent variable Y is represented by coefficient c, and its impact on the mediator variable M is represented by coefficient a. The coefficient b represents the effect of the mediator variable M on the dependent variable Y, after taking into account the influence of the independent variable X. Once the mediator variable M has been taken into account, the coefficient c' shows the direct impact of the independent variable X on the dependent variable Y. e_1, e_2, e_3 are regression residuals. The size of the mediating effect is measured by c, $c = c' + ab$, $c' = ab$.

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Based on the analysis in section 2.5, this study believes that the digital economy development might affect the urban-rural income gap through the optimization and upgrading of the industrial structure. To empirically verify the existence of this mechanism, this study constructs a mediating effect empirical model by referring to the method of Wen and Ye (2014). In this study, the independent variable X in Figure 3.1 represents the improved digital economy development index (DEDI), while the dependent variable Y is the urban-rural income gap represented by the Theil index (URIG). The Industrial Structure Optimization Index (OIS) and the Industrial Structure Upgrading Index (UIS) serve as the mediating variables M, with the inclusion of control variables (CV) ED, ED^2, FE, EA, EO, and UR. The mediating effects of OIS and UIS were tested separately, and the specific models are as follows:

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i. Model for testing the mediating effect of OIS

$$URIGI = cDEDI + CV + e_1 \quad (3.13)$$

$$OIS = aDEDI + CV + e_2 \quad (3.14)$$

$$URIGI = c'DEDI + bOIS + CV + e_3 \quad (3.15)$$

ii. Model for testing the mediating effect of UIS

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$$URIGI = cDEDI + CV + e_1 \quad (3.16)$$

$$UIS = aDEDI + CV + e_2 \quad (3.17)$$

$$URIGI = c'DEDI + bUIS + CV + e_3 \quad (3.18)$$

3.3 Methods of analysing data

To investigate the impact of digital economy development on the urban-rural income gap and then mediating effect of OIS and UIS on it in 30 provinces of China from 2013 to 2022, this study is conducted in four stages. Firstly, preliminary tests are conducted, including the Spearman rank order correlation coefficient test, multicollinearity test, panel unit root test, and cointegration test. Secondly, static and dynamic models are used to test whether the impact of digital economy development on the urban-rural income gap is an inverted U-shaped one from a aggregate perspective. Thirdly, a grouping regression method is applied for regional heterogeneity testing to achieve the objectives of studying the impact of digital economy development on the urban-rural income gap from disaggregate aspects. Finally, an intermediate effect test method is employed to examine whether the optimization and upgrading of industrial structure acts as an intermediary in the process of digital economy development affecting the urban-rural income gap.

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3.3.1 Preliminary test

To ensure the accuracy and reliability of subsequent model estimation results, this study conducted preliminary tests on the relevant variables as discussed in Section 3.2. These tests not only verified the appropriateness and consistency of the data but also provided a solid foundation for further model development and analysis.

3.3.1.1 Correlation coefficient test

Correlation tests are key statistical tools used to examine whether there is a relationship between variables and to what extent they are correlated (Gogtay & Thatte, 2017). This study employs two commonly used correlation analysis methods: Pearson correlation coefficient and Spearman rank correlation coefficient. Each has distinct advantages, making them suitable for different types of data and scenarios.

The Pearson correlation coefficient is a parametric test that is best suited for continuous variables that follow a normal distribution and exhibit a linear relationship. It measures the strength of the linear association between two variables, producing a correlation coefficient between -1 and 1, where 1 indicates perfect positive correlation, -1 indicates perfect negative correlation, and 0 indicates no correlation. When the data meets the assumption of linearity, Pearson's correlation provides an efficient and straightforward measure of association. For a sample of size n, the n raw scores X_i,

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Y_i are converted to ranks $R(X_i)$, $R(Y_i)$, and r_s is computed as:

$$r_s = \rho_{R(X),R(Y)} = \frac{cov\big(R(X), R(Y)\big)}{\delta_{R(X)}\delta_{R(Y)}} \tag{3.19}$$

Where r donates the usual Pearson correlation coefficient, but applied to the rank variables, $cov\big(R(X), R(Y)\big)$ is the covariance of the rank variables, $\delta_{R(X)}\delta_{R(Y)}$ are the standard deviations of the rank variables.

However, for data that do not follow a normal distribution or exhibit non-linear relationships, the Spearman rank correlation coefficient is more appropriate. As a non-parametric method, Spearman's correlation does not require assumptions about the data distribution and is less sensitive to outliers (Myers & Sirois, 2005). It measures the monotonic relationship between variables based on their rankings, assessing whether the relationship between two variables is consistently increasing or decreasing. In the field of statistics, Spearman's rank correlation coefficient, denoted by the Greek letter ρ or r_s and named after Charles Spearman, is a nonparametric metric for rank correlation, specifically measuring the statistical dependence between the rankings of two variables (Spearman, 2007). It evaluates the extent to which the association between two variables can be characterized by a monotonic function.

Only if all n ranks are distinct integers, it can be computed using the popular formula, where $d_i = R(X_i)-R(Y_i)$

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$$r_s = 1 - \frac{6\sum d_i^2}{n(n^2-1)} \tag{3.20}$$

Where if r_s=1, it indicates a perfect positive correlation; If r_s=-1, it signifies a perfect negative correlation; and if r_s=0 there is no correlation between the variables.

In Stata, the null hypothesis for the Spearman rank correlation coefficient test asserts that the rank correlation coefficient between two variables is zero, implying no monotonic relationship in the population. Specifically, the null hypothesis can be expressed as: H0: r_s=0. During the Spearman rank correlation coefficient test in Stata, the aim is to assess whether the observed sample rank correlation coefficient is statistically significant under the null hypothesis, thereby determining whether there is a monotonic relationship between the two variables. If the p-value is less than the significance level (typically 0.05), we reject the null hypothesis, concluding that there is a significant rank correlation relationship between the two variables.

In this study, Pearson correlation is applied to analyze the relationships between linear, continuous variables, while Spearman's rank correlation is used to handle non-linear relationships, ordinal data, or cases involving outliers. By employing both methods, the study gains a more comprehensive understanding of the correlations between variables, ensuring robustness and accuracy in the findings.

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3.3.1.2 Multi-collinearity test

If the data matrix X does not have full column rank (column rank less than K), meaning that one explanatory variable can be expressed linearly by other explanatory variables, then there exists strict multicollinearity. In this case, $(X'X)^{-1}$ does not exist, and the population parameter β is not identifiable, making it impossible to define the least squares estimator. Strict multicollinearity rarely occurs in real-world data, and if it does, Stata produces warnings about it, but users need to address the issue manually, typically by removing redundant variables.

More commonly encountered is approximate (non-strict) multicollinearity. This is characterized by a situation where the coefficient of determination (denoted as (R^2)) obtained from regressing the k-th explanatory variable x_k on the remaining explanatory variables $\{x_{1,\dots,}x_{k-1,}x_{k+1}, \dots, x_K\}$ is relatively high. In the presence of approximate multicollinearity, OLS (Ordinary Least Squares) remains the best linear unbiased estimator, meaning it still has the smallest variance among all linear unbiased estimators. However, this does not imply that the variance of the OLS estimator is small in absolute terms (Daoud, 2017).

Due to the existence of multicollinearity, the matrix ((X'X) becomes almost singular, making ($(X'X)^{-1}$ large in some sense. This leads to an increase in the variance of the estimator Var(b/x) = $\sigma^2 (X'X)^{-1}$, making the estimation of coefficients

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less accurate. In such cases, Typical symptoms of multicollinearity include a high overall coefficient of determination (R^2) and a significant F-test, but non-significant t-tests for individual coefficients, or coefficient estimates that are unreasonable or even contrary to theoretical expectations. Another possible symptom is that adding or removing explanatory variables causes significant changes in coefficient estimates (e.g., when the newly added explanatory variable is collinear with existing ones).

It can be proven that the k-th element on the main diagonal of the covariance matrix is:

$$Var(b_k|X) = \frac{\sigma^2}{(1 - R_k^2)S_{kk}} \tag{3.21}$$

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Where S_{kk} represents the sum of squares of deviations of x_k reflecting the magnitude of variation. If x_k varies very little, it is difficult to accurately estimate the effect of x_k on y In extreme cases, when x_k remains constant, S_{kk}, making it impossible to estimate b_k entirely. In equation 3.21, more attention should be paid to (1- R_k^2). Therefore, the Variance Inflation Factor (VIF) for the k-th explanatory variable x_k is defined as:

$$VIF_k = \frac{1}{1 - R_k^2} \tag{3.22}$$

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The larger the VIF, the more severe the multicollinearity. The Variance Inflation Factor (VIF), as a tool for detecting multicollinearity, possesses advantages such as quantifying the degree of multicollinearity, being straightforward to use, having strong interpretability, identifying problematic variables, and having broad applicability. The calculation of VIF provides a concrete numerical measure of the linear relationships among explanatory variables, allowing researchers to quickly discern potential multicollinearity issues and take appropriate measures to enhance the robustness of regression models. If VIF < 10, it generally indicates the absence of a severe multicollinearity problem (Curto & Pinto, 2011). Due to the limitations of the Spearman correlation coefficient test, which can only detect pairwise correlations and cannot ascertain whether multicollinearity issues exist among multiple variables, multiple collinearity tests are introduced.

3.3.1.3 Panel unit root tests

In order to avoid pseudo-regression and ensure the validity of the estimation results, the smoothness of each panel series should be tested and examining the data's units root properties is the first step in validating the panel cointegration of the variables (Dickey et al., 1986). Various methodologies are available for examining the existence of unit roots in panel data. These include the Fisher-type augmented Dickey–Fuller (ADF) test, the Levin–Lin–Chu (LLC) test, the IM–Pesaran–Shin (IPS) test, the

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Harris–Tzavalis (HT) test, and the LM test (Atems & Jones, 2015). Chen Q. (2014) notes that the HT and IPS tests are particularly appropriate for short panel data, where T is fixed. Consequently, these methods are primarily employed for unit root testing in the following analysis.

To test whether $\{y_{it}\}$ contains a unit root, consider the following panel autoregressive model:

$$y_{it} = \rho y_{i,t-1} + z_{it}^{'}\gamma_i + \mathcal{E}_{it} \tag{3.23}$$

Where i=1,…, n represents individuals unit, t=1,…, T_i, represents time unit. $\mathcal{E}_{it}$ represents stationary disturbances. Due to the possible existence of autocorrelation in the disturbance term, Levin, Lin, and Chu (2002) introduced high-order differenced lagged terms:

$$\Delta y_{it} = \delta y_{i,t-1} + \sum_{j=1}^{p_i} \theta_{ij}\, \Delta y_{i,t-j} + z_{it}^{'}\gamma_i + \mathcal{E}_{it} \tag{3.24}$$

Where δ represents the common autoregressive coefficient (common root); the lag order p_i can vary across different entities; $\{\varepsilon_{it}\}$ denotes a stationary ARMA process; ε_{it} for different entities are mutually independent but allow for heteroskedasticity. By introducing a sufficiently high order of lagged variance terms, ε_{it} can be ensured to be white noise.

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Equation 3.23 is a dynamic model and includes individual fixed effects, resulting in dynamic panel biases. Therefore, if an OLS regression is conducted directly, the estimates $\hat{\delta}$ and corresponding t-statistics is biased and do not follow an asymptotic normal distribution, hence requiring correction for the t-statistics. As the lag orders p_i in Equation 3.23 are unknown, the specific steps of the LLC test are as follows: In the first step, for each panel unit i, regress Δy_{it} on $\left(z_{it}^{'},\ \sum_{j=1}^{p_i}\Delta y_{i,t-j}\right)$ to obtain the residuals $\hat{e}_{it}$; regress $y_{i,t-1}$ on $\left(z_{it}^{'},\ \sum_{j=1}^{p_i}\Delta y_{i,t-j}\right)$ to obtain the residuals $\hat{v}_{i,t-1}$. In the second step, considering that different panel units may have heteroskedasticity, the residuals from the first step are standardized as follows:

$$\tilde{e}_{it} \equiv \hat{e}_{it}/\hat{\sigma}_{\varepsilon i}, \tilde{v}_{i,t-1} \equiv \hat{v}_{i,t-1}/\hat{\sigma}_{\varepsilon i} \tag{3.25}$$

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Where $\hat{\sigma}_{\varepsilon i}$ represents the standard error of ε_{it}.The third step involves conducting a mixed regression using all the data as follows:

$$\tilde{e}_{it} = \delta\tilde{v}_{i,t-1} + \tilde{\varepsilon}_{it} \tag{3.26}$$

Where the estimation of $\hat{\delta}$ and its corresponding t-statistic t_{δ}, can be obtained. However, if individual fixed effects are present, t_{δ} diverges to negative infinity. To address this, LLC proposes a bias-adjusted t statistic, denoted as t_{δ}^{*}, which follows a standard normal distribution in large samples. Similar to the ADF test, the LLC test is also a left-tailed test, with the rejection region confined to the far left of the distribution.

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The LLC test assumes the absence of cross-sectional correlation. If this assumption is violated, the LLC test may suffer from size distortion (O'Connell, 1998). To mitigate potential cross-sectional correlation, LLC suggests first demeaning the panel data by subtracting the mean of each cross-sectional unit before conducting the LLC test. Levin et al. (2002) suggested that the panel unit root test model can be more effective compared to individual unit root tests. Individual unit root tests often lack power to detect deviations from equilibrium, especially in smaller sample sizes. The hypothesis of the LLC test can be expressed as follows:

H_0: There is a unit root

H_1: There is no unit root

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In this context, the null hypothesis posits that the series possesses a unit root or is non-stationary, while the alternative hypothesis suggests that the series lacks a unit root or is stationary. For instance, if the obtained value is significant at the 1%, 5%, and 10% significance levels, respectively, it implies rejecting the null hypothesis, indicating that the series lacks a unit root and is stationary. Conversely, if the value is not significant at the given significance level, the test fails to reject the null hypothesis, suggesting that the series possesses a unit root and is non-stationary.

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i. HT Test

Harris and Tzavalis (1999) proposed a test statistic based on fixed T as $N \to \infty$. Assuming equal autoregressive coefficients across equations 3.22 yields:

$$y_{it} = \rho y_{it-1} + z_{it}^{'} \gamma_i + \varepsilon_{it} \quad (3.27)$$

Where ρ represents the common root. ε_{it} follows an iid normal distribution, hence it has homoscedasticity. Under the condition of H0: ρ =1, Harris and Tavalie (1999) derived the expressions for the expected value μ and the variance σ^2 of the OLS estimator $\hat{\rho}$ (as a function of T), and demonstrated that when T is fixed and n approaches infinity, z follows a standard normal distribution. Based on this large-sample distribution, a one-sided left test is then conducted. Harris-Tzavalis (HT) panel unit root test can be formulated as follows:

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H_0: $\delta_i = 0$ (There is a unit root)

H_1: $\delta_i < 0$ (There is no unit root)

The null hypothesis (H_0) asserts the presence of a unit root, indicating that the sequence is non-stationary. Conversely, the alternative hypothesis posits the absence of a unit root in the panel data, signifying that the sequence is stationary. The process of determining whether the HT test is passed typically involves the following steps: Firstly, compute the corresponding test statistic based on the selected form of the HT test, often standardizing it for significance testing. Next, establish the significance

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level, usually set at 0.05, according to the researcher's preference. Subsequently, compare the computed HT test statistic with the critical value corresponding to the chosen significance level. If the statistic exceeds the critical value, there is sufficient evidence to reject the null hypothesis, suggesting the absence of a unit root in the panel data and indicating stationarity in the sequence. Conversely, if the statistic is less than or equal to the critical value, the null hypothesis is accepted, implying the presence of a unit root in the panel data and suggesting non-stationarity in the sequence. This process enables researchers to make judgments regarding the presence of a unit root based on the specified significance level.

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ii. IPS test

The limitations of the LLC and HT tests lie in the requirement that the autoregressive coefficients, denoted by δ, be equal for each individual, which may pose a too restrictive assumption in practice due to varying economic regularities across different countries or regions owing to institutional and cultural differences. To overcome this drawback, Im, Pesaran, and Shin (2003) (hereafter referred to as IPS) proposed the following panel unit root test. Assuming there are n mutually independent entities in the panel data, the following DF regressions are conducted separately for each entity:

$$\Delta y_{it} = \delta_i y_{it-1} + z_{it}^{'} \gamma_i + \varepsilon_{it} \qquad (3.28)$$

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Where δ_i represents the autoregressive coefficient for entity i, and ε_{it} follows a mutually independent normal distribution (with uncorrelated disturbances) but allows for heteroskedasticity. Under the fixed effects assumption, as n approaches infinity or remains fixed, the null hypothesis for panel unit root is H_0: $\delta_i=0$, $\forall$ I, while the alternative hypothesis is that the proportion of entities following a stationary process is greater than zero, meaning that as n approaches infinity, n_1/n converge to some nonzero positive number, where n $denote_1$ is the number of entities following a stationary process.

If t_i denotes the t-statistic for individual i (the ADF statistic), and calculate the sample mean of all indiciduals t-statistics denoted by $\bar{t}$ (referred to as 1-bar in Stata 18). Im, Pesaran, and Shin (2003) provided critical values for the $\bar{t}$ distribution. Stata also reports another statistic $\tilde{\bar{t}}$ (referred to as t-tilde-bar in Stata), which differs from $\bar{t}$ only in the estimation of the variance of disturbances in Equation (3.28). Furthermore, $\tilde{\bar{t}}$ can be standardized to construct the following statistic $Z_{\bar{t}}$ (referred to as Z-t-tilde-bar in Stata):

$$Z_{\tilde{\bar{t}}} = \frac{\tilde{\bar{t}} - E(\tilde{\bar{t}})}{\sqrt{Var(\tilde{\bar{t}})/\mathrm{n}}} \rightarrow N(0,1) \qquad (3.29)$$

Where $E(\tilde{\bar{t}})$ and $Var(\tilde{\bar{t}})$ represent theoretical mean and variance of $\bar{t}$, which can be obtained through reference tables. Due to the assumption of independence among these n time series, the central limit theorem applies, hence the asymptotic distribution of $Z_{\bar{t}}$ is standard normal. The IPS test is also a left one-sided test.

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If autocorrelation exists in the disturbances ε_{it} of equation (3.28), it can be eliminated by introducing differencing with lagged terms. That is, the following ADF-style regressions are conducted separately for each individual just like equation 3.23.

Where different individuals may have different lag orders p_i (determined by information criteria), and the assumption is (T,n) tends to infinity. The remaining steps of the test are similar to the case of no autocorrelation in disturbances, and its statistic is denoted as $W_{\bar{t}}$ (referred to as W-tilde-bar in Stata), corresponding to the $Z_{\bar{t}}$ statistic mentioned earlier.

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IPS (Im et al., 2003) overcomes the potential drawback of LLC by allowing different sequences to have different δ in the panel. This model is to determine whether unit root exist or not exist in the panel data and the hypotheses of the IPS test can be written as follows:

H_0: $\delta_i = 0$ (There is a unit root)

H_1: $\delta_i < 0$ (There is no unit root)

The null hypothesis suggests that all series have a unit root, denoted as H_0: $\delta_i = 0$ for all i, against the alternative hypothesis proposing that only certain series have

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a unit root, denoted as H_1: $\delta_i < 0$, for at least one series. The null hypothesis of IPS test indicates that the series is non-stationary or possesses a unit root, while the alternative hypothesis suggests that all series are stationary or lack a unit root. For instance, if the p-value for the IPS test is not significant at the specified significance level, it implies that the test fails to reject the null hypothesis, indicating that the series has a unit root and is non-stationary. Conversely, the rejection of the null hypothesis occurs when the p-value is significant. The IPS model can be described as follows:

$$\Delta Y_{it} = \delta_i Y_{i,t-1} + z_{it}^{'}\gamma_i + \varepsilon_{it} \quad (3.30)$$

Where i = 1, 2, …, N regions observed over t = 1, 2, …, T, ε_{it} ~IID(0,σ^2).

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3.3.1.4 Panel cointegration test

The cointegration test and estimation of non-stationary time series variables have gained widespread recognition (Lau et al., 2019). Cointegration test is conducted to examine whether there exists a long-term equilibrium relationship among multiple variables in time series data (Abbasi et al., 2021). The purpose of this test is to determine whether non-stationary time series variables form a stable cointegration relationship over the long run, implying that their linear combination becomes stationary (Kremers et al., 1992). The reason for conducting cointegration tests lies in the potential presence of unit roots in non-stationary time series, which may impact

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the robustness of the model. A significant result from the cointegration test indicates the existence of a cointegrating relationship, suggesting that even if the original data are non-stationary, their linear combination forms a long-term equilibrium (Westerlund & Edgerton, 2007). Through the application of cointegration tests and ECMs, researchers can capture both long-term and short-term dynamics among variables more accurately, thereby improving the reliability and interpretability of time series analysis (Ouedraogo, 2013).

The commonly employed methods for panel data cointegration testing are the Pedroni test (Pedroni, 1999), the Westerlund test (Westerlund & Edgerton, 2007), as well as others such as the Kao test (Kao, 1999). Among them, the Pedroni test stands out for its applicability to concurrently test cointegration relationships in both stationary and non-stationary panel data, making it versatile across various panel data structures and providing a comprehensive tool for the holistic analysis of cointegration relationships (Herzer & Vollmer, 2012). And the Westerlund test excels in addressing heterogeneity in panel data and exhibits a relatively straightforward computational process, rendering it widely applicable (Westerlund & Edgerton, 2007). Given the complementary advantages of these two tests, this study opts for the Westerlund and Pedroni tests to conduct a more comprehensive and precise exploration of cointegration relationships within panel data.

Pedroni test and Westerlund test are conducted using significance testing

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methods. Significance testing is a procedure that uses sample results to verify the validity of a hypothesis. The fundamental idea behind significance testing lies in a test statistic (as an estimator) and the sampling distribution of this statistic under the null hypothesis. Based on the calculated statistic from the data at hand, a decision is made on whether to accept the null hypothesis.

Pedroni (2004) introduced seven test statistics that test the null hypothesis of no cointegration in nonstationary panels. It allows heterogeneity in the panel, both in the short-run dynamics as well as the long-run slope and intercrept coefficients. The test can include common time dummies to address cross-sectional dependency by time demeaning the data for each variables as follows:

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$$\overline{y_t} = \frac{\sum_{i=1}^{N} y_{it}}{N} \tag{3.31}$$

Where y is dependent variables and t = 1,...,T and i = 1,...,N index the time-series and cross-sectional units, respectively. To compute the test statistics, estimate 3.31 by OLS, for each cross-section. Where x is independent variables, k is the number of x and β is the coefficient. μ_{it}represents the error term.

$$y_{it} = \alpha_i + \beta_{1i}x_{1it} + \beta_{2i}x_{2it} + \ldots + \beta_{ki}x_{kit} + \mu_{it} \tag{3.32}$$

It is assumed that the slope coefficients and the intercept can vary across cross-section units. The within-dimension based test statistics, panel-p and panel-t, are computed by taking the first-difference of the original series and estimating the residuals:

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$$\Delta y_{it} = \sum_{j=1}^{k} \beta_{ji} \Delta x_{jit} + v_{it} \tag{3.33}$$

The long run variance, of the residuals is calculated by using Newey and Kenneth (1987) estimator. Where p_i represents the autoregressive order of the time series variable y_i.

$$\widehat{\sigma}_{v,t}^2 = \frac{1}{T}\sum_{t=1}^{T} \hat{v}_{it}^2 + \frac{2}{T}\sum_{j=1}^{p_i}\left(1 - \frac{j}{p_i + 1}\right)\sum_{t=j+1}^{T} \widehat{v_{it}}\,\widehat{v_{it-j}} \tag{3.34}$$

To calculate the non-parametric statistics, panel-p and group-p, the following regression equation is to be estimated with the residual obtained from equation 3.31.

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$$\hat{\mu}_{it} = \widehat{\phi}_i \hat{\mu}_{it-1} + \varepsilon_{it} \tag{3.35}$$

Where $\widehat{\phi}_i$ represents the estimated autoregressive coefficient for individual I and ε_{it} represents the random error term at time t.

Then the long-run variance $\widehat{\sigma}_i^2$ and the contemporaneous variance $\hat{s}_i^2$ of $\hat{\varepsilon}_{it}^2$ is computed.

$$\hat{s}_i^2 = \frac{\sum_{t=1}^{T} \hat{\varepsilon}_{it}^2}{T} \tag{3.36}$$

For the calculation of $\widehat{\sigma}_i^2$, Petroni (1995) used $4\left(\frac{T}{100}\right)^{\frac{2}{9}}$ as the lag truncation function for the Newey-West kernel estimation as recommended in Newey and West

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(1994). The nearest integer is taken as the lag length for different T dimensions. The parametric test statistics, panel-t and group-t, are estimated with the residuals $\hat{\mu}_{it}$ obtained from regression 3.31.

$$\hat{\mu}_{it} = \hat{\phi}_i \hat{\mu}_{it-1} + \sum_{j=1}^{k} \hat{\delta}_{ji} \Delta\hat{\mu}_{t-1} + \varepsilon_{it}^{*} \tag{3.37}$$

The variance of ε_{it}^{*} $\hat{s}_i^{*2}$ is computed as

$$\hat{s}_i^{*2} = \frac{\sum_{t=1}^{T} \hat{\varepsilon}_{it}^{*2}}{T} \tag{3.38}$$

To determine the lag truncation order of the ADF t-statistics, the step-down procedure and the Schwarzt lag order selection criterion are used. And between-dimension-based statistics are the group mean approach extensions of the within-dimension-based ones. The group p statistic has the best power among the test statistics of Pedroni (1999). Group p statistic is as follows:

$$T\sqrt{N}\tilde{Z}_{\hat{p}N,T^{-1}} = T\sqrt{N} \sum_{i=1}^{N} \left(\sum_{t=1}^{T} \hat{u}_{i,t-1}^{-2} \right)^{-1} \sum_{t=1}^{T} \left(\hat{\mu}_{i,t-1} \Delta\hat{\mu}_{it} - \hat{\lambda}_i \right) \tag{3.39}$$

For DOLS regression, the model is as follows:

$$y_{it} = \alpha_i + \beta_i x_{it} + \sum_{j=-p}^{p} \gamma_{ij} \Delta x_{i,t-j} + \mu_{it}^{*} \tag{3.40}$$

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Where i= 1,2,…， N is the number of units in the panel, t=1,2,…， T is the number of time periods, j=1,2,…， p is the number of lags and leads in the DOLS regression, β_i is the slope coefficient , and x_{it} is the explanatory variable. The β coefficient and associated t statistics are then averaged over the entire panel by using Pedroni's group mean method. Where Z_{it} is the $2(p+1) \times 1$ vector of regressors including the lags and leads of the differenced explanatory variable.

$$\widehat{\beta}^{*}_{GM} = \left[\frac{1}{N}\sum_{i=1}^{N}\left(\sum_{t=1}^{T} Z_{it}Z_{it}^{'}\right)^{-1}\left\{\sum_{t=1}^{T} Z_{it}(y_{it} - \bar{y}_i)\right\}\right] \tag{3.41}$$

Pedroni's PDOLS estimator is averaged along the between-dimension. Accordingly, the null hypothesis,

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$$H_0: \beta_i = \beta_0$$

Against the alternative,

$$H_1: \beta_i \neq \beta_0$$

The statistic is as the follows:

$$t_{\widehat{\beta}^{*}_{GM}} = \frac{1}{\sqrt{N}}\sum_{i}^{N} t_{\widehat{\beta}^{*}_{i}} \tag{3.42}$$

The null (H0) and alternative hypotheses (H1) for the Pedroni test are:

H_0: There is no cointegration present in any of the panels.

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H_1: The variables are cointegrated across all panels.

If the p-value of the Phillips–Perron is less than 0.05, it indicates rejection of the null hypothesis, and the existence of cointegration is confirmed.

The principle of the Westerlund test is based on the theory of unit root tests, which is used to examine whether variables in panel data share a common unit root, indicating the presence of a cross-sectional unit root problem. The purpose of the test is to determine whether there exists a long-term stable relationship among the variables (Westerlund, 2007). The error correction model is as follows:

$$\Delta y_{it} = \delta_i^{'} d_t + \alpha_i (y_{it-1} - \beta_i^{'} x_{it-1}) + \sum_{j=1}^{p_i} \alpha_{ji} \Delta y_{it-j} + \sum_{j=0}^{p_i} \gamma_{ji} \Delta x_{it-j} + e_{it} \qquad (3.43)$$

Where $d_t = (1, t)^{'}$ now holds the deterministic components, with $\delta_i = (\delta_{1i}, \delta_{2i})^{'}$ being the associated vector of parameters. The panel statistics are complicated by the fact that the both the parameters and dimension, therefore, a three-step procedure to implement these test is as follows:

The first step is the same as for the group mean statistics and involves determining p_i, the individual lag order:

$$\Delta \tilde{y}_{it} = \Delta y_{it} - \hat{\delta}_i^{'} d_t - \hat{\lambda}_i^{'} x_{it-1} - \sum_{j=1}^{p_i} \hat{\alpha}_{ji} \Delta y_{it-j} - \sum_{j=0}^{p_i} \hat{\gamma}_{ji} \Delta x_{it-j} \qquad (3.44)$$

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And

$$\Delta\tilde{y}_{it-1} = \Delta y_{it-1} - \hat{\delta}_i' d_t - \hat{\lambda}_i' x_{it-1} - \sum_{j=1}^{p_i} \hat{\alpha}_{ji}\, \Delta y_{it-j} - \sum_{j=0}^{p_i} \hat{\gamma}_{ji}\, \Delta x_{it-j} \quad (3.45)$$

The second step involves using $\Delta\tilde{y}_{it}$ and $\Delta\tilde{y}_{it-1}$ to estimate the common error correction parameter α and its standard error. In particular, it is computed as follows:

$$\hat{\alpha} = \left(\sum_{i=1}^{N} \sum_{t=1}^{T} \hat{y}_{it-1}^2 \right)^{-1} \sum_{i=1}^{N} \sum_{t=1}^{T} \frac{1}{\hat{\alpha}_i(1)} \tilde{y}_{it-1} \Delta\tilde{y}_{it} \quad (3.46)$$

The standard error of $\hat{\alpha}$ is given by

$$SE(\hat{\alpha}) = \left((\hat{S}_N^2)^{-1} \sum_{i=1}^{N} \sum_{t=1}^{T} \tilde{y}_{it-1}^2 \right)^{-1/2} \quad (3.47)$$

$where \hat{S}_N^2 = \frac{1}{N} \sum_{i=1}^{N} \hat{S}_i^2$. The third step is to compute the panel statistics as:

$$P_\tau = \frac{\hat{\alpha}}{SE(\hat{\alpha})} and P_\alpha = T\hat{\alpha} \quad (3.48)$$

For the Westerlund test in Stata 18, the hypotheses are as follows:

H0: There is no cointegration present in any of the panels.

H1: The variables are cointegrated in some of the panels. Or the variables are cointegrated in all the panels.

If the p-value of the Variance ratio is less than 0.05, it indicates rejection of the null hypothesis, and the existence of cointegration is confirmed.

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3.3.2 Model estimation

To test Hypothesis 1, this study first selects the appropriate static panel model using the F Test, Breusch-Pagan (BP) Test, and Hausman Test. Based on the estimation results, it assesses the appropriateness of incorporating relevant control variables, the quadratic term of the independent variable, and the lagged dependent variable. Subsequently, the study employs the system Generalized Method of Moments (GMM) to estimate the dynamic panel model, ensuring robustness in addressing potential endogeneity issues, and tests the conclusions related to Hypothesis 1.

3.3.2.1 Static panel model test

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This study utilizes balanced short panel data. One extreme strategy for estimating panel data is to treat it as cross-sectional data and perform a pooled regression. Another extreme approach is to estimate a separate regression equation for each individual. The former approach overlooks unobservable or omitted heterogeneity between individuals, which may be correlated with explanatory variables and lead to inconsistent estimates. The latter approach neglects commonalities between individuals and may result in insufficient sample sizes. Consequently, a practical compromise is often employed, wherein individual regression equations are assumed to have identical slopes but varying intercepts, capturing heterogeneity. If the individual disturbance terms are correlated with one or more explanatory variables,

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the model is referred to as a fixed effects model (FE). If the disturbances are uncorrelated with the explanatory variables, the model is termed a random effects model (RE). In addition, in recent years, the two-way fixed effects model has become a commonly used panel data approach. It is employed to control for the influence of both individual fixed effects and time fixed effects in panel data, allowing for more accurate estimation of the relationships between variables.

In this section, static models are initially utilized, employing F-test, BP-test, and Hausman test to determine the appropriate type of effects model for this study. Subsequently, the chosen effects model incorporates the quadratic term of the digital economy development level, control variables and one-period lag of urban-rural income gap index in a sequential manner. The necessity of adding each variable is assessed based on regression results.

In general, when conducting regression analysis to study relationships in panel data static model estimation, it is typically categorized into three types: the Fixed Effects (FE) model, the Pooled (POOL) model (which employs ordinary least squares regression, also known as Mixed Effects), and the Random Effects (RE) model (Abdullah, Sahudin, & Bahrudin, 2022). F-tests, Breusch-Pagan (BP) tests, and Hausman tests are employed to determine the most suitable estimation.

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As is shown in Table 3.7, F-test is is used to compare which one, between the fixed effects model and the Pooled model, is more suitable for this study. The null hypothesis of the F-test posits that the intercept terms of different cross-sectional models are the same. If the p-value of the F-test is less than 0.05, rejecting the null hypothesis indicates that the fixed effects model is more suitable for the data than the mixed effects model. Conversely, if the p-value of the F-test is greater than 0.05, accepting the null hypothesis suggests that the mixed effects model is more appropriate for the study data compared to the fixed effects model.

BP test is used to compare which one, between the random effects model and the POOL model, is more suitable for this study. Breusch and Pagan (1980) introduced the LM statistic based on residuals from the panel random effects model. The null hypothesis of the Breusch-Pagan test is that there is no heteroscedasticity in the error terms of the regression model. In the BP test, if the p-value is less than 0.05, the null hypothesis is rejected, indicating the presence of random effects, and the random effects model is chosen. If the p-value is greater than 0.05, the null hypothesis is accepted, and the POOL model is chosen.

Hausman test could be used to compare which one, between the fixed effects model and the POOL model, is more suitable for this study (Hiestand, 2005). Starting from the fundamental definition, one can utilize the examination of whether individual effects are correlated with other explanatory variables as a basis for

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selecting between fixed effects and random effects models. The null hypothesis is that there is no correlation between individual effects and explanatory variables in the fixed effects model, indicating that the explanatory variables are unrelated to individual effects. If the p-value is less than 0.05, the null hypothesis is rejected, indicating that the fixed effects model is chosen. If the p-value is greater than 0.05, the null hypothesis is accepted, and the radom model is chosen.

Table 3.7

Model Selection Tests and Conclusions

Test Type	Test Purpose	Test Value	Test Conclusion
F-test	Comparison between FE model and POOL model	$p < 0.05$	FE model
BP Test	Comparison between RE model and POOL model	$p < 0.05$	RE model
Hausman Test	Comparison between FE model and RE model	$p < 0.05$	FE model

Source, Sheng et al. (2023)

3.3.2. 2Static panel model estimation

To ensure the inclusion of the quadratic term of the digital economy development level index, and the effectiveness of the control, models 3.49， 3.50， 3.51 and 3.52 are introduced. By applying the validated effects model obtained from the above tests, regressions are conducted on 3.49， 3.50, 3.51 and 3.52, respectively, to observe whether their R^2 continuously improves. If R^2 consistently increases, it indicates an

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enhancement in the goodness of fit, suggesting the effectiveness of incorporating that variable (Cameron & Windmeijer,1997). These result provide the necessary foundation for validating the establishment of dynamic panel model, which is to fulfil research hypothesis 1.

$$URIG_{j,t} = \alpha_j + \alpha_{11} DEDI_{j,t} + \varepsilon_{j,t} \quad (3.49)$$

$$URIG_{j,t} = \alpha_j + +\alpha_{11} DEDI_{j,t} + \beta_j X_{j,t} + \varepsilon_{j,t} \quad (3.50)$$

$$URIG_{j,t} = \alpha_j + +\alpha_{11} DEDI_{j,t} + \alpha_{12} DEDII_{j,t}^2 + \varepsilon_{j,t} \quad (3.51)$$

$$URIG_{j,t} = \alpha_j + +\alpha_{11} DEDI_{j,t} + \alpha_{12} DEDI_{j,t}^2 + \beta_j X_{j,t} + \varepsilon_{j,t} \quad (3.52)$$

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3.3.2.3 Dynamic panel model estimation

Many economic theories suggest that individuals' current behavior is influenced by past behavior due to inertia or partial adjustment (Thaler, 2016). When explanatory variables in panel models include lagged values of the dependent variable, it is termed dynamic panel data, abbreviated as DPD. In this study, with T=10 and N=30, where T<N, it constitutes short panel dynamic data. Under the assumption of spherical disturbances, 2SLS is the most efficient. However, if disturbances exhibit autocorrelation, a more effective estimation method is the generalized method of

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moments (GMM). Common estimation methods for short dynamic panel data include Difference GMM, Level GMM, and System GMM (Chen, 2014).

Difference GMM eliminates variables that do not change over time when differencing, thereby avoiding bias in estimating the coefficients of these variables. Moreover, if the dependent variable exhibits high persistence, meaning that the autoregressive coefficient is close to 1, it may lead to weak instrument problems or even invalid instruments. To address these issues, Arellano and Bover (1995) proposed Level GMM. It uses differenced variables as instruments for the levels and ensures that the error terms are free from autocorrelation and unrelated to individual effects. Blundell and Bond (1998) combined difference GMM and level GMM into a single system for GMM estimation, referred to as System GMM. Compared to difference GMM, System GMM enhances estimation efficiency and allows for the estimation of coefficients of variables that do not change over time (Chen, 2014).

System GMM can be implemented using either one-step or two-step approaches. The two-step System GMM estimation involves two stages: first, estimating fixed effects or using a one-step estimator, and second, using the estimates from the first stage to estimate the parameters of the model. This method reduces the variance of parameter estimates, thereby improving the efficiency and accuracy of the estimation (Roodman, 2009). Therefore, this study employs the two-step system GMM estimation method to empirically analyze dynamic panel model (3.12) and test whether research hypothesis 1 is right or not.

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Including the lagged dependent variable as an explanatory variable exacerbates the issue of endogeneity in the model. This results in the violation of the assumption that explanatory variables are uncorrelated with the error term, rendering the use of fixed effects or random effects models inappropriate. Consequently, such an approach would yield biased and inconsistent estimates and fail to address the endogeneity problem (Han & Zhang, 2017; Qiu & Ma, 2015).

Arellano and Bond (1991) first pointed out that using difference GMM (DIF-GMM), by taking the first differences and using the lagged levels of the variables as instruments, can effectively address this issue. However, they also noted that difference GMM estimates may suffer from the problem of weak instruments. System GMM was proposed by Arellano and Bover (1995) and Blundell and Bond (1998). The system GMM also collects endogeneity but now by introducing more instruments to dramatically improve efficiency of the estimatator. It transforms the instruments to make them uncorrelated (exogenous) with the fixed effects. It builds a system of two equation: the initial equation and the transformed one.

$$Initial\,model:\ lnY_{it} = \emptyset lnY_{it-1} + \beta X_{it}^{'} + (\eta_i + \varepsilon_{it}) \qquad (3.53)$$

$$Transformedmodel: \Delta lnY_{it} = \emptyset \Delta lnY_{it-1} + \beta \Delta X_{it}^{'} + \Delta \varepsilon_{it} \qquad (3.54)$$

Assuming that equation 3.31 represents a random walk model and that Y is persistent. the application of the difference GMM estimator yields both biased and

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inefficient estimates of ∅ in finite samples, particularly when when T is short. In this framework, one equation is expressed in levels form while utilizing first differences as instruments. Conversely, the second equation is expressed in first-differenced form, employing levels as instruments. This approach incorporates a greater number of moment conditions; however, Monte Carlo evidence indicates that when T is short and the dependent variable exhibits persistence, there are notable gains in precision, and the small-sample bias is mitigated.

It is noteworthy that GMM estimation encompasses one-step and two-step methods. In the presence of autocorrelation and heteroskedasticity in panel data, the two-step method may underestimate the standard deviation, thereby affecting estimation efficiency, but it generally yields more robust estimation results compared to the one-step method. Consequently, this paper employs the two-step system GMM to estimate the relationship between the digital economy development and the urban-rural income gap. Additionally, due to the inclusion of moment constraints in the GMM estimation method, it is necessary to conduct tests for autocorrelation and the validity of instrumental variables. This study utilizes the AR (AutoRegressive) test to examine the existence of autocorrelation, with the null hypothesis being no autocorrelation. While the test is less stringent for first-order autocorrelation, it does not tolerate second-order autocorrelation (Han & Zhang, 2017; Zhou et al.,2024). The Hansen test is employed to assess the validity of the instrumental variables, with the null hypothesis stating that the instrumental variables are valid (Zhou et al. , 2024)

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3.3.2.4 Dynamic panel model test

The primary purpose of model diagnostics is to ensure that the selected statistical model meets specific assumptions and conditions before applying a particular estimation method. By conducting diagnostics tests, researchers can verify whether the model conforms to the prerequisites of the chosen estimation method, ensuring the reliability and effectiveness of the estimation results. Common tests conducted before employing System GMM include overidentification tests and tests for serial correlation. These assessments contribute to enhancing the accuracy and interpretability of the established model, guaranteeing the effective application of the chosen estimation method given the model structure.

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i. Overidentification test

The Hansen Test (Hansen & Hayter, 1982) and Sargan tests are statistical tests used in the context of instrumental variable (IV) regression models, particularly in econometrics and quantitative research. These tests serve specific purposes in evaluating the validity of instrumental variables and the overall model specification. The advantage of the Hansen statistic lies in its comprehensive consideration of the heterogeneity of moments across different time points and cross-sections, making it particularly suitable for relatively small samples (Hansen & Hayter, 1982). It can

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provide a more thorough assessment of the effectiveness of instrumental variables. Although the Sargan statistic is primarily employed to assess over-identification, it is relatively less comprehensive than the Hansen statistic as it focuses more on over-identification and overlooks heterogeneity issues. Considering these factors, the ultimate choice of the Hansen test ensures a more comprehensive and accurate evaluation of instrumental variable effectiveness.

Finding out whether the instrumental variables are entirely exogenous is the goal of the test. The efficiency of the instrumental variables cannot be assessed if the number of variables used is equal to the number of parameters that need to be estimated. However, if the number of instrumental variables exceeds the number of parameters to be estimated, there are additional instrumental variables available for testing. The null hypothesis for overidentification test is that all instrumental variables are exogenous. If the result of overidentification test showed that the p-value was higher than 0.10, then the null hypothesis could not be rejected. A p-value between 0.1 and 0.25 is usually considered to indicate very good results (Roodman, 2009).

ii. Autocorrelation test

In most cases, random disturbances exhibit first-order autocorrelation and lack higher-order autocorrelation. For such cases, the system generalized method of moments (GMM) approach is typically a suitable choice. The system GMM method

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can provide consistent estimation results in the presence of first-order autocorrelation and can effectively control the impact of auto-correlation by using instrumental variables, thereby obtaining efficient estimates. Therefore, when facing the situation where random disturbances exhibit first-order auto-correlation but lack higher-order auto-correlation, the system GMM method is a common and effective choice.

The null hypothesis is that the first-order and second-order auto-correlation coefficient of the disturbance term is zero, meaning that there is no first-order and second order auto-correlation in the random disturbance term. If the value of AR(1)<0.01 and AR(2)>0.1, it indicates that the null hypothesis of no first-order serial correlation is rejected and the null hypothesis of no second-order serial correlation could not be rejected. Therefore, the GMM model is an effective choice.

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3.3.3 Heterogeneity test

In order to test research hypothesis 2, a heterogeneity test is employed in this study. The heterogeneity test is a crucial tool in statistical analysis designed to assess whether there are significant differences in variance among distinct groups (Petitti, 2001). Four commonly employed heterogeneity testing methods include Levene's Test, Brown-Forsythe Test, Bartlett's Test, and Grouped Regression. As a potent statistical approach, grouped regression offers distinct advantages, notably its efficacy in conducting heterogeneity tests, enabling a nuanced understanding of specific

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characteristics within different subgroups. It facilitates comparisons of variable effects, explication of model gap, and identification of latent trends. In essence, Grouped Regression serves as a robust methodology, contributing to a comprehensive exploration of heterogeneity and model variations within a data set.

As previously mentioned, Mainland China can be divided into four economic areas: the Eastern region, the Central region, the Western region, and the Northeast region. A grouped regression approach is employed to conduct a regional heterogeneity test, which aims to test Research Hypothesis 2. Specifically, we estimate panel data for each of these four regions using the static panel model in Equation 3.11 and the dynamic panel model in Equation 3.12. To ensure the robustness of the results, we conduct the grouped regression analysis using both the fixed effects model and the system GMM. Analyzing the results and variations across these regions allows us to assess whether there is regional heterogeneity in the impact of digital economy development on the urban-rural income gap.

3.3.4 Mediating effect test

In order to test research hypothesis 3 and 4, mediating effect testing methods are introduced in this study. Mackinnon et al. (2002) classified 14 mediating effect testing methods into three categories, including the casual steps approach (e.g., The Stepwise Coefficient Regression Test), the difference in coefficients method, and the products

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of coefficients method (e.g., the Sobel test and bootstrap test) (where the meanings of a, b, c, and c' are described in Figure 3.1) (Gonzalez & MacKinnon, 2021; MacKinnon et al., 2002; Wen & Ye, 2014). Due to its simplicity and ease of understanding, the casual steps approach has become the most widely used method for testing mediating effects to date. However, this approach has several drawbacks (Hayes, 2009; MacKinnon et al., 2002; Preacher & Hayes, 2008). The difference in coefficients method, on the other hand, suffers from a high Type I error rate (up to 100%) when a or b are not both zero. Moreover, it is challenging to apply this method to more complex analyses involving multiple mediator variables or moderated mediating models, and thus, it is rarely used in such contexts (Preacher & Hayes, 2008; Wen et al., 2022).

In regards to the testing method for mediating effects, Baron and Kenny first proposed the stepwise coefficient testing method in the middle 1980s (Zhao et al., 2010). The specific testing steps are as follows: firstly, test the significance of the coefficient c, then test a and b separately. If a, b, and c all pass the significance test, then mediating effects are present. Otherwise, no mediating effect has occurred. However, this testing method requires assumptions to be made for all regressions, which leads to a high number of assumptions and lower work efficiency. In cases where the mediating effect is weak, there is a high probability of obtaining a conclusion that lacks mediating effects. Wen (2014) and other scholars refer to the

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Sobel test method derived by Sobel M.E. in the early 1980s and improved the Sobel test method to replace the defective stepwise testing method. They constructed a complete mediating effect testing process, which has been widely recognized by many scholars and is still in use today.

However, due to the innovation and development of data statistical methods, the shortcomings of this method have gradually been exposed. In addition, this test is mainly designed for large sample data, with complex statistical calculations that do not meet the needs of small sample data. Zhao et al. (2010) summarize a process for using the Bootstrap method to perform mediating tests to address the shortcomings of previous mediating test methods. He believes that the Bootstrap method is one of the most ideal methods for testing the significance of coefficient products. Chen et al. (2014) make improvements to the testing analysis depth and effectiveness of the Bootstrap method. In his influential 1986 work, Tukey examines the concept of robustness in statistics, highlighting the necessity of employing diverse testing methods to ensure the stability and reliability of statistical results (Tukey, 1986). Building on this foundational perspective, this study incorporates three distinct testing methods to leverage their unique advantages, thereby ensuring both robustness and reliability in the estimation results. By applying these three mediating testing approaches, the study provides a comprehensive evaluation of the mediating effects of OIS and UIS.

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3.3.4.1 Stepwise coefficient regression test

The first method is the casual steps approach, known as the stepwise coefficient regression proposed by Baron and Kenny (1986). The stepwise coefficient regression method consists of three steps (Baron & Kenny, 1986; Judd & Kenny, 1981; Wen Zh et al., 2004):

The first step involves testing the coefficient c in equations 3.13 and 3.16, which represents the total effect of the independent variable DEDI on the dependent variable URIG. The second step involves testing the coefficient a in equations 3.14 and 3.17, representing the relationship between the independent variable DEDI and the mediator OIS or UIS. The third step involves controlling for the mediator OIS or UIS and testing the coefficients c' and b in equations 3.15 and 3.18, respectively.

If the coefficient c is significant, the coefficient a is significant, and the coefficient b is significant, then the partial mediating effect is considered significant. If the coefficient c is significant, the coefficient a is significant, and the coefficient b is significant, but the coefficient c' in equations 3.14 and 3.18 is not significant, it is referred to as complete mediation. The effect size of a mediating effect is commonly measured using ab/c or ab/c'. Despite its widespread use, the casual steps approach has been controversial since its inception.

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Firstly, the casual steps approach sets the significant influence of the independent variable on the dependent variable (i.e., significant c) as a prerequisite for testing the mediating effect. That is, if the coefficient c is not significant, there is no mediating effect. However, some scholars argue that this prerequisite is unnecessary. Its existence leads many mediation studies, which may have been meaningful, to halt at the first step, suppressing the development and application of mediation research. This is because mediating effects may still exist even when the coefficient c is not significant (Fairchild & McQuillin, 2010; MacKinnon & Fairchild, 2009; Preacher & Hayes, 2008; Shrout & Bolger, 2002). Shrout and Bolger (2002) pointed out that when ab and c' have opposite directions, it may lead to a non-significant coefficient c. Preacher and Hayes (2008) noted that in models with two mediator variables, if the directions of the two mediating effects are opposite, it may also result in a non-significant coefficient c. Rucker et al. (2011) conducted simulation studies to examine the possibility of significant mediating effects when the coefficient c is not significant. The simulation results showed that when the sample sizes were 50 and 100, the probabilities of significant mediating effects 0.16 when the coefficient c was not significant 0.2 were as high as 48.2% and 44.5%, respectively. The casual steps approach infers the presence of mediating effects through a series of hypothesis tests rather than directly testing whether the mediating effect ab is significantly different from zero. Therefore, it cannot directly provide a point estimate of the mediating effect or a confidence interval for the mediating effect (Fairchild &

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McQuillin, 2010; Cheong, 2011; Mackinnon & Fairchild, 2009; Preacher & Hayes, 2008).

The product of coefficients method, unlike the casual steps approach, directly tests whether the mediating effect ab is significantly different from zero. It does not require the coefficient c to be significant as a prerequisite for testing the mediating effect. This method can directly provide point estimates and confidence intervals for the mediating effect. Additionally, simulation studies by Mackinnon (2002) have shown that the statistical power of the product of coefficients method is superior to that of the casual steps approach. Therefore, the product of coefficients method has gradually gained favor among many researchers.

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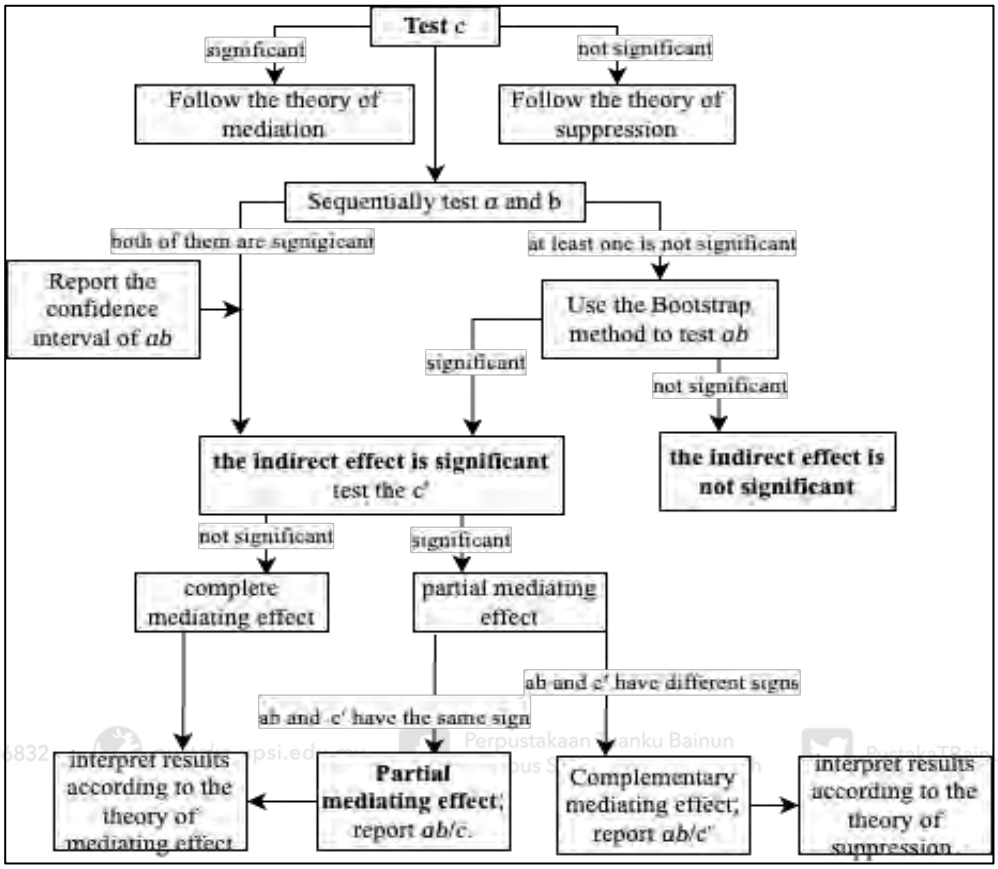
The product of coefficients method can be divided into two types (Fang et al., 2012). One type is the Sobel test, which is based on the assumption that the sampling distribution of the mediating effect is normal. The other type is the asymmetric confidence interval method, which is based on the assumption that the sampling distribution of the mediating effect is non-normal. The testing procedures are generally similar, as illustrated in Figure 3.2 (Wen & Ye, 2014).

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Figure 3.2

Mediating Effect Test Principle



3.3.4.2 Sobel test

The Sobel test is a statistical method used to assess the significance of a mediating effect in a mediation analysis. It evaluates whether the indirect effect (mediated effect) of an independentt variable on a dependent variable through a mediator is significantly different from zero. It is specifically designed to test the significance of the mediating effect in a causal model. This indirect effect is the product of two coefficients: the effect of the independent variable on the mediator (path a) and the

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effect of the mediator on the dependent variable (path b). The Sobel test is based on the standard error of the indirect effect and follows a normal distribution under certain assumptions (Wen et al., 2022). The Sobel test calculates the significance of the mediating effect using the following formula:

$$Z = \frac{ab}{\sqrt{a^2 s_b^2 + b^2 s_a^2}} \tag{3.55}$$

Where S_a is the standard error of coefficient a; S_b is the standard error of coefficient b. The test compares the calculated Z-statistic to a standard normal distribution to determine statistical significance. If the Z-statistic is significantly different from zero, it suggests a significant mediating effect. A significant Z-value suggests that the mediator variable does carry some of the effect of the independent variable on the dependent variable. While the Sobel test provides a straightforward way to test for mediation, it has limitations, including sensitivity to sample size and the normality assumption of the distribution of the indirect effect. Bootstrapping methods, which do not assume normality and are robust in smaller samples, are increasingly favored over the Sobel test.

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3.3.4.3 Bootstrap test

The Bootstrap method is a non-parametric statistical estimation technique in statistics. Its essence lies in resampling the observed data to make statistical inferences about the characteristics of the population distribution. Because this method fully utilizes the given observed data, it does not require additional assumptions about the model or additional observations. Moreover, it possesses robustness and high efficiency. Since the 1980s, with the introduction of computer technology into statistical practice, this method has become increasingly popular. Firstly, Bootstrap, through resampling, can avoid the sample reduction problem caused by Cross-Validation. Secondly, Bootstrap can also be used to introduce randomness into data.

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Bootstrap test is a type of asymmetric confidence interval method that abandons the assumption of a normal distribution for the sampling distribution of the mediating effect, without imposing restrictions on its sampling distribution. Bootstrap test can adapt to various sample sizes and different mediating effect models, and various statistical software commonly used can perform Bootstrap test calculations. In this study, Bootstrap was used to test the mediating effect, set at 1000 iterations with a 95% confidence interval. If this confidence interval does not include 0, the null hypothesis that the coefficient product is 0 is rejected, indicating a significant mediating effect.

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3.4 Summary

In conclusion, this chapter outlines the research methodology applied in the study in detail. The discussion consisted of the data, model specification and methods of analysing data. Data applied in this study are from the year 2013 until the year 2022 based on 30 provinces in China. This research use the DEDI and the URIG to measure the independent variable and the dependent variable, respectively. ED, EO, FE, EA and UR are employed as control variables. The change in the industrial structure is measured from two perspectives: optimization of the industrial structure (OIS) and upgrading of the industrial structure (UIS), both of which serve as mediating variables.

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To achieve the research objective 1, this study generates an improved digital economy development index (DEDI) to measure the level of digital economy development in China. Unlike existing indices that often suffer from limitations such as the omission of key sectors like digital finance and inadequate weight allocation, this study introduces a refined index system. It incorporates four dimensions: Digital Economy Development Carrier, Digital Industrialization, Industrial Digitization, and Digital Economy Development Environment. Specific improvements include the addition of digital finance indicators, the application of the entropy weighting method to enhance objectivity, and the clear definition of measurement units for each indicator. This comprehensive approach ensures a more accurate and reliable

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assessment of digital economy development, tailored to the specific conditions of provincial-level China.

To achieve the research objective 2, a dynamic panel model was employed. The dependent variable of this model is the urban-rural income gap index, while the independent variables include the digital economy development index, its square term, and the lagged one-period urban-rural income gap index, along with control variables. To accomplish the research objective 3, a mediating effect model was introduced. The methods of analysing data in this chapter are preliminary test (spearman rank-order correlation coefficient test, multicollinearity test, panel unit root test and panel cointegration test), model estimation (static model test, static model estimation, dynamic panel model test and dynamic panel model estimation), heterogeneity test and mediating effect test (stepwise coefficient regression test, Sobel test and bootstrap test). The results from these tests are further reported and discussed in Chapter 4.

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CHAPTER 4

FINDINGS

4.0 Introduction

This chapter reports the findings on the analyses of the improved digital economy development index (DEDI), the urban-rural income gap index (URIG), and explores the impact of digital economy development on the urban-rural income gap. Additionally, it examines the mediating role that the upgrading and optimization of the industrial structure played between digital economy development and the urban-rural income gap. This chapter is organized as follows. Section 4.1 discusses the results of generating variables. Section 4.2 discussed the results of the preliminary test. Section 4.3 discusses the results of system generalized method of moments (System GMM). Section 4.4 discusses the results of heterogeneity test. Section 4.5 presents the results of the mediating effect. And section 4.6 concludes the chapter. It should be noted that all the test results in this chapter are derived using the statistical software Stata 18.

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4.1 Variables measurement

This section primarily provides the computed indices for all the variables involved in this study. It specifically includes the following subsections: 4.1.1 Improved Digital Economy Development index (DEDI); 4.1.2 urban-rural income gap index (URIG); 4.1.3 mediating variables index and 4.1.4 control variables.

4.1.1 Improved digital economy development index (DEDI)

The results of the improved digital economy development index (DEDI), as presented in Table 4.1, fulfilling Objective 1. When using the entropy method, a greater gap in the standardized data corresponds to a higher weight. Changes in values provide indication that the larger the contribution to digital economy development, the higher the comprehensive values, indicating a higher level of digital economy development. From Table 4.1, it can be observed that the varying weights assigned to the four primary indicators reflect the relative importance of different components in the current development of the digital economy.

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Table 4.1

The Results of Improved Digital Economy Development Index (DEDI)

Primary indicators	Weight	Secondary indicators	Unit	Weight
Digital Economy development carrier	0.4560	Internet broadband access port density	Unit/km^2	0.1141
		Proportion of Internet users to resident population	%	0.0205
		Number of domain names per capita	Unit/person	0.1106
		Density of mobile base stations	Unit/km^2	0.1045
		Cell phone penetration rate	Unit/person	0.0183
		Density of fiber optic cable lines	km/km^2	0.0881
Digital industrialization	0.2638	Proportion of software business revenue to GDP.	%	0.0976
		Proportion of information technology services revenue to GDP	%	0.1109
		Proportion of total telecom business to GDP	%	0.0554
Industrial digitization	0.1228	Proportion of enterprises with e-commerce trading activities	%	0.0181
		Proportion of enterprise e-commerce to GDP	%	0.0504
		Number of computers used by enterprises per 100 people	Unit	0.0284
		Number of websites per 100 enterprises	Unit	0.0073
		Digital Inclusive Finance Index	/	0.0185

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Primary indicators	Weight	Secondary indicators	Unit	Weight
Digital economy development environment	0.1574	Fixed asset investment in information transmission, computer services and software industry per capita	Yuan/person	0.0347
		R&D expenditure of industrial enterprises above scale	Ten Billion Yuan	0.0869
		Proportion of information transmission, software and information technology service industry employed persons to total urban employment population.	%	0.0357

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This approach, which allocates weights based on the specific significance of each component, proves to be more reasonable and aligned with practical considerations compared to an equal-weight allocation method. The use of the entropy method effectively eliminates subjective influences, ensuring that the weight allocation is objective and scientifically grounded (Odu, 2019). By quantifying the information content of each indicator, the entropy method guarantees that the true contributions of each component to the evaluation of digital economy development are adequately reflected, thereby enhancing the reliability of the evaluation results (Zhang et al., 2022b).

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Specifically, the weight of digital economy development carriers stands at 45%, signaling their substantial contribution to the DEDI. Digital infrastructure, serving as the backbone of the digital economy, is indispensable, and continued investment, particularly in underdeveloped regions, is critical to bridging the regional development gap. Similarly, digital industrialization holds a 26.38% weight, emphasizing the substantial role of the information technology services sector, particularly its revenue contributions to GDP, in driving digital economy growth.

The weights for industrial digitization and the digital economy development environment are 12.28% and 15.74%, respectively, reflecting their respective contributions. These figures reflect the ongoing rapid development of the digital

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economy, where industrial digitization is still in its early phase, and certain statistical indicators may remain underdeveloped. Nevertheless, these components are integral to the overall advancement of the digital economy. The objective assignment of weights using the entropy method further underscores the scientific rationale and practicality of the evaluation system, accurately reflecting the dynamic and multifaceted nature of digital economy development.

This conclusion highlights the robustness of using the entropy method for constructing a comprehensive digital economy evaluation system, providing a clearer understanding of the importance of the different factors shaping this sector.

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The original data related to the digital economy development of each province are weighted, as outlined in Table 4.1, and subsequently incorporated into Formula 3.6. Then, the DEDI for each provinces is obtained. Using the obtained DEDI, the results for each province from 2013 to 2022 are presented in Table 4.3. From a national average perspective, China's digital economy (DEDI) has continuously developed over the past decade. As shown in Table 4.2, there is a growth from 0.097 in 2013 to 0.226 in 2022, with an average annual growth rate of 13.25%. The standard deviation is increasing from 2013-2022, which indicates increasing divergence. Additionally, the growth rate of the median has been increasing, demonstrating the strong momentum of China's digital economy.

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Table 4.2

Statistical Characters of Improved Digital Economy Development Index from 2013-2022

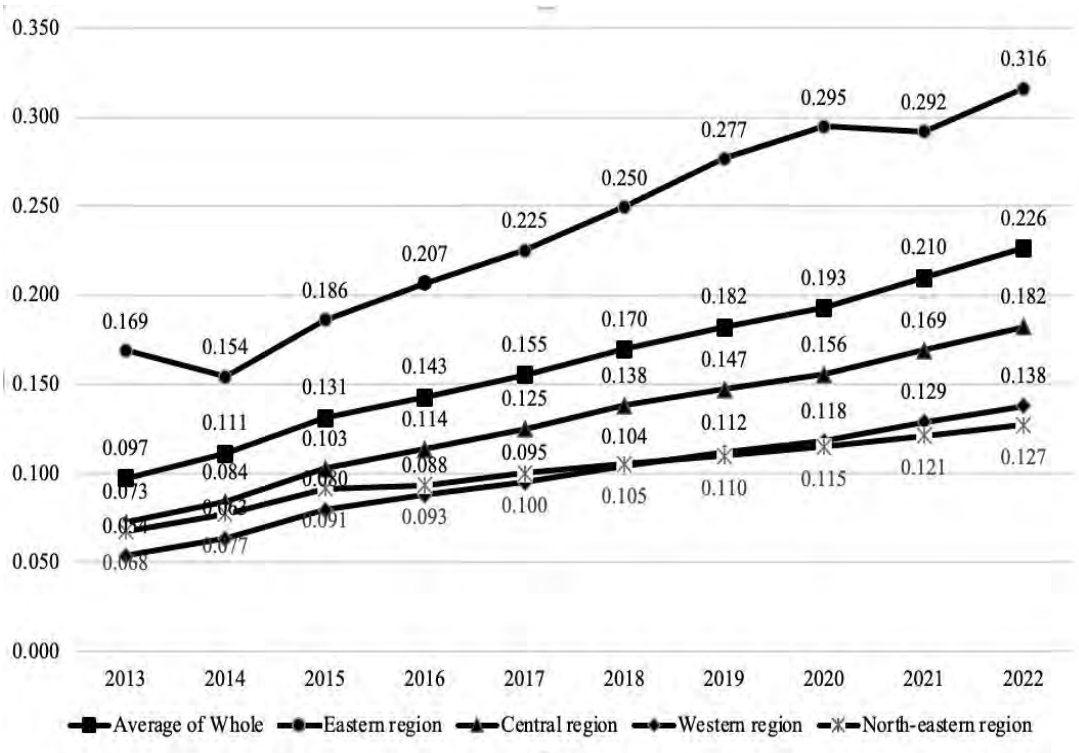
Year	Mean	SD	Max	Min	Growth rate of median
2013	0.096	0.073	0.303	0.036	
2014	0.110	0.080	0.335	0.042	0.145
2015	0.131	0.087	0.372	0.059	0.353
2016	0.142	0.094	0.413	0.063	0.471
2017	0.154	0.102	0.452	0.066	0.597
2018	0.168	0.113	0.513	0.071	0.746
2019	0.181	0.124	0.566	0.073	0.872
2020	0.191	0.133	0.598	0.077	0.978
2021	0.208	0.146	0.655	0.086	1.151
2022	0.224	0.161	0.712	0.095	1.319

From a regional perspective (Figure 4.1), there are inequality in the development of the digital economy (DEDI) among the four major economic regions.

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Figure 4.1

Digital Economy Development Index in China and Subregions over the Past Decade



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By 2022, the average Digital Economy Development Index (DEDI) is highest in the Eastern region, reaching a value of 0.316. The Central region follows as the second-highest with a DEDI of 0.182. The Western region ranks third, with a DEDI of 0.138, while the Northeast region has the lowest average DEDI at 0.127. These differences are largely the result of China's pursuit of coordinated regional development, which has involved the implementation of various policy strategies aimed at balancing growth across different regions. Specifically, policies designed to promote the Eastern region's leadership in digital development, alongside strategies such as Western Development, revitalization of the Northeast, and the rise of the Central region, have been integral to fostering economic growth across China's regions (Guo et al., 2020). These strategies have contributed to gradual improvements in regional economic conditions. In parallel, the increasing use of advanced technologies such as the Internet, artificial intelligence (AI), and big data has positioned the digital economy as a pivotal driver of high-quality economic growth. However, the uneven distribution of resources, combined with differences in policy orientation, has caused significant disparities in the development of the digital economy across the four major economic regions of China.

When considering the regional average annual growth rates of the digital economy, the Western region has the highest growth rate, followed closely by the Central region. The Northeast region ranks third in terms of growth rate, while the

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Eastern region shows the lowest rate of growth among the four regions. Specifically, the Western region's DEDI grew from 0.054 in 2013 to 0.138 in 2022, reflecting an average annual growth rate of 15.68%. The Central region's DEDI increased from 0.073 in 2013 to 0.182 in 2022, with an average annual growth rate of 15.15%. The Northeast region, which started at 0.068 in 2013, reached 0.127 by 2022, resulting in an average annual growth of 8.77%. The Eastern region experienced growth from 0.169 in 2013 to 0.316 in 2022, translating into an average annual increase of 8.69%. These figures highlight a notable lack of convergence in digital economy development between the Eastern, Central, Western, and Northeastern regions. Instead, regional inequalities have become more pronounced over time. This divergence may be attributed to factors such as resource endowment, policy priorities, and the Siphoning Effect, which have caused the Eastern region to advance at a significantly faster pace than the other regions. The Western and Northeastern regions, on the other hand, have lagged behind in terms of digital economy development. While regional policies have made a positive impact on achieving some degree of coordination, especially in the integration of the digital economy, they have not been sufficient to bridge the gap in digital economy development across the regions. Therefore, there is a need for further refinement of regional development policies, particularly those aimed at promoting digital economy growth, in order to reduce these regional disparities.

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As one of the most economically developed regions in China, the Eastern region has consistently maintained a high level of DEDI, despite occasional fluctuations. This region demonstrates a steady upward trend in digital economy development, reinforcing its leadership position in the sector. Despite fluctuations, the overall trend is clearly positive, signaling that the Eastern region has managed to sustain its lead in digital economy development. In comparison, the Central region's DEDI is slightly lower than that of the Eastern region but still shows a positive growth trajectory. Although there were notable fluctuations in certain years, such as in 2018, the Central region's DEDI has generally followed an upward trajectory, suggesting that the region has been catching up to the Eastern region in digital economy development. The Western region, starting from a relatively low DEDI, has experienced the most rapid growth among all four regions. With an average annual growth rate of 15.68%, the Western region has achieved the fastest digital economy growth over the past decade, reflecting the effectiveness of targeted policies such as the Western Development strategy. This growth has been the result of concerted efforts to direct resources, including human capital, finances, and technology, to the Western region.

Meanwhile, the Northeastern region, which had a higher starting point than the Western region, has seen a more stable but slower growth rate, with an average annual increase of 8.77%. This more moderate growth trajectory suggests that the

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Northeastern region faces different challenges in digital economy development compared to the Western region. Nonetheless, the region has made steady progress in its digital economy growth, though it still lags behind the Eastern and Central regions. The rapid growth of the Western and Central regions can be directly linked to the implementation of China's regional development policies. The Western Development strategy and the rise of the Central region have promoted the flow of resources to these regions, stimulating the growth of their digital economies. These strategies have helped accelerate the growth of digital infrastructure and digital economy-driven industries in these regions, allowing them to make significant strides over the past decade.

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Overall, the data reveals that while the Eastern region continues to lead in digital economy development, the Central and Western regions have made substantial progress. The Eastern region's digital economy growth remains dominant, but the Central and Western regions have demonstrated notable improvements, closing the gap in relative terms. However, the disparity in digital economy development across regions remains a key challenge. This suggests that more focused efforts are needed to ensure that digital economy policies continue to promote convergence and balance across all regions. Future policy initiatives should focus on addressing the specific needs of each region, taking into account factors such as resource endowment, technological infrastructure, and human capital, in order to further reduce regional

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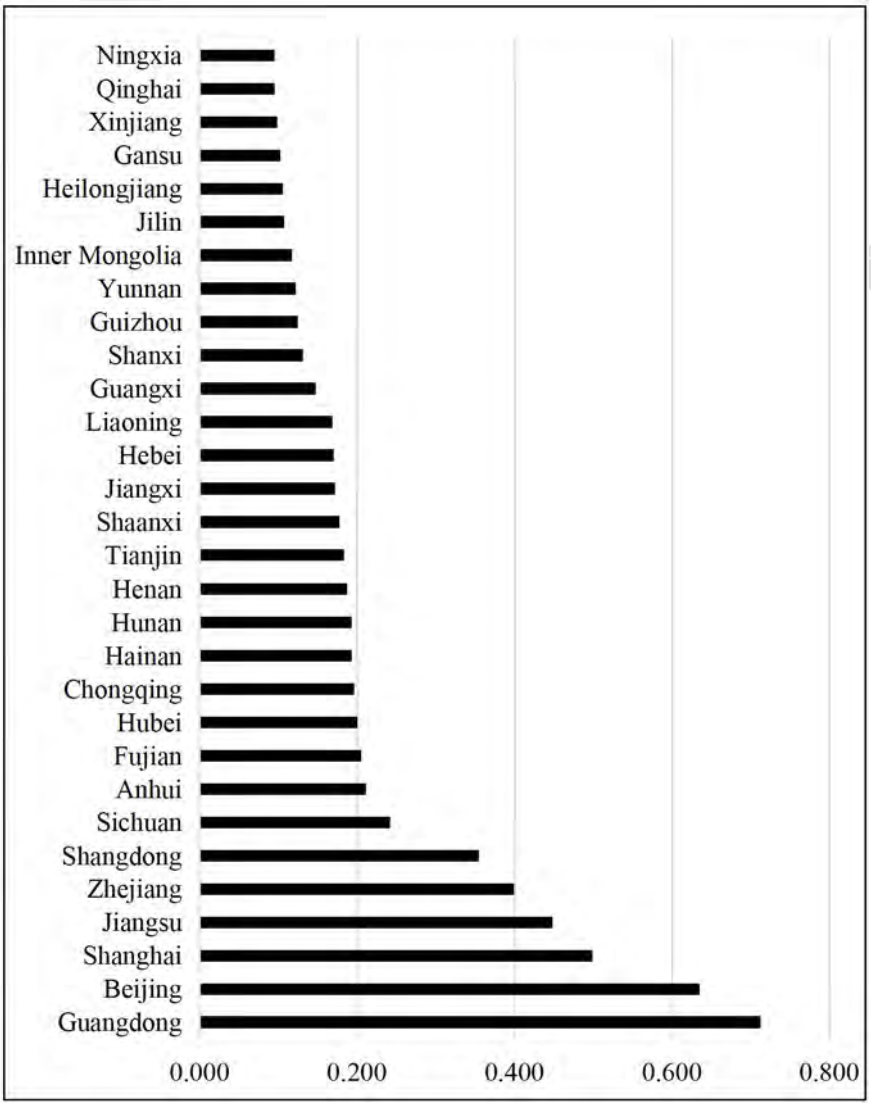
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disparities and promote more equitable development of the digital economy across China.

When it comes to the provincial level, the ranking of DEDI among various provinces in China for the year 2022 is depicted in Figure 4.2 and Table 4.3.

Figure 4.2

Ranking of Provinces in Terms of the DEDI in 2022



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Table 4.3

The Results of The Improved Digital Economy Development index (DEDI) for Chinese Provinces

Areas	Province	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Eastern Region	Beijing	0.285	0.315	0.348	0.365	0.390	0.429	0.471	0.515	0.576	0.635
	Tianjin	0.082	0.094	0.111	0.114	0.120	0.131	0.153	0.164	0.170	0.183
	Hebei	0.079	0.087	0.103	0.119	0.133	0.139	0.144	0.151	0.161	0.170
	Shangdong	0.145	0.162	0.189	0.221	0.245	0.276	0.271	0.277	0.315	0.354
	Jiangsu	0.244	0.265	0.294	0.313	0.341	0.358	0.377	0.402	0.426	0.448
	Shanghai	0.194	0.246	0.275	0.300	0.320	0.344	0.380	0.408	0.451	0.499
	Zhejiang	0.182	0.199	0.241	0.255	0.277	0.300	0.328	0.345	0.371	0.399
	Fujian	0.100	0.111	0.132	0.142	0.159	0.174	0.183	0.182	0.195	0.205
	Guangdong	0.303	0.335	0.372	0.413	0.452	0.513	0.566	0.598	0.655	0.712
	Hainan	0.077	0.088	0.103	0.114	0.125	0.141	0.149	0.164	0.178	0.193
	Mean	0.169	0.154	0.186	0.207	0.225	0.250	0.277	0.295	0.292	0.316
Central Region	Shanxi	0.054	0.062	0.075	0.083	0.089	0.100	0.104	0.109	0.120	0.131
	Anhui	0.077	0.091	0.114	0.126	0.140	0.157	0.171	0.179	0.195	0.211
	Jiangxi	0.064	0.075	0.095	0.098	0.115	0.126	0.137	0.149	0.162	0.172
	Henan	0.080	0.093	0.115	0.131	0.140	0.151	0.154	0.158	0.172	0.187
	Hubei	0.083	0.094	0.114	0.129	0.141	0.153	0.167	0.174	0.187	0.200
	Hunan	0.077	0.088	0.103	0.114	0.125	0.141	0.149	0.164	0.178	0.193
	Mean	0.073	0.084	0.103	0.114	0.125	0.138	0.147	0.156	0.169	0.182

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Areas	Province	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Wester-n Region	Inner Mongolia	0.049	0.056	0.070	0.078	0.082	0.084	0.089	0.095	0.108	0.117
	Guangxi	0.055	0.064	0.076	0.086	0.092	0.104	0.117	0.127	0.137	0.147
	Chongqing	0.069	0.084	0.103	0.119	0.132	0.146	0.156	0.168	0.183	0.196
	Sichuan	0.091	0.105	0.128	0.144	0.164	0.182	0.202	0.215	0.230	0.242
	Guizhou	0.043	0.054	0.070	0.082	0.089	0.097	0.102	0.105	0.115	0.124
	Yunnan	0.051	0.061	0.078	0.085	0.089	0.097	0.104	0.111	0.117	0.122
	Shaanxi	0.066	0.078	0.095	0.109	0.117	0.129	0.143	0.149	0.164	0.177
	Gansu	0.042	0.051	0.066	0.069	0.072	0.078	0.083	0.087	0.096	0.102
	Qinghai	0.036	0.042	0.059	0.063	0.066	0.071	0.073	0.077	0.086	0.095
	Ningxia	0.043	0.052	0.066	0.067	0.073	0.078	0.079	0.082	0.089	0.095
	Xinjiang	0.045	0.051	0.064	0.063	0.068	0.077	0.081	0.084	0.093	0.098
	Mean	0.054	0.063	0.080	0.088	0.095	0.104	0.112	0.118	0.129	0.138
North-ea stern Region	Liaoning	0.103	0.115	0.133	0.128	0.134	0.141	0.150	0.156	0.162	0.168
	Jilin	0.050	0.059	0.071	0.076	0.084	0.090	0.091	0.096	0.101	0.107
	Heilongjiang	0.050	0.058	0.070	0.076	0.082	0.085	0.088	0.093	0.100	0.106
	Mean	0.068	0.077	0.091	0.093	0.100	0.105	0.110	0.115	0.121	0.127

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The figure reveals a significant gap in the level of digital economy development across China's provincial-level regions, reflecting an imbalance in their progress towards digital economy development. As of 2022, the national average level of digital economy development is 0.222, and only seven provinces exceed this average level, namely Guangdong, Beijing, Shanghai, Jiangsu, Zhejiang, Shandong and Sichuan.

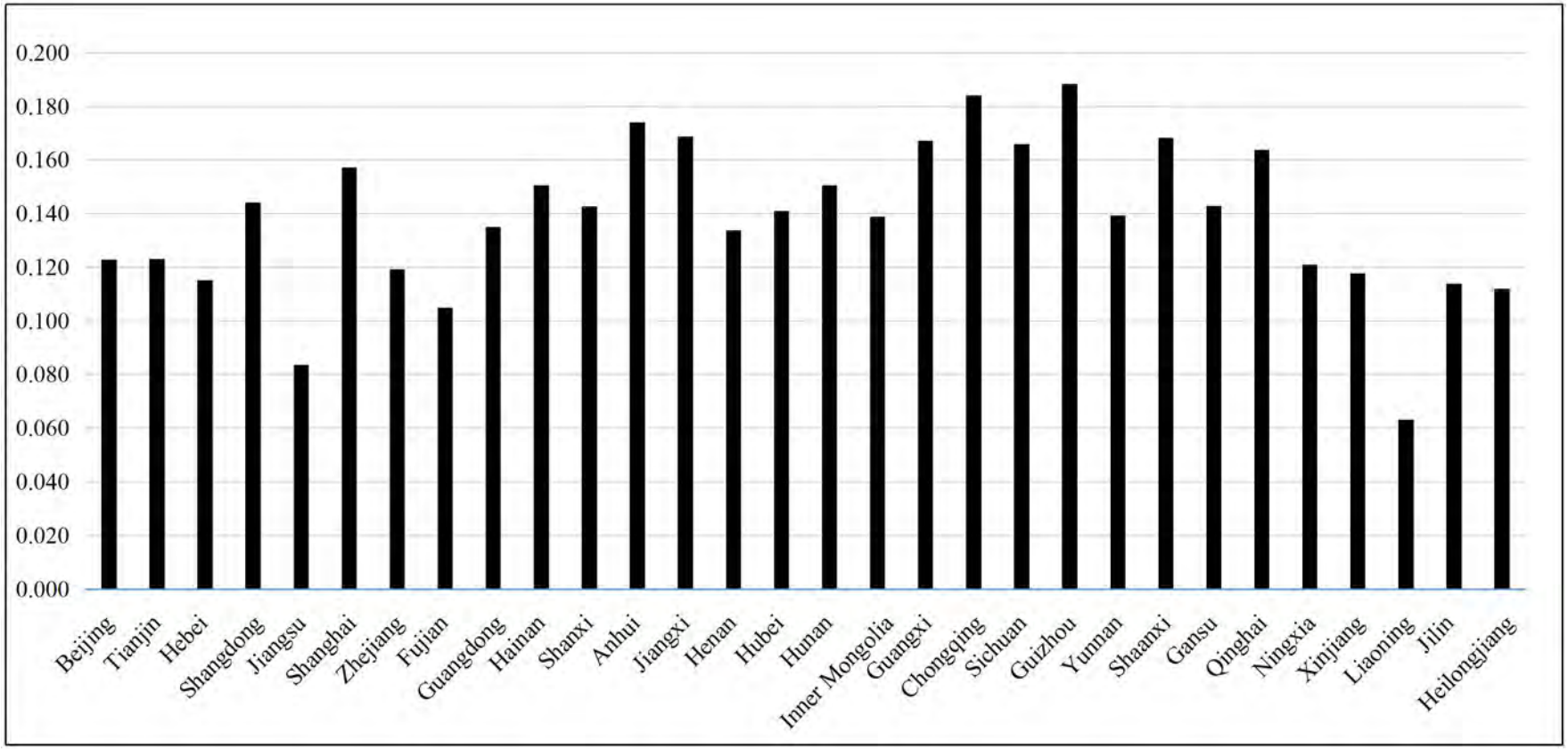
From Figure 4.3, the growth rate of digital economy development by province from 2013-2022 is presented. The average annual growth rate varies considerably from province to province. Guizhou province, located in the Western region, has experienced the highest average annual growth rate, with an impressive increase of 18.8%. Following closely are Chongqing province and Anhui province, both from the Central region, with growth rates of 18.4% and 17.4%, respectively. Among them, Liaoning province has the lowest average annual growth rate of 6.3%.

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Figure 4.3

Average Annual Growth Rate of Digital Economy Development Index



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4.1.2 Urban-rural income gap index (URIG)

The URIG is analyzed statistically by year as a whole and the results are shown in Table 4.4. Table 4.5 presents the urban-rural income gap index (URIG) calculated using Equation (3.7) for each province in China from 2013 to 2022.

Table 4.4

Statistical Characters of URIG from 2013 to 2022

Year	Mean	Standard Deviation	Max	Min	Decline rate of median
2013	0.0976	0.0415	0.1870	0.0210	
2014	0.0923	0.0391	0.1780	0.0210	-0.0543
2015	0.0894	0.0376	0.1710	0.0200	-0.0837
2016	0.0866	0.0366	0.1690	0.0200	-0.1130
2017	0.0838	0.0352	0.1640	0.0190	-0.1414
2018	0.0804	0.0337	0.1580	0.0190	-0.1762
2019	0.0763	0.0319	0.1530	0.0190	-0.2186
2020	0.0697	0.0299	0.1440	0.0180	-0.2855
2021	0.0656	0.0283	0.1350	0.0180	-0.3275
2022	0.0621	0.0268	0.1280	0.0170	-0.3634

From Tables 4.4 and 4.5, the URIG reflecting urban-rural income gap demonstrated a slightly downward trend during this period. The decline in URIG is closely linked to the attention and efforts of the Chinese government, especially due to the introduction of the Rural Revitalization strategy, which has played a significant role in promoting rural development and increasing the income of rural residents.

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Table 4.5

The URIG for Chinese Provinces from 2013 to 2022

Region	Provinces	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	Decline
	Beijing	0.033	0.032	0.032	0.031	0.031	0.031	0.030	0.029	0.027	0.027	0.1818
	Tianjin	0.022	0.021	0.020	0.020	0.019	0.019	0.019	0.018	0.018	0.017	0.2273
	Hebei	0.091	0.086	0.083	0.081	0.079	0.076	0.072	0.067	0.061	0.057	0.3736
	Shanghai	0.021	0.021	0.022	0.021	0.021	0.020	0.020	0.019	0.018	0.018	0.1429
Eastern	Jiangsu	0.065	0.061	0.058	0.056	0.054	0.051	0.049	0.045	0.043	0.040	0.3846
Region	Zhejiang	0.053	0.050	0.048	0.046	0.044	0.042	0.039	0.036	0.035	0.032	0.3962
	Fujian	0.079	0.074	0.071	0.069	0.066	0.063	0.060	0.055	0.051	0.051	0.3544
	Shangdong	0.092	0.086	0.082	0.079	0.076	0.075	0.072	0.067	0.062	0.058	0.3696
	Guangdong	0.076	0.073	0.070	0.068	0.067	0.064	0.062	0.056	0.054	0.052	0.3158
	Hainan	0.096	0.089	0.084	0.080	0.077	0.076	0.075	0.067	0.063	0.055	0.4271
	Mean	0.0628	0.0593	0.057	0.0551	0.0534	0.0517	0.0498	0.0459	0.0432	0.0407	0.3519
	Shanxi	0.112	0.105	0.103	0.099	0.096	0.090	0.084	0.078	0.073	0.071	0.3661
	Anhui	0.103	0.096	0.093	0.091	0.088	0.085	0.082	0.076	0.072	0.069	0.3301
Central	Jiangxi	0.091	0.087	0.083	0.080	0.078	0.075	0.071	0.067	0.063	0.060	0.3407
Region	Henan	0.094	0.089	0.087	0.083	0.081	0.078	0.073	0.064	0.061	0.056	0.4043
	Hubei	0.078	0.074	0.071	0.071	0.070	0.068	0.066	0.062	0.058	0.055	0.2949
	Hunan	0.112	0.107	0.103	0.100	0.098	0.094	0.091	0.084	0.079	0.076	0.3214
	Mean	0.0983	0.0930	0.0900	0.0873	0.0852	0.0817	0.0778	0.0718	0.0677	0.0645	0.3438

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Region	Provinces	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	Decline
Wester-n Region	Inner Mongolia	0.105	0.100	0.097	0.094	0.091	0.086	0.079	0.069	0.064	0.060	0.4286
	Guangxi	0.132	0.125	0.119	0.113	0.108	0.101	0.094	0.084	0.079	0.073	0.4470
	Chongqing	0.097	0.091	0.085	0.080	0.076	0.072	0.068	0.063	0.059	0.056	0.4227
	Sichuan	0.112	0.106	0.101	0.097	0.094	0.090	0.086	0.080	0.076	0.072	0.3571
	Guizhou	0.186	0.174	0.166	0.160	0.154	0.149	0.141	0.131	0.126	0.121	0.3495
	Yunnan	0.172	0.164	0.157	0.152	0.147	0.143	0.136	0.125	0.121	0.113	0.3430
	Shaanxi	0.138	0.130	0.124	0.120	0.115	0.110	0.104	0.096	0.090	0.086	0.3768
	Gansu	0.187	0.178	0.171	0.169	0.164	0.158	0.153	0.144	0.135	0.128	0.3155
	Qinghai	0.142	0.133	0.134	0.130	0.125	0.118	0.110	0.104	0.096	0.093	0.3451
	Ningxia	0.114	0.107	0.103	0.099	0.094	0.091	0.085	0.077	0.071	0.068	0.4035
	Xinjiang	0.115	0.111	0.118	0.116	0.113	0.106	0.097	0.085	0.080	0.073	0.3652
	Mean	0.1378	0.1303	0.1275	0.1236	0.1189	0.1140	0.1076	0.0992	0.0935	0.0885	0.3578
North-eas tern Region	Liaoning	0.077	0.075	0.072	0.069	0.067	0.066	0.061	0.052	0.048	0.046	0.4026
	Jilin	0.066	0.063	0.065	0.063	0.062	0.061	0.059	0.052	0.048	0.044	0.3333
	Heilongjiang	0.067	0.061	0.061	0.060	0.059	0.054	0.050	0.040	0.038	0.038	0.4328
	Mean	0.0700	0.0663	0.0660	0.0640	0.0627	0.0603	0.0567	0.0480	0.0447	0.0427	0.3900

Note, Decline indicates (initial value - final value)/initial value

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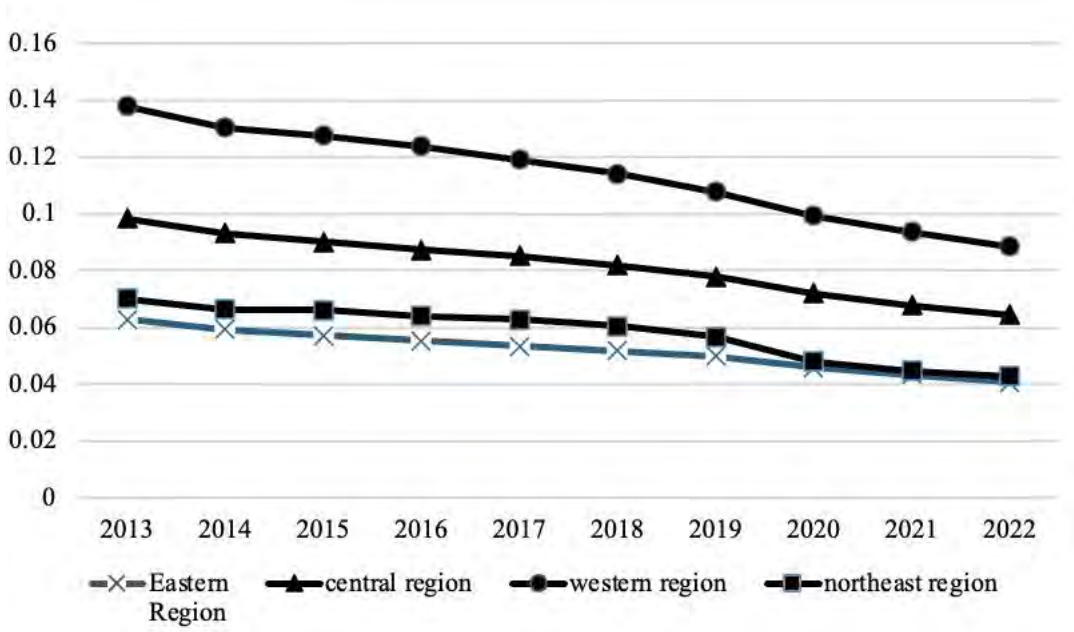
However, the gap persists among the four economic regions, whether considering absolute values or the extent of the decline. In 2022, among the four economic regions, the Western region had the highest average URIG, standing at 0.0885. The Central region followed with a slightly lower value of 0.0645, while the Northeast region had an average URIG of 0.0427. The Eastern region exhibited the smallest URIG, measuring 0.0407. Over the past decade, the Northeastern region experienced the most substantial reduction in the URIG among the four economic regions, with a notable decline of 39%. Following closely, the Western region showed the second-largest reduction in URIG. In contrast, the Central region exhibited the smallest reduction, with a decrease of 34.38%. Among the four economic regions, the Eastern region has the lowest urban-rural income gap, indicating a relatively smaller overall gap. However, within the Eastern region, the URIG is highest in Shandong Province and lowest in Tianjin, with a difference of 0.041, representing the largest intra regional disparity in the urban-rural income gap. The Western region exhibits the largest overall urban-rural income gap, with the highest URIG observed in Qinghai and the lowest in Inner Mongolia, differing by 0.033. In the Central region, the intra-regional URIG varies by 0.015, with the highest in Shanxi and the lowest in Hubei. The Northeastern region shows the smallest intra-regional gap, with a URIG of 0.008 between the highest and lowest, making it the region with the least inequality among the four regions. These findings underscore the pronounced inequality in the urban-rural income gap across different provinces within each economic region.

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Figure 4.4

URIG in Four Economic Regions over the Past Decade



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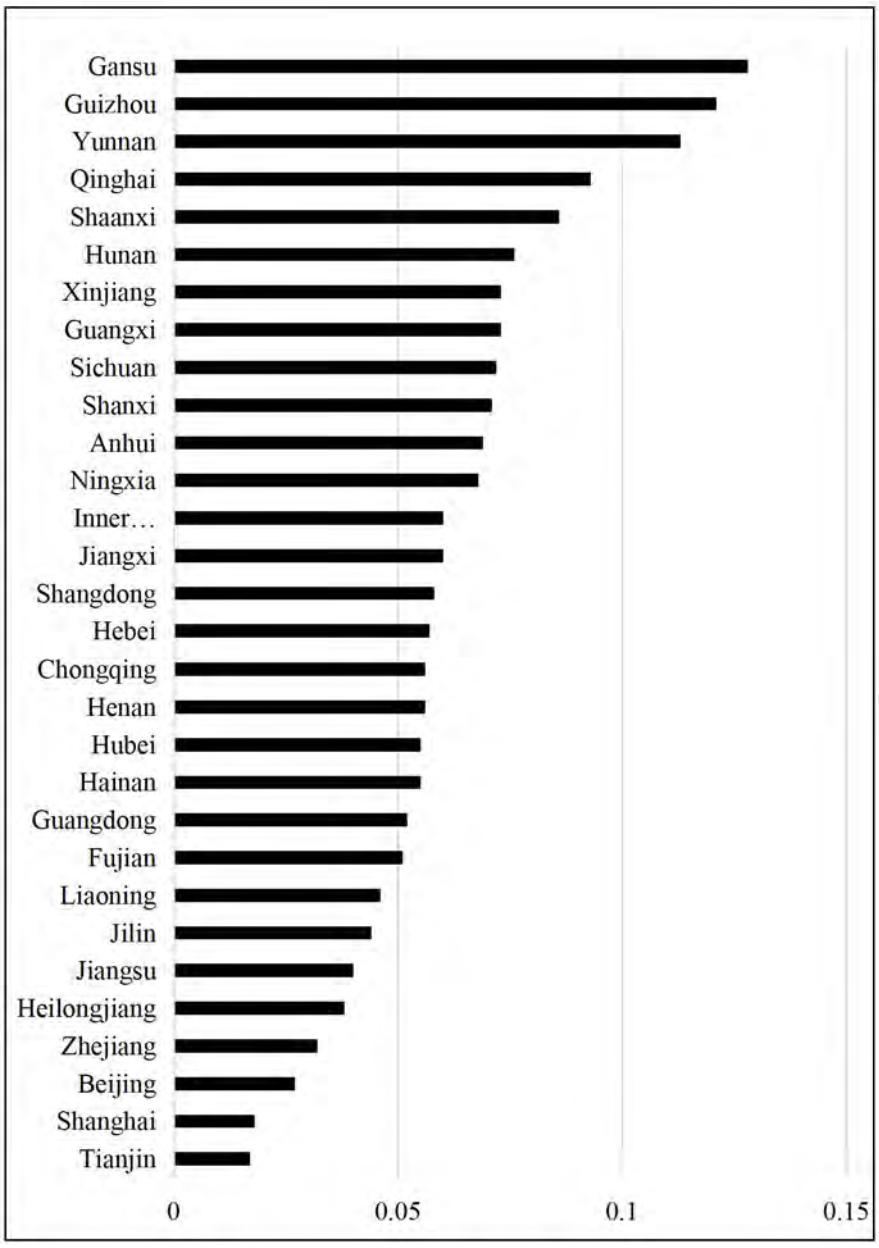
At the provincial administrative level in 2022, as shown in Table 4.5 and Figure 4.5， Tianjin exhibited the smallest urban-rural income gap nationally, with a URIG value of 0.017, followed by Shanghai at 0.018. Notably, both provinces are situated in the Eastern region. Conversely, Gansu, located in the Western region, recorded the highest URIG at 0.128. Over the past decade, the most significant reduction in URIG was observed in Guangxi, which is located in the Western region, with a remarkable decrease of 44.7%. In contrast, Shanghai which represents the Eastern region, demonstrated the smallest reduction, with a decrease of 14.29%.

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Figure 4.5

Ranking of Provinces in Terms of the URIG in 2022



4.1.3 Mediating variables

The mediating variables in this study are OIS and UIS. And the measurement results are shown in Table 4.6 and 4.7.

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Table 4.6

The OIS for 30 Provinces from 2013 to 2022

Region	Province	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Eastern	Beijing	0.028	0.026	0.026	0.027	0.027	0.026	0.025	0.015	0.015	0.014
Region	Tianjin	0.042	0.041	0.039	0.037	0.037	0.035	0.034	0.022	0.018	0.018
	Hebei	0.117	0.118	0.121	0.113	0.106	0.091	0.085	0.045	0.049	0.056
	Shangdong	0.166	0.153	0.144	0.140	0.135	0.127	0.118	0.106	0.099	0.099
	Jiangsu	0.077	0.073	0.064	0.064	0.061	0.059	0.054	0.049	0.047	0.047
	Shanghai	0.030	0.019	0.023	0.028	0.023	0.022	0.021	0.023	0.023	0.022
	Zhejiang	0.044	0.038	0.032	0.026	0.023	0.017	0.013	0.008	0.008	0.007
	Fujian	0.090	0.091	0.087	0.075	0.073	0.076	0.070	0.059	0.058	0.059
	Guangdong	0.089	0.077	0.068	0.058	0.053	0.046	0.038	0.029	0.030	0.028
	Hainan	0.089	0.080	0.075	0.064	0.068	0.063	0.056	0.045	0.049	0.051
	Mean	0.077	0.072	0.068	0.063	0.061	0.056	0.051	0.040	0.040	0.040
Central	Shanxi	0.260	0.263	0.200	0.181	0.209	0.205	0.197	0.145	0.199	0.239
Region	Anhui	0.187	0.170	0.152	0.149	0.151	0.161	0.156	0.094	0.092	0.099
	Jiangxi	0.151	0.136	0.113	0.097	0.091	0.081	0.068	0.053	0.055	0.054
	Henan	0.196	0.182	0.158	0.137	0.121	0.109	0.101	0.081	0.075	0.109
	Hubei	0.279	0.253	0.233	0.212	0.202	0.202	0.188	0.103	0.103	0.122
	Hunan	0.246	0.253	0.258	0.252	0.250	0.248	0.231	0.082	0.084	0.085
	Mean	0.220	0.210	0.186	0.171	0.171	0.168	0.157	0.093	0.101	0.118

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Region	Province	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Wester-n	Inner										
Region	Mongolia	0.239	0.227	0.223	0.221	0.223	0.218	0.220	0.221	0.283	0.312
	Guangxi	0.263	0.256	0.237	0.193	0.169	0.144	0.110	0.076	0.075	0.082
	Chongqing	0.181	0.168	0.149	0.127	0.127	0.122	0.113	0.108	0.106	0.120
	Sichuan	0.212	0.198	0.184	0.170	0.162	0.163	0.154	0.129	0.137	0.159
	Guizhou	0.396	0.371	0.357	0.341	0.311	0.285	0.252	0.208	0.209	0.241
	Yunnan	0.396	0.371	0.357	0.341	0.311	0.285	0.252	0.208	0.209	0.241
	Shaanxi	0.703	0.641	0.555	0.514	0.489	0.464	0.366	0.194	0.222	0.262
	Gansu	0.532	0.513	0.469	0.438	0.415	0.406	0.377	0.235	0.227	0.267
	Qinghai	0.174	0.171	0.178	0.186	0.191	0.185	0.169	0.097	0.116	0.165
	Ningxia	0.315	0.259	0.221	0.206	0.187	0.164	0.154	0.119	0.153	0.202
	Xinjiang	0.332	0.325	0.283	0.261	0.253	0.268	0.216	0.179	0.211	0.298
	Mean	0.339	0.318	0.293	0.269	0.256	0.245	0.217	0.171	0.184	0.219
North-ea	Liaoning	0.123	0.116	0.117	0.145	0.155	0.163	0.160	0.133	0.137	0.165
stern	Jilin	0.221	0.229	0.232	0.252	0.259	0.251	0.237	0.216	0.229	0.240
Region	Heilongjiang	0.155	0.122	0.078	0.070	0.057	0.060	0.055	0.041	0.058	0.089
	Mean	0.166	0.156	0.142	0.156	0.157	0.158	0.151	0.130	0.141	0.165

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Table 4.7

The UIS for 30 Provinces from 2013 to 2022

Region	Provinces	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Eastern Region	Beijing	4.032	4.136	4.575	4.768	4.894	5.022	5.234	5.244	4.540	5.283
	Tianjin	1.222	1.271	1.387	1.589	1.691	1.727	1.804	1.809	1.718	1.656
	Hebei	0.889	0.921	1.022	1.059	1.153	1.259	1.349	1.334	1.223	1.226
	Shangdong	0.896	0.955	1.030	1.110	1.161	1.242	1.322	1.370	1.340	1.317
	Jiangsu	0.918	0.972	1.017	1.092	1.091	1.114	1.169	1.202	1.139	1.110
	Shanghai	1.784	1.912	2.183	2.474	2.445	2.466	2.716	2.788	2.832	2.888
	Zhejiang	0.961	0.956	1.025	1.103	1.171	1.214	1.296	1.372	1.304	1.270
	Fujian	0.758	0.754	0.812	0.870	0.942	0.926	0.98	1.027	1.001	0.995
	Hainan	2.186	2.213	2.283	2.502	2.548	2.727	2.923	3.132	3.231	3.120
	Mean	1.516	1.566	1.704	1.841	1.900	1.966	2.088	2.142	2.036	2.096
Central Region	Shanxi	0.689	0.781	1.129	1.195	1.075	1.151	1.161	1.164	0.864	0.756
	Anhui	0.799	0.842	0.980	1.068	1.137	1.226	1.266	1.292	1.274	1.234
	Jiangxi	0.665	0.704	0.801	0.900	0.946	1.067	1.090	1.119	1.078	1.063
	Henan	0.738	0.785	0.842	0.906	0.943	1.070	1.131	1.201	1.225	1.181
	Hubei	0.899	0.940	1.007	1.061	1.145	1.189	1.223	1.440	1.351	1.295
	Hunan	0.920	0.963	1.036	1.159	1.291	1.391	1.353	1.339	1.318	1.297
	Mean	0.785	0.836	0.966	1.048	1.090	1.182	1.204	1.259	1.185	1.138

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Region	Provinces	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
	Inner Mongolia	1.014	1.057	1.148	1.175	1.255	1.271	1.270	1.205	0.904	0.824
	Guangxi	1.157	1.172	1.269	1.369	1.429	1.481	1.533	1.622	1.485	1.465
	Guangdong	1.032	1.040	1.110	1.216	1.285	1.322	1.390	1.426	1.368	1.342
	Chongqing	1.018	1.012	1.077	1.162	1.222	1.286	1.348	1.331	1.332	1.319
	Sichuan	0.873	0.939	1.022	1.174	1.309	1.396	1.418	1.453	1.427	1.400
Wester-n	Guizhou	1.199	1.203	1.210	1.222	1.328	1.397	1.426	1.446	1.442	1.433
Region	Yunnan	1.189	1.238	1.345	1.461	1.556	1.529	1.504	1.497	1.446	1.382
	Tibet	1.758	1.744	1.778	1.722	1.621	1.437	1.454	1.451	1.530	1.426
	Shaanxi	0.716	0.751	0.881	0.948	0.951	0.972	1.021	1.116	0.977	0.895
	Gansu	1.003	1.062	1.324	1.459	1.575	1.599	1.676	1.758	1.567	1.455
	Qinghai	1.215	1.283	1.368	1.348	1.282	1.267	1.287	1.337	1.221	1.037
	Ningxia	0.998	1.027	1.098	1.153	1.098	1.171	1.185	1.221	1.012	0.904
	Xinjiang	1.031	1.052	1.292	1.367	1.346	1.387	1.47	1.469	1.216	1.095
	Mean	1.093	1.122	1.225	1.290	1.327	1.347	1.383	1.410	1.302	1.229
Northeas	Liaoning	0.873	0.994	1.176	1.359	1.376	1.375	1.393	1.429	1.307	1.244
tern	Jilin	1.289	1.286	1.279	1.383	1.459	1.491	1.525	1.478	1.435	1.459
Region	Heilongjiang	0.789	0.946	1.286	1.478	1.656	1.784	1.846	1.953	1.788	1.644
	Mean	0.984	1.075	1.247	1.407	1.497	1.550	1.588	1.620	1.510	1.449

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As shown in Table 4.6, from 2013 to 2022 the overall trend of industrial structure optimization, as measured by OIS, has shown a declining trend, indicating a general move towards a more optimizational industrial structure nationwide. Meanwhile, it is noteworthy that in 2020 and 2022, many provinces experienced a slight increase in OIS. For example, Hebei, Shanxi, and Hunan. This can be attributed to the combined effects of digital economy development and external economic shocks.

In 2022, the province with the smallest OIS for industrial structure optimization is Zhejiang in the eastern region, registering 0.007, while the largest is Xinjiang in the Western regions at 0.298. This, to some extent, suggests that Zhejiang province has achieved the highest level of industrial structure optimization, whereas Xinjiang province has the lowest. From the national average level, the OIS value is 0.137. There are 13 provinces with OIS values exceeding the national average level, and these provinces are mainly located in the Central and Western regions. This phenomenon is primarily attributed to the Chinese government's policy focus in 2020 on developing the real economy and promoting new industrialization (Shi, 2024).

Among four economic regions, the Western region has the highest average OIS at 0.219, followed by the Northeast region with 0.165. The Central region ranks third with a value of 0.118, while the Eastern region has the lowest OIS at 0.040. In

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the Eastern region, the OIS is generally low and shows a continuous downward trend. Specifically, in Beijing, Shanghai, and Zhejiang, the OIS is relatively low, indicating a more rational industrial structure that is still improving. Shandong and Jiangsu have higher OIS in 2013, but it has declined annually, reflecting the ongoing process of industrial structure optimization. The OIS in the Central region is relatively high but shows a downward trend: In Shanxi, Henan, and Hubei, the OIS is higher, with significant fluctuations observed in Shanxi between 2013 and 2022. Overall, the Central region exhibits substantial efforts in industrial structure adjustment, although the process is relatively slow, with some provinces experiencing a rise in the OIS around 2020. The OIS in the Western region is generally high, indicating significant potential for further industrial structure adjustments. Provinces like Shaanxi and Gansu have high OIS but show a significant downward trend, especially in Shaanxi, where the OIS dropped from 0.703 in 2013 to 0.194 in 2020. In Inner Mongolia and Xinjiang, the OIS saw an increase around 2020, possibly due to fluctuations in resource-dependent industries. The OIS in the Northeastern region is at a medium level among the regions but is highly volatile. In Liaoning and Jilin, the OIS fluctuates significantly between 2013 and 2022, indicating instability in industrial structure adjustments. Heilongjiang's OIS is relatively low in 2013 and remains at a low level in the subsequent years.

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The UIS for the industrial structure upgrading is calculated as illustrated in Table 4.7. From 2013 to 2022, except for Inner Mongolia and Ningxia, the UIS for the remaining provinces all exhibites an upward trend. Inner Mongolia decreases from 1.014 to 0.824, and Ningxia decreases from 0.998 to 0.904. This suggests that the vast majority of provinces in China experience an mprovement in industrial structure upgrading from 2013 to 2022. In 2022, Beijing exhibites the highest UIS, recorded at 5.283, while Shanxi reportes the lowest value at 0.756. Beijing, as the capital and economic center of China, allocates more resources to science and technology innovation and research and development (R&D). It attracts a substantial pool of high-caliber talent and is home to higher education institutions and research organizations. Its economic structure predominantly leans toward high technology, services, and innovative industries, which typically boast higher value-added and innovativeness, thereby propelling the advancement of industrial structure upgrading. While, Shanxi, characterized as a major province in coal energy, is influenced by a resource-oriented economy, predominantly relying on traditional heavy industry and resource development. These industries have lower value-added, leading to slower progress in industrial structure upgrading.

In terms of regional analysis, in 2022, the Eastern region exhibits the highest average UIS at 2.096, followed by the Northeast region at 1.449. The Western region ranks third with a UIS of 1.229, while the Central region has the lowest UIS at 1.138.

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To a certain extent, this indicates that the Eastern region has the highest level of industrial structural upgrading, while the Central region has the lowest. Examining the trends in UIS values across the four economic regions over the past decade, an overall upward trend is observed. The Northeast region experiences the most significant increase with a rise of 0.473, followed by the Western region at 0.449. The Eastern region shows an increase of 0.382, while the Western region has the smallest increase at 0.125. This suggests that the inequality in industrial sophistication among the four economic regions is narrowing over time.

4.1.4 Control variables

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Table 4.8 provides a descriptive statistical analysis of the control variables, reflecting the sample size, mean, standard deviation, as well as the maximum and minimum value.

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Table 4.8

Statistical Description of Control Variables

Region	Stats	ED	EO	FE	EA	UR
Eastern region	Mean	11.314	0.519	0.187	10.037	0.707
	Std.dev.	0.426	0.301	0.062	1.091	0.125
	Max	12.156	1.342	0.357	12.701	0.938
	Min	10.415	0.097	0.107	8.706	0.480
	Observations	100	100	100	100	100
Central region	Mean	10.832	0.115	0.212	9.325	0.560
	Std.dev.	0.275	0.033	0.033	0.394	0.051
	Max	11.430	0.207	0.290	10.198	0.647
	Min	10.372	0.055	0.159	8.599	0.436
	Observations	60	60	60	60	60
Western region	Mean	10.739	0.114	0.327	8.923	0.547
	Std.dev.	0.324	0.078	0.112	0.576	0.078
	Max	11.477	0.411	0.643	10.066	0.710
	Min	10.003	0.008	0.168	7.679	0.379
	Observations	110	110	110	110	110
Northeastern region	Mean	10.712	0.164	0.258	9.748	0.641
	Std.dev.	0.206	0.079	0.059	0.280	0.048
	Max	11.139	0.300	0.398	10.247	0.730

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Region	Stats	ED	EO	FE	EA	UR
Northeastern region	Min	10.376	0.071	0.156	9.387	0.557
	Observations	30.000	30.000	30.000	30.000	30.000
	Mean	10.947	0.254	0.250	9.457	0.613
	Std.dev.	0.432	0.262	0.101	0.885	0.115
China	Max	12.156	1.342	0.643	12.701	0.938
	Min	10.003	0.008	0.107	7.679	0.379
	Observations	300	300	300	300	300

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From the perspective of economic development (ED), which characterizes the level of economic development, the Eastern region exhibits the highest value at 11.314, with the Central and Western regions following closely at 10.832 and 10.739, respectively. The Northeast region ranks fourth with a value of 10.947. This indicates significant regional inequality in economic development, with the Eastern region having the highest level and the Northeast region having the lowest. Moreover, the Eastern region has the highest standard deviation, followed by the Western region, while the Northeast region has the smallest standard deviation. This suggests that the greatest internal inequality within regions is found in the Eastern region, whereas the Northeast region exhibits the least inequality.

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From the perspective of economic openness (EO), the national average level is 0.254. The Eastern region exhibits the highest level of EO at 0.519, followed by the Northeast region with a value of 0.164, which ranks second. The Central and Western regions follow in third and fourth places, with EO values of 0.115 and 0.114, respectively. This indicates that the Eastern region has the highest degree of openness to the outside world, followed by the Northeast region, while the Western region shows the lowest level of openness. Furthermore, the Eastern region also has the largest standard deviation at 0.301, signifying substantial variability in the degree of openness among its provinces. In contrast, the standard deviations for the other regions are all in single digits. This suggests that the gap in the level of openness among provinces is most pronounced within the Eastern region.

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From the perspective of the indicator representing government fiscal expenditures (FE), the highest value is observed in the Western region at 0.327. The Northeast region ranks second with a value of 0.258, followed by the Central region in third place, and the Eastern region with the lowest value at 0.187. This indicates that in recent years, the national fiscal investment in the Western region has been the most substantial. Additionally, it can be noted that the Western region also has the largest standard deviation at 0.112, while the standard deviations for other regions are in the single digits. This suggests significant inequality in fiscal expenditure efforts among provinces within the Western region. This region, characterized by harsh natural conditions and lower economic development, experiences significant government fiscal expenditures due to its status as as a national development priority, highlighting the notable differences in fiscal expenditure efforts among provinces within the Western region.

In terms of educational attainment (EA), the national average duration of education is 9.457 years. The Eastern region has the highest average educational duration at 10.037 years, followed by the Northeast region at 9.748. The Central and Western regions are positioned third and fourth with educational durations of 9.325 and 8.923 years, respectively. Within each region, the Eastern region has the largest standard deviation at 1.091, indicating relatively small differences in educational attainment among provinces within the four economic regions.

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From the perspective of urbanization rate (UR), the national average is 0.613. The Eastern region has the highest urbanization rate at 0.707, followed by the Northeast region at 0.641. The Central and Western regions are positioned third and fourth with urbanization rates of 0.56 and 0.547, respectively. This indicates the presence of regional heterogeneity in Urbanization Rate as well. The Eastern region exhibits the highest urbanization rate, while the Western region has the lowest.

4.2 Results of preliminary test

This section presents the test results for the preliminary tests mentioned in Chapter 3, section 3.4.1. Specifically, section 4.2.1 provides the results of the correlation test, section 4.2.2 presents the results of the multi-collinearity test, section 4.2.3 discusses the results of the panel unit root tests, and section 4.2.4 covers the results of the panel cointegration test.

4.2.1 Results of correlation test

"Pearson and Spearman correlation coefficients were used to assess linear and rank relationships between variables, as shown in Table 4.9. These results inform the subsequent modeling process.

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Table 4.9

Results for the Pearson's Correlation and Spearman' rank Correlation Test

Correlation Coefficient	URIG	DEDI	ED	EO	FE	EA	UR
URIG		-0.669***	-0.756***	-0.669***	0.512***	-0.769***	-0.852***
DEDI	-0.563***		0.830***	0.688***	-0.686***	0.501***	0.646***
ED	-0.769***	0.781***		0.617***	-0.549***	0.669***	0.848***
EO	-0.625***	0.752***	0.702***		-0.586***	0.474***	0.592***
FE	0.545***	-0.492***	-0.478***	-0.415***		-0.313***	-0.427***
EA	-0.768***	0.585***	0.746***	0.674***	-0.354***		0.812***
UR	-0.843***	0.643***	0.859***	0.759***	-0.364***	0.872***	

Note: ***p<0.01,**p<0.5,*p<0.1,Lower-triangular cells report Pearson's correlation coefficients, upper-triangular cells are Spearman's rank correlation

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In the table, the lower-triangular cells report the Pearson correlation coefficients, which are commonly used to measure the linear relationships between variables. The results reveal significant negative correlations between URIG and DEDI, ED, EO, and UR, while a significant positive correlation between FE and URIG is noted. All of these correlations are significant at the 1% level, indicating clear linear associations among the variables (Field, 2013; Cohen, 1988).

Meanwhile, the upper-triangular cells present Spearman's rank correlation coefficients, which are typically used to assess monotonic relationships between variables, including non-linear relationships. In this analysis, the results of the Spearman correlation coefficients align with those of the Pearson coefficients, both showing significance at the 1% level. This suggests that despite the presence of both linear and non-linear relationships, they collectively indicate a strong association between the variables. This finding provides critical insights for subsequent modeling, improving our understanding of the relationships among the variables and supporting the interpretability and predictive power of the model (Tabachnick & Fidell, 2013).

4.2.2 Results of multi-collinearity test

Multicollinearity refers to the presence of high correlations among explanatory variables, which can distort the results of regression analyses (Kim & Cho, 2019). To

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assess multicollinearity in this study, the Variance Inflation Factor (VIF) is calculated for each variable.

The VIF values for all variables are below the commonly accepted threshold of 10, indicating the absence of severe multicollinearity issues (O'Brien, 2007). The core explanatory variable, DEDI, has a VIF of 3.78, which suggests that multicollinearity does not significantly affect the regression model. This analysis fulfills the necessary conditions for a robust model, ensuring that the regression estimates remain stable and interpretable.

Table 4.10

Results for Multi-collinearity Test

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Variable	VIF	1/VIF
UR	8.890	0.113
ED	6.370	0.157
EA	4.250	0.236
DEDI	3.780	0.265
EO	3.480	0.287
FE	1.390	0.719
Mean VIF	4.69	

Note: Number of obs =300; F(6,303)= 218.99; Prob>F=0.0000; R-squared = 0.7875; Root MSE = 0.01648

4.2.3 Results of panel unit root tests

Prior to examining the causal relationship between the dependent variable URIG and the focused explanatory variable DEDI, along with the control variables ED, EO, FE,

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EA, and UR, it is essential to assess the stationarity of the variables across 30 provinces in Mainland China. Two tests, the Im-Pesaran-Shin (IPS) test and the Harris-Tzavalis (HT) test, are conducted to determine whether the variables contain unit roots as mentioned in Chapter 3, section 3.3.1. The null hypothesis for the IPS, and HT tests is that there is a unit root. The results of the IPS test and HT test are presented in Tables 4.11, and 4.12, respectively.

Table 4.11

Results for IPS Test

Variables	Statistic	p-value	Decision
URIG	0.1726 (0.4)	0.5685	Non-Stationary
ΔURIG	-4.7341***(1)	0.0000	I(1)
DEDI	-0.5433 (0.4)	0.9999	Non-Stationary
ΔDEDI	-6.2665***(1)	0.0000	I(1)
$DEDI^2$	13.9674 (0.23)	1.0000	Non-Stationary
$\Delta DEDI^2$	-7.0318 ***(0.6)	0.0000	I(1)
ED	1.0355 (0.5)	0.8498	Non-Stationary
ΔED	-6.0453***(0.7)	0.0000	I(1)
ED^2	1.2778 (0.47)	0.8993	Non-Stationary
ΔED^2	-6.2034 ***(0.7)	0.0000	I(1)
EO	-0.6823 (0.4)	0.2475	Non-Stationary
ΔEO	-7.7582***(0.5)	0.0000	I(1)
FE	0.7830 (0.17)	0.7832	Non-Stationary
ΔFE	-7.4759 ***(0.5)	0.0000	I(1)
EA	2.9855 (0.27)	0.9986	Non-Stationary
ΔEA	-12.9276***(0.57)	0.0000	I(1)
UR	0.6297 (0.27)	0.7355	Non-Stationary
ΔUR	-6.6579***(0.53)	0.0000	I(1)

Note, ***, ** and * implies the significance at the 1%, 5% and 10% level respectively; The term ΔVariable represents the first-order difference of the variable. I(1) represents the integrated of order one. The numbers in ( ) represent lag average length which is determined via Bayesian Information Criterion (BIC)

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Table 4.11 displays the results for the IPS test, revealing that the p-values for the original data sequences of URIG, DEDI, $DEDI^2$, ED, ED^2, EO, FE, EA and UR are as follows: 0.5685, 0.9999, 1.0000, 0.8498, 0.8993, 0.2475, 0.7832, 0.9986 and 0.7355, respectively. At a 1% significance level, the null hypothesis cannot be rejected for these variables, indicating the presence of a unit root in the original data sequences. After performing first-order differencing on all variables, all variables passed the significance test at the 1% significance level. This indicates that after the first-order differencing, the null hypothesis is rejected for all variables, suggesting the absence of a unit root. Therefore, all variables are integrated of order one (Im et al., 2003).

Table 4.12 presents the results of the HT unit root test for each variable. The test results indicate that the original sequences of all variables are non-stationary, as the p-values are significantly higher than 0.1, leading to the acceptance of the null hypothesis, which posits the presence of a unit root. Specifically, the test statistics for variables such as URIG, DEDI, $DEDI^2$, and ED show p-values close to 1, strongly suggesting that these variables possess a unit root, thereby confirming the non-stationarity of their original sequences (Harris & Tzavalis, 1999).

However, after performing the first-order differencing of these variables, denoted as ΔVariable, the p-values drop significantly to 0.0000, and the test statistics become significant at the 1% level. This indicates that the differenced variables are stationary, implying that all variables are integrated of order one, denoted as I(1).

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Table 4.12

Results for HT Test

Variables	Statistic	p-value	Decision
URIG	0.5414	0.9946	Non-Stationary
ΔURIG	0.1293 ***	0.0000	I(1)
DEDI	0.6641	1.0000	Non-Stationary
ΔDEDI	0.2551***	0.0000	I(1)
$DEDI^2$	1.0792	1.0000	Non-Stationary
$\Delta DEDI^2$	0.3304***	0.0000	I(1)
ED	0.6541	1.0000	Non-Stationary
ΔED	0.2392 ***	0.0000	I(1)
ED^2	0.6517	1.0000	Non-Stationary
ΔED^2	0.2249 ***	0.0000	I(1)
EO	0.5008	0.9731	Non-Stationary
ΔEO	0.2277 ***	0.0000	I(1)
FE	0.3992	0.6445	Non-Stationary
ΔFE	-0.1276***	0.0000	I(1)
EA	0.8268	0.9760	Non-Stationary
ΔEA	-0.1436***	0.0000	I(1)
UR	0.8257	0.9747	Non-Stationary
ΔUR	-0.0268***	0.0000	I(1)

Note, ***, ** and * implies the significance at the 1%, 5% and 10% level respectively; The term ΔVariable represents the first-order difference of the variable. I(1) represents the integrated of order one.

In summary, the results of IPS test and HT test suggest that all variables for the 30 provinces in Mainland China are not in stationary and unit root exists in the series in the level difference form. But all variables for 30 provinces in China are in stationary and unit root does not exist in the series for first difference form. This also shows that the series is integrated of order one, i.e.,I(1). The null hypothesis for the IPS and HT tests is rejected, with results statistically significant at the 1% level. Thus satisfying the premise that the cointegration test is of the same order of integration order (Engle, 1987), the panel cointegration test could be carried out.

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4.2.4 Results of panel cointegration test

If the original sequences become stationary after first-order differencing, and the cointegration test for the original sequences is successful, it typically suggests the existence of a long-term equilibrium relationship among the original sequences, indicating a common trend in their fluctuations (Feng et al., 2023). The presence of cointegration implies that, even if these sequences may not be stationary individually, their linear combinations might exhibit stationarity (Hendry & Juselius, 2023). The advantage of using the original data lies in its ease of interpretation and the retention of more information.

Hence, after performing panel root test, panel cointegration test is employed to examine the cointegration relationship multiple variables based on 30 provinces. Table 4.13 presents the results of the Westerlund test and Pedroni test. It is evident that the p-values of the Variance ratio and Modified Phillips–Perron t statistics in the Westerlund test are both 0.000, significantly lower than 0.01. Hence, the null hypothesis that there is no cointegration among the variables is rejected. This indicates that there is a significant cointegration relationship among them. Similarly, the Pedroni test results show that both the p-values of the Modified Phillips-Perron t statistic and the Augmented Dickey-Fuller t statistic are significantly less than 0.01. So the null hypothesis of no cointegration among the variables is rejected, indicating the presence of cointegration among them.

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Table 4.13

Results for Panel Cointegration Test

Cointegration Test	Statistical test	Statistics	p-value	Decision
Westerlund test	Variance ratio	6.9635 ***	0.0000	Cointegrated
	Modified Phillips–Perron t	10.4358***	0.0000	
Pedroni Test	Phillips–Perron t	-42.5297***	0.0000	Cointegrated
	Augmented Dickey–Fuller t	-22.0639 ***	0.0000	

Note, ***, ** and * implies the significance at the 1%, 5% and 10% level respectively

In conclusion, while all variables are stationary after first differencing, the cointegration tests reveal the presence of a cointegration relationship among them. Cointegration implies that even if the variables themselves are not stationary, their linear combination might be stationary, indicating a long-term stable relationship that can be analyzed within the same regression model. Therefore, these results indicate that the original sequences in section 4.1 can be used in regression modeling, according to Chen (2014).

4.3 Results of model estimation and test

This section provides the test results for the model estimation as mentioned in Chapter 3, section 3.3.2. Specifically, section 4.3.1 and 4.3.2 include the results for static panel model test and estimation. The results of dynamic panel model estimation and test are in section 4.3.3 and 4.3.4. Collectively, these results provide evidence for hypothesis 1.

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4.3.1 Results of static panel model test

As is mentioned in Chapter 3, F-test, BP-test, and Hausman test are employed to determine the appropriate type of effects for static panel model in this study. And Table 4.14 shows the results of these tests.

Table 4.14

Results of F Test, BP Test and Hausman Test

Test Type	Test Purpose	Test Value	Decision
F-test	Comparison between FE model and POOL model	p-value =0.0000< 0.05	FE model
BP Test	Comparison between RE model and POOL model	p-value=0.0000 < 0.05	RE model
Hausman Test	Comparison between FE model and RE model	p-value= 0.0012< 0.05	FE model

At first, the p-value from the F-test is below 0.05, prompting the rejection of the null hypothesis that the pooled ordinary least squares (POOL) model is suitable. This outcome indicates that the fixed effects (FE) model is a more appropriate choice. Similarly, the Breusch-Pagan (BP) test also yields a p-value under 0.05, enabling the rejection of the null hypothesis that the random effects (RE) model is more appropriate than the POOL model. This result suggests that the RE model is less suitable. Lastly, the Hausman test provides a p-value below 0.05, leading to the rejection of the null hypothesis that the random effects model is appropriate. This

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reinforces the conclusion that the fixed effects model is more suitable than the random effects model. Therefore, for the static panel model estimation in this study, the fixed effects model is deemed the most suitable (Sheng et al., 2023).

4.3.2 Results of static panel model estimation

i. Results of benchmark regression

As mentioned above, the FE model is the most effective model for the static panel model in this study. Therefore, this section uses fixed effects model to perform benchmark regression estimates for the corresponding parameters in the static panel model of Chapter 3. And the results are presented in Table 4.15.

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Table 4.15

Results of the Benchmark Regression

Variables	3.49	3.50	3.51	3.52	FE_TW
	URIG	URIG	URIG	URIG	URIG
DEDI	0.153***	0.009	0.046***	0.076***	0.101***
	(0.012)	(0.010)	(0.021)	(0.026)	(0.028)
ED		-0.371***		-0.363***	-0.387***
		(0.044)		(0.044)	(0.040)
ED^2		0.015***		0.015***	0.017***
		(-0.002)		(0.002)	(0.002)
EO		-0.007*		-0.009**	-0.001
		(0.004)		(0.004)	(0.004)
FE		0.025***		0.020**	0.034***
		(0.008)		(0.009)	(0.011)
EA		-0.007***		-0.006***	-0.002
		(0.002)		(0.002)	(0.002)
UR		-0.086***		-0.093***	-0.062***
		(0.016)		(0.016)	(0.014)
$DEDI^2$			-0.051***	-0.069***	-0.075***
			(0.028)	(0.025)	(0.026)
Year Fixed	Yes	Yes	Yes	Yes	Yes
Province Fixed	Yes	Yes	Yes	Yes	Yes
Constant	0.105***	2.391***	0.134***	2.375***	2.346***
	(-0.006)	(-0.241)	(-0.006)	(0.238)	(0.216)
N	300.000	300.000	300.000	300.000	
R^2_A	0.290	0.907	0.628	0.910	

Note, Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; The numbers in parentheses represent the standard errors of the coefficient estimates, which are used to assess the precision of the estimated values.

It is evident that the adjusted R-squared value is 0.290 when solely considering DEDI. Upon the inclusion of control variables, the adjusted R-squared value increases to 0.907. With the addition of the squared term of DEDI, the adjusted R-squared value becomes 0.628. Furthermore, incorporating both the squared term of DEDI and control variables yields the adjusted R-squared value of 0.910. The

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increasing R-squared values indicate an improvement in goodness of fit (Chicco et al., 2021), underscoring the necessity of including both the squared term of DEDI and control variables in this study. The last column of Table 4.15 presents the regression results after fixing both time and individual effects. It can be observed that the inverse U-shaped relationship holds regardless of whether individual fixed effects or two-way fixed effects are used.

ii. Results of the effects of adding one-period lag of URIG variables test

The data from 30 provinces of China from 2013-2022 are successively incorporated into the regression by adding lags of the dependent variable (URIG) for one, two, and three periods, as shown in Table 4.16.

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It can be observed that the highest R2 value is achieved when incorporating the lag of one period, the significance of the estimation results remains consistent with the results in Table 4.15 at the same time. Consequently, this study ultimately adopts a dynamic panel model, adding one-period lag of URIG as one of the independent variables (Chicco et al., 2021). Overall, the dynamic panel model (Model) is proven to be suitable for this study.

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Table 4.16

Results of the Effects of Adding One-period Lag of URIG

URIG	(1)	(2)	(3)	(4)
DEDI	0.086***	0.080***	0.107***	0.077*
	(0.028)	(0.017)	(0.030)	(0.043)
$DEDI^2$	-0.077***	-0.070***	-0.088***	-0.059
	（0.026）	（0.015）	（0.027）	（0.037）
$URIG_{j,t-1}$		0.850***		
		（0.035）		
$URIG_{j,t-2}$			0.681***	
			（0.056）	
$URIG_{j,t-3}$				0.471***
				（0.086）
Constant	2.360***	0.187	0.653**	1.429***
	（0.243）	（0.167）	（0.271）	（0.397）
Control Variables	Yes	Yes	Yes	Yes
Year Fixed	Yes	Yes	Yes	Yes
Province Fixed	Yes	Yes	Yes	Yes
N	300	279	248	217
R^2_A	0.866	0.905	0.827	0.788

Note, Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; $URIG_{j,t-1}$ represents the lagged one period of URIG; $URIG_{j,t-2}$ represents the lagged two periods of URIG; $URIG_{j,t-3}$ represents the lagged three periods of URIG

4.3.3 Results of dynamic panel model estimation

As mentioned in Section 4.3.2, the specified dynamic panel model (Model 3.12) is suitable for this study. This section presents the estimation results of the dynamic panel model. The two-step System GMM method, as proposed by Blundell and Bond (1998), is employed to efficiently estimate parameters in the presence of dynamic relationships and unobserved heterogeneity. This method is particularly beneficial for panel data analysis, as it effectively addresses issues related to initial conditions and

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moment restrictions (Arellano & Bover, 1995). The estimation results are shown in Table 4.17.

Table 4. 17

Results of Dynamic Panel Model Estimation-System GMM

Variables	Coefficient	Corrected std.err.	z	P>|z|	[95%conf.	interval]
URIG $_{jt-1}$	0.946	0.027	35.370	0.000	0.893	0.998
DEDI	0.074	0.016	4.460	0.000	0.041	0.106
$DEDI^2$	-0.082	0.019	-4.210	0.000	-0.120	-0.044
ED	-0.167	0.030	-5.520	0.000	-0.226	-0.107
ED^2	0.007	0.001	5.400	0.000	0.004	0.009
EO	-0.013	0.005	-2.710	0.007	-0.023	-0.004
FE	-0.030	0.011	-2.760	0.006	-0.052	-0.009
EA	0.001	0.001	0.850	0.395	-0.002	0.004
UR	0.014	0.016	0.870	0.385	-0.018	0.046
Constant	0.973	0.173	5.640	0.000	0.635	1.311
Arellano-Bond test for AR(1)		z = -2.72		Pr > z =	0.007	
Arellano-Bond test for AR(2)		z = -0.23		Pr > z =	0.821	
Hansen test		chi2(5 = 22.84		Prob > chi2 = 0.197		

The coefficient for DEDI is approximately 0.074, indicating a positive and statistically significant relationship with the urban-rural income gap at the 1% significance level. On the other hand, the coefficient for the squared term of DEDI is around -0.082, which is negative and also statistically significant at the 1% level. The inflection point of this relationship is observed at a DEDI value of 0.45. This suggests that, at the initial stages of digital economy development, the urban-rural income gap tends to widen. However, as digital economy development progresses and reaches a certain threshold, the gap between urban and rural incomes begins to narrow.

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In addition, the coefficient for ED is -0.167, with the squared term of ED having a coefficient of 0.007. Both coefficients are statistically significant at the 1% level, as evidenced by their p-values, which are very close to zero. This implies a U-shaped relationship between ED and the urban-rural income gap, where the gap initially decreases but subsequently increases as economic development advances. The inflection point for this U-shaped relationship occurs at an ED value of 11.98.

The coefficients for EO and FE are -0.013 and -0.03, with p-values of 0.007 and 0.006, respectively. The coefficients of EO and FE are negative and both pass the significance test at the 1% level. This suggests that the higher of government fiscal system and the level of economic openness the lower the URIG. It is evident that improving fiscal expenditure and promoting the urbanization process can be beneficial in narrowing the urban-rural income gap. The coefficients of EA and UR are about 0.001 and 0.014, with p-values of 0.395 and 0.385, respectively. The coefficients of EA and UR are both positive, but neither passes the significance test. Therefore, based on the data in this study, the impact of the level of economic openness and education attainment on the urban-rural income gap is not statistically significant.

Compared with the results of the static panel model estimation in Table 4.15, the dynamic panel model estimation has the following advantages:

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First, from the perspective of model design, the static model fails to adequately account for the dynamic effects of time on the urban-rural income gap. It assumes income inequality across different periods are independent of each other, overlooking the possibility of lagged effects from one period to the next (Baltagi, 2008). However, the urban-rural income gap typically exhibits persistence, where disparities in one period can significantly influence the gap in the subsequent period (Bond, 2002). The dynamic panel model addresses this issue by introducing lagged variables (e.g., $URIG_{jt-1}$ in Table 4.17). The results in Table 4.17 show that the coefficient for the lagged one-period urban-rural income gap is 0.946, and it is statistically significant at the 1% level, indicating strong persistence. This dynamic aspect not only reflects real-world conditions but also demonstrates that the dynamic model is better suited for estimating long-term effects (Arellano & Bond, 1991).

Second, the inverted U-shaped relationship between digital economy development and the urban-rural income gap is validated in both the static and dynamic models. In the static model, the coefficient for DEDI is 0.101, while the squared term $DEDI^2$ has a coefficient of -0.075, both significant at the 1% level. This implies that in the initial stages of digital economy development, the urban-rural income gap widens, but as development progresses, the gap begins to narrow. Similarly, in the dynamic model, the coefficients of DEDI and $DEDI^2$ are 0.074 and -0.082, respectively, further supporting the existence of an inverted U-shaped relationship. This pattern aligns with Kuznets' (1955) inverted U hypothesis, which

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suggests that income inequality increases in the early stages of economic growth but narrows as growth continues. In the context of the digital economy, related studies (e.g., Zhong et al., 2024) also support the notion that early-stage digital economy development exacerbates the urban-rural income gap, while wider adoption of digital technologies eventually reduce it.

From the perspective of estimation accuracy, the dynamic panel model provides more robust results. Using the System GMM method, the dynamic model overcomes the limitations of the static model in addressing endogeneity issues (Blundell & Bond, 1998). Results in Table 4.17 show that the estimation results pass the Arellano-Bond first-order autocorrelation test (p=0.007), with no evidence of second-order autocorrelation (p=0.821). Furthermore, the Hansen test results indicate that the instruments are not over-identified (p=0.197), suggesting that the dynamic model's estimates are robust. While the static model provides significant coefficients, it fails to address endogeneity, which may result in biased estimates (Roodman, 2009b). Therefore, by controlling for endogeneity and lagged effects, the dynamic panel model offers more reliable estimates.

Finally, the dynamic panel model incorporates both lagged effects and endogenous control mechanisms, providing a more comprehensive framework for examining the long-term impact of digital economy development on the urban-rural income gap. While the static model reveals relationships within a specific period, it

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lacks the ability to explain long-term effects. In contrast, the dynamic model offers a more comprehensive perspective, showing that while digital economy development initially widens the income gap, it effectively narrows the gap once development reaches a certain level. This conclusion is consistent with related studies, which suggest that the impact of digital economy development on income inequality is nonlinear at different stages (Hsieh & Klenow, 2009).

In summary, while both the static and dynamic models confirm the inverted U-shaped impact of digital economy development on the urban-rural income gap, confirming Research Hypothesis 1, the dynamic model provides more accurate and robust estimates by capturing lagged effects and controlling for endogeneity. The results of the dynamic panel model are better aligned with the research hypothesis and more accurately explain the dynamic changes and long-term trends in the urban-rural income gap. According to the new economic growth theory, during the early stages of digital economy development, resources and technology are typically concentrated in urban areas, which may lead to a widening income gap between urban and rural regions. However, as the digital economy advances, inclusive growth theory suggests that it enhances rural production efficiency, reduces transaction costs, and increases market participation, which gradually helps to narrow the urban-rural income gap. Additionally, the theory of industrial integration explains that the merging of digital and traditional industries optimizes resource allocation and enhances rural development potential, further contributing to the reduction of income disparity between urban and rural areas.

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4.3.4 Results of dynamic panel model test

As explained in Chapter 3 section 3.3.2.4, the Hansen test is used to assess the validity of instrumental variables by checking for overidentification. In Table 4.17, the p-value for the Hansen test is 0.197, which falls within the acceptable range of 0.1 to 0.25. This result implies failure to reject the null hypothesis, suggesting that the instrumental variables are exogenous. Consequently, there are no overidentification issues, and the instruments used in the model are valid (Roodman, 2009b).

Furthermore, the p-value for AR(1) is 0.007, which is less than the 0.01 significance level, indicating the presence of first-order autocorrelation in the differenced disturbances. However, the p-value for AR(2) is 0.821, which exceeds the threshold of 0.1, suggesting no second-order autocorrelation in the differenced disturbances. These results confirm that while the model exhibits first-order autocorrelation, there is no evidence of second-order autocorrelation, fulfilling the necessary requirements for the application of the dynamic panel model (Arellano & Bond, 1991).

In conclusion, the specification tests validate the model's structure, allowing the use of the system GMM approach for estimating the dynamic panel model (Blundell & Bond, 1998). This method effectively addresses issues of endogeneity and ensures that the model's estimates are robust and reliable.

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4.4 Results of heterogeneity test

Grouped regression analysis is a widely employed method for testing heterogeneity, effectively revealing characteristic differences among various groups (Elder-Vass, 2016). In this study, the four major regions of China (Eastern, Central, Western, and Northeast) are suitable for grouped regression analysis due to significant differences in their levels of digital economy development, industrial structure, and resource endowment. This method not only refines the understanding of how digital economy development impacts the urban-rural income gap but also helps uncover complex relationships within each region. Additionally, this study employs both fixed effects and system GMM models for regional heterogeneity testing. This ensures that regional and time effects are controlled while addressing endogeneity issues, thereby enhancing the robustness of the results (Tan et al.,2022; Shi, 2024). The regression results are summarized and presented in Table 4.18.

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Table 4. 18

Results of Heterogeneity Test

Variables	Eastern region		Central region		Western region		Northeastern region	
	Fixed	Sys-GMM	Fixed	Sys-GMM	Fixed	Sys-GMM	Fixed	Sys-GMM
URIG $_{jt-1}$		0.958***		0.964***		0.957***		0.675***
		(0.006)		(0.027)		(0.014)		(0.036)
DEDI	0.024**	0.040**	0.215	0.110	-0.025**	-0.034**	0.806**	0.785***
	(0.026)	(0.023)	(0.139)	(0.077)	(0.093)	(0.039)	(0.295)	(0.138)
$DEDI^2$	-0.035*	-0.039*	-0.370	-0.385	0.103**	0.134**	-2.182***	-2.737***
	(0.023)	(0.019)	(0.421)	(0.279)	(0.245)	(0.132)	(1.083)	(0.744)
ED	-0.426***	-0.023**	-0.272	-0.165	-0.065	-0.003	-1.192**	-0.527
	(0.051)	(0.013)	(0.182)	(0.121)	(0.078)	(0.042)	(0.565)	(0.355)
ED^2	0.018***	0.004**	0.012	0.008	0.001	0.001	0.055**	0.025
	(0.002)	(0.003)	(0.008)	(0.005)	(0.004)	(0.002)	(0.026)	(0.017)
EO	-0.009**	-0.004	-0.079**	-0.019	-0.062***	-0.002	0.016	0.025***
	(0.003)	(0.003)	(0.029)	(0.012)	(0.014)	(0.002)	(0.042)	(0.002)
FE	0.014	0.004	-0.011	-0.004	-0.035**	-0.001	-0.008	-0.043***
	(0.009)	(0.005)	(0.041)	(0.017)	(0.015)	(0.002)	(0.022)	(0.010)
EA	0.000	0.001	-0.007**	-0.002***	-0.004*	-0.003	-0.012**	-0.010***
	(0.002)	(0.001)	(0.003)	(0.001)	(0.002)	(0.007)	(0.006)	(0.002)
UR	-0.057***	-0.009*	-0.168**	-0.174*	-0.144***	-0.003	-0.146	-0.111**

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Variables	Eastern region		Central region		Western region		Northeastern region	
	Fixed	**Sys-GMM**	**Fixed**	**Sys-GMM**	**Fixed**	**Sys-GMM**	**Fixed**	**Sys-GMM**
	(0.012)	(0.008)	(0.068)	(0.017)	(0.042)	(0.007)	(0.121)	(0.054)
AR(1)		0.076		0.012		0.065		0.018
AR(2)		0.291		0.613		0.786		0.397
Sargan		0.420		0.685		0.354		0.181
N	100	100	60	60	110	110	30	30
R^2_A	0.926		0.943		0.958		0.934	

Note, Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; and the values in parentheses are clustering robust standard errors.

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The results show that there is regional heterogeneity in the impact of digital economy development on the urban-rural income gap. Specifically, the results of the static and dynamic regressions are basically the same, showing that the impact of DEDI on the URIG is an inverted U-shape in the Eastern region, the Central region and the Northeastern region, while in the Western region, it is U-shaped. Moreover, this inverted U-shaped relationship is not significant in the Central region and passes the 5% significance level in the Eastern region, while the significance level is 1% in the Northeastern region. The U-shaped relationship is significant at the 5% level in the Western region. In addition, the inflection point of the inverted U-shape varies from region to region. Overall, the heterogeneity test of this study shows that the impact of digital economy development on urban-rural income gap is heterogeneous, confirming Research Hypothesis 2.

In the Eastern region, both estimation methods reveal a statistically significant positive effect of digital economy development on the urban-rural income gap, indicated by coefficients of DEDI being 0.024 (Fixed) and 0.040 (Sys-GMM). The squared term ($DEDI^2$) shows a negative coefficient (-0.035 for Fixed and -0.039 for Sys-GMM), suggesting an inverted U-shaped relationship, where initial benefits are followed by diminishing returns as development progresses.

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In the Central region, the coefficients for DEDI are not statistically significant, indicating that digital economy development has not yet exerted a measurable impact on the urban-rural income gap. Conversely, in the Western region, the coefficients for DEDI are negative (-0.025 for Fixed and -0.034 for Sys-GMM), while the squared term ($DEDI^2$) is positive (0.103 for Fixed and 0.134 for Sys-GMM), suggesting a U-shaped relationship. This indicates that the initial improvements in the income gap are followed by an increase in inequality as the digital economy evolves.

In the North-eastern region, the DEDI has a significant positive impact (0.806 for Fixed and 0.785 for Sys-GMM) on the urban-rural income gap, with the squared term showing a strong negative coefficient (-2.182 for Fixed and -2.737 for Sys-GMM), further reinforcing the notion of an inverted U-shaped effect.

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Besides that, the results indicate that the impact of control variables on the urban-rural income gap also shows regional heterogeneity across the four major economic regions. Notably, ED has a significant effect in the Eastern and Northeastern regions (although the System GMM results for the Northeastern region are not significant, possibly due to the small sample size, which may reduce the accuracy of the estimation. Therefore, the fixed effects regression results are more reliable for this region). However, in the Central and Western regions, the impact of ED is not significant. The Eastern region, characterized by a higher level of economic development and a relatively mature economic structure, demonstrates a more

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pronounced impact of ED on the urban-rural income gap. This can be attributed to the region potentially experiencing a process where the income gap initially narrows and then widens as economic growth progresses. In contrast, the impact of ED on the urban-rural income gap in the Central and Western regions is not significant, likely due to the relatively lagging economic development in these areas. Economic growth in these regions has not yet reached a level sufficient to significantly alter the urban-rural income gap. Moreover, the income gap in these regions is likely influenced more by other factors, such as policy interventions and industrial structure, rather than being solely explained by economic growth. Consequently, the effect of ED on the urban-rural income gap in the Central and Western regions does not exhibit statistical significance. Moreover, the other control variables including urbanization level (UR), average years of education (EA), degree of openness (EO), and fiscal expenditure (FE) all exhibit regional heterogeneity in their impact on the urban-rural income gap.

Overall, the results of heterogeneity test suggest that the impact of digital economy development on the urban-rural income gap exhibits significant heterogeneity across regions. In the Eastern and Northeastern regions, a noticeable inverted U-shaped relationship emerges, where the digital economy development initially widens the urban-ruralgap but narrows it as development progresses. In contrast, the Western region displays a U-shaped pattern, where the gap decreases in

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the early stages, only to widen again later. Meanwhile, the Central region's digital economy development has yet to show a significant effect, likely reflecting its early development phase. This variation can be attributed to differences in economic development stages, policy support and industrial structures across regions. And the findings highlight the importance of tailored policy interventions, considering regional structural factors and development potential, to narrow the urban-rural income gap and promote sustainable digital economy development. A more detailed analysis and discussion are provided in Chapter 5.

4.5 Results of mediating effect test

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This section provided the test results for the three mediating effect tests as mentioned in Chapter 3, section 3.4.3. Specifically, it includes: Section 4.4.1 Results of Stepwise Coefficient Regression Test, Section 4.4.2 Results of Sobel Test, and Section 4.4.3 Results of Bootstrap Test.

4.5.1 Results of stepwise coefficient regression test

Stepwise Coefficient Regression Test is a widely used method for examining mediating effects in the field of econometrics (Baron & Kenny, 1986; Judd & Kenny, 1981; Wen et al., 2022). It involves testing the sequential relationships between an independent variable, mediator, and dependent variable to determine the significance

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of the mediating effect. And the main steps of the stepwise method are as follows: (i) test the coefficient c (i.e., test H0:c=0); (ii) sequentially test the coefficients a (i.e., test H0: a=0) and b (i.e., test H0:b=0), which is referred to in the literature as the test of joint significance (Hayes, 2009). If (i) the coefficient c is significant, and (ii) both coefficients a and b are significant, then the mediating effect is significant. For a complete mediating process, it is also required that (iii) the coefficient c′ is not significant. The detailed procedure is outlined in Figure 3.2 in Chapter 3. The results of the tests are presented in Table 4.19 and 4.21.

i. Results stepwise coefficient regression test with OIS as the mediator

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Table 4.19 presents the results of the stepwise coefficient regression test for the mediating effect of optimization of industrial structure (OIS). The testing process is analyzed based on the mediating effect test principle illustrated in Figure 3.2, as follows:

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Table 4.19

Results of Stepwise Coefficient Regression Test with OIS as the Mediator

Variables	Model 3.13	Model 3.14	Model 3.15
	URIG	OIS	URIG
DEDI	0.023**	-0.270***	0.025***
	（0.009）	（0.055）	（0.010）
ED	-0.415***	-2.001***	-0.400***
	（0.039）	（0.237）	（0.044）
ED^2	0.018***	0.094***	0.018***
	（0.002）	（0.011）	（0.002）
EO	0.004	-0.056**	0.004
	（0.004）	（0.026）	（0.004）
FE	0.033***	0.163**	0.031***
	（0.011）	（0.066）	（0.011）
EA	-0.002	-0.021**	-0.002
	（0.002）	（0.009）	（0.002）
UR	-0.059***	-0.077	-0.058***
	（0.015）	（0.089）	（0.015）
OIS			0.008
			（0.010）
Year Fixed	Yes	Yes	Yes
Province Fixed	Yes	Yes	Yes
N	300	300	300

*Note,*Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; N represents the number of observed values.

Step 1: Test the coefficient c. Since the coefficient c (DEDI in Model 3.13) is significant, the next step continued according to the mediation theory. And the coefficient of DEDI is 0.023 ($p < 0.05$, indicating that the variable DEDI has a direct positive effect on URIG.

Step 2: Sequentially test the coefficients a and b. In Model 3.14, the coefficient of DEDI is a. And in Model 3.15, the coefficient of OIS is b. a is

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significant at 1% level, while b is not significant at all. So next step was to use the bootstrap method to test a*b. the results are listed in Table 4.20. The bs1 respects indirect effect and the bs2 respects direct effect. Since the p value of bs1 is 0.57, which is more than 0.05, the indirect effect is not significant. Therefore, following Figure 3.2, the indirect effect is not significant. That is to say the mediating effect of OIS is not significant. therefore Research Hypothesis 3 is rejected.

Table 4. 20

*Results of Bootstrap Test with a*b*

	Coefficient	std.err.	z	P>|z|	LLCI	ULCI
bs1	-0.00207	0.004137	-0.5	0.570	-0.009211	0.0050751
bs2	0.025336	0.0090708	2.79	0.005	0.006083	0.0445649

Note, LLCI refers to the lower limit of the 95% confidence interval of the estimate, and ULCI refers to the upper limit of the 95% confidence interval of the estimate. The bs1 respects indirect effect and the bs2 respects direct effect.

ii. Results of stepwise coefficient regression test with UIS as the mediator

Table 4.21 presents the results of stepwise coefficient regression analysis for the mediating effect of upgrading of industrial structure (UIS).

Step 1: Test the coefficient c. The path coefficient from DEDI to URIG is c (0.023), which is statistically significant at the 5% level. This result indicates that the

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variable DEDI has a direct positive effect on URIG. Based on the mediation theory, the subsequent steps are performed to further explore the mediating effects.

Table 4. 21

Results of Stepwise Coefficient Regression Test with UIS as the Mediator

Variables	Model 3.16	Model 3.17	Model 3.18
	URIG	UIS	URIG
DEDI	0.023**	0.737**	0.017**
	（0.009）	（0.339）	（0.009）
ED	-0.415***	-0.144	-0.414***
	（0.039）	（1.450）	（0.037）
ED^2	0.018***	-0.039	0.019***
	（0.002）	（0.067）	（0.002）
EO	0.004	-0.338**	0.006
	（0.004）	（0.157）	（0.004）
FE	0.033***	0.055	0.032***
	（0.011）	（0.402）	（0.010）
EA	-0.002	0.124**	-0.003**
	（0.002）	（0.057）	（0.001）
UR	-0.059***	-0.659	-0.053***
	（0.015）	（0.544）	（0.014）
UIS			0.008***
			（0.002）
Year Fixed	Yes	Yes	Yes
Province Fixed	Yes	Yes	Yes
N	300	300	300

Note, Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; N represents the number of observed value.

Step 2: Sequentially test the coefficients a and b. In Model 3.17, the coefficient of DEDI is a; while in Model 3.18, the coefficient of UIS is b. DEDI has a significant positive impact on UIS, with a coefficient of 0.737, significant at the 1% level. The path coefficient from UIS to URIG is 0.008, also statistically significant at

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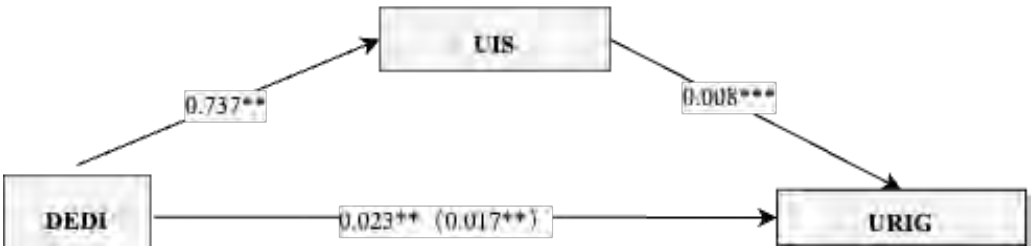
the 1% level. This implies that the development of the digital economy facilitates the upgrading of the industrial structure, which in turn affects the urban-rural income gap. Then it indicates the indirect effect is significant. Next step is to test the coefficient c'.

Step 3: Test the coefficient c'. In Model 3.18, the coefficient of DEDI is c'. Since the coefficient c' is significant at 5% level. Partial mediating effect established. Because a*b and c′ have the same sign, the partial mediating effect accounts for 25% of the total effect. That is to say the mediating effect of UIS is proven and Research Hypothesis 4 is proved. The significance of these two paths indicates that the development of the digital economy influences the urban-rural income gap not only directly but also indirectly through the upgrading of the industrial structure. And the mediating effect path route of UIS is as Figure 4.6.

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Figure 4.6

Mediating Effect Path Route of UIS



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4.5.2 Results of sobel test

The Sobel test is a statistical method used to evaluate the significance of the mediating effect in mediation analysis, determining whether the indirect effect of an independent variable on a dependent variable through a mediator is significantly different from zero. It relies on the product of two coefficients: the effect of the independent variable on the mediator and the effect of the mediator on the dependent variable. By calculating a Z-statistic based on the standard error of the indirect effect, the test compares this statistic to a standard normal distribution (Sobel, 1982). A significant Z-statistic indicates a meaningful mediating effect, suggesting that the mediator carries some influence from the independent variable to the dependent variable (Wen et al., 2022)

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i. Results of sobel test with OIS as the mediator

Table 4.22 presents the results of the second type of mediating effect test, the Sobel test, used to examine the mediating effect of OIS. Based on the conclusion in Section 4.3.1 that the fixed effects model is more suitable, year and province fixed effects are controlled for in this analysis. The results indicate that the p-value of the Sobel test is 0.463, which is more than 0.05, indicating that there is no significant mediating effect at the 5% significance level. What is more, both of the p values of coefficient b and indirect effect are more than 0.05 , further indicating the lack of a significant

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mediating effect. These suggest that OIS doesn't play a mediating role in the impact of digital economy development on the urban-rural income gap, which strengthened the reliability of the results of Stepwise Coefficient Regression Test.

Table 4.22

Results of Sobel-Goodman Mediation Tests with OIS as the Mediator

DEDI→OIS→URIG	Coefficient	Standard error	Z	P-value
Sobel	-0.002	0.003	-0.733	0.463
Goodman-1 (Aroian)	-0.002	0.003	-0.719	0.472
Goodman-2	-0.002	0.003	-0.749	0.454
a coefficient	-0.27	0.055	-4.88	0.000
b coefficient	0.008	0.01	0.742	0.458
Indirect effect	-0.002	0.003	-0.733	0.463
Direct effect	0.025	0.01	2.662	0.008
Total effect	0.023	0.009	2.559	0.011

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ii. Results of sobel test with UIS as the mediator

Table 4.23 presents the results of the second mediating analysis method, specifically the Sobel test, applied to examine the mediating effect of UIS. As concluded in Section 4.3.1, the fixed effects model is more suitable, so we control for year and province fixed effects in this analysis to account for their potential influence on the results. The Sobel test's p-value of 0.002, which is less than 0.05, indicating that at the 1% significance level, there is evidence of a significant mediating effect, supporting that UIS plays a partial mediating role in the impact of digital economy development on the urban-rural income gap. Additionally, the p-values for both the b coefficient

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and the indirect effect are less than 0.05, further confirming the significance of the mediating effect. Therefore, it can be concluded that UIS plays a partial mediating role in the impact of digital economy development on the urban-rural income gap. According to the Sobel test results, the indirect effect of UIS accounts for 33.5% of the total effect, calculated by comparing the indirect effect to the total effect. This further supports UIS's partial mediating role in this relationship. The results are consistent with those obtained in the stepwise coefficient regression test.

Table 4.23

Results of Sobel-Goodman Mediation Tests with UIS as the Mediator

DEDI→UIS→URIG	Coefficient	Standard error	Z	P-value
Sobel	0.034	0.011	3.155	0.002
Goodman-1(Aroian)	0.034	0.011	3.117	0.002
Goodman-2	0.034	0.011	3.196	0.001
a coefficient	4.669	1.022	4.567	0.000
b coefficient	0.007	0.002	4.365	0.000
Indirect effect	0.034	0.011	3.155	0.002
Direct effect	0.067	0.028	2.39	0.017
Total effect	0.101	0.028	3.613	0.000
Proportion of total effect that is mediated: 0.335 ;				
Ratio of indirect to direct effect: 0.504				
Ratio of total to direct effect: 1.504				

4.5.3 Results of bootstrap test

The Bootstrap test is the most widely used approach for directly testing the significance of the product of coefficients (Chen et al., 2013; Jiang et al., 2015; Wen

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et al., 2022). It involves a resampling technique that repeatedly draws Bootstrap samples to estimate the values of coefficients a and b. By calculating the Bootstrap confidence intervals for the product term ab, if the interval does not include zero, it indicates that the mediating effect is significant (Wen et al., 2022). And the results are presented in Table 4.24 and 4.25.

Because in section 4.3.1 we concluded that fixed effects model works better, we control for year and province fixed effects in this testing process. Table 4.24 presents the results of the bootstrap test with OIS as the mediator. bs1 represents the mediating effect (a*b), while bs2 corresponds to the direct effect (c). The 95% confidence interval for bs1 is (-0.010, 0.006), which includes 0. This implies the indirect effect (mediating effect) is not significant. This is consistent with the results of the Stepwise Coefficient Regression Test.

Table 4.24

Results of Bootstrap Test with OIS as the Mediator

	Coefficient	**std.err.**	**z**	**P>|z|**	**LLCI.**	**ULCI**
bs1	-0.002	0.004	-0.49	0.623	-0.010	0.006
bs2	0.025	0.010	2.49	0.013	0.005	0.045

Note, LLCI refers to the lower limit of the 95% confidence interval of the estimate, and ULCI refers to the upper limit of the 95% confidence interval of the estimate. bs1 is the mediating effect and bs2 is the direct effect.

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Controlling for year and province fixed effects in this testing process, Table 4.25 presents the results of the bootstrap test with UIS as the mediator. bs1 represents the mediating effect (a*b), while bs2 corresponds to the direct effect (c). The output results indicate 95% confidence intervals for bs1 as (0.033, 0.0641) and for bs2 as (0.014, 0.120), both excluding 0. This implies the presence of a significant partial mediating effect of industrial structure upgrading, which is in line with the results of Stepwise Coefficient Regression Test.

Table 4. 25

Results of Bootstrap Test with UIS as the Mediator

	Coefficient	std.err.	z	P>|z|	LLCI	ULCI
bs1	0.034	0.016	2.17	0.030	0.033	0.064
bs2	0.067	0.027	2.49	0.013	0.014	0.120

Note, LLCI refers to the lower limit of the 95% confidence interval of the estimate, and ULCI refers to the upper limit of the 95% confidence interval of the estimate. . bs1 represents the mediating effect and bs2 is the direct effect.

4.6 Summary

This chapter discusses the results of the tests conducted to achieve the objectives mentioned in Chapter 1, section 1.4 and to examine the research hypothesis presented in section 1.5. The first research objective, which is To generate an improved and comprehensive digital economy development index (DEDI) in Mainland China, is addressed in section 4.1. The varying weights assigned to the four primary indicators reflect the relative importance of different components in the current development of

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the digital economy. This approach, which allocates weights based on the specific significance of each component, proves to be more reasonable and aligned with practical considerations compared to an equal-weight allocation method. The results shows that the digital economy development carrier has made a relatively significant contribution to the digital economy development index. And the performance of digital economy development index (DEDI) of each province has consistently increased from 2013 to 2022 and there is regional inequality among the four economic regions during this period. Thus, Research Objective 1 has been successfully achieved.

Next, preliminary tests for correlation between variables, multicollinearity, the stationarity of panel data sequences, and the existence of long-term cointegration relationships are conducted. The results show that there is significant correlation between the variables and no severe multicollinearity. The original series of the panel data are not stationary, but they all become stationary after first-order differencing. The results of the cointegration test show that there is a long-term cointegration relationship between the original series of the panel data. Therefore, the the original sequences in section 4.1 could be used to do data analyzing. This has laid the groundwork for subsequent analyses and further testing in the following sections.

The findings of the analysis conducted to achieve the second objective, which is examining the impact of digital economy development on the urban-rural income gap from both aggregate and disaggregate perspectives, are presented in Section 4.3.

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Specifically, in Section 4.3.1, the results of the static panel model test indicate that the fixed effects model is the most suitable for estimation in this study, compared with the pooled and random effects models. Section 4.3.2 utilizes the fixed effect model for the benchmark regression. By adding the square terms of DEDI and the control variables, the results show that the adjusted R-squared values are increasing and the significance of variables has not received an impact. Therefore, the increase in R-squared values indicates improved goodness of fit, verifying the effectiveness of adding control variables and square terms of DEDI. The inverted U-shaped relationship between the core explanatory variable (DEDI) and the dependent variable (URIG) still holds after adding both time and individual double fixed effects. Because of the consideration that the urban-rural income gap affects by the historical level, the lagged term of the dependent variable is added, and the results show that the inclusion of a lagged period of the model has the highest R-squared value. Therefore, this study employed the dynamic panel model. Furthermore, using the system-GMM, the estimation results of dynamic panel model reveal that the impact of the digital economy development on rural urban income gap shows an inverted U-shape, confirming the research hypothesis 1 from Chapter 1. Subsequently, the autocorrelation test shows that there is first order autocorrelation but not second order autocorrelation. The over-identification test shows that there is no weak instrumental variable problem using the system GMM.

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To test Research Hypothesis 2, the grouped regression approach is employed to conduct a regional heterogeneity test. The results confirm the existence of regional heterogeneity in the impact of digital economy development on the urban-rural income gap across the four economic regions. Specifically, both the static and dynamic regression results are largely consistent, revealing an inverted U-shaped relationship between digital economy development and the urban-rural income gap in the eastern, central, and northeastern regions, while a U-shaped relationship is observed in the western region. Furthermore, this inverted U-shaped relationship is not statistically significant in the central region, but it is significant at the 5% level in the eastern region and at the 1% level in the northeastern region. The U-shaped relationship in the western region is significant at the 5% level. Additionally, the inflection point of the inverted U-shaped relationship varies in eastern region and northeastern region. Therefore, both Research Hypothesis 2 and Objective 2 are confirmed.

Next, the Stepwise Coefficient Regression Test, Sobel Test, and Bootstrap Test are employed to test Research Hypotheses 3 and 4. The results from all three methods indicate that the mediating effect of OIS is not significant, while the mediating effect of UIS is significant. Thus, Research Objective 3 is achieved.

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CHAPTER 5

DISCUSSIONS, CONCLUSIONS AND RECOMMENDATIONS

5.0 Introduction

This chapter provides a comprehensive summary and discussion of the research findings from Chapters 1 through 4. It delves into the implications of relevant policies, highlights certain limitations of the study, and puts forth constructive recommendations. Section 5.1 addresses the conclusions and discussions of the research findings. Sections 5.2 and 5.3 respectively discuss the pertinent policy implications and offer useful suggestions to overcome the limitations identified in this study. Finally, section 5.4 presents a concluding summary of this chapter.

5.1 Summary and results discussions of the study

This discussion builds upon the groundwork laid in Chapters 1 and 2. The primary focus of these chapters is to elucidate the relationship among digital economy development, industrial structure optimization and upgrading, and the rural-urban income gap, from the perspectives of research background, theory, and literature. This

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includes examining various factors influencing the gap. The vibrant development of the digital economy has not only profoundly impacted various aspects of socio-economic life but has also extended to the urban-rural income gap. For a long time, China has grappled with the significant problem of a large urban-rural income gap, making the impact of digital economy development on this gap a subject of considerable concern. This study is rooted in multiple theoretical frameworks, including the New Economic Growth Theory, Urban and Rural Dual Economic Structure Theory, Information Asymmetry Theory, Inclusive Growth Theory, Petty-Clark Theorem, Rostow's Theory of Dominant Industries, and Industrial Convergence Theory, providing a broad theoretical foundation.

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The motivation for this study lies in incorporating data as a new factor in economic growth into the production function, reconstructing the production factor system, expanding the assumptions of increasing returns to scale in economic growth theory, and pushing the boundaries of traditional economic growth theory. The development of a data-based digital economy breaks through geographical limitations, impacts market participant behavior, and ultimately influences the income gap under the dual effects of digital dividends (Employment effects, Financial effects, Market participation effects) and the digital divide (access, application, income divide). The study examines the mechanisms by which digital economy development influences the urban-rural income gap, thereby contributing to the identification of strategies for leveraging digital economy growth to reduce this gap. This aligns with the study's

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overall objective of the study, which is to investigate the impact of digital economy development on rural urban income gap and determine whether the optimization and upgrading of industrial structure play a mediating effect role in this process. The literature review, framed within the context of digital economy development and the urban-rural income gap, explores previous research on the relationship between digital economy development, the urban-rural income gap, and industrial structure. Overall, existing studies offer valuable insights into the relationship between digital economy development and the urban-rural income gap, providing a solid foundation and valuable guidance for this research. However, notable research gaps remain: issues related to the measurement of digital economy development continue to be a hot topic with no universally accepted index system; conclusions regarding the impact of digital economy development on the urban-rural income gap are inconsistent; and there is a lack of studies examining the mechanisms through which digital economy development affects the urban-rural income gap.

The content of the forthcoming paragraph and subsequent discussions originates from Chapter 3, which provides a detailed exposition of methodology, including data, model specification and methods of analysing data. Data section primarily introduces and explains the dataset, data sources, and sample size utilized in the study. Model specification encompasses three main components: First, based on the widely cited digital economy development index system by Liu (2020) in China National Knowledge Infrastructure (CNKI), the original three primary indicators and

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eight secondary indicators have been expanded to four primary indicators and seventeen secondary indicators, according to existing literature and national industry classification standards. The entropy method was employed for weight calculation to minimize subjectivity. On this basis, the digital economy development index for 30 provinces in mainland China was calculated. This discussion provides essential methodological insights necessary for achieving the first research objective, which is to analyze digital economy development in mainland China. Second, the specification details the measurement techniques for dependent variables, control variables, and mediating variables. Finally, it introduces the three main econometric models employed in this study to achieve research objectives 2 and 3: static panel models, dynamic panel models, and mediating effect models.

The methods of analysing data section discusses the empirical work of the methodology, which comprises a preliminary test, model estimation, heterogeneity test and mediating effect test. The preliminary test includes the correlation coefficient test, multicollinearity test, panel unit root tests, and panel cointegration test. The correlation coefficient test (i.e., Pearson correlation coefficient, Spearman rank correlation coefficient) assesses the strength and direction of the correlation relationship between the variables, ensuring that they are related but not perfectly collinear, which would indicate redundancy. The multicollinearity test is conducted to detect the presence of high correlations among independent variables, which can inflate the variance of coefficient estimates, undermining the reliability of regression

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results. The panel unit root tests (i.e., IPS test and HT test) are applied to determine the stationarity of the panel data, ensuring that the variables are stable over time, which is a prerequisite for meaningful long-term analysis. Following this, the panel cointegration test checks for a long-term equilibrium relationship between the variables, which is crucial for validating the consistency and reliability of the model estimation results.

Additionally, Chapter 3 includes a discussion on model estimation to provide clear guidelines for ensuring the accuracy and reliability of both the static and dynamic model estimations. This discussion covers appropriate tests and procedures to validate the robustness of these models. The results aim to test the first research hypothesis. A static panel data model is examined using the F test, Breusch-Pagan (BP) test, and Hausman test to determine the most appropriate specification among the fixed effects model (FE), random effects model (RE), and pooled effects model (POOL).

Specifically, if the p-value of the F test is less than 0.05, the fixed effects model is preferred over the pooled effects model. Similarly, if the p-value of the Breusch-Pagan (BP) test is less than 0.05, the random effects model is favored over the pooled effects model. Finally, if the p-value of the Hausman test is less than 0.05, the fixed effects model is preferred over the random effects model. The selected model is then used to incorporate key variables, such as the squared term of the DEDI, control variables, and the lagged dependent variable. If R^2 consistently increases, it

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indicates an enhancement in the goodness of fit, suggesting the effectiveness of incorporating that variable to further validate the model's reliability. The selected model from the tests above is then used for a preliminary estimation of the impact of digital economy development on the urban-rural income gap. Next, dynamic panel model estimation, critical for understanding lagged effects and addressing potential endogeneity issues, is performed using the System Generalized Method of Moments (GMM). This method is selected for its ability to handle the complexities of dynamic panel data, particularly when the data exhibits first-order autocorrelation. To ensure the reliability of the model, diagnostic tests such as the Sargan test for overidentification and the AR test for autocorrelation are conducted. These tests confirm the validity of the instrumental variables and the absence of second-order autocorrelation, thereby enhancing the robustness of the estimation results. This methodological rigor ensures that the study's findings are both reliable and applicable to the analysis of the digital economy's impact on the urban-rural income gap.

The subsequent heterogeneity test employs a group regression method to examine whether there is regional heterogeneity in the impact of digital economy development on the urban-rural income gap within China's four economic regions. To ensure the robustness of the results, this study used both fixed effect and system GMM methods. This provides methodological support for testing research hypothesis 2, which suggests regional heterogeneity in the impact of the digital economy development on the urban-rural income gap.

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Finally, the Stepwise Coefficient Regression Test, Sobel Test, and Bootstrap Test are employed to test the mediating effects of OIS and UIS. These tests offer instruments to empirically test the mediating effects and provide methodological support for testing research hypothesis 3 and 4. For Stepwise Coefficient Regression Test, the influential modified procedure by Wen et al. (2014) is employed (Figure 3.2). Specifically, this process involves three steps: Step 1: Test the total effect of DEDI to URIG coefficient c. If c is significant, proceed according to the theory of mediating effect. If not significant, follow the theory of suppression effect. Step 2: Test the coefficients a and b, where a represents the effect of DEDI on the mediator variable, b represents the effect of the mediator variable on the URIG. If both coefficients are significant, move to Step 3. If either coefficient is not significant, use the Bootstrap method to test a*b. If a*b is significant, proceed to Step 3; if not significant, it indicates that the indirect effect is not significant. Step 3: Test the coefficients c'. c' is the direct effect coefficient of DEDI to URIG. If c' is not significant, this suggests a complete mediating effect of the mediator variable. . If c' is significant, it indicates a partial mediating effect. Additionally, check the sign of a*b and c'. If they have the same sign, report a partial mediating effect and calculate the proportion of mediating effect as a*b/c. If they have opposite signs, report a suppression effect and calculate the proportion of suppression effect as a*b/c. The second mediating effect test method is Sobel test. If the p value of Sobel test is less than 0.05, it indicates that the mediating effect is statistically significant. The last mediating effect test method is

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Bootstrap method. In this study, the Bootstrap method is set with 1000 iterations and a 95% confidence interval. If this confidence interval does not include 0, the null hypothesis that the coefficient product is 0 is rejected, indicating a significant mediating effect.

The subsequent analysis is grounded in the content of Chapter 4. The tests outlined in Chapter 3 are performed, presented, and examined in Chapter 4. These findings are crucial to this research as they contribute to fulfilling the study's objectives and addressing the research questions. In pursuit of the first research objective, this study improved the existing digital economy development index. As it is mentioned in Chapter 3, the digital economy development is made up by four dimensions, namely digital economy development carrier, digital industrialization, industrial digitization, and digital economy development environment. Based on the data from 30 provinces of China from 2013-2022, the results of the improved digital economy development index reveal that the four dimensions of DEDI contributes proportions of 45.6%, 26.38%, 12.28%, and 15.74%, respectively. This underscores the predominant contribution of digital economy development carrier to the digital economy development index, followed by digital industrialization. Compared to the index by Liu et al. (2020), the top five provinces in digital economy rankings are the same, but their positions differ. This is partly due to the difference in data collection periods. this study captures the latest dynamic changes brought about by the development of the digital economy in the early stages of the 14th Five-Year Plan.

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Especially in the context of increasing digital economy infrastructure and policy support, detailed secondary indicators such as the significant increase in rural Internet penetration rate have made the regional rankings obtained in this study different from the study by Liu et al.(2020) and partly because the secondary indicators in this study are more detailed.

The results of the improved digital economy development index (DEDI) indicate that from a national average perspective, China's digital economy has continuously developed over the past decade. there is growth from 0.097 in 2013 to 0.226 in 2022, with an average annual growth rate of 13.25%. Additionally, the growth rate of the median has been increasing, demonstrating the strong momentum of China's digital economy. From a regional perspective, significant inequality exists in the development of the digital economy across the four major economic regions. followed by the Central region, the Western region, and the Northeast region with the lowest DEDI. However, when considering the average annual growth rate of the improved digital economy development index (DEDI), the Western region leads, closely followed by the Central region. The Northeast region ranks third in growth rate, while the Eastern region experiences the slowest growth. At the provincial level, there is significant inequality in the development of the digital economy across China' s provinces, reflecting uneven progress in this area. As of 2022, the national average level of DEDI stands at 0.222, with only seven provinces exceeding this average. Analyzing the growth rates of DEDI from 2013 to 2022, considerable differences are

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observed among the provinces. Guizhou exhibits the fastest growth rate, followed closely by Chongqing and Anhui, while Liaoning has the slowest growth rate.

Results of the urban-rural income gap index show a gradual reduction in urban-rural income gap both nationally and in each region from 2013 to 2022. However, significant inequality persists among the four economic regions, both in absolute values and the extent of reduction. At the provincial level in 2022, Tianjin has the smallest urban-rural income gap index at 0.017, followed by Shanghai with 0.018. Both of them from the Eastern region. Gansu, from the Western region, registers the highest urban-rural income gap index at 0.128. Over the past decade, Guangxi from the western region has witnessed the most substantial decline in the urban-rural income gap index at 44.7%, whereas Shanghai, from the Eastern region, has the smallest decline at 14.29%.

The main reasons for the differences in the level of digital economy development between different regions and provinces are analyzed as follows: Firstly, coastal and economically advanced regions such as Guangdong, Beijing, Shanghai, Jiangsu, and Zhejiang exhibit markedly higher levels of digital economy development compared to other provinces. Notably, Guangdong's DEDI approaches 0.7, indicating its leading position nationwide. This is closely associated with these regions' higher levels of economic development, technological innovation, and infrastructure construction. In particular, Guangdong, as a major economic province and a hub for

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technological innovation in China, far surpasses other provinces, underscoring its strong momentum in driving digital transformation. Beijing and Shanghai are the municipalities directly under the central government of China,and seen as provincial administrative units. Beijing is the capital of China, serving as the political, cultural, and international exchange center of the country.

Shanghai is China's economic center, a hub for technological innovation, and an international exchange center. Secondly, the digital economy development levels in the central and western provinces, including Ningxia, Qinghai, Xinjiang, and Gansu, are comparatively low, with indices below 0.1. This may be attributed to these regions' weaker economic foundations, relatively underdeveloped information infrastructure, and limited scope and depth of digital economy applications. This phenomenon highlights the regional imbalances China faces in promoting integrated digital economy development. Lastly, it also indicates that some central provinces, such as Henan, Hunan, and Anhui, have moderate levels of digital economy development. Although these provinces do not match the economic prosperity of the eastern coastal regions, they have made notable progress in advancing digital transformation in recent years, signaling an acceleration in digital economy development within central China. The average digital economy development index for the 30 provinces in 2022 is 0.226, with only seven provinces exceeding this mean level. This also reflects the great differences in the level of digital economy development in different provinces. The top two performers originate from the Eastern region, whereas the lowest performer hails from the Western region.

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Next, prior to conducting the model estimation, a series of preliminary tests (the correlation coefficient test, multi-collinearity test, panel unit root tests, and panel cointegration test) are carried out to ensure the accuracy and reliability of estimation results. The results of correlation coefficient tests (the Spearman rank-order correlation coefficient test and spearman test) indicate that significant relationships between the variables, with urban-rural income gap index (URIG) showing a strong negative correlation with both the digital economy development index (DEDI) and economic openness (EO), while DEDI has a strong positive correlation with economic openness (EO) and economic development (ED). Subsequently, the multi-collinearity test revealed that the VIF values are all below 10, indicating that there is no multicollinearity among the variables. This suggests that the observed high correlation among the variables is not attributable to multicollinearity. Furthermore, the panel unit root tests results are carried out to determine the stationary of the data. The results of the unit root test for IPS test and HT test show that all variables (i.e., URIG, DEDI, EA, EO, UR, FE, ED) are not stationary variables in the original data. However, after applying first-order differencing, all variables passed the unit root test at the 1% significance level, indicating that all data series are integrated of order one. Despite the non-stationarity of the original data series, the panel cointegration test results show a significant long-term relationship at the 1% significance level: urban-rural income gap index (URIG), improved digital economy development index (DEDI), economic developement (ED), economic openness (EO), government fiscal

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expenditure level (FE), education level (EA), and urbanization level (UR). This finding suggests a long-term cointegrating relationship among these variables, confirming the suitability and reliability of the data for subsequent analysis.

Following the completion of preliminary tests, this study employs the static panel model and the dynamic panel model to achieve the second specific research objective. The static panel model is introduced to examine the effects of incorporating the squared term of the independent variable, control variables, and the lagged term of the dependent variable into the model, while also providing an initial estimation of the relationship between the independent and dependent variables. Prior to estimating the static panel model, model selection tests, including the F-test, BP-test, and Hausman test, are conducted to identify the most appropriate model.

The result of F test shows that FE model is better than POOL model. The result of BP test shows that RE model is better than POOL model. Then the result of the Hausman test shows that FE model is better than RE model. Hence, the FE Model is deemed the most suitable for static panel model of this study. Using the FE model, the results of the benchmark regression show that sequentially adding the squared term of DEDI and control variables continuously improves the goodness-of-fit. This indicates that the inclusion of this variable is necessary. Additionally, the results from the two-way fixed effects estimation are consistent with those from the individual fixed effects model, confirming the existence of an inverted U-shaped relationship.

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Subsequent results of regression for the lagged effect of the dependent variable indicate that the highest goodness of fit (R^2) is achieved with the inclusion of a one-period lag, reaching 0.905. Consequently, this study continues to use the dynamic panel model to test Research Hypothesis 1, adding a one-period lag of URIG as one of the independent variables.

For the dynamic panel model test, the result of the Hansen test yields a p-value of 0.197, falling between 0.1 and 0.25. It indicates that all the instrumental variables are effective and there are no over-identification issues. Additionally, the p-value for AR(1) is 0.007, which is less than 0.01. And the p-value for AR(2) is 0.821, which is more than 0.1. The results of the autocorrelation test indicate that there is autocorrelation in the first-order differenced disturbances and no autocorrelation in the second-order differenced disturbances. In conclusion, the estimation of the dynamic panel model using the system GMM approach is suitable. The results of the dynamic panel model estimation using System GMM reveal that the coefficient of DEDI is positive and significant and the coefficient of its square term is negative and significant. That is to say, the impact of DEDI on URIG exhibits an inverted U-shape, with an inflection point at 0.45. This finding confirms research hypothesis 1. As of 2022, the average level across the 30 provinces is 0.222, remaining on the left side of the inverted U-shaped curve.

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We can conclude that the impact of DEDI on URIG exhibits an inverted U-shape. This conclusion suggests that the level of digital economy development initially widens the urban-rural income gap. However, as the digital economy develops to a certain level, the urban-rural income gap tends to narrow with the progression of digital economy development. Previous research supports the relationship between digital economy development and the urban-rural income gap, as evidenced by findings from Zhong et al. (2024), Zhou et al. (2024), and Peng and Zheng (2022). The result that most provinces are still on the left side of the inverted U-shape is consistent with Peng and Zheng (2022) and Zhou et al.(2024), indicating that the digital economy initially widens and then narrows the urban-rural income gap. The main reasons for the differing conclusions include: first, the variation in research periods, such as Liu (2021), which focuses on the time frame from 2013 to 2020; different time frames can significantly impact the findings and interpretations regarding digital economy development.

Second, we generate an improved digital economy development index, which is more comprehensive, may also affect the results (as discussed in Section 4.3.4). Collectively, these factors contribute to the inconsistencies observed in the literature regarding the impact of the digital economy on various economic outcomes.

The heterogeneity test results indicate significant regional variation in the impact of digital economy development on the urban-rural income gap, supporting

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Research Hypothesis 2. Specifically, an inverted U-shaped relationship between digital economy development and the urban-rural income gap is observed in the Eastern, Central, and Northeastern regions, though this relationship is significant only in the Eastern and Northeastern regions. the inflection point in these regions suggests that while initial digital economy growth may widen the income gap, further development eventually helps to narrow it.

Overall, we can conclude that the analysis underscores the significant regional heterogeneity in the influence of digital economy development on the urban-rural income gap across Mainland China. This finding aligns with existing studies, such as those by Tu et al. (2024) and Jiang et al. (2022). Specifically, the results indicating that the impact of digital economy development on the urban-rural income gap follows an inverted U-shape in the Eastern is consistent with the findings of Peng and Zheng (2022). This phenomenon can be attributed to three primary factors, as follows: First, the stage of economic development and corresponding policy support play a crucial role. In the early phases of economic growth, the Eastern region, benefiting from its advantageous geographic location, open-door policies (Zhang et al., 2018), and infrastructure (Lai et al., 2021), attracted substantial investment and resources. During this period, digital economy growth is primarily focused on urban areas, leading to rapid urban economic expansion.

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However, due to the relatively underdeveloped rural areas, this growth initially widen the urban-rural income gap. As the digital economy further evolved, rural areas in the eastern region start to gain from the expansion of digital infrastructure, increase information technology adoption, and the proliferation of e-commerce. Consequently, productivity and income levels in these rural areas began to rise, gradually narrowing the urban-rural income gap. Second, the delayed manifestation of the spillover effects of the digital economy is significant. In the initial stages, technology and resources concentrated in urban centers, creating a first mover effect.

Over time, however, these benefits began to diffuse into rural areas, leading to a spillover effect (Tao et al., 2024). This process implies that while the digital economy may initially widen the urban-rural income gap, the eventual diffusion of benefits accelerates income growth in rural areas, thereby narrowing the gap. Thirdly, industrial upgrading and changes in rural employment patterns are critical. The digital economy development has driven the optimization and upgrading of the industrial structure in the Eastern region, transitioning from traditional manufacturing to high-tech industries and services (Liu & Chen, 2021). As rural populations migrate to urban areas for employment in these emerging industries, labor mobility helps reduce the urban-rural income gap. Simultaneously, the digital economy is fostering new employment opportunities within rural areas, such as rural e-commerce, which further contributes to the growth of rural incomes.

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Additionally, the results showing an insignificant relationship in the Central region align with the findings of Le et al. (2023). These regression results for the Central region suggest that the impact of the digital economy development on the urban-rural income gap is not yet evident and may still be in its developmental stage, with effects that have not fully manifested. The significant coefficients observed for the lagged dependent variable indicate that historical inequality might still be the predominant factor influencing the urban-rural income gap. This is a side note of the necessity of choosing a dynamic panel model for this study. The non-significance of DEDI could imply that the current economic structure or the relatively slow adoption of digital technologies in the Central region limits the digital economy's potential to affect the urban-rural income gap at this stage (Huang & Dou, 2024). This situation necessitates more targeted policies aimed at accelerating the development of digital infrastructure and ensuring that the benefits of digital economy development are more evenly distributed across both urban and rural areas.

Additionally, the U-shaped impact observed in the Western region corroborates the findings of Wang and Zhang (2023). In the early stage of the development of the digital economy in this region, the digital economy development helps to reduce the urban-rural income gap. This is largely due to government-targeted poverty alleviation policies (Zeng & Zhang, 2024) and the promotion of digital infrastructure (Zhou et al., 2022) in rural areas, which significantly improve income levels. The negative FE coefficient in the regression

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results is also supports this. However, as the digital economy reaches a certain level of development, its effects shift, leading to a widening of the urban-rural income gap. Initially, the digital economy facilitates benefits like job creation and improved market access, which contribute to reducing the income inequality between urban and rural areas (Karine, 2021). Yet, over time, wealth begins to concentrate in urban centers, thereby exacerbating income inequality. Rural regions often struggle to keep pace with the technological advancements and skill requirements necessary to compete. This phenomenon leads to the Matthew Effect, where digital technologies disproportionately benefit more developed areas, further increasing inequality in less developed regions (Li, 2023).

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Lastly, the results indicating that the impact of digital economy development on the urban-rural income gap in the northeastern region follows an inverted U-shape align with the findings of Dai and Guo (2023). Initially, the income gap widens with the development of the digital economy, reaching a turning point at 0.185 or 0.142, after which it starts to narrow. Currently, the average DEDI in the provinces of the Northeast region is 0.127, still position on the left side of the inverted U-shape. The reason is that the Northeast region is a well-known area for old industrial and heavy industrial concentration in China, resulting in a significant urban-rural divide (Ding et al., 2023). The digital economy typically develops first in urban areas with more robust infrastructure, primarily benefiting urban residents and further enhancing their income. Conversely, rural areas experience barriers related to access, application, and

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income, limiting the digital economy's impact on these communities. The development of the digital economy in recent years initially had a greater impact on the income gap between urban and rural areas. However, with economic restructuring and the development of the digital economy, the rural economy has begun to receive more support and the income gap has narrowed. The Northeast Revitalisation Policy and the Digital Rural Development Programme have played a role in improving the conditions for the digital economy in rural areas, helping to narrow the income gap between urban and rural areas (Pan et al., 2023).

The findings suggest that while digital economy development can potentially reduce the income gap, its impact is not uniform and depends on the region's stage of development, policy environment, and infrastructural capacity. Therefore, tailored regional policies are crucial to maximize the benefits of digital economy development and address the varying challenges faced by different regions. These policies should focus on enhancing digital infrastructure in rural areas, promoting inclusive growth, and ensuring that the benefits of digital innovation are distributed equitably across both urban and rural communities.

Finally, the results discussion of the mediating effect test indicates that the mediating effect of industrial structure optimization (OIS) is not significant, whereas industrial structure upgrading (UIS) plays a significant partial mediating effect role in the impact of digital economy development on the urban-rural income gap. To be specific, the results of the Stepwise coefficient regression test show that the

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coefficient b is not significant when testing the mediating effect of OIS, suggesting that this mediating effect is not significant. However, when testing the mediating effect of UIS, the coefficients c, a,b and c' are all significant at a 5% level, and a*b and c′ share the same sign, a partial mediating effect is confirmed. This partial effect accounts for 25% of the total effect, thereby establishing the mediating role of UIS. The Sobel test results for the mediator variable OIS indicate that p-values are greater than 0.05, while for UIS, p-values are less than 0.05. This suggests that 33.5% of the total effect is mediated by UIS. Additionally, the bootstrap test results for OIS indicate that the 95% confidence interval is (-0.010, 0.006) including 0. The bootstrap test results for UIS indicate that the 95% confidence interval is (0.034, 0.016) excluding 0.

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We can conclude that the mediating effect of UIS is confirmed while the mediating effects of OIS is rejected. In other words, research hypothesis 3 (H3) is rejected and research hypothesis 4 (H4) is confirmed. The mediating effect of UIS in the relationship between digital economy development and urban-rural income gap is supported by previous researchers, including studies by Chen et al (2024), Li et al. (2024) and Wang and Wan (2024). In the stepwise regression test, the coefficient b for URIG is positive, indicating that UIS tends to widen the urban-rural income gap. This finding is consistent with the results reported by Xiao et al. (2022). This effect is primarily attributed to China's ongoing transition towards capital-intensive industries, particularly the rise of the tertiary sector, especially in commercial services. Although this sector absorbs a large labor force, its entry barriers are generally higher than those

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of the secondary sector, meaning that most rural laborers still find employment in the lower-barrier secondary industries. In the short term, the high returns on capital will likely exacerbate the urban-rural income gap. However, in the long run, as China's first Lewis turning point is reached and the current two-child policy is implemented, the demographic dividend is gradually disappearing. The resulting labor shortages will stimulate the growth of capital-intensive industries. During this transition from labor-intensive to capital-intensive industries, the demand for higher-skilled labor will increase, potentially raising incomes and gradually narrowing the urban-rural income gap.

However, this outcome depends on the continued development of the economy.But the result of the mediating effects of OIS differs from those of existing studies by Li et al. (2024) and Zhang (2023). The discrepancy with the findings of Li et al. (2024) may primarily stem from the different variable choices. Li et al. (2024) used agricultural industrial structure upgrading as the mediating variable and the per capita net income of farmers as the dependent variable, which differs from the variables selected in this study. The divergence from Zhang (2023) can be attributed to two main reasons. First, Zhang (2023) used data from 197 cities, which increased the sample size but compromised the comprehensiveness of the digital economy development index, as only 9 secondary indicators are utilized compared to the 17 secondary indicators in this study. Second, while Zhang (2023) used ordinary least squares (OLS) regression without considering fixed effects, this study employed a

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fixed-effects model based on relevant tests to ensure the accuracy of the estimation results. The reasons for the non-significance of the mediating role of industrial structure optimization are summarized as follows: firstly, although the development of the digital economy is generally considered to facilitate the optimization of the industrial structure, in reality, it tends to concentrate resources and capital in a few specific sectors, such as high-tech and information technology industries (Chen et al., 2022). This concentration leads to a lower-than-expected overall level of industrial structure optimization. Such a biased developmental trend enables certain industries to upgrade rapidly while marginalizing others, thereby hindering the balanced development of the overall industrial structure.

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Furthermore, the digital economy's development typically sees earlier adoption and diffusion in more economically developed cities and regions, whereas its penetration in rural and underdeveloped areas is considerably slower. This discrepancy results in significant differences in the advancement of industrial structure optimization between urban and rural areas, as well as across different regions, impeding the formation of a cohesive enhancement effect. Consequently, the optimization of the industrial structure cannot effectively mediate the impact of the digital economy development on the urban-rural income gap.

In summary, the findings from Chapter 4 suggest that: (i) From 2013 to 2022, the DEDI in 30 provinces across mainland China has consistently risen. And the

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digital economy has flourished more prominently in first-tier areas such as Beijing and Guangdong. When viewed separately from the four economic regions, the digital economy development index is highest in the Eastern region, followed by the Central region, the Northeastern region, and lastly the Western region. Moreover, the inequality in the DEDI among regions has not gradually narrowed over time. Regarding the urban-rural income gap, there is an overall decreasing trend across 30 provinces in mainland China.

However, some provinces exhibit fluctuations. Regionally, the income gap between urban and rural areas is most pronounced in the Western region, followed by the Central region, which exhibits a greater gap than the Northeastern region. The Eastern region, in turn, has the smallest urban-rural income gap among the four regions. (ii) The impact of digital economy development on the urban-rural income gap in mainland China follows an inverted U-shaped pattern from 2013 to 2022 an aggregate perspective. The majority of provinces are currently positioned on the left side of the inverted U-shape. There is regional heterogeneity in the impact of the digital economy development on the urban-rural income gap from disaggregate perspectives across different regions. (iii) the upgrading of industrial structure (UIS) plays a crucial mediating role in the impact of digital economy development on the urban-rural income gap. While the optimization of industrial structure (OIS) does not. In light of these findings, policymakers should be attentive to adopting corresponding measures to anticipate and manage the inverted U-shaped turning point in digital

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economy development. Simultaneously, a nuanced approach tailored to specific regional characteristics is imperative, avoiding one-size-fits-all solutions.

5.2 Policy implications

The first policy implication of this study emerges from the results of the improved digital economy development index (DEDI) across 30 provinces and four economic regions in China. The findings highlight a significant inequality in the level of digital economy development among provinces and regions, with the majority of provinces falling below the average DEDI. Therefore, regions lagging in digital economy development should actively learn from more advanced regions to close this gap. Additionally, while the overall trend shows a decreasing urban-rural income gap, certain provinces experience periods of stagnation in some years. Policymakers should be attentive to these fluctuations and remain vigilant against the potential widening of the urban-rural income gap. Meanwhile, from the perspective of the internal structure of the DEDI, it is influenced by various factors which could be divided into four dimensions: digital economy development carrier, digital industrialization, industrial digitization, and digital economy development environment. Therefore, to enhance the value of the DEDI, measures should be taken across the four dimensions.

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Firstly, it is imperative to strengthen the development of digital economy development carrier. Specifically, this includes moderately advancing the construction of digital economy infrastructure in urban and rural areas, orderly promoting the construction of network infrastructure, and steadily advancing the development of intelligent and efficient integrated infrastructure.

Secondly, it is essential to persist in enhancing support for digital industrialization. Leading regions in digital industry development should capitalize on their advantages in scientific research and innovation, put more focus on strategic emerging industries, and increase investment. Attention should be paid to the radiating and driving effect on surrounding areas. Regions with a certain foundation in digital industry should refine their efforts in traditional digital industry advantage areas. Underdeveloped rural areas in digital industry should expedite the investigation of the digital industry situation, actively undertake labor-intensive and resource-intensive digital industries, and fully engage in external exchanges.

Thirdly, it is crucial to strengthen the integrated development of the digital economy and the real economy and accelerate the transformation of industrial digitization. This includes deepening the transformation of industrial digitization and promoting the development of the industrial Internet. There should be vigorous development of the digital transformation of the service industry, enhancement of the level of intelligent logistics, development of digital trade, and exploration of new models and formats of e-commerce such as cross-border e-commerce, live

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e-commerce, and social e-commerce. Accelerating the development of agricultural digitization transformation is also essential, involving the establishment of agricultural Internet of Things in areas such as large-scale planting, livestock breeding, and quality and safety, as well as the promotion of the application of agricultural robots, plant protection drones, unmanned driving tractors, and the development of rural e-commerce.

Fourthly, it is essential to emphasize inclusiveness and prudence, improve the digital economy development environment, and achieve urban-rural data sharing. Establishing urban-rural digital resource sharing centers is key to promoting bidirectional flow of urban-rural data. Data sources for the data sharing center can include relevant data released by national departments, or data released by individuals, enterprises, or research institutions, or data jointly published by data center managers and individuals, enterprises, or research institutions. Formulating platform data usage rules and encouraging multi-party participation to promote the standardized and healthy development of the platform economy are essential steps. There should be a timely review of existing policy tools and improvements or introduction of relevant laws and regulations as necessary. Strengthening cooperation among all parties, clarifying respective responsibilities, and establishing online-offline linkage mechanisms are crucial. Optimization and enhancement of the digital business environment are also necessary, involving breaking down data barriers and improving online government service capabilities. Adherence to the principle of encouraging

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innovation, being inclusive and prudent, and protecting the equal entry of various market entities in accordance with the law should be upheld.

The second policy implication arises from the observed inverted U-shaped relationship between digital economy development and the urban-rural income gap in mainland China. This relationship indicates that during the initial stages of digital economy development, the urban-rural income gap tends to widen. However, after reaching a critical turning point, further development begins to narrow this gap. At present, most regions in China remain on the left side of this curve, where digital economy growth is still expanding the income gap. Only a few provinces, such as Guangdong Beijing and Shanghai, have progressed beyond this turning point. To accelerate the transition past this critical point, it is crucial to enhance the overall strategy for digital economy development in China. This includes constructing robust digital information infrastructure, promoting the widespread application of 5G, driving industrial digitization, developing smart cities, and fostering digital villages. Efforts should also be focused on advancing digital industries such as the industrial Internet and artificial intelligence, improving digital economy governance, unlocking the potential of data, empowering the economy, and enriching people's lives. Regions like Beijing, Shanghai, and Guangdong, with their comprehensive advantages in technology, economy, and talent, should position themselves as global hubs for the digital economy by fully deploying digital technologies, industries, transformation processes, and data elements. Meanwhile, the Central and Western regions should

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leverage their unique advantages in location, resources, and industries to cultivate new strengths in specific sectors of the digital economy.

As regions move beyond the turning point, the digital economy's development will begin to narrow the urban-rural gap through the realization of the digital dividend. Achieving this requires the construction of digital infrastructure, which remains underdeveloped in rural areas compared to urban centers. Therefore, it is essential to plan strategically and increase investment in rural digital infrastructure to close the urban-rural digital divide and consequently reduce the income disparity between urban and rural residents. Key initiatives should include strengthening rural mobile Internet and broadband communication networks, promoting digital television to enhance information exchange between urban and rural areas, and advancing the smart and digital transformation of water conservancy, roads, logistics, and other critical facilities. These efforts will facilitate the circulation of goods between urban and rural areas, enabling rural residents to participate more actively in market transactions and improve their income. Additionally, promoting intelligent equipment and mobile Internet applications tailored to agricultural production and rural life, constructing agricultural and rural remote sensing satellites, and improving agricultural meteorological monitoring networks will make agricultural production more efficient and expand the channels for agricultural product sales.

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The third policy implication arises from the results of regional heterogeneity. The results highlight the heterogeneous impact of the digital economy development on the urban-rural income gap, which necessitates the formulation of differentiated strategies for digital economy development based on regional characteristics and advantages. The analysis reveals that the Eastern and Western regions exhibit opposite trends. The Eastern and Northeastern regions should leverage their strengths in markets, talent, and industries to build a comprehensive digital economy development chain. This approach would effectively enhance urban and rural innovation capabilities, accelerate the transition past the inflection point, and move towards the right side of the inverted U curve, thereby narrowing the urban-rural income gap. In Western region, investing in education and skills training is crucial to enhance digital literacy among rural residents, improving their employability and engagement with digital platforms (Matli & Ngoepe, 2020; Wang X. et al., 2023). Additionally, enhancing the accessibility of digital infrastructure, including internet connectivity and e-commerce opportunities, can facilitate greater market participation for rural communities (Karine, 2021). Furthermore, promoting the diffusion of technology and innovation from urban to rural areas is vital for sustaining initial gains and preventing further income inequality. Policies fostering collaboration between urban and rural areas can ensure that technological advancements benefit all regions equitably (Pandey et al., 2021).

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The Central region should actively learn from the digital economy development experiences of both the Eastern and Western regions, fully harnessing the digital dividend to further narrow the urban-rural income gap. Therefore, policymakers must remain vigilant against the risk of polarization in the Eastern regions while simultaneously promoting the development of the digital economy in the Central, Western, and Northeastern regions. This approach would raise the level of digital economy development and facilitate an earlier arrival at the turning point in the inverted U-shaped relationship, thereby contributing to a reduction in the urban-rural income gap.

The fourth policy implication is derived from the distinct mediating roles of industrial structure optimization (OIS) and industrial structure upgrading (UIS) in the relationship between digital economy development and the urban-rural income gap. Specifically, the findings suggest that while OIS does not significantly mediate this relationship, UIS plays a crucial partial mediating role. Therefore, when designing comprehensive strategic plans, it is essential to integrate the optimization and upgrading of industrial structure within the framework of digital economy development, with a focus on fostering deep integration between the digital economy and traditional agriculture. This approach will facilitate coordinated development among the primary, secondary, and tertiary industries.

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The specific strategies are as follows: Promote Digital Transformation in Agriculture: Research, develop, and promote sensors, controllers, and intelligent communication devices tailored for agricultural production. Provide incentives such as subsidies and tax breaks to encourage farmers and new agricultural management entities to adopt precision farming techniques. Additionally, accelerate the application of the Internet of Things (IoT) in agricultural processing, and enhance research and development in automated equipment to improve the intelligence level of agricultural production. This will enable the visualization of agricultural processes and traceability of final products.

Develop the Tertiary Industry in Rural Areas: Leverage the unique resource endowments of rural areas to foster the growth of the tertiary industry. Utilize the Internet to promote rural culture by disseminating content with local cultural characteristics on platforms like Douyin and Kuaishou, and by employing dedicated personnel to manage these accounts. This approach can increase rural residents' income through live-streaming sales, advertising, and other avenues. Additionally, innovative service models such as online farming can be developed. By utilizing digital technologies like the Internet and cloud computing, the entire process of agricultural production can be visualized, enabling customers to engage in activities such as land contracting, crop planting, and fertilizing online, while farmers execute these tasks in reality, collecting service fees in return.

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Establish a Networked Collaborative Development Platform: Create a platform that connects different regions and enterprises, facilitating communication and collaboration among them. The government should provide policy and technical guidance for industrial development through this platform, and promote activities related to the digital economy. Enterprises on the platform should be encouraged to actively participate in building the digital industrial chain. Furthermore, by inviting experts, scholars, and research institutions in the field of the digital economy to join the platform, sections dedicated to sharing experiences and exchanging knowledge on digital economy development can be established, further enhancing collaborative efforts.

5.3 Recommendation of the study

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The discussions of the suggestions in this section are based on the limitations stated in Chapter 1, Section 1.7. For instance, first, this study generates the improved digital economy development index (DEDI) from four dimensions of digital economy development, namely digital economy development carriers, digital industrialization, industrial digitization, and the digital economy development environment. With the further development of the digital economy, future researchers can focus on new forms of digital economy development to explore more dimensions or secondary indicators in order to generate the digital economy development index more comprehensively. This could lead to a more accurate assessment of the level of digital economy development.

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Secondly, this study limits its sample to the 30 provinces of mainland China, including Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia, Liaoning, Jilin, Heilongjiang, Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong, Henan, Hubei, Hunan, Guangdong, Guangxi, Hainan, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang. Future researchers can, on one hand, conduct research from larger units (such as different countries) or from smaller administrative units (such as city-level or country-level). On the other hand, they can also expand the sample size by including special administrative regions like Hong Kong and Macau. Additionally, this study only utilizes annual-based datasets from 2013 to 2022. Future researchers can consider using datasets with different bases (such as daily, monthly, or annual) and can potentially increase the period of the time series to obtain different perspectives and more meaningful results for future studies.

Third, the regression analysis only considers a limited number of macroeconomic variables. Regarding the indirect impact of digital economy development on the urban-rural income gap, only industrial structure as a mediating variable is considered. Future researchers can further explore adding more reasonable control variables to the model to obtain more accurate research results. Furthermore, exploring additional mediating variables or moderating variables (such as digital inclusive finance, government support intensity, industrial chain, industry integration etc.) can lead to a more in-depth analysis of the mechanism through which digital economy development affects the urban-rural income gap.

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5.4 Summary

In conclusion, this study aims to investigate the influence of digital economy development on the urban-rural income gap. It pursues three specific research objectives. Firstly, to generate the digital economy development index. Secondly, to assess the impact of digital economy development on the urban-rural income gap from both aggregate and disaggregate perspectives. Lastly, to examine the mediating effect of industrial structure on the relationship between digital economy development and the urban-rural income gap. The study is conducted using data from 30 provinces in mainland China, including Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia, Liaoning, Jilin, Heilongjiang, Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong, Henan, Hubei, Hunan, Guangdong, Guangxi, Hainan, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang, spanning from 2013 to 2022. Through the discussions presented in Chapter 4, this study successfully achieves its objectives and provides insights to address the research questions outlined in Chapter 1.

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This study has the potential to make valuable contributions to government policymakers by assisting them in crafting more effective digital economy development policies aimed at narrowing the urban-rural income gap, fostering balanced urban-ruraldevelopment, and enhancing future economic performance. Additionally, the findings and methodologies employed in this study can offer

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valuable insights and serve as a resource for other researchers working in similar areas, thereby enriching their understanding and approach to related studies.

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