THE IMPACT OF FINANCIAL DEVELOPMENT AND DIGITAL TECHNOLOGY DEVELOPMENT ON URBAN-RURAL INCOME INEQUALITY IN SELECTED ASIAN COUNTRIES

BY

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DECLARATION

We hereby declare that:

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PREFACE

The economic development of Asian countries has brought significant improvements in income levels and living standards. However, this growth has not been evenly distributed, especially between rural and urban areas. In countries such as China, India, Malaysia, Japan, and South Korea, which have differences in economic structure, access to resources, and development opportunities, have contributed to persistent rural-urban income inequality. This imbalance remains a major concern, as it affects social stability, economic efficiency, and long-term sustainable development.

Next, financial development and digital technology development play a crucial role in shaping how resources, opportunities, and information are distributed across regions. Financial development affects access to credit and investment, which may benefit either a wider population or remain concentrated in urban areas. Similarly, digital technology improves connectivity and market access but may also create disparities due to limited infrastructure and skills in rural areas. Therefore, both factors can either reduce or widen rural–urban income inequality depending on their level of accessibility.

This study examines how financial development and digital technology development affect rural-urban income inequality in selected Asian countries. It aims to provide a clearer understanding of how these factors influence income distribution and offers insight for policymakers to promote more inclusive and balanced economic development.

ABSTRACT

This study investigates how financial development and digital technology development can impact urban-rural income inequality in Asian countries, namely China, India, Malaysia, Japan, and South Korea, covering the period from 1994 to 2020. The main objective is to examine whether these factors contribute significantly to narrowing or widening the income gap between rural and urban areas. To detect stationarity in data, panel unit root tests, including Levin, Lin & Chu (LLC), Im, Pesaran and Shin, Augmented Dickey-Fuller (ADF), and Phillips-Perron (PP). Furthermore, the cointegration test, including Pedroni and Kao, is to examine the long-run relationship among the variables. The Panel Autoregressive Distributed Lag (ARDL) is used to analyze both short-run and long-run relationships between variables in panel data, even when the variables have different levels of stationarity (I(0) or I(1)). This study finds that both financial development and digital technology development have a statistically significant relationship with rural–urban income inequality. Additionally, findings show that financial development leads to widening of the rural-urban income inequality, while digital technology development helps to narrow the rural-urban income gap in Asian countries. The research recommends that policymakers and governments should reduce rural-urban income inequality by improving rural financial access (microfinance, digital banking) and expanding digital infrastructure (internet, mobile networks, affordable devices). They should also promote rural job creation, reduce urban resource concentration, and support trade policies that improve rural market access and export opportunities.

Keywords: Financial Development, Digital Technology Development, Rural-Urban Income Inequality, Asian Countries, Panel ARDL

Subject area: HC10-1085 Economic history and conditions

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LIST OF ABBREVIATIONS

RUII	Rural-Urban Income Inequality
FD	Financial Development
DTD	Digital Technology Development
INQ	Income Quotient
DDT	Digital Divide Theory
ED	Economic Development
URB	Urbanization
TO	Trade Openness
ARDL	Autoregressive Distributed Lag
LLC	Levin-Lin-Chu
IPS	Im-Pesaran-Shin
ECM	Error Correction Model
ECT	Error Correction Term
PMG	Pooled Mean Group
GMM	Generalized Method of Moments

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CHAPTER 1: RESEARCH OVERVIEW

1.0 Introduction

This chapter provides an overview of the study, including the definition, significance, and trends of rural–urban income inequality, financial development, and digital technology development. The analysis focuses on five Asian countries—China, India, Malaysia, Japan, and South Korea—with particular attention to the impact of financial development and digital technology development on rural–urban income inequality. The chapter also outlines the problem statement, research objectives, research questions, and the significance of the study. Furthermore, it reviews the relevant literature, including theoretical review, empirical evidence, hypothesis development, and identifies literature gaps. In addition, the chapter discusses the methodological framework, covering data sources, data collection methods, research design, and analytical approaches.

1.1 Research Background

This research will focus on the role of financial development and digital technology development in rural-urban income inequality and will mainly focus on five Asian countries, which include China, India, Malaysia, Japan, and South Korea. To suggest whether financial development and digital technology development widen or narrow the urban and rural income gap from 1994 to 2020 by using the Panel

ARDL approach. Due to a large population in China and India, increasing inequality in China and India strongly shapes income distribution in Asia. Additionally, Japan and South Korea are technology and finance leaders, while Malaysia represents a middle- income country in Southeast Asia, which balances emerging and advanced economies in the region. Rural-urban income inequality is represented by a difference in income levels, living standards, and access to opportunities between individuals living in urban and in rural areas. It is an important factor affecting social stability and equal opportunities within a country, and it has a significant impact on socioeconomic development across Asian economies (Zou et al., 2025). Many economists argue that rising inequality can be a key driver of economic instability and financial crises (Stiglitz, 2009).

China's income inequality is characterized by rural-urban inequality, but the inequality within rural and urban areas has constantly increased. Urban households typically enjoy higher income, better educational opportunities, and superior infrastructure, while rural populations often depend on agriculture, informal labor, and have limited access to essential services like financial institutions or the financial market in most Asian countries. China and India, because of their substantial population sizes, have a significant influence on the overall patterns of regional inequality. In China, income inequality is largely shaped by the rural-urban gap, yet differences within rural and urban areas have also been impacted alongside China's rapid economic growth. (Imai & Malaeb, 2018).

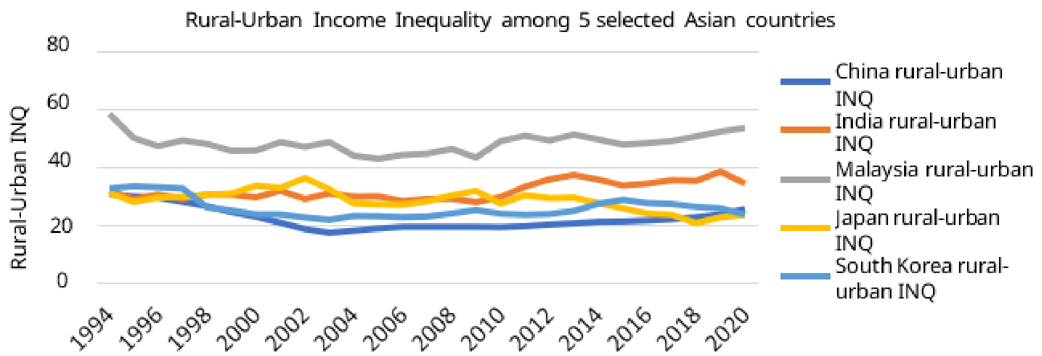

Figure 1.1: Rural-Urban Income Inequality among 5 selected Asian Countries.

Note. From World Development Indicators, Author's own calculation.

Other than that, Imai and Malaeb (2018) find that faster non-agricultural or industrial growth tends to widen the rural–urban income gap over time, whereas agricultural growth shows little direct effect on this gap. Moreover, while accelerated agricultural growth significantly reduces inequality within rural areas, rapid industrial growth has the opposite effect, increasing rural inequality over time. Figure 1.1 presents rural–urban income inequality across the five selected countries. Rural-urban income inequality (RUII) is proxied by comparing the value added per worker in agriculture to that in the industrial sector, expressed as a ratio. A value above 100 indicates that rural income is growing faster than urban income. In contrast, a value below 100 suggests that urban income levels remain higher than those in rural areas (Gollin et al., 2013; Sehrawat & Gini, 2015). According to Figure 1.1, the overall range of rural-urban income inequality for China, India, Malaysia, South Korea, and Japan is between 17 and 58 from 1994 to 2020. Across all five countries, the values remain well below 100 and involve a stable trend, confirming that industrial or urban workers consistently earn more than agricultural or rural workers throughout the period. If the value of the rural-urban INQ ratio increases over time, which means the country's income gap is reducing since the rural workers are catching up with urban workers, however, if the rural-urban INQ ratio decreases over time, urban workers' earnings grow faster, which widens the country's income gap. Compared among countries, Malaysia records the highest rural-urban INQ ratio, with values ranging from 43 to 55, which the rural-urban income inequality is better than others. China's rural-urban income inequality ratio is quite moderate after 2002, with a range is in between 18 and 25, the lowest among the other five countries, which means there is a huge income gap between urban and rural areas. The rural-urban INQ ratio for India, Japan, and South Korea is quite moderate which in a ranging between 20 to 39 for these three countries from 1994 to 2020.

Furthermore, financial development represents the advancements of financial institutions, markets, and instruments that support the efficient allocation of resources, encourage savings, and expand access to credit. It involves improvement in the financial system, including the pooling of savings, channeling capital to efficient investment, spreading risks, and enabling the exchange of goods and services. These developments play a crucial role in shaping savings and investment behavior as well as enhancing the effectiveness of how funds are distributed (Svirydzenka, 2016). Financial development is a key factor in promoting a country's economic growth. A well-functioning financial system enables households to save, access credit, invest in opportunities, and generate income. Across Asia, many countries experienced substantial financial development characterized by improvements in financial inclusion, deepening capital markets, and enhanced regional financial integration, which can boost economic growth, reduce reliance on the traditional banking system (Teo et al., 2006).

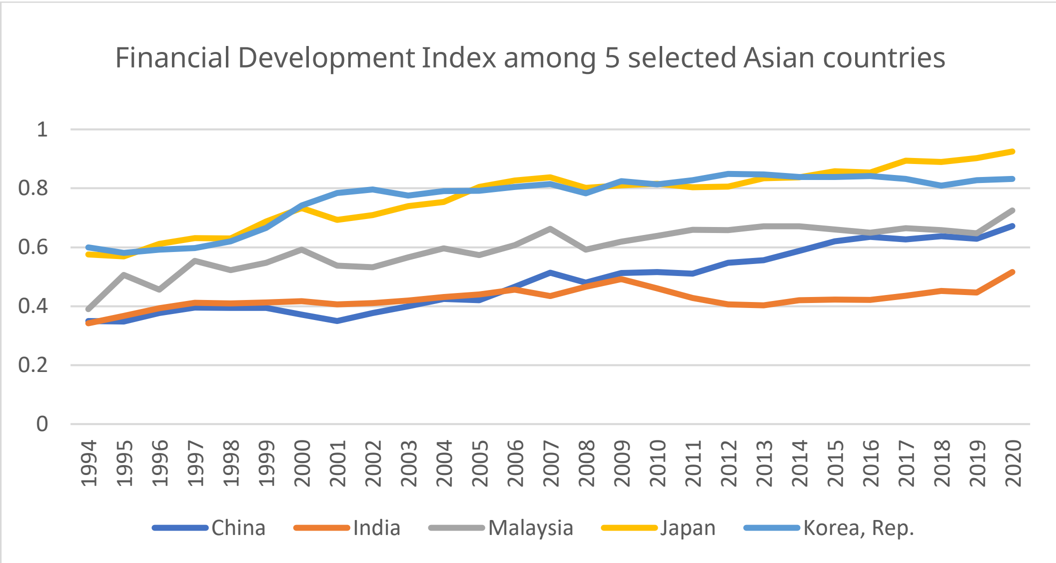

Figure 1.2: Financial Development Index among 5 selected Asian Countries. Note. From World Development Indicators, Author's own calculation.

Based on the graph, the level of financial development among the five selected Asian countries, including Malaysia, Japan, South Korea, China, and India, shows an overall upward trend from 1994 to 2020, even though the level of development varies greatly among countries.

Firstly, Japan consistently records the highest level of financial development among the five countries. The index increased steadily from 0.576 in 1994 to 0.925 in 2020, which indicates a highly mature financial system. This reflects Japan's involvement in a stable banking sector, developed capital markets, and strong financial infrastructure compared to others. Japan's long history of banking, advanced market mechanisms, and post-crisis reforms has reinforced financial stability and efficiency, enabling the country to maintain its position as one of the most financially developed economies in Asia (Bank of Japan, 2020).

Similar to Japan, Korea demonstrates a relatively high level of financial development over the study period. The index rose from approximately 0.6 in 1994 to about 0.832 in 2020. Despite minor fluctuations over time, the overall trend indicates a steady upward movement. The graph observe that Korea's financial development mainly increased in 1997 and 1998 to become more stable and efficient. One of the main reasons was the financial restructuring that occurred after the Asian Financial Crisis. Korea implemented major reforms to stabilize and modernize its financial system. These reforms included strengthening bank supervision, improving corporate governance, and restricting weak financial institutions (Shabsigh, G., 2013).

Thirdly, Malaysia shows moderate but stable financial development. The index gradually increased from 0.39 in 1994 to 0.725 by 2020. This steady improvement suggests ongoing financial sector reforms, expansion of banking services, and development of financial markets in Malaysia. Malaysia's financial system is still developing, but it has shown consistent progress over time.

Other than that, China has made significant improvements in financial development. The index rose from 0.35 in 1994 to 0.672 by 2020. Indicating that it is a rapid expansion of China's financial sector, financial liberalization policies, and the rise of digital finance platforms. Financial reforms and the transition toward a more market-based financial system can increase financial institutions and markets, while the rapid growth of fintech and digital payment systems further improved financial access and efficiency (Zhang, L., 2021).

Lastly, India indicates the lowest financial development index among the five countries, although there is a gradual improvement, the index fluctuates between 0.35 and 0.5 over 1994 to 2020. This is attributed to restricted access to financial services in rural areas. Despite improvements in access to bank accounts, still many people, especially in rural or low-income populations do not use financial services actively. Moreover, India's financial system faced a lot of problem including high non-performing loans, inefficient credit allocation, and others, which may limit the efficiency and stability of financial development (Schipke, A., et al, 2023).

Last but not least, Digital Technology Development (DTD) represents a central aspect of a nation's digital economy, highlighting the progress made in building and utilizing digital infrastructure, platforms, and innovations. It involves the expansion of technologies like artificial intelligence (AI), big data, cloud computing, the Internet of Things (IoT), and blockchain. These technologies streamline production, logistics, and financial services, which boost productivity and competitiveness. A country that invests in DTD strengthens its position in the global economy and attracts foreign investments, trade opportunities, and innovation ecosystems. DTD is a foundation for sustainable economic growth, reducing inequality, and improving governance. Asia has seen a growth in e-commerce and digital payments, driven by widespread internet and smartphone adoption. Additionally, digital payment solutions have gained a lot of adoption, with mobile payments, contactless payments, and digital banking platforms becoming more popular, secure, and convenient financial services (Lugtu, 2023).

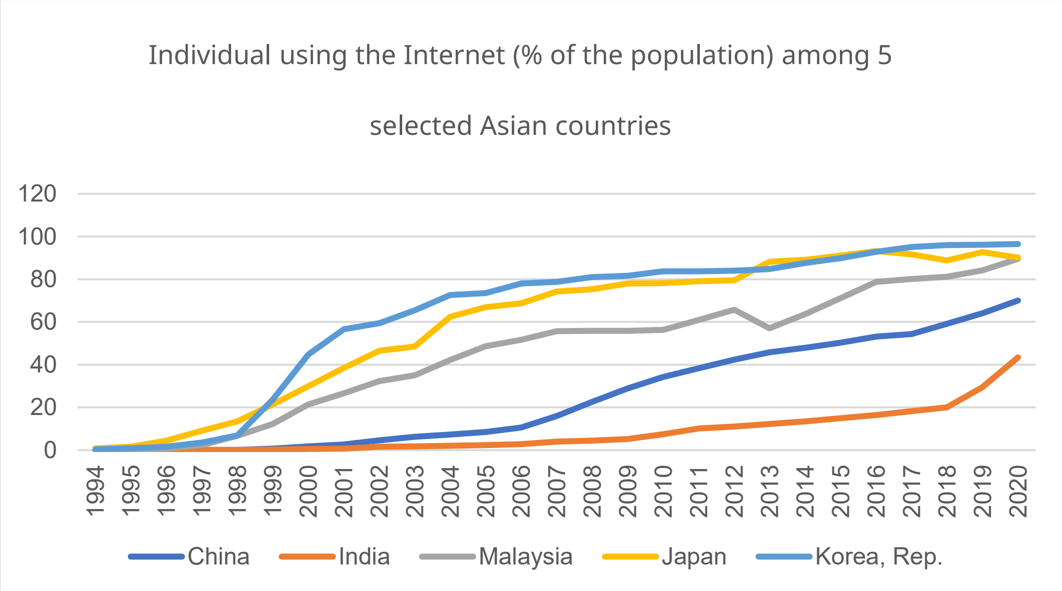

Figure 1.3: Individuals using the Internet (% of the population) among 5 selected Asian Countries. Note. From World Development Indicators, Author's own calculation.

From 1994 to 2020, the percentage of individuals using the internet increased significantly in China, India, Malaysia, Japan, and South Korea. This reflects the rapid expansion of digital infrastructure, increasing smartphone penetration, and broader access to online services over time. However, the five countries show different patterns of digital adoption depending on their economic development, technology infrastructure, and government digital policies.

South Korea experienced the highest level of internet usage, which increased from 0.31% to 96.51%. A particularly sharp increase from 1998 to 2001, which rose from 6.78% to 56.6%. This rapid growth can be attributed to the widespread adoption of high-speed internet services, as South Korea maintains some of the fastest and most affordable residential internet connections in the world (Bang & Choi, 2011). Consequently, South Korea has maintained one of the highest internet penetration rates globally, driven by strong government investment in broadband and advanced ICT infrastructure.

Besides that, Japan also shows a significant increase in internet usage, rising from 0.8% to 90.22% during the study period. This high internet penetration may be due to its advanced technological infrastructure and high-income economy. Commercial internet services became available in Japan in the early 1990s, and the country experienced rapid broadband expansion in the early 2000s due to the strong competition and technological development in the telecommunications sector. Therefore, Japan represents a mature digital economy, where internet adoption occurred early and eventually stabilized at high levels as the market approached saturation (Sunada et al, 2011).

In contrast, India was the lowest and slowest growth among these selected countries. India's internet usage kept remained below 1% of its population from 1994 to 2001. Although the internet growth was slow initially. India experienced faster growth after around 2015, which increased from 14.9 in 2015 to 43.41 in 2020. Despite this improvement, India still lags behind other countries. This may be due to limited telecommunications infrastructure, especially in rural areas. A large share of India's population resides in rural areas, slowing the overall national growth rate of internet usage. In addition, India is a developing economy with lower average income levels, which reduces purchasing power and slows the adoption of internet technologies such as computers, smartphones, and internet subscriptions (Singh, 2010).

Malaysia and China also experienced substantial growth in internet usage from 1994 to 2020. However, the growth patterns differ slightly between the two countries. In China, internet usage remained relatively low and increased slowly during the early years, but it began to rise rapidly after around 2007, reflecting the rapid expansion of digital infrastructure, broadband services, and smartphone adoption. In contrast, Malaysia experienced a more gradual and consistent increase in internet penetration, supported by government initiatives to improve digital connectivity and information and communication (ICT) infrastructure (Hilbert, 2016).

1.2 Research Problem

Rural-urban income inequality has remained one of the most pressing socio-economic challenges in Asia, particularly in emerging economies such as India, China, and Malaysia, as well as in advanced nations like Japan and South Korea. Even though substantial economic growth, structural transformation, and poverty alleviation have been achieved over the last several decades, rural areas often lag significantly behind urban regions in household income, access to services, and economic opportunities. For example, China's urban per capita disposable income yielded a rural-urban income ratio in 2023 is 2.39:1 (NBOSOC, 2024). The rural-urban income ratio in India is 2.1:1, meaning that urban incomes are significantly higher than rural incomes (Liao et al., 2025). Similar trends are shown by Malaysia in 2022, the rural-urban income ratio is 1.83:1 (DOSM, 2023). Although advanced economies such as Japan and South Korea show narrow gaps due to stronger social protection systems and more balanced regional development, income inequality between urban and rural areas remains observable (İşcan & Lim, 2021; Chakraborty et al., 2020). This ongoing inequality continues to limit inclusive development and creates obstacles to achieving the Sustainable Development Goals (SDGs), especially Goal 10, which focuses on reducing inequality (Bhandari, 2024).

Financial development and digital technology are widely recognized as potential equalizers of opportunity. Financial development can enhance access to credit, payments, savings, and investment to rural households (Yang et al., 2024), while digital technology development, such as e-commerce platforms and mobile banking, enables individuals in rural areas to connect to urban markets by bridging geographical barriers (Zhang & Li, 2024). However, their actual effects on narrowing or widening the rural-urban income gap are unclear and remain underexplored, especially in the context of Asia-Pacific countries (Vo et al., 2023). On one hand, some studies argue that financial deepening and digital access reduce inequality by empowering rural households and enabling income mobility (Li et al, 2024; Shen et al., 2025). On the other hand, research also highlights that limited financial inclusion or inadequate digital infrastructure in rural households could exacerbate inequality instead of reducing it (Peng et al, 2023). Therefore, it remains unclear whether, and under what conditions, financial development and digital technology development mitigate or exacerbate the rural-urban income gap in Asia-Pacific contexts.

This discrepancy highlights some critical research gaps, such as the lack of comparative cross-country evidence in Asia that integrates the consequences of financial development and digital technology in shaping rural-urban income inequality. It is crucial to analyze them collectively because each nation has a unique background, including technology inclusion, policy, digital penetration rates, and rural-urban structural characteristics. Few studies have looked into how these factors affect both emerging and advanced Asian economies, whereas most studies have looked at them separately. Furthermore, most of the studies employ the conventional regression method instead of panel unit root tests and the panel ARDL approach. Given the socio-economic importance of reducing inequality in Asia, clarifying whether financial development and digital technology mitigate or exacerbate the rural-urban income gap is both urgent and valuable. A clearer understanding will not only contribute to academic debates on inequality and development but also provide policymakers with evidence-based guidance for designing financial and digital technologies strategies tailored to national contexts.

Each country have implemented policy initiatives aimed at reducing rural–urban income inequality. For instance, the Chinese government has introduced targeted poverty alleviation strategies, including substantial investment in rural infrastructure and the implementation of the “New Socialist Countryside” program (Li & Sicular, 2014). In India, the Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA) was introduced to expand job opportunities in rural areas and strengthen infrastructure development. (Dutta et al., 2014). Similarly, South Korea introduced the “New Village Movement” to improve rural living conditions and enhance the quality of life of rural residents (Wen et al., 2025). Japan employs the Chiho Sosei policy, which funds rural revitalization projects such as agriculture subsidies and infrastructure development in depopulated areas (Kitagawa, 2024). Under the New Economic Policy (NEP), Malaysia has promoted rural infrastructure (roads, electricity), FELDA land development schemes, and income support for farmers (Tey et al., 2019). However, rural–urban income disparities remain remarkably persistent even after decades of extensive policy interventions across Asia. This implies that policy interventions may continue to fail without a deeper understanding of how financial development and digital technology interact with structural and institutional conditions. Therefore, addressing this gap is not only important from an academic perspective but also essential for designing more effective and context-specific strategies to achieve inclusive growth in the Asia-Pacific.

1.3 Research Questions

1. Does financial development have a significant impact on rural–urban income inequality in selected Asian countries?
2. Does digital technology have a significant effect on urban–rural income inequality in selected Asian countries?

1.4 Research Objectives

The main objective of this study is to investigate the relationship between financial development and digital technology development on rural-urban income inequality in selected Asian countries, including India, China, Japan, South Korea, and Malaysia.

1. To investigate whether financial development has a significant impact on rural–urban income inequality in selected Asian countries.

2. To examine whether digital technology development is significant in rural–urban income inequality in selected Asian countries.

1.5 Significance of Study

This study seeks to examine how financial development and digital technology development influence rural–urban income inequality in five selected Asian countries. This study examines five countries with distinct characteristics, all of which experience rural–urban income inequality. The objective is to explore the underlying causes of these disparities. By considering these differing contexts, the study looks into the impact of financial development and digital technology development on income inequality. Rural-urban income inequality is closely linked with the objectives of Sustainable Development Goal 10 (SDG 10), which emphasizes reducing income inequality and ensuring equality of opportunity for everyone, regardless of religion, origin, or economic status within countries. Disparities between rural and urban areas in terms of income highlight structural imbalances that hinder inclusive growth. To sum up, addressing these inequalities is essential for establishing SDG 10, as narrowing the rural-urban gap contributes to social cohesion, balanced economic development, and greater equity in opportunities and outcomes.

Firstly, by focusing on five Asian countries, current research offers and provides a clear perspective and understanding of how financial development and digital technology development can impact income disparities between rural and urban areas. This contributes to academic literature by offering insights into the mechanisms that increase or decrease financial development and digital technology development, either exacerbating or reducing inequality.

Secondly, this paper provides a comparative analysis on five Asian countries—China, India, Malaysia, Japan, and South Korea, over the period from 1994 to 2020. Previous research has rarely examined this specific combination of countries, and particularly in relation to the joint effects of financial development and digital technology development on rural–urban income inequality. So, by addressing these gaps, this study enhances the understanding of how financial development and digital technology shape the rural– urban income gap across these five countries.

Lastly, the findings of this study will provide useful insights for governments and policymakers in reducing rural-urban income inequality, which is important for ensuring sustainable economic prospects in the five selected Asian countries. It allows governments to better understand how financial development and digital technology development influence rural–urban income inequality, thereby supporting the formulation of appropriate policies to reduce the income gap between rural and urban areas.

CHAPTER 2: LITERATURE REVIEW

2.1 Theoretical Reviews

2.1.1 Financial Development

This study investigates the relationship between financial development and rural-urban income inequality by applying the Financial Development Theory, particularly the inequality-widening and inequality-narrowing hypotheses, to explain how financial development influences income disparities between urban and rural areas. The inequality-widening hypothesis suggests that credit allocation tends to favor urban and wealthier individuals, who are more likely to provide collateral and demonstrate higher repayment capacity. As a result, individuals with limited funding frequently struggle to secure loans, even in developed financial markets, deepening the country's income inequality. In contrast, the inequality-narrowing hypothesis argues that the expansion of the financial sector can improve access to credit for previously excluded low-income groups, thereby promoting more inclusive financial participation.

2.1.1.1 Inequality-Widening Hypothesis

The Inequality-Widening Hypothesis argues that economic growth, structural changes, technology and skill disparities, financial development, and globalization may contribute to an expansion of the rural-urban income gap.

This study focuses specifically on the role of financial development in shaping rural-urban income inequality. As financial development develops, disparities between urban and rural incomes may increase. This growing gap can be attributed to various challenges in financial markets, such as transaction costs, information asymmetry, insufficient collateral, and limited credit history, all of which can limit credit access for low-income groups (Beck et al., 2007). It limits rural households' access to benefits, leaving them dependent only on their restricted savings and income. This hypothesis indicates that financial development may tend to favor wealthier groups or urban areas. Additionally, urban households with a substantial income can provide collateral and are more likely to repay loans, whereas rural households with a lower income may find it difficult to acquire loans (Zal Yıldırım & Yüncü, 2025). Furthermore, Financial markets, such as stocks, bonds, and mutual funds, create opportunities. Wealthy households can invest and earn returns, whereas households with low incomes are excluded (Clarke et al., 2006). Since urban and educated populations have more financial knowledge, they make use of complex financial tools. Rural households may not benefit equally because of a lack of awareness or sense of financial expertise. (Greenwood & Jovanovic, 1990).

2.1.1.2 Inequality-Narrowing Hypothesis

On the other hand, the inequality-narrowing hypothesis argues that improvements in financial development can lessen and reduce the inequality in income between urban and rural areas. When there is a financial development, this hypothesis indicates that rural households gain easier access to banking, credit, and insurance, and they can invest in education or small business. This helps to raise the rural areas' productivity and income, gradually narrowing the rural-urban income inequality (Zal Yildirim & Yüncü, 2025). Furthermore, microfinance, mobile banking, and rural credit schemes reduce barriers that traditionally solely favoured urban areas. When the financial system is inclusive for rural households, they may have easier access to credit and capital (Burgess & Pande, 2005). Other than that, savings and investment opportunities increase since they can participate in formal savings schemes such as banks, pension funds, insurance companies, and others to make rural income more stable and predictable (Omar & Kazuo Inaba, 2020). Other than that, financial development encourages small and medium enterprises (SMEs) in rural areas by giving them loans, which involves job creation and business growth, so it spreads resources more evenly, supporting rural populations and reducing reliance on agriculture, which increases the income for rural populations (Seven et al., 2016).

2.1.2 Digital Technology Development

To understand the impact of digital technology on rural-urban income inequality, it is important to draw upon established economic and technological theories. This theory discusses how digital technologies spread across regions and also why their impact on income distribution may differ between urban and rural areas. The study applies the Digital Divide Theory.

2.1.2.1 Digital Divide Theory

Digital Divide Theory (DDT) explains how unequal access to digital technologies leads to differences in individuals' opportunities and outcomes. This reflects entrenched socio-economic structures rather than temporary gaps (Van Dijk, 2006). At its foundation, the theory should incorporate three key dimensions, which are access, usage, and outcomes. Digital access plays an essential role in narrowing the digital divide; it highlights the differences in the availability of digital infrastructure, such as internet connectivity, devices, and stable electricity. The second dimension, usage, emphasizes individuals' digital skills and the ability to effectively leverage technology for meaningful purposes. This level explores how digital engagement impacts real-world outcomes and opportunities for individuals and groups (Reddick et. al., 2024). Building on the traditional three-dimensional framework of access, usage, and outcomes, later scholars refined the model by distinguishing access into four sub-dimensions, which are motivation, material, skills, and usage access (Lamberti et al., 2020). Importantly, the divide is dynamic, shifting with technological evolution and adoption rates, yet it also risks becoming stratified, where disadvantaged groups remain persistently behind.

Applied to rural-urban inequality, urban populations generally benefit from better infrastructure and digital literacy programs, which enhance their human capital and productivity. Conversely, rural populations often face poor connectivity, fewer resources, and limited exposure to digital training, reinforcing cycles of poverty and exclusion (Saleminl et al., 2017; OECD, 2021). Socio-economic and cultural factors influence both Internet access and usage, which represents the first-level digital divide. Importantly, the theory suggests that even when physical access barriers are reduced, skills and usage divided may persist, leading to a 'second-level divide', and this can affect individuals' life prospects and the opportunities available to them (third-level divide) (DiMaggio & Hargittai, 2001). Thus, DDT underscores the possibility of entrenched inequality unless targeted interventions are implemented. In this way, DDT provides a structural lens, explaining why the benefits of digital learning and technology adoption may be unevenly distributed, thereby widening the rural–urban income gap unless equity-focused policies are enacted.

2.1.3 Control Variables: Economic Development, Urbanization and Trade Openness

This study incorporates three control variables: economic development, urbanization, and trade openness. The Kuznets Hypothesis is used to explain the relationship between economic development and rural–urban income inequality, while the Lewis Dual-Sector Model is applied to describe the link between urbanization and rural–urban income inequality. Furthermore, the Stolper-Samuelson theorem describes how trade openness is linked to rural–urban income inequality.

2.1.3.1 Kuznets Hypothesis

This study adopts the Kuznets hypothesis to explain the relationship between economic development and rural-urban income inequality. This hypothesis suggests an inverted U-shaped relationship, where rural–urban income inequality first rises in the early phase of economic development due to structural information and rural-urban migration, but decreases at later stages as income distribution improves (Kuznets, S., 1995). This is because in the early phase of development, the transition from an agriculture-driven economy to one based on industry and urban development creates income disparities between rural and urban populations. However, as development progresses, factors such as improved education, institutional development, and redistributive policies reduce inequality (Deininger & Squire, 1998; Ravillion, 2001).

2.1.3.2 Lewis Dual-Sector Model

To understand the impact of urbanization on rural-urban income inequality, it is important to consider structural transformation theories. This study applies to the Lewis Dual-Sector Model, developed by Arthur Lewis (1954), which describes the transfer of labour from low-productivity rural areas to more productive urban sectors. Rural areas often experience surplus labor with low marginal productivity, while urban industrial sectors offer higher wages and better employment opportunities. As labor migrates to urban areas, overall productivity and income levels increase, contributing to economic growth and structural transformation. This process may help reduce rural-urban income inequality over time, as rural workers gain access to higher-paying urban employment opportunities.

2.1.3.3 Stolper-Samuelson Theorem

Lastly, the Stolper-Samuelson theorem is applied to describe how trade openness relates to rural–urban income inequality. It is derived from the Heckscher-Ohlin model; this theory presents how trade openness affects income distribution by altering the returns to factors of production (Stolper & Samuelson, 1941). In developing economies such as China, India, and Malaysia, where low-skilled labour is relatively abundant, trade liberalization raises the demand for goods that are labour-intensive, which in turn raises wages for low-skilled workers. So, rural incomes are expected to increase, leading to a reduction in rural-urban income inequality. However, in economies where capital or skilled labour is relatively abundant, trade openness may widen income inequality (Heckscher & Ohlin, 1991).

2.2 Empirical Review

2.2.1 Financial Development

Many empirical studies have examined the rural-urban income inequality using various econometric models. Empirical studies show an insignificant effect in narrowing rural-urban income inequality. Law and Tan (2009), using quarterly data for Malaysia from 1980 to 2000 and applying the ARDL bounds testing approach, find that financial development, whether measured through banking sector indicators, stock market capitalization, or financial aggregates, is statistically insignificant in narrowing rural-urban income inequality in Malaysia. Sehrawat and Giri (2015) report that financial development does not help to reduce rural-urban income inequality. In order to prevent inequality from getting worse, they recommend policies that encourage financial growth, such as expanding access to financing.

Some empirical shows a mixed effect, such as Turkish researchers using panel data for 31 emerging and developing economies over the period 2000 to 2019 with a system GMM model, the study finds that banking development widens income inequality between rural and urban, while stock market development and financial openness help reduce it. The results highlight that the structure of the financial system matters more than its size in shaping inequality outcomes (Zal Yıldırım & Yüncü, 2025). Based on past findings, Zhang and Chen (2015), using annual data for China over the period 1978 to 2013 and employing a structural vector auto-regression (SVAR) model, find that financial scale (FIR) and efficiency (FER) raise rural–urban income inequality in the short term but lower it in the long term. Results also show that urbanization initially narrows the gap before turning positive, while fiscal expenditures widen inequality in the short run but help reduce it over time.

Moreover, Demirgüç-Kunt and Levine (2009) mentioned that financial development that enhances financial services and runs on an intensive margin could widen the distribution of income. Ang (2010) investigates the factors that influence the Gini coefficient in an autoregressive distributed lag model and, using the ARDL limits technique and the ECM cointegration test, concludes that the financial system's underdevelopment impacts the poor more than the rich, leading to wider income inequality between rural and urban. Perugini and Tekin (2022) indicate that, across the 48 middle- and high-income nations, Financial development is generally associated with higher income inequality, but this effect weakens as the quality of governance-related institutions improves.

However, Nokulunga Mbona (2022) reports that the overall financial sector development, including institutional development and market development, helps to reduce rural–urban income inequality. Kappel (2010) states that financial development lowers income inequality while promoting economic growth; however, the development of the stock market has a less significant but still significant impact than that of the credit market, illustrating that both markets contribute to the help of low-income households in high-income nations. Bittencourt (2006) demonstrates that expanded access to credit and financial markets reduces income disparity and enhances economic well-being in Brazil. Moreover, Liang’s (2006) empirical result indicates that China’s financial development significantly helps to reduce rural-urban income inequality. Lastly, Shahbaz and Islam (2011) suggest that inequality in income is reduced by financial development and made worse by financial instability. The results also showed that the distribution of income in Pakistan has greatly improved due to the poor's easy access to financial markets and effective credit funding.

2.2.2 Digital Technology Development

Numerous empirical studies have examined how digital technology influences rural-urban income inequality and produced mixed findings. Some studies show positive effects in narrowing inequality. For instance, Wang et al. (2021), using provincial panel data, find that internet development combined with FDI and urbanization alleviates provincial rural-urban income disparities. Furthermore, Zhang et al. (2024), using panel data, also reach a similar conclusion, which is that digital economic development significantly narrows rural-urban income gaps, particularly in regions with lower human capital endowments. Similarly, Su and Ren (2025) apply a two-way fixed effects model using multi-country data and find that rural e-commerce helps narrow the income gap, with internet usage levels acting as a partial mediator.

Conversely, some studies caution that digital technology may widen income inequality between rural and urban. Peng and Dan (2023), applying the entropy value method, reveal a U-shaped relationship in China. Digital economy development initially narrows and later widens the rural-urban income gap. Deng et al. (2023), using city-level data, similarly highlight that although both urban and rural incomes increase with digitalization, the gains are disproportionately larger for urban residents, resulting in a widening of the rural-urban income gap. Beyond China, Mwansa et al. (2025) document in rural South Africa that over half of the population lacked reliable internet, leading to restricted access to education, healthcare, and economic participation. This reinforces existing rural–urban inequalities and limits the transformative potential of digital technology.

Overall, these findings indicate that the relationship between digital technology and rural-urban income inequality remains inconclusive but highly dependent upon national contexts. Factors such as institutional capacity, infrastructure, and digital literacy play a decisive role in shaping whether digitalization acts as an equalizer or an amplifier of inequality.

2.2.3 Control Variables

The use of control variables in this study is crucial for capturing the more significant rural-urban income gap in five Asian nations. By accounting for relevant effects, the research gives a more accurate and realistic view of the income disparity between rural and urban areas. Control factors such as Economic Development (ED), Urbanization (URB), and Trade Openness (TO) are included for their possible influence on rural-urban income inequality, resulting in a more intensive and thorough analysis.

2.2.3.1 Control Variables: Economic Development

Firstly, ED refers to a qualitative measure of how that growth improves lives and society, which plays an important role in rural-urban income inequality since it can strongly influence income distribution. Studies consistently find that higher ED narrows the rural-urban income gap, which is significantly negative at 1% significance level in China (Deng, X. et al, 2023). A country's income level contributes to reducing income inequality in the Asia-Pacific region (Koh et al., 2022). However, Economic growth can widen the rural-urban income gap in India (Tiwari et al 2010), and ED significantly affects the efficiency of income allocation, thereby impacting the disparity between urban and rural incomes (Yan, D. et al, 2025).

2.2.3.2 Control Variables: Urbanization

Urbanization is the process by which an increasing of the population lives in urban areas, leading to the expansion and development of cities. It reflects population migration and structural transformation, which may influence the income distribution between rural and urban areas. It is essential to include urbanization as a control variable in this study since it allows the model to account for structural demographic changes that may independently impact rural-urban income inequality, ensuring the estimated impacts on financial development and digital technology are more accurate (Zhao & Liu, 2022). Empirical studies indicate that higher urbanization levels can contribute to narrowing the rural-urban income gap. For example, Xia et al (2024) and Liang & Liu (2026) promote that regions with advancing urbanization experience greater labor mobility and better integration into the labor market, which narrows the rural-urban income gaps. Similarly, Sun & Kuang (2023), Jiang & Han (2023), and Yan et al (2024) also point out that the rural-urban income gap will gradually decrease as urbanization, partly due to the diffusion of technology and capital from urban to rural areas.

2.2.3.3 Control Variables: Trade Openness

Trade openness refers to how freely a country permits the movement of goods, services, and capital across its borders, reflecting its involvement in the global trading system. Trade openness is included as control variables since it can influence regional income differences since urban areas often benefit more from trade and also affect employment and industrial system (Perez & Krivonos, 2021). Historical studies show that trade openness can affect the rural-urban income gap through several channels. For instance, Koh et al (2022), Liu et al (2023) reveal that increasing trade openness contributes to reducing income inequality through industrial development and labor mobility. In contrast, Wan et al (2007) and Zhang et al (2011) reported that trade openness may widen the rural-urban income gap, as export-oriented industries are mainly concentrated in urban regions. These differing results suggest that the impact of trade openness on urban–rural income inequality may depend on a country’s stage of economic development and its regional structural features.

2.3 Proposed Theoretical / Conceptual Framework

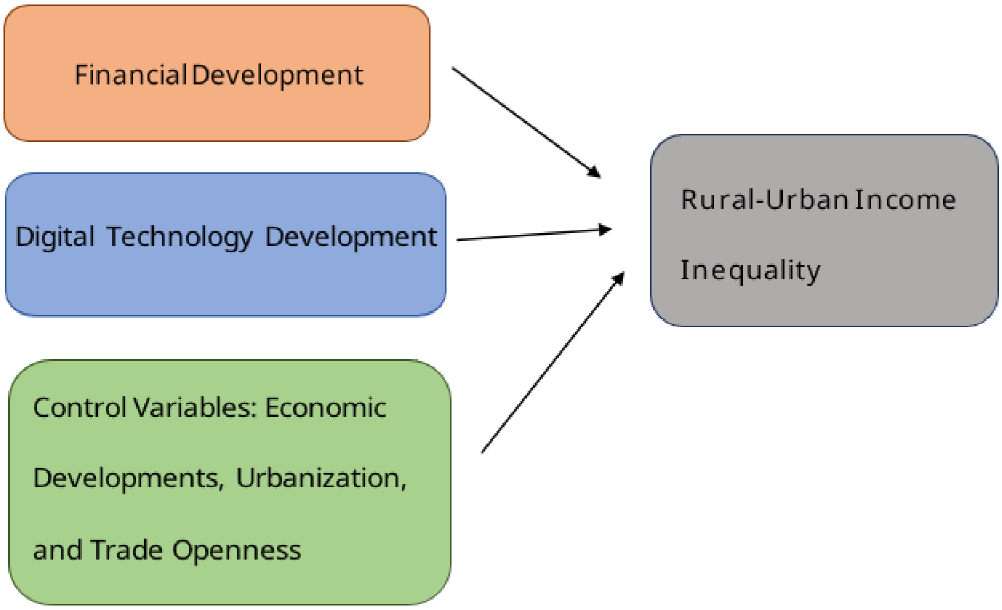

Figure 2.3 Conceptual Framework. Note. Author's own graph

The conceptual framework illustrates the hypothesized relationships among the study variables. In this framework, financial development and digital technology serve as independent variables, while the urban–rural income inequality gap is the dependent variable. In addition, several control variables, including GDP per capita, urbanization rate, and trade openness, are incorporated to account for potential confounding effects and to ensure a more accurate estimation of the relationships. As shown in Figure 2.3, the model proposes that financial development and digital technology influence the rural-urban income inequality either positively (widening) or negatively (reducing), alongside the effects of the control variables.

2.3.1 Expected Relationship between Financial Development and Rural-Urban Income Inequality

Although existing studies report inconsistent results regarding the link between financial development and income inequality, financial resources are typically concentrated in urban regions where financial institutions are more developed, which can lead to unequal access for rural populations. According to Credit Rationing Theory, proposed by Joseph Stiglitz and Andrew Weiss (1981), financial markets may allocate credit inefficiently due to information asymmetry. Banks prefer to lend to lower-risk borrowers, such as urban residents or high-income households, resulting in limited access to finance for rural households. As a result, financial development may reinforce existing inequalities when financial resources are disproportionately concentrated in urban areas, thereby widening the rural–urban gap (Wang et al., 2023; Zhang et al., 2025). Furthermore, financial development does not necessarily lead to improvement in financial inclusion, as it may disproportionately benefit urban populations where financial institutions are concentrated (Ozili, 2018). Therefore, although financial development has the potential to reduce inequality, its effect may not be evenly distributed. Hence, this study expects that improvement in financial development will increase rural-urban income inequality.

2.3.2 Expected Relationship between Digital Technology Development and Rural-Urban Income Inequality

Although some studies suggest that digital technology development may widen inequality due to unequal access and differences in digital skills, it is generally recognized as a key driver of inclusive and sustainable economic growth. By reducing transaction costs and lowering information barriers, digital platforms enhance rural residents' access to markets, financial services, and employment opportunities (Wen et al. 2024). Digital technology in rural communities facilitates the acquisition of agricultural information and allows involvement in a range of online economic activities. Furthermore, the digital economy can empower disadvantaged groups by providing timely access to job information and flexible engagement in non-agricultural employment, thereby enhancing household earnings, diversifying income sources, and gradually narrowing the income gap between rural and urban residents (Zhang & Li, 2024). Nevertheless, as digital technologies become more widely diffused and accessible across regions, the digital divide is expected to narrow gradually, allowing rural populations to increasingly benefit from digital opportunities. Therefore, this study assumes that an increase in digital technology development will reduce rural–urban income inequality.

2.3.3 Expected Relationship between Control Variables: Economic Development, Urbanization, and Trade Openness

Economic development plays a significant role in shaping income distribution. While the early stages of development may be associated with rising inequality, Simon Kuznets (1995) proposed that economic development may reduce income inequality in the long term. Empirical studies show that the stabilization of currency and fiscal policy, and open markets and other liberalized financial policies may increase the rural resident income. The income will increase until the same level as other families' income in society. They emphasize there is not a 'trickle-down' effect, even though wealthier groups benefit first and any advantages are later expected to spread to lower-income groups (Dollar & Kraay, 2002). Therefore, economic development is expected to decrease rural-urban income inequality in this study.

Urbanization reflects the movement of labor from low-productivity rural sectors to high-productivity urban sectors. When urbanization increases, it facilitates job opportunities, improves accessibility to education and public services, and enhances the income-generating capacity for rural migrants. As more rural residents transition to urban areas for work, the income gap between rural and urban populations is expected to narrow. Previous empirical studies show that urbanization promotes labor mobility and structural transformation, which will reduce income inequality (Wan et al., 2022; Nguyen, 2019). As a result, this study shows urbanization is expected to reduce rural-urban income inequality.

Trade openness captures a country's level of participation in the global economy and influences the distribution of income. While some studies highlight uneven benefits, others suggest that trade can enhance rural income through increased agricultural exports, improved market access, and greater participation in global value chains. Through trade liberalization, rural producers can access larger markets, benefit from higher demand for agricultural goods, and obtain better prices for their products. In addition, trade openness encourages investment in rural infrastructure and productivity, which further supports income growth in less developed regions (Winters et al., 2004; Dollar & Kraay, 2004). In conclusion, trade openness is expected to contribute to a reduction in rural-urban income inequality in this study.

2.4 Hypothesis Development

2.4.1 Financial Development and Rural-Urban Income Inequality

H0: Financial development does not have a significant effect on rural–urban income inequality in the selected Asian countries.

H1: Financial development has a significant effect on rural–urban income inequality in the selected Asian countries.

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2.4.2 Digital Technology Development and Rural-Urban Income Inequality

H0: Digital technology development does not have a significant effect on rural–urban income inequality in the selected Asian countries.

H1: Digital technology development has a significant effect on rural–urban income inequality in the selected Asian countries.

2.5 Literature Gap

Despite extensive research on the effects of financial development and digital technology on rural–urban income inequality, several gaps remain. Firstly, many previous studies concentrate on developed economies or single-country contexts, such as studies confined to Chinese provinces. There is a lack of comparative cross-country evidence within Asian countries that simultaneously examines the variables, including financial development and digital technology development in influencing rural-urban income inequality. It is significant since each country involves different characteristics, including different levels of financial market development, technology adoption, digital inclusion, and government policy framework. Secondly, most existing research focuses on either financial development or digital technology development, with a limitation on the integration of both factors in explaining rural-urban income inequality. Thirdly, much of the existing research relies on conventional regression methods, including pooled OLS, Fixed Effects (FE), and Random Effects (RE), which may not adequately capture dynamic adjustments across countries. To address this limitation, this study employs panel unit root tests together with the panel ARDL approach, allowing for the estimation of both short-run and long-run effects while accommodating differences in adjustment speeds across countries. Finally, findings remain inconclusive, while some studies argue that financial development and digital technology development promote inclusive growth, others highlight their tendency to reinforce inequalities, particularly when resources are disproportionately concentrated in urban areas. Addressing these gaps, the study contributes new empirical evidence by examining both factors simultaneously, thereby contributing to a more holistic and policy-relevant understanding of inequality in selected Asian countries.

CHAPTER 3: METHODOLOGY

3.1 Research Design

This study adopts a quantitative approach, which involves analyzing numerical data to measure variables and test hypotheses. The research focuses on five Asian countries, including China, India, Malaysia, Japan, and South Korea over the period from 1994 to 2020. The choice of these countries is based on their diverse levels of economic development, financial development, and technological advancement, which provide a comprehensive perspective on the dynamics of rural-urban inequality. The study relies on secondary data, and the data is compiled into a balanced panel dataset covering 27 years. This study uses data from 1994 to 2020 because the mid-1990s mark the beginning of widespread internet diffusion and digital technology development in many Asian countries. The World Wide Web became publicly accessible during this period, and the internet infrastructure began expanding rapidly (Comin & Hobijin, 2010). Other than that, one of the reasons is that complete and consistent data for all variables are only available up to 2020. Some indicators, particularly the financial development index and certain rural-urban income indicators, are not consistently available for all selected countries after 2020. The use of incomplete data may result in an unbalanced panel dataset, which may reduce the reliability and comparability of the empirical results. Therefore, this study focuses on the period from 1994 to 2020 to maintain a balanced panel for econometric analysis (Baltagi, 2008 & Wooldridge, 2010).

3.2 Sampling Design

The target population of this study comprises rural and urban household incomes in five Asian countries, namely China, India, Malaysia, Japan, and South Korea. These countries were purposively selected as representing different stages of financial and digital technology development. China and India, as large emerging economies with substantial populations, reflect rapid growth alongside persistent inequality. Malaysia represents a middle-income economy undergoing transition, while Japan and South Korea are advanced economies with highly developed financial systems and widespread digital adoption. This variation provides a meaningful basis for comparison, allowing the study to examine both commonalities and differences in how financial and digital development influence rural-urban income inequality. The dataset consists of annual observations spanning the period from 1994 to 2020.

3.3 Data Collection Method

This study examines the effects of financial development and digital technology development on rural–urban income inequality. To better understand the role of financial and digital technology development toward rural- urban income inequality among five Asian countries, a panel of selected countries with a period from 1994 to 2020 is chosen for this research.

Rural–urban income inequality (RUII), the dependent variable of this study, is measured using the rural–urban income quotient (INQ). Due to the limited availability of consistent income data across countries, a proxy based on sectoral productivity is employed. In this approach, the rural sector is represented by agricultural value-added per worker, while the urban sector is proxied by industrial value-added per worker. The rural–urban INQ is calculated as the ratio of agricultural to industrial value-added per worker, multiplied by 100. This ratio provides an indirect measure of the relative development gap between rural and urban areas. The RUII variable is constructed by the authors using data obtained from the World Bank's World Development Indicators (WDI) database. Although this proxy may not fully capture all dimensions of income inequality, it provides a reasonable approximation of rural–urban economic disparities due to data limitations across countries. Previous studies have suggested that differences in productivity between agriculture and industry are a key determinant of the urban-rural income gap (Wang & Du, 2026; Liu et al.,2024; Liao et al., 2025).

Financial Development (FD), the independent variable, is measured by the Financial Development Index, which is sourced from the International Monetary Fund (IMF). Financial development refers to the improvements in financial institutions, markets, and instruments that facilitate the allocation of resources, the mobilization of savings, and the provision of credit. Financial development refers to improvements in the financial system, including the pooling of savings, allocation of capital to productive investments, monitoring of investment activities, risk diversification, and the facilitation of the exchange of goods and services. These functions may affect savings and investment decisions as well as the efficiency of capital allocation (Katsiaryna Svirydzenka, 2016). The financial development index typically ranges between 0 and 1, where higher values indicate a more advanced level of financial development, while lower values represent weaker financial development. It offers a comprehensive measure by incorporating multiple dimensions of the financial system, including depth, access, and efficiency (IMF, 2025). While previous empirical studies have often proxied financial development using single indicators such as the ratio of private credit to GDP or stock market capitalization to GDP. However, these indicators do not capture the multidimensional nature of financial development. By employing FDI, the study captures the extent to which financial development contributes to narrowing or widening income gaps across the selected countries.

The independent variables, Digital Technology Development (DTD), is proxied by the indicator of individuals using the internet (% of population), with data obtained from the World Bank. This indicator reflects the level of digital connectivity and the diffusion of digital technologies across the population. This measure has been commonly applied in empirical research on the effects of digitalization on economic outcomes (Oloyede et al., 2023). Previous research suggests that internet development can improve access to information, enhance labor market efficiency, and create new opportunities for employment and entrepreneurship, thereby influencing income distribution between urban and rural areas (Li et. al., 2024). However, this indicator may not fully capture the nature of digital technology development, which also includes advanced technologies such as artificial intelligence, cloud computing, and big data. Additionally, internet penetration measures access rather than the quality of digital infrastructure or the effective use of digital technologies. Despite these limitations, it remains a commonly adopted proxy for digital development due to its availability and comparability across countries (Shuai & Li, 2025).

To account for macroeconomic and demographic influences, this study introduces three control variables. First, economic development (ED) is measured by GDP per capita, which reflects the level of development in each country. Second, urbanization (URB), defined as the increase in the concentration of population in urban areas, is proxied by the proportion of urban population as a share of total population, and it may have implications for rural–urban income inequality. Third, trade openness (TO) is measured by the ratio of the total trade to GDP, calculated as the sum of exports and imports relative to total GDP. This indicator reflects the degree of a country's integration into the global economy and the intensity of cross-border flows of goods, services, and capital, which may subsequently influence rural-urban income inequality. All data are obtained from the World Development Indicators (World Bank).

3.3.1 Data Description

Table 3.3.1:

Source and Measurement of Each Variable

Variables	Indicator	Proxy	Source of Data
Rural-urban income inequality	RUII	Rural urban INQ	WDI
Financial development	FD	Financial development index	IMF
Digital technology development	DTD	Individuals using the internet (% Of population)	World bank
Economic development	ED	GDP per capita	World bank
Urbanization	URB	Urban population (% of total population)	World bank
Trade openness	TO	Trade (% of gdp)	World bank

Note. From WDI, IMF, The World Bank

3.4 Model Specification

This study employs panel data analysis to investigate the effects of financial development, digital technology, and selected control variables on rural–urban income inequality across five Asian countries. To avoid omitted variable bias, several control variables are included, which are economic development, urbanization, and trade openness. The empirical specification is presented as follows:

$$Rural - Urban\ INQ_{it} = f(FDI_{it}, DTD_{it},\ ED_{it}, URB_{it}, TO_{it})$$

where:

$Rural - Urban\ INQ_{it}$ = Rural–Urban Income Inequality (dependent variable), measured by the ratio between agricultural value-added per worker and industrial value-added per worker, for the country i at time t.

FDI_{it} = Financial Development (main independent variable), measured by Financial Development Index

DTD_{it}= Digital Technology Development (main independent variable), measured by the percentage of individuals using the Internet in the total population.

ED_{it} = Economic Development (control variable), measured by GDP per capita.

URB_{it} = Urbanization (control variable), measured by the share of urban population in total population.

TO_{it} = Trade Openness (control variable), measured by trade as a percentage of GDP.

Accordingly, the econometric model is specified as:

$$Rural - Urban\ INQ_{it} = \beta_0 + \beta_1 FDI_{it} + \beta_2 DTD_{it} + \beta_3 ED_{it} + \beta_4 URB_{it} + \beta_5 TO_{it} + \mu_{it}$$

where:

β_0 = Intercept

β_1 - β_5 = Coefficient of the explanatory variables

μ_{it} = Error term

To capture potential nonlinear relationships and ensure robustness, the log-linear specification is adopted. Following prior studies, this study adopts a log-linear (double-log) specification. The log transformation not only stabilizes variance and mitigates heteroskedasticity but also enables coefficient estimates to be interpreted as elasticities, which provides more meaningful insights into the proportional effects of financial development and digital technology on rural–urban income inequality (Liang, 2023; Zhong et al., 2022). Therefore, the log-linear model is specified as:

$$ln(Rural - Urban\ INQ_{it}) = \beta_0 + \beta_1\ ln(FDI_{it}) + \beta_2\ ln(DTD_{it}) + \beta_3 \ln(ED_{it}) + \beta_4 \ln(URB_{it}) + \beta_5 \ln(TO_{it}) + \mu_{it}$$

Based on the empirical discussions in Chapter 2, the expected signs of the coefficients are that Financial Development (FD) is expected to have a significant negative relationship with rural-urban income inequality (RUII), suggesting that higher financial development may widen the income gap. For Digital technology development (DTD), economic development (ED), urbanization (URB), and trade openness (TO) are expected to have positive relationships with RUII, suggesting that increases in these variables may help to narrow the rural-urban income gap.

3.5 Model Selection

3.5.1 Panel Unit Root Test

It is important to determine whether the series is stationary or non-stationary in order to avoid the problem of spurious regression. Therefore, unit root tests are conducted for this purpose. A panel unit root test extends the standard unit root test to panel data, providing higher statistical power than individual time series unit root tests. It examines whether variables across multiple cross-sections and time periods are stationary, while improving test efficiency and accounting for heterogeneity. Panel unit root tests are employed to assess whether variables are stationary and determine their order of integration, typically classified as I(0) or I(1). A variable is classified as I(0) if it is stationary at level, meaning its mean and variance remain constant over time, whereas an I(1) variable is non-stationary in level but becomes stationary after first differencing (Engle & Granger, 1987). This distinction is important because the panel autoregressive distributed lag (ARDL) models requires variables to be I(0) or I(1), while excluding I(2) series (Pesaran et al., 1999). I(2) variables refer to the variable that becomes stationary only after second differencing, and they are excluded because excessive differencing may destroy or eliminate the long-run relationship.

To ensure robustness, this study employs several panel unit root tests. The Levin-Lin-Chu (LLC) test assumes a common unit root process across all cross-sections, implying homogeneity in the autoregressive coefficient among individuals. However, the LLC framework still allows heterogeneity in individual intercepts, time trends, error variances, and serial correlation structures (Levin et al., 2002). In contrast, the Im-Pesaran-Shin (IPS) test relaxes the assumption of homogeneity by allowing the autoregressive coefficient to vary across cross-sections, making it more suitable for panels with diverse units (Im et al., 2003). The Fisher-type test, proposed by Maddala and Wu (1999) and extended using the Phillips-Perron (PP) approach, aggregates individual unit root test statistics from each cross- sectional unit, providing greater flexibility in handling unbalanced panels. Since these tests have varying power and underlying assumptions, applying multiple tests (LLC, IPS, and Fisher-PP) enhances consistency and robustness in identifying the integration order (Breitung & Pesaran, 2008).

The hypotheses are defined as follows:

$H_0 = \textit{The variable contains a unit root (non} - \textit{stationary)}.$

$H_1 = \textit{The variable did not contain a unit root (stationary)}.$

3.5.2 Cointegration test

Before applying the ARDL approach, it is important to test whether a long-run equilibrium relationship exists among the variables. This is important because the ARDL model requires cointegration to ensure meaningful long-run estimates. In this study, the Pedroni and Kao cointegration tests are applied to examine the presence of a long-run equilibrium relationship among the variables. The Pedroni (2004) cointegration test allows for heterogeneity across panel members while assessing cointegration in panel data settings, meaning that each cross-sectional unit may have different intercepts and dynamic structures. Despite this heterogeneity, the test is capable of evaluating the presence of a long-run relationship using pooled statistics. In addition, the Kao Cointegration Test (Kao, 1999) is also applied as a complementary approach. Similar to the Pedroni test, it is a residual-based approach used to examine whether a long-run equilibrium relationship exists among variables in panel data. However, it assumes homogeneous slope coefficients across cross-sectional units.

The hypotheses are defined as follows:

$H_0 = There\ is\ no\ cointegration\ in\ the\ models.$
$H_1 = There\ is\ cointegration\ in\ the\ models.$

3.5.3 Panel Autoregressive Distributed Lag

This study utilises the Panel Autoregressive Distributed Lag (Panel ARDL) model to examine dynamic relationships among the variables. The Panel ARDL approach is suitable for datasets containing a mix of I(0) and I(1) variables, while excluding I(2) series. It is commonly used to analyse both short-run and long-run relationships among economic variables (Pesaran et al 1999). The Panel ARDL approach includes lagged values of both dependent and independent variables, enabling it to capture dynamic adjustments over time. Since the dependent variable (Rural-Urban INQ_{it}), such as rural-urban income inequality, depends not only on the current independent variables, such as financial development and digital development, but also on its past values. This study incorporates lags because economic and social processes take time to adjust, and past values of variables influence current outcomes. Without lags, the model may misrepresent or underestimate effects. Behavioral adjustments, such as delayed responses by households and firms, and institutional factors like policy implementation, also justify the inclusion of lags (Gujarati et al., 2009).

The Panel ARDL regression model is:

$$RUII_{it} = \alpha_i + \sum_{j=1}^{p} \lambda_{ij} RUII_{i,t-j} + \sum_{j=0}^{q} \beta_{1ij} FD_{i,t-j} + \sum_{j=0}^{q} \beta_{2ij} DTD_{i,t-j} + \sum_{j=0}^{q} \beta_{3ij} ED_{i,t-j} + \sum_{j=0}^{q} \beta_{4ij} URB_{i,t-j} + \sum_{j=0}^{q} \beta_{5ij} TO_{i,t-j} + \varepsilon_{it}$$

where:

α_i = intercept

p = lag length of the dependent variable

q = lag length of the independent and control variable

ε_{it} = error term

Furthermore, the model can be reformulated into an Error Correction Model (ECM), which separates between short-run dynamics and long-run equilibrium relationships. The ECM incorporates an error correction term (ECT) that reflects the speed of adjustment back to long-run equilibrium following short-run deviations. A negative and statistically significant ECT coefficient indicates the existence of cointegration among the variables.

Cointegration refers to a situation in which a linear combination of non-stationary variables becomes stationary, indicating that the variables move together in the long-run despite short-run deviations. Although temporary disequilibrium may occur, the variables tend to converge back to their long-run equilibrium over time. To estimate both short-run and long-run effects simultaneously, this study employs the Pooled Mean Group (PMG) estimator developed by Pesaran, Shin, and Smith (1999), which is suitable for small samples (Haug, 2002 & Alimi, 2002). The PMG approach restricts long-run coefficients to be homogeneous across countries while permitting heterogeneity in short-run dynamics, intercepts, and error variances, thereby capturing both common long-run relationships and country-specific adjustments.

The ECM version of the Panel ARDL model is:

$$\Delta RUII_t = \phi\big(RUII_{i,t-1} - \beta_1 FD_{i,t-1} - \beta_2 DTD_{i,t-1} - \beta_3 ED_{i,t-1} - \beta_4 URB_{i,t-1} - \beta_5 TO_{i,t-1}\big) + \sum_{j=1}^{p-1} \lambda_{ij} \Delta RUII_{i,t-j} + \sum_{j=0}^{q-1} \theta_{1ij} \Delta FD_{i,t-j} + \sum_{j=0}^{q-1} \theta_{2ij} \Delta DTD_{i,t-j} + \sum_{j=0}^{q-1} \theta_{3ij} \Delta ED_{i,t-j} + \sum_{j=0}^{q-1} \theta_{4ij\Delta} URB_{i,t-j} + \sum_{j=0}^{q-1} \theta_{5ij} \Delta TO_{i,t-j} + \varepsilon_{it}$$

where:

ϕ = Speed of adjustment

λ_{ij}= Lagged dependent variable

β_j = Long-run coefficients of independent variables

θ_j = Short-run coefficient of independent variables

3.6 Diagnosis Checking

Although diagnostic tests are important in econometric analysis, this study focuses on estimating long-run relationships using the Panel ARDL framework. In particular, the ARDL model is implemented through the Pooled Mean Group (PMG) estimator developed by Pesaran et al (1999), which incorporates lagged variables that help address issues such as autocorrelation and endogeneity. Furthermore, the primary focus of this study is on the long-run equilibrium relationship and the error-correction dynamics result. This study conducts limited diagnostic testing and focuses primarily on key estimation and model selection procedures, including unit roots, cointegration test, ECM analysis, and optimal lag selection. Previous studies including Garidzirai & Muzindutsi, and Mestiri, applying Panel ARDL have emphasized the importance of establishing long-run relationships and selecting appropriate estimators, while placing less emphasis on extensive residual diagnostic testing (Menegaki, A. N. 2019).

CHAPTER 4: DATA ANALYSIS

4.0 Introduction

This chapter presents the empirical results and findings derived from the models introduced in the previous chapter. The analysis is organized into two main sections. The first part presents the descriptive statistics and correlation analysis, providing an overview of the data distribution and the relationships between the independent variables and dependent variables. The second part focuses on the regression results, which examine the relationship between rural–urban income inequality (RUII) and the explanatory variables, namely financial development (FD), digital technology development (DTD), economic development (ED), urbanization (URB), and trade openness (TO).

4.1 Descriptive Statistics

Table 4.1.1:

Summary of Descriptive Analysis

Variable	RUII	FD	DTD	ED	URB	TO
Mean	31.2931	0.6099	40.3675	14603.57	61.9688	70.2573
Median	29.2309	0.6070	38.5321	8899.345	68.7650	47.7418
Maximum	58.2267	0.9250	96.5051	49145.28	91.7810	220.4068
Minimum	17.5191	0.3420	0.0011	347.7342	26.3710	15.8103
Std. Dev.	9.6406	0.1653	34.0891	14902.18	22.1308	55.8161
Skewness	0.8771	0.1049	0.1905	0.8036	-0.3693	1.3922

Kurtosis	2.7644	1.7270	1.4868	2.1157	1.6276	3.6910
Jarque-Bera	17.6206	9.3628	13.6971	18.9295	13.6623	46.2984
Probability	0.0001	0.0093	0.0011	0.0001	0.0011	0.0000
Observation	135	135	135	135	135	135

Note. Author's own table

Table 4.1.1 presents the descriptive results for five countries from 1994 to 2020, totaling 135 observations. The mean value of rural-urban income inequality (RUII) is 31.2931, with a standard deviation of 9.6406, resulting in a coefficient of variation of 0.3081. This indicates moderate variation in income inequality across the selected countries. The minimum and maximum values of 17.5191 and 58.2267 suggest that income disparities vary notably across countries and over time. Furthermore, the range-to-mean ratio of 1.3 implies that some extreme values exist in the sample. The positive skewness (0.8771) indicates that the distribution of RUII is moderately right-skewed.

Financial Development (FD) has a mean of 0.6099 and a standard deviation of 0.1653, resulting in a coefficient of variation of 0.2710, which suggests relatively low variation. Combined with a range-to-mean ratio of 0.9559, this indicates an overall moderate variation across countries. The skewness of 0.1049 is close to zero, indicating an approximately symmetric distribution. Digital Technology Development (DTD) records a mean of 40.3675 and a standard deviation of 34.0891, which indicates high volatility across the countries. The maximum and minimum values are 96.5051 and 0.0011, further highlighting the substantial differences in digital development levels. The skewness value (0.149) is close to zero, suggesting a relatively symmetric distribution.

For the control variable economic development (ED), the mean is 14603.57, with a relatively large standard deviation of 14902.18, indicating substantial income disparities across China, India, Malaysia, Japan, and Korea. The skewness value of

0.8036 suggests a moderately right-skewed distribution, implying that a small number of countries record relatively high GDP per capita. Urbanization records a mean of 61.9688 and a standard deviation of 22.1308, with minimum and maximum values of 26.3710 and 91.7810, respectively. The coefficient of variation (0.35) and range-to-mean ratio (1.056) indicate moderate variation in urbanization levels. The negative skewness value (-0.3693) suggests a slight concentration of observations above the mean. Lastly, the mean value and standard deviation of trade openness (TO) are 70.2573 and 55.8161, indicating considerable variation in countries' integration into the global economy. The high positive skewness (1.3922) suggests that some countries are much more open to trade than others.

The Jarque-Bera test results show that all variables are not normally distributed, as their probabilities are below 0.05, leading to the rejection of the null hypothesis of normality. These deviations are common in macroeconomic and cross-country datasets due to heterogeneity across observations (Gujarati & Porter, 2021). Overall, the descriptive statistics reveal substantial cross-country heterogeneity, particularly in economic development, digital development, and trade openness.

4.1.2 Correlation Analysis

Table 4.1.2:

Summary of Correlation Analysis

	RUII	**FD**	**DTD**	**ED**	**URB**	**TO**
RUII	1					
FD	-0.1249	1				
DTD	-0.0520	0.8900	1			
ED	-0.2025	0.8260	0.6382	1		
URB	0.0267	0.9265	0.7614	0.8246	1	

TO	0.7254	0.0289	0.1118	-0.2664	0.1469	1

Note. Author's own graph

Table 4.1.2 shows the correlation matrix among the variables. Financial Development (FD), Digital Technology Development (DTD), and Economic Development (ED) have a negative correlation with Rural-Urban Income Inequality (RUII), although the relationships are relatively weak. In contrast, Trade Openness (TO) shows a strong positive correlation with RUII (0.7254), indicating that higher trade openness is associated with greater income inequality. Urbanization demonstrates only a very weak positive relationship with RUII. Furthermore, the relatively high correlation among independent variables, particularly FD, URB, and DTD, indicates possible multicollinearity, which may distort the magnitude and direction of the estimated coefficients in the regression model.

4.2 Panel Unit Root Test

Table 4.2.1:

Panel Unit Root Tests for the Overall Sample

	Constant				**Constant with Trend**			
	Levin, Lin & Chu test	Im, Pesaran and Shin	ADF	PP	Levin, Lin & Chu test	Im, Pesaran and Shin	ADF	PP
In Level								
ln $RUII$	-0.4573	-0.4080	10.3572	15.2526	-0.1585	0.1829	7.4954	13.2666
ln FD	-2.4791	-0.8759	13.8717	19.9976**	-0.3826	-0.6235	10.6869	24.5851***
ln DTD	-13.6216***	-15.0614***	72.8795***	122.802***	-15.0260***	-13.0001***	336.868***	312.637***
ln ED	-0.6856	0.8528	7.4149	6.1898	0.2262	-0.3987	12.2518	5.6437
ln URB	-2.7591***	-2.2109**	28.4108***	41.4078***	-1.2654	0.3528	14.6884	15.6888
ln TO	-0.4466	0.6333	6.3424	7.4417	1.1804	2.3070	2.9549	3.4250

Notes: *indicates significance at 10% level, ** indicates significance at 5% level, *** indicates significance at 1% level. Author's own table

Table 4.2.2:

Panel Unit Root Test for First Difference

	Constant				Constant with Trend			
	Levin, Lin & Chu test	Im, Pesaran and Shin	ADF	PP	Levin, Lin & Chu test	Im, Pesaran and Shin	ADF	PP
In 1st difference								
ln $RUII$	-0.5406	-3.5291***	32.5110***	71.2270***	-0.1991	-3.2204***	28.1533***	63.2032***
ln FD	-2.6410***	-5.0937***	44.8480***	71.8562***	-2.7863***	-4.1042***	34.8029***	304.521***
ln DTD	-4.9880***	-4.4824***	42.3843***	46.2260***	0.66821	-1.6604**	17.9641*	98.9185***
ln ED	-4.2610***	-4.9003***	43.5346***	56.1971***	-3.0449***	-3.3519***	29.6268***	40.1884***
ln URB	-1.1837	-0.1878	9.5004	17.4023*	-2.8625***	-3.3438***	31.9293***	27.7805***
ln TO	-3.6063***	-3.5504***	30.9123***	61.7517***	-3.6629***	-3.3387***	28.0905***	56.4325***

Notes: * indicates significance at 10% level, ** indicates significance at 5% level, *** indicates significance at 1% level. Author's own table

A panel unit root test is conducted to determine whether variables in panel data are stationary or non-stationary. A stationary series is a time series where its statistical features do not change over time. However, non-stationary data may result in misleading or spurious regression outcomes, as stochastic trends among variables may produce misleading interpretations. The test is used to detect or identify whether a time series contains a unit root, which helps determine if it is stationary or needs differencing to become stationary. Ensuring stationarity enhances the reliability of the long-run regression model and supports a more explicit understanding of each variable, including rural–urban income inequality, financial development, digital technology development, economic development, urbanization, and trade openness. This study employs four panel unit root tests, which are the Levin-Lin-Chu (LLC) test, the Im, Pesaran and Shin (IPS) test, the ADF-Fisher Chi-square, and PP-Fisher Chi-square tests. These tests are performed under both constant and constant-with-trend specifications, each of which is based on different assumptions and has its own limitations.

Table 4.2.1 shows the results of the panel unit root tests for the logarithmic levels of the variables, which include lnRUII, lnFD, lnDTD, lnED, lnURB, and lnTO. However, Table 4.2.2 presents the results for the first-differenced form of the logged variables. Since it stabilizes the variance and normalizes the distribution of the data, all variables are transformed into natural logarithms to enhance consistency and comparability across the dataset.

The results in Table 4.2.1 indicate that only the Digital Technology Development variable is stationary, as it does not contain a unit root in level form. In addition, the PP test rejects the null hypothesis for the Financial Development variable at the 1% and 5% significance levels under both constant and constant-with-trend specifications, respectively, which the variable is considered stationary. Moreover, the control variable, Urbanization, is found to be stationary under the constant (intercept) specification. The remaining variables are non-stationary.

Economic Development, and Trade Openness become stationary across all panel unit root tests at the 1% significance level under both intercept and intercept-with-trend models. The Rural-Urban Income Inequality variable is also stationary at the 1% significance level, except under the LLC test. In contrast, the Digital Technology Development variable is found to be stationary at the 1% significance level across all panel unit root tests under the constant specification. However, the Urbanization variable remains non-stationary at first difference under the LLC, IPS, and ADF tests with constant specification.

The stationary results indicate that all variables are either integrated of order I(0), or I(1). This is an important requirement for long-run regression analysis, particularly for the Panel ARDL approach, as it permits the use of a mixture of I(0) and I(1) variables. So, the variables can be included in both levels and first difference forms, to make sure the validity and reliability of the estimated long-run and short-run relationships.

4.3 Cointegration test

Table 4.3.1:

Pedroni cointegration test

Test Type	**Statistic**	
	Individual Intercept	**Individual Intercept and Individual Trend**
Panel PP-Statistic	-1.1797	-0.9162
Panel ADF-Statistic	-0.7953	-0.8925
Group PP-Statistic	-0.2889	-0.4474

Group ADF-Statistic	-0.4167	-0.4328

Notes: *indicates significance at 10% level, ** indicates significance at 5% level, *** indicates significance at 1% level. Author's own table

Table 4.3.1 reports the results of the Pedroni residual cointegration test used to examine the long-run relationship among the variables. The findings show that both panel and group statistics, including PP-statistic and ADF-statistic, are insignificant at the 10% significance level. Since the p-values are greater than the significance level under both individual intercept and the individual intercept with trend specifications, the null hypothesis cannot be rejected. This suggests that no cointegration exists among the variables, implying the absence of a long-run relationship based on the Pedroni test.

Table 4.3.2:

Kao cointegration test

Test Type	**Individual Intercept**
ADF	-2.2460**

Notes: *indicates significance at 10% level, ** indicates significance at 5% level, *** indicates significance at 1% level. Author's own table

Table 4.3.2 reports that the Kao residual cointegration test shows significant ADF statistics at the 5% level of significance. The null hypothesis of no cointegration is rejected since the P-Value is less than the significance level under the individual intercept. So, there is cointegration among the variables, suggesting the existence of a long-run relationship among the variables for the Kao cointegration test.

In summary, the Pedroni cointegration test does not reject the null hypothesis of no cointegration, suggesting the absence of a long-run relationship. However, the Kao test shows statistically significant results, suggesting the presence of cointegration. The conflicting findings may be due to differences in model assumptions, particularly regarding cross-sectional heterogeneity. Therefore, the Panel ARDL model is estimated, and the significance of the error correction term (ECT) is used as further evidence of a long-run relationship among the variables.

4.4 Panel ARDL

Table 4.4.1:

Panel ARDL, long run equation, dependent lags: 2, dynamic regressors:3 lags

Variable	Coefficient	Std. Error	Test statistic	P-value
ln FD	-0.734480***	0.088962	-8.256077	0.0000
ln DTD	0.091010***	0.012340	7.374890	0.0000
ln ED	0.293476***	0.013591	21.59388	0.0000
ln URB	-6.633513***	0.303997	-21.82102	0.0000
ln TO	0.306439***	0.052723	5.812231	0.0000

Notes: *indicates significance at 10% (0.1) level, ** indicates significance at 5% (0.05) level, *** indicates significance at 1% (0.01) level. Author's own graph

Table 4.4.1 presents the long-run estimation results. It indicates that all explanatory variables are statistically significant, as their probability values are close to zero, which rejects the null hypothesis. This result indicates a stable long-run relationship between rural-urban income inequality (RUII) and the explanatory variables. In this study, RUII is measured as the ratio of agriculture value-added per worker to industrial value-added per worker. Hence, a higher RUII indicates a narrowing rural-urban income gap, while a lower RUII reflects a wider gap. Financial Development (FD) and Urbanization (URB) show a negative relationship with RUII, suggesting that improvements in financial development and urbanization will decrease the value of RUII, which widens the income inequality in the long run. Specifically, as 1% increase in FD will reduce the value of RUII by 0.7345%, ceteris paribus. In contrast, Digital Technology Development (DTD), Economic Development (ED), and Trade Openness (TO) have a positive relationship with RUII, when these factors increase may contribute to reducing the income disparities over time.

Table 4.4.2:

Panel ARDL-ECM, short run equation, dependent lags:2, dynamic regressor: 3 lags

Variable	Coefficient	Std. Error	Test statistic	P-value
ECT_{t-1}	-0.828881*	0.458562	-1.807568	0.0782
D(ln RUII(-1))	0.455769*	0.265779	1.714841	0.0941
D(ln FD)	-0.188827	0.502766	-0.375577	0.7092
D(ln FD(-1))	-0.639886	0.654234	-0.978069	0.3339
D(ln FD(-2))	-0.281832	0.576883	-0.488543	0.6278
D(ln DTD)	-0.001569	0.052129	-0.030107	0.9761
D(ln DTD(-1))	0.002424	0.047833	0.050667	0.9598
D(ln DTD(-2))	-0.066685	0.128048	-0.520778	0.6054
D(ln ED)	-0.250535	0.184079	-1.361023	0.1811
D(ln ED(-1))	-0.181317**	0.067531	-2.684952	0.0105
D(ln ED(-2))	-0.076185	0.175622	-0.433803	0.6668
D(ln URB)	-18.38396	29.66698	-0.619678	0.5390
D(ln URB(-1))	23.55194	51.12863	0.460641	0.6476
D(ln URB(-2))	-38.70397	60.66921	-0.637951	0.5271
D(ln TO)	-0.062123	0.164698	-0.377192	0.7080
D(ln TO(-1))	-0.013244	0.103786	-0.127613	0.8991

D(ln TO(-2))	-0.131138**	0.052698	-2.488455	0.0171
C	23.34423*	12.81758	1.821267	0.0761

Notes: *indicates significance at 10% level, ** indicates significance at 5% level, *** indicates significance at 1% level. Author's own graph

Table 4.4.2 reports the short-run dynamics derived from the Error Correlation Model (ECM). The error correction term (ECT) is negative (-0.8289) and significant at the 10% level (p=0.0782), providing evidence of a long-run equilibrium relationship among the variables. The coefficient implies that approximately 82.95% of the short-run disequilibrium is corrected in each period, indicating a relatively fast adjustment towards the long-run equilibrium. In the short run, most explanatory variables are statistically insignificant, suggesting these variables do not have a significant impact on rural-urban income inequality (RUII) in the short-run period. However, the significant ECT indicates that deviations from the long-run equilibrium are gradually corrected over time, thereby supporting the long-run results reported in Table 4.4.1. ED is significant at the first lag (ln ED(-1)) at the 5% significant level. Since a higher RUII indicates a narrower income gap, the negative coefficient of (ln ED(-1)) implies that a 1% increase in ED in the previous period will widen the rural-urban income gap in the short run. Similarly, TO also exhibits a negative relationship at the second lag (ln TO(-2)) at 5% significance level. The negative coefficient indicates that 1% increase in TO may reduce 0.1311% in the value of RUII, which will widen the income gap in the short run. The lagged dependent variable, ln(RUII)(-1), is marginally significant at the 10% level (p = 0.0941), suggesting some persistence in income inequality over time.

4.5 Results and Findings

Table 4.5:

Comparisons between the Expected Relationship and Findings

Main Variables	Expected relationship between independent variables	Research Findings
Financial Development	Significant (Negative)	Significant (Negative)
Digital Technology Development	Significant (Positive)	Significant (Positive)

Control Variables	Expected relationship between independent variables	Research Findings
Economic Development	Significant (Positive)	Significant (Positive)
Urbanization	Significant (Positive)	Significant (Negative)
Trade Openness	Significant (Positive)	Significant (Positive)

Note. Author's own table

Since this study employed rural-urban income inequality, the rural sector is represented by agricultural value-added per worker, while the urban sector is represented by industrial value-added per worker, which used the ratio of agricultural value-added per worker to industrial value-added per worker as a proxy. Meant that if there is an increase in the value of RUII, there is a narrowing in rural-urban income inequality. In contrast, if there is a decrease in the value of RUII, it means there is a widening in rural-urban income inequality.

Table 4.4 presents a comparison between the expected relationship and research findings. FD has a negative relationship with expected and research findings. This suggests that higher FD is associated with a larger rural-urban income inequality. In the case of digital technology development, a significant positive relationship was expected and is supported by the results. Improvements in digital technology development contribute to reducing the rural–urban income disparity.

Other than that, for control variables, economic development shows a significant positive relationship in both expected and research findings, which suggests that ED narrows the rural-urban income inequality. Urbanization was expected to narrow the rural-urban income gap. However, the results suggest that it contributes to a widening of the gap. This outcome can be explained by the concentration of economic activities and resources in urban areas, which reinforces regional development. (Henderson, 2003). Additionally, according to the Harris–Todaro Model, migration is driven by expected income differences between rural and urban areas. Although many individuals migrate in search of better opportunities, only a portion secure high-paying jobs, while others remain unemployed or work in low-wage informal sectors. As a result, this situation widens the income disparity between rural and urban areas. (Harris & Todaro, 1970). Lastly, trade openness shows a significantly positive relationship, as expected. Trade openness tends to narrow the rural-urban income gap, which matches the research findings by Winter (2004) and Dollar & Kraay (2004).

CHAPTER 5: DISCUSSION, CONCLUSION, AND IMPLICATIONS

5.0 Major Findings of the Study

This study finds a significant negative relationship between financial development and rural–urban income inequality, implying that higher financial development is associated with a wider income gap between rural and urban areas. This may be attributed to the unequal distribution of financial resources, where financial institutions tend to lend to lower-risk borrowers, such as urban residents or high-income households, rather than rural households. In addition, financial institutions are more developed in urban areas than in rural areas, which supports the inequality-widening hypothesis (Wang et al., 2023; Zhang et al., 2025).

In contrast, digital technology development shows a significant positive relationship with RUII, suggesting that an increase in digital technology development helps to narrow the rural–urban income gap. The expansion of digital technologies in rural areas improves access to information and job opportunities and boosts income diversification, thereby reducing rural–urban income inequality (Zhang & Li, 2024).

Overall, the findings highlight the different roles of financial development and digital technology development in shaping rural–urban income inequality.

5.1 Implications of the Study

Despite decades of policy interventions across Asia, rural–urban income inequality remains persistent. This suggests that existing policies may be insufficient without a deeper understanding of how financial development and digital technology interact with underlying structural and institutional factors. So, filling this gap is important for creating more effective, suited policies that support inclusive growth in the Asia-Pacific region.

Based on the findings in the previous chapter, financial development is found to have a significant negative relationship with rural-urban income inequality across the five Asian countries, indicating that higher financial development is associated with a widening income gap between rural and urban areas. This is because financial institutions generally prefer to lend to low-risk borrowers, such as urban residents or individuals with higher incomes, rather than to those in rural areas. Moreover, financial services are more advanced and accessible in urban regions compared to rural areas. Therefore, governments should implement policies that improve rural access to financial services, such as expanding microfinance institutions, digital banking, and other services targeted at rural households and small-scale farmers. This would help ensure the financial development benefits both rural and urban populations equally and may reduce the rural-urban income inequality.

Furthermore, the results indicate a significant relationship between digital technology development and rural–urban income inequality, suggesting that higher levels of digital technology development are associated with a reduction in the income gap between rural and urban areas. When rural areas gain access to digital tools such as internet connectivity, mobile applications, and e-learning platforms, they are able to improve access to information and employment opportunities. This enables rural individuals to explore multiple sources of income, thereby promoting income diversification. So, policymakers should treat digital technology not just as a tool for economic growth, but as a strategy to reduce countries' income disparities by empowering rural areas individually. They can expand rural digital infrastructure, such as investing in high-speed internet, mobile networks, and affordable digital devices for rural communities.

Last but not least, the control variable includes economic development, urbanization, and trade openness, which all show a significant to rural-urban income inequality, indicating that macroeconomic factors play an important role in income distribution. The positive effect of economic development, which narrows rural-urban income inequality. Suggest that policymakers should promote sustainable and inclusive growth to ensure a balance of rural and urban income inequality. However, the study finds that urbanization widens rural-urban income inequality, implying that the government can reduce the concentration of resources in urban areas and create more job opportunities in rural areas. Furthermore, the significance of trade openness and the narrowing of rural-urban income inequality indicate that policymakers should continue to support international trade while ensuring that rural sectors benefit through improved market access and export opportunities.

5.2 Limitations of the Study

This research on rural-urban income inequality is subject to several limitations. Firstly, this study adopts a macro-level approach using country-level data, which focuses on overall trends but may not capture micro-level variations within countries. Differences across regions, households, and individuals are not considered, which may limit a deeper understanding of rural-urban income inequality.

Secondly, this study adopts a static framework that focuses on the average relationship between each variable over the sample period. As a result, it may not fully capture the dynamic changes in the relationship between financial development, digital technology development, and rural-urban income inequality over time. In particular, potential dynamic changes arising from economic shocks, policy shifts, or technological transitions are not explicitly examined.

5.3 Recommendations for Future Research

Future research can adopt a micro-level approach by using household or individual-level data to better capture variations in income distribution between rural and urban areas. Additionally, future studies may incorporate regional or state-level data to examine spatial disparities within countries, which provide deeper insights. The use of more advanced methodologies and higher-frequency data is also recommended to improve the robustness of the results.

Furthermore, future studies may consider using dynamic models, such as Generalized Method of Moments (GMM) approach or time-varying techniques, to better capture changes in relationships over time. Moreover, incorporating structural break analysis and higher-frequency data can help examine the impact of economic shocks, policy changes, and technological transitions on rural-urban income inequality.

References

Alimi, R. S. (2014). ARDL Bounds Testing Approach to cointegration: A Re-examination of Augmented Fisher Hypothesis in an open economy. Asian Journal of Economic Modelling. 2(2), 103-114. DOI: 10.18488/journal.8.2014.22.103.114

Ang, J.B., 2010. Finance and inequality: the case of India. South. Econ. J. 76 (3), 738–761. https://doi.org/10.4284/sej.2010.76.3.738.

Baltagi, B. H. (2008). Econometrics Analysis of Panel Data (4th ed). Wiley. https://doi.org/10.1007/978-3-030-53953-5

Bang, J., & Choi, I. (2011). South Korea. In *Advances in electronic commerce (AEC) book series/Advances in electronic commerce series* (pp. 197–219). https://doi.org/10.4018/978-1-59140-315-9.ch011

Bank of Japan. (2020). *Financial System Report*. Reports & Research Papers. https://www.boj.or.jp/en/research/brp/fsr/data/fsr201022a.pdf

Barro, R. J. (2000). Inequality and Growth in a Panel of Countries. *Journal of Economic Growth*, *5*(1), 5–32. http://www.jstor.org/stable/40216021

Beck, T., Demirgüç-Kunt, A., & Levine, R. (2007). Finance and income inequality: What do the data tell us? Southern Economic Journal, 72(3), 578-596. https://doi.org/10.1007/s1088700790106?urlappend=%3Futm_source%3Dresearchgate.net%26utm_medium%3Darticle

Bhandari, M. P. (2024). What is next for the sustainable development goals, what are the challenges concerning SDG 10—reduced inequalities? *Sustainable Earth Reviews*, *7*(1). https://doi.org/10.1186/s42055-024-00093-8

Bittencourt, Manoel F. (2006). Financial Development and Inequality: Brazil 1985-1999. http://dx.doi.org/10.2139/ssrn.957250

Breitung, J., & Pesaran, M. H. (2008). Unit roots and cointegration in panels. *Econometric Theory*, 24(2), 249–280. https://www.ifo.de/DocDL/cesifo1_wp1565.pdf

Burgess, R., & Pande, R. (2005). Do rural banks matter? Evidence from the Indian social banking experiment. American Economic Review, 95(3), 780–795. https://doi.org/10.1257/0002828054201242

Chakraborty, A., Inoue, H., Fujiwara, Y. (2020) Economic complexity of prefectures in Japan. https://doi.org/10.48550/arXiv.2002.05785

Clarke, G. R. G., Xu, L. C., & Zou, H. F. (2006). Finance and income inequality: What do the data tell us? Southern Economic Journal, 72(3), 578-596. https://doi.org/10.2307/20111834

Comin, D. & Hobijin, B. (2010). An Exploration of Technology Diffusion. American Review.100(5). pp 2031-2059. https://www.jstor.org/stable/4103875

Deininger, K. & Squire, L. (1998). New ways of looking at old issues: inequality and growth. Journal of Development Economics. 57(2). 259-287. https://doi.org/10.1016/S0304-3878(98)00099-6

Demirgüç-Kunt, A., Levine, R., 2009. Finance and inequality: Theory and evidence. Annu. Rev. Finance Economics. 1 (1), 287–318. https://doi.org/10.1146/annurev.financial.050808.114334.

Deng, X., Guo, M., & Liu, Y. (2023). Digital economy development and the urban-rural income gap: Evidence from Chinese cities. *PLoS ONE*, *18*(2), e0280225. https://doi.org/10.1371/journal.pone.0280225

Department of Statistics Malaysia. (2023). *Household Income Survey Report 2022*. Putrajaya: DOSM. https://storage.dosm.gov.my/technotes/hies_income.pdf

Digital divides. (2021). OECD. https://www.oecd.org/en/topics/digital-divides.html

DiMaggio, P., & Hargittai, E. (2001). From the “digital divide” to “digital inequality”: Studying internet use as penetration increases. Princeton Center for Arts and Cultural Policy Studies.

Dollar, D. and Kraay, A,. (2002). 'Growth is Good for the Poor', Development Research Group, World Bank, Washington D.C.

Dollar, D., & Kraay, A. (2004). Trade, growth, and poverty. *The Economic Journal*, *114*(493), F22–F49. https://doi.org/10.1111/j.0013-0133.2004.00186.x

Dutta, P., Murgai, R., Ravallion, M., & van de Walle, D. (2014). *Right to work? Assessing India's employment guarantee scheme in Bihar.* World Bank Economic Review, 28(3), 413–445.

Engle, R. F., & Granger, C. W. J. (1987). Co-Integration and error correction: representation, estimation, and testing. *Econometrica*, *55*(2), 251. https://doi.org/10.2307/1913236

Frank, M., Jadick, M.J., Minnick, C., Williams, R. (n.d.). *DoD, Anthrax, and the Internet.* The University of Oklahoma. https://www.ou.edu/deptcomm/dodjcc/groups/99A2/theories.htm

Garidzirai, R. & Muzindutsi, P.F. (2020). A Panel ARDL Analysis of the Productivity of Key Economic Sectors Contributing to Local Economic Growth in an Emerging Country. STUDIA UNIVERSITATIS BABEȘ-BOLYAI OECONOMICA. 65(1). 39-53. DOI: 10.2478/subboec-2020-0003

Goldberg, P. K., & Pavcnik, N. (2007). Distributional effects of globalization in developing countries. *Journal of Economic Literature*, *45*(1), 39–82. https://doi.org/10.1257/jel.45.1.39

Gollin, D., Lagakos, D. & Waugh, M. E. (2013). The agricultural Productivity Gap. National Bureau of Economic Research.https://doi.org/10.1093/qje/qjt056

Greenwood, J., & Jovanovic, B. (1990). *Financial development, growth, and the distribution of income*. Journal of Political Economy, 98(5), 1076–1107。

Halton, C. (2025). *Diffusion of Innovations Theory: Definition and Examples*. Investopedia. https://www.investopedia.com/terms/d/diffusion-of-innovations-theory.asp

Hao, Y., Wei, Y., Sui, X., & Huang, Z. (2012). Trade and rural–urban income inequality: Evidence from China. https://doi.org/10.3868/s060-001-012-0024-4

Harris. J.R. & Todaro, M.P. (1970). *Migration, unemployment and development: A two-sector analysis.* The American Economic Review, 60(1), 126-142. https://doi.org/10.1016/0165-1765(84)90160-5

Haug, A.A., (2002). Temporal aggregation and the power of cointegration tests: A monte carlo study. Xford Bulletin of Economics and Statistics, 64(4): 399-412

Heckscher, E.F. & Ohlin, B. (1991). *Heckscher-Ohlin Trade Theory,* MIT Press.

Helpman, E., Itskhoki, O., Muendler, M., & Redding, S. J. (2016). Trade and Inequality: From Theory to Estimation. *The Review of Economic Studies*, *84*(1), 357–405. https://doi.org/10.1093/restud/rdw025

Henderson, J.V. (2003). *The urbanization process and economic growth: The so-what question.* Journal of Economic Growth, 8(1), 47-71. https://doi.org/10.1023/A:1022860800744

Hilbert, M. (2016). The bad news is that the digital access divide is here to stay: Domestically installed bandwidths among 172 countries for 1986–2014. *Telecommunications Policy, 40*(6), 567–581.

Im, K. S., Pesaran, M. H., & Shin, Y. (2003). Testing for unit roots in heterogeneous panels. *Journal of Econometrics*, 115(1), 53–74. https://doi.org/10.1016/s0304-4076(03)00092-7

Imai, S.K. & Malaeb, B., (2018). IFAD RESEARCH SERIES 27 - Asia’s rural-urban disparity in the context of growing inequality. IFAD Research Series 280076, International Fund for Agricultural Development (IFAD). DOI: 10.22004/ag.econ.280076

İşcan, T. B., & Lim, K. M. (2021). Structural transformation and inequality: The case of South Korea. *Economic Modelling*, *107*, 105735. https://doi.org/10.1016/j.econmod.2021.105735

JARQUE, Carlos M. and BERA, Anil K. (1980) *Efficient Tests for Normality, Homoscedasticity and Serial Independence of Regression Residuals*. Economics Letters 6, 255-259. https://doi.org/10.1016/0165-1765(80)90024-5

Jiang, T., & Han, J. (2023). The effect of industrial structure adjustment and economic development quality on transitional China’s urban–rural income inequity. *Frontiers in Environmental Science*, *11*. https://doi.org/10.3389/fenvs.2023.1084605

Kao, C. (1999). *Spurious regression and residual-based tests for cointegration in panel data.* Journal of Econometrics. 90(1). 1-44. https://doi.org/10.1016/S0304-4076(98)00023-2

Kappel, Vivien, The Effects of Financial Development on Income Inequality and Poverty (2010). CER-ETH - Center of Economic Research at ETH Zurich, Working Paper No. 10/127. http://dx.doi.org/10.2139/ssrn.1585148

Katsiaryna Svirydzenka. 2016. Introducing a New Broad-based Index of Financial Development. *International Monetary Fund*. 2016(005). 43. https://doi.org/10.5089/9781513583709.001

Kerner, S. M. (2024). *Diffusion of innovations theory: Definition and examples*. WhatIs. https://www.techtarget.com/whatis/feature/Diffusion-of-innovations-theory-Definition-and-examples

Kitagawa, F. (2024). Lessons from the Japanese 'regional revitalisation' – impacts of regional industrial policies through decentralisation. *Contemporary Social Science*, 1–20. https://doi.org/10.1080/21582041.2024.2433018

Kocsis, D., & Xiong, J. (2022). A divide quantified—exploring the relationship between ICT infrastructure diffusion and income inequality. *Journal of Electronic Business & Digital Economics*, *1*(1/2), 34–49. https://doi.org/10.1108/jebde-09-2022-0033

Koh S. G. M., Lee, G. H. Y., & Siah, A. K. L. (2022). The Resurgence of Income Inequality in Asia-Pacific: The Role of Trade Openness, Educational Attainment and Institutional Quality. Jurnal Ekonomi Malaysia 56(3), 12-22. http://dx.doi.org/10.17576/JEM-2022-5603-01

Kuznets, S. (1955) Economic Growth and Income Inequality. The American Economic Review, 45, 1-28.

Lamberti, G., Lopez-Sintas, J., & Sukphan, J. (2020). The social process of internet appropriation: Living in a digitally advanced country benefits less well-educated Europeans. *Telecommunications Policy*, *45*(1), 102055. https://doi.org/10.1016/j.telpol.2020.102055

Law, S. H., & Tan, H. B. (2009). The role of financial development on income inequality in Malaysia. *Journal of Economic Development*, *34*(2), 153.

Levin, A., Lin, C., & Chu, C. J. (2002). Unit root tests in panel data: asymptotic and finite-sample properties. *Journal of Econometrics*, *108*(1), 1–24. https://doi.org/10.1016/s0304-4076(01)00098-7

Lewis, W. A. (1954). *Economic development with unlimited supplies of labour*. The Manchester School, 22(2), 139–191.

Li, H., Li, Q., Xu, Z., & Ye, X. (2024). Digital Technologies. *Journal of Digital Economy*, *3*, 240–248. https://doi.org/10.1016/j.jdec.2025.02.001

Li, S., & Sicular, T. (2014). The distribution of household income in China: inequality, poverty and policies. *The China Quarterly*, *217*, 1–41. https://doi.org/10.1017/s0305741014000290

Li, X., He, P., Liao, H., Liu, J., & Chen, L. (2024). Does network infrastructure construction reduce urban–rural income inequality? Based on the “Broadband China” policy. *Technological Forecasting and Social Change*, *205*, 123486. https://doi.org/10.1016/j.techfore.2024.123486

Liang, K., & Liu, W. (2026). Digital Infrastructure and Urban-Rural Income Gap: Empirical Evidence from China. *International Review of Economics & Finance*, 105003. https://doi.org/10.1016/j.iref.2026.105003

Liang, S. (2023). International trade and urban-rural income inequality in China. *Applied Economics Letters*,*31*(13), 1243–1246. https://doi.org/10.1080/13504851.2023.2178622

Liang, Z. (2006). Financial Development and Income Distribution: A system GMM Panel Analysis with Application to Urban China. *Journal of Economic.* 31(2). 1-21.

Liao, R., Wei, Y., Bai, Y., & Liu, J. (2025). Bridging the divide: how agricultural technological innovation narrows the urban–rural income gap in China. *Frontiers in Sustainable Food Systems*, *9*. https://doi.org/10.3389/fsufs.2025.1595161

Liu, J., Puah, C.-H., Arip, M. A., & Jong, M.-C. (2023). Impacts of Digital Financial Inclusion on Urban–Rural Income Disparity: A Comparative Research of the Eastern and Western Regions in China. Economies, 11(11), 282. https://doi.org/10.3390/economies11110282

Liu, S., Tang, X., & Zhao, Y. (2024). Global value chain participation, employment structure, and Urban–Rural income gap in the context of sustainable development. *Sustainability*, *16*(5), 1931. https://doi.org/10.3390/su16051931

Lugtu, R. (2023). *The State of Digital Transformation in Asia | Institute for Digital Transformation*. https://www.institutefordigitaltransformation.org/the-state-of-digital transformation-in-asia/

Maddala, G. S., & Wu, S. (1999). A comparative study of unit root tests with panel data and a new simple test. *Oxford Bulletin of Economics and Statistics*, 61(S1), 631–652. https://doi.org/10.1111/1468-0084.0610s1631

Mbona, Nokulunga. (2022). Impacts of Overall Financial Development, Access and Depth on Income Inequality. Economies 10: 118. https://doi.org/10.3390/economies10050118

Menegaki, A. N. (2019). The ARDL method in the energy-growth nexus field; Best Implementation strategies. Economies, 7(4), 105. DOI: 10.3390/economies7040105

Mestiri, S. (2025). Modeling the Unemployment Rate using the Panel ARDL. Journal of Smart Economic Growth. 10(1). https://orcid.org/0000-0002-2060-3242

Mwansa, G., Ngandu, M.R. & Mkwambi, Z. (2025). Bridging the digital divide: exploring the challenges and solutions for digital exclusion in rural South Africa. *Discov glob soc* **3**, 54. https://doi.org/10.1007/s44282-025-00189-2

Nguyen Minh, H., Nguyen Dang, L., & Pham, T. K. (2019). Impact of Urbanization on Income Inequality: A Study in Vietnam. Journal of Risk Financial Management, 12, 1-14. https://doi.org/10.3390/jrfm12030146

Oloyede, A. A., Faruk, N., Noma, N., Tebepah, E., & Nwaulune, A. K. (2023). Measuring the impact of the digital economy in developing countries: A systematic review and meta- analysis. *Heliyon*, *9*(7), e17654. https://doi.org/10.1016/j.heliyon.2023.e17654

Omar, M.A., Inaba, K. (2020). Does financial inclusion reduce poverty and income inequality in developing countries? A panel data analysis. *Economic Structures* 9, 37 https://doi.org/10.1186/s40008-020-00214-4

Ozili, P. K. (2018). Impact of digital finance on financial inclusion and stability. *Borsa Istanbul Review*, *18*(4), 329–340. https://doi.org/10.1016/j.bir.2017.12.00

Pedroni, P. (2004). Panel Cointegration: Asymptotic and Finite Sample Properties of Pooled Time Series Tests with an Application to the PPP Hypothesis. *Econometric Theory.* 20. 597-625. DOI: 10.1017/S0266466604203073

Peng, Z., & Dan, T. (2023). Digital dividend or digital divide? Digital economy and urban-rural income inequality in China. *Telecommunications Policy*, *47*(9), 102616. https://doi.org/10.1016/j.telpol.2023.102616

Perez-Silva, R., & Krivonos, E. (2021). The effects of trade openness on rural-urban sectoral employment, wages, and earnings: Evidence from Peru's second wave of trade liberalization. *Journal of International Trade & Economic Development*, *30*(8), 1138–1167. https://doi.org/10.1080/09638199.2021.1936134

Perugini, C., Tekin, ˙I., 2022. Financial development, income inequality and governance institutions. Panoeconomicus 69 (3), 353–379. https://doi.org/10.2298/PAN191022004P.

Pesaran, M. H. and Shin, Y. (1999). An Autoregressive Distributed Lag Modelling Approach to Cointegration Analysis. In S. Storm (Ed.), Econometrics and Economic Theory in the 20th Century: The Ragnar Frisch Centennial Symposium, Cambridge University Press, Cambridge, Chapter 11, pp. 371–413

Pesaran, M. H., Shin, Y., & Smith, R. P. (1999). Pooled mean group estimation of dynamic heterogeneous panels. *Journal of the American Statistical Association*, *94*(446), 621–634. https://doi.org/10.1080/01621459.1999.10474156

Pesaran, M.H., Y. Shin and R.J. Smith, (2001). Bounds testing approaches to the analysis of level relationships. Journal of Applied Econometrics, 16(3): 289-326.

Ravallion, M. (2001). *Growth, Inequality and Poverty: Looking Beyond Averages*. World Development. 29(11). 1803-1815. https://doi.org/10.1016/S0305-750X(01)00072-9

Reddick, C., Enriquez, R., Harris, R., & Flores, J. (2024). Understanding the levels of digital inequality within the city: An analysis of a survey. *Cities*, *148*, 104844. https://doi.org/10.1016/j.cities.2024.104844

Salemink, K., Strijker, D., & Bosworth, G. (2017). Rural development in the digital age: A systematic literature review on unequal ICT availability. *Journal of Rural Studies*, 54, 360–371.

Schipke, A., Turunen, J., Choueiri, N. & Marie, A. G. W. (2023). *India's financial system*. Building the Foundation for Strong and Sustainable Growth.

International Monetary Fund. https://doi.org/10.5089/9798400223525.071

Sehrawat, M., Giri, A.K., 2015. Financial development and income inequality in India: an application of ARDL approach. Int. J. Soc. Econ. 42, 64–81. https://doi.org/10.1108/IJSE-09-2013-0208.

Seven, U., & Coskun, T. (2016). Does financial development reduce income inequality and poverty? Evidence from emerging countries. Emerging Markets Review, 26, 34-63. https://doi.org/10.1016/j.ememar.2016.02.002

Shabsigh, G. (2013). *Republic of Korea Financial System Stability Assessment*. International Monetary Fund. https://www.imf.org/external/pubs/ft/scr/2014/cr14126.pdf

Shahbaz, M. & Islam, F. (2011). Financial Development and Income Inequality in Pakistan: An Application of ARDL Approach. *Journal of Economic Development.* 36(1). 35-58. DOI : 10.35866/caujed.2011.36.1.003

Shen, C., Wu, X., Shi, L., Wan, Y., Hao, Z., Ding, J., & Wen, Q. (2025). How does the digital economy affect the urban–rural income gap? Evidence from Chinese cities. *Habitat International*, *157*, 103327. https://doi.org/10.1016/j.habitatint.2025.103327

Shen, T., Chen, Y., & Ruan, H. (2025). Moderating role of regional financial development in the relationship between digital infrastructure and Urban–Rural income gap. *Finance Research Letters*, *81*, 107484. https://doi.org/10.1016/j.frl.2025.107484

Shuai, Y., Li, W. & Huang, F. The impact of internet use on the well-being of rural residents: evidence from formerly impoverished areas in China. *Humanit Soc Sci Commun* **12**, 1500 (2025). https://doi.org/10.1057/s41599-025-05737-4

Singh, S. (2010). Digital divide in India. *International Journal of Innovation in the Digital Economy*, *1*(2), 1–24. https://doi.org/10.4018/jide.2010040101

STATISTICAL COMMUNIQUÉ OF THE PEOPLE'S REPUBLIC OF CHINA ON THE 2023 NATIONAL ECONOMIC AND SOCIAL DEVELOPMENT. (2024). National Bureau of Statistics of China. https://www.stats.gov.cn/english/PressRelease/202402/t20240228_1947918.html

Stolper, W.F. & Samuelson, P.A. (1941). *Protection and Real Wages.* Review of Economic Studies, 9(1), 58-73.

Stiglitz, J. (2009). The global crisis, social protection and jobs. *International Labour review.* 148(1-2). 1-13. https://doi.org/10.1111/j.1564- 913X.2009.00046.x

Stiglitz, J. E., & Weiss, A. (1981). Credit Rationing in Markets with Imperfect Information. *The American Economic Review*, *71*(3), 393–410. http://www.jstor.org/stable/1802787

Su, Y., & Ren, R. (2025). Can the Development of Rural E-Commerce Narrow the Urban-Rural Income Gap? Evidence from a Quasi-Natural Experiment in National Comprehensive Demonstration Counties for E-Commerce in Rural Areas. *Finance Research Letters*, 108216. https://doi.org/10.1016/j.frl.2025.108216

Sun, X., & Kuang, X. (2023). Will advances in digital technology reduce the rural-urban income gap? *Economic Research-Ekonomska Istraživanja*, *36*(3). https://doi.org/10.1080/1331677x.2023.2194954

Sunada, M., Noguchi, M., Ohashi, H., & Okada, Y. (2011). Coverage area expansion, customer switching, and household profiles in the Japanese broadband access market. *Information Economics and Policy*, 23(1), 12–23. https://doi.org/10.1016/j.infoecopol.2010.02.004

Tahmasebi, F. (2023). The Digital Divide: A Qualitative study of technology access in Rural communities. *AI And Tech in Behavioral and Social Sciences*, *1*(2), 33–39. https://doi.org/10.61838/kman.aitech.1.2.6

Teo, L., Cowen, D., Shah, H., Salgado, R., & Zanello, A. (2006). Financial integration in Asia: recent developments and next steps. *IMF Working Paper*, *06*(196), 1. https://doi.org/10.5089/9781451864564.001

Tey, N. P., Lai, S. L., Ng, S. T., Goh, K. L., & Osman, A. F. (2019). INCOME INEQUALITY ACROSS STATES IN MALAYSIA. *PLANNING MALAYSIA*, *17*. https://doi.org/10.21837/pm.v17i10.625

Tiwari, Kumar, A. & Muhammad, S. (2010). Does financial development increase rural-urban income inequality? Cointegration analysis in the case of Indian economy. Munich Personal RePEc Archive. https://mpra.ub.uni-muenchen.de/27093/

Van Dijk, J. A. (2006). Digital divide research, achievements and shortcomings.

Poetics, *34*(4–5), 221–235. https://doi.org/10.1016/j.poetic.2006.05.004

Vo, D. H., Pham, A. T., Tran, Q., & Vu, N. T. (2023). The long-run effects of financial development on income inequality: Evidence from the Asia-Pacific countries. *Heliyon*, *9*(8), e19000. https://doi.org/10.1016/j.heliyon.2023.e19000

Wan, G., Lu, M., & Chen, Z. (2007). GLOBALIZATION AND REGIONAL INCOME INEQUALITY: EMPIRICAL EVIDENCE FROM WITHIN CHINA. *Review of Income and Wealth*, *53*(1), 35–59. https://doi.org/10.1111/j.1475-4991.2007.00217.x

Wan, G., Zhang, X., & Zhao, M. (2022). Urbanization can help reduce income inequality. *Npj Urban Sustainability*, *2*(1). https://doi.org/10.1038/s42949-021-00040-y

Wang, C., Du, Y. The impact of the factor mobility on urban-rural income inequality: evidence from China. *Environ Dev Sustain* (2026). https://doi.org/10.1007/s10668-026-07455-6

Wang, L., Wu, X., & Chu, N. (2023). Financial development, technological innovation and urban-rural income gap: Time series evidence from China. *PLoS ONE*, *18*(2), e0279246. https://doi.org/10.1371/journal.pone.0279246

Wang, M., Yin, Z., Pang, S., & Li, Z. (2021). Does Internet development affect urban-rural income gap in China? An empirical investigation at provincial level. *Information Development*, *39*(1), 107–122. https://doi.org/10.1177/02666669211035484

Wang, Y., Wang, X., Zhou, H., Chen, X., & Mao, X. (2025). Industrial digitalization and Urban-Rural Income Gap: An Empirical Analysis Based on Data from 30 Provinces in China. *Economic Analysis and Policy*. https://doi.org/10.1016/j.eap.2025.08.001

Wen, C., Xiao, Y., & Hu, B. (2024). Digital financial inclusion, industrial structure and urban–Rural income disparity: Evidence from Zhejiang Province, China. *PLoS ONE*, *19*(6), e0303666. https://doi.org/10.1371/journal.pone.0303666

Wen, X., Li, Y., Zhou, M., Feng, F., & Wang, P. (2025). Rural digitization and the urban–rural income gap: a perspective of factor flow. *Frontiers in Sustainable Food Systems*, *9*. https://doi.org/10.3389/fsufs.2025.1647632

Westerlund, J. (2007). *Testing for error correction in panel data*. Oxford Bulletin of Economics and Statistics, 69(6), 709–748. https://doi.org/10.1111/j.1468-0084.2007.00477.x

Winters, L. A., McCulloch, N., & McKay, A. (2004). Trade liberalization and Poverty: The evidence so far. *Journal of Economic Literature*, *42*(1), 72–115. https://doi.org/10.1257/002205104773558056

Wooldridge, J. M. (2010). Ecometrics Analysis of Cross Section and Panel Data (2nd ed.). MIT Press. https://www.jstor.org/stable/j.ctt5hhcfr

Xia, H., Yu, H., Wang, S., & Yang, H. (2024). Digital economy and the urban–rural income gap: Impact, mechanisms, and spatial heterogeneity. *Journal of Innovation & Knowledge*, *9*(3), 100505. https://doi.org/10.1016/j.jik.2024.100505

Yan, D., Sun, W., Li, P., Liu, C., & Li, Y. (2024). Effects of economic growth target on the urban–rural income gap in China: An empirical study based on the urban bias theory. *Cities*, *156*, 105518. https://doi.org/10.1016/j.cities.2024.105518

Yang, N., Ao, X., & Tu, Y. (2024). The impact of digital financial development on rural household income mobility. *Finance Research Letters*, *63*, 105368. https://doi.org/10.1016/j.frl.2024.105368

Zal Yıldırım, Z. & Yüncü, I. S. (2025). Financial development, international financial integration, and income inequality: An emerging market perspective. *Researcher in International Business and Finance.* https://doi.org/10.1016/j.ribaf.2025.102917

Zhang, H., Chen, W., & Zhang, J. (2011). Urban–rural income disparities and development in a panel data set of China for the period from 1978 to 2006. *Applied Economics*, *44*(21), 2717–2728. https://doi.org/10.1080/00036846.2011.566197

Zhang, J., & Li, M. (2024). Digital technology access, labor market behavior, and income inequality in rural China. *Heliyon*, *10*(14), e33528. https://doi.org/10.1016/j.heliyon.2024.e33528

Zhang, L. (2021). *China's Financial Innovation: Process, Drive, and Impacts.* The Oxford Handbook of China Innovation. Pg 610-624.

Zhang, Q. & Chen, R. (2015). Financial development and income inequality in

China: An application of SVAR approach. *Information Technology and Quantitative Management.* 55. 774-781.

Zhang, W., Han, J., Işık, C., Song, J., Liu, X., Dembińska, I., & Radulesu, M. (2025). Inequality in the digital economy: The impact of artificial intelligence on income gap—an empirical analysis based on county-level data from China. *Cities*, 166, 106280. https://doi-org.libezp2.utar.edu.my/10.1016/j.cities.2025.106280

Zhang, Y., Hainan, L., Feng, F., & Wu, X. (2024). Digital Economy, education, human capital and urban–rural income disparity. *Finance Research Letters*, *71*, 106464. https://doi.org/10.1016/j.frl.2024.106464

Zhao, X., & Liu, L. (2022). The impact of urbanization level on Urban–Rural Income Gap in China based on spatial econometric model. *Sustainability*, *14*(21), 13795. https://doi.org/10.3390/su142113795

Zhong, S., Wang, M., Zhu, Y., Chen, Z., & Huang, X. (2022). Urban expansion and the urban–rural income gap: Empirical evidence from China. *Cities*, *129*, 103831. https://doi.org/10.1016/j.cities.2022.103831

Zhu, J., Li, Z., & Wang, H. (2023). Internet Development and Urban–Rural Consumption Inequality: Evidence from Chinese Cities. *Sustainability*, *15*(12), 9755. https://doi.org/10.3390/su15129755

Zou, G., Fan, B. & Yang, C. (2025). Research on the impact of public data openness on urban-rural income inequality. *Finance Research Letters.* 79. https://doi.org/10.1016/j.frl.2025.107193

Appendices

Appendix 4.1.1: Descriptive Statistics

Date: 03/27/26 Time: 15:54
Sample: 1 135

	RUII	FD	DTD	ED	URB	TO
Mean	31.29312	0.609941	40.36754	14603.57	61.96880	70.25732
Median	29.23094	0.607000	38.53210	8899.345	68.76497	47.74182
Maximum	58.22668	0.925000	96.50510	49145.28	91.78099	220.4068
Minimum	17.51908	0.342000	0.001070	347.7342	26.37102	15.81031
Std. Dev.	9.640624	0.165349	34.08914	14904.18	22.13075	55.81611
Skewness	0.877079	0.104864	0.190512	0.803616	-0.369285	1.392246
Kurtosis	2.764449	1.727010	1.486773	2.115664	1.627643	3.690955
Jarque-Bera	17.62063	9.362757	13.69708	18.92952	13.66227	46.29835
Probability	0.000149	0.009266	0.001061	0.000078	0.001080	0.000000
Sum	4224.572	82.34200	5449.619	1971481.	8365.788	9484.738
Sum Sq.	144654.2	53.88735	375705.0	5.86E+10	584047.0	1083841.
Sum Sq. Dev.	12454.18	3.663614	155717.3	2.98E+10	65629.19	417468.8
Observations	135	135	135	135	135	135

Appendix 4.1.2: Correlation Analysis

	RUII	FD	DTD	ED	URB	TO
RUII	1.000000	-0.124931	-0.051958	-0.202510	0.026684	0.725377
FD	-0.124931	1.000000	0.890003	0.826031	0.926511	0.028857
DTD	-0.051958	0.890003	1.000000	0.638231	0.761446	0.111766
ED	-0.202510	0.826031	0.638231	1.000000	0.824558	-0.266365
URB	0.026684	0.926511	0.761446	0.824558	1.000000	0.146924
TO	0.725377	0.028857	0.111766	-0.266365	0.146924	1.000000

Appendix 4.2.1: Panel Unit Root Test in Level with Intercept

Panel unit root test: Summary
Series: RUII
Date: 03/27/26 Time: 13:10
Sample: 1994 2020
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-0.45730	0.3237	5	125
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-0.40802	0.3416	5	125
ADF - Fisher Chi-square	10.3572	0.4097	5	125
PP - Fisher Chi-square	15.2526	0.1231	5	130

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: FD
Date: 03/27/26 Time: 13:19
Sample: 1994 2020
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-2.47912	0.0066	5	125
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-0.87589	0.1905	5	125
ADF - Fisher Chi-square	13.8717	0.1789	5	125
PP - Fisher Chi-square	19.9976	0.0293	5	130

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: DTD
Date: 03/27/26 Time: 13:24
Sample: 1994 2020
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-13.6216	0.0000	5	125
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-15.0614	0.0000	5	125
ADF - Fisher Chi-square	72.8795	0.0000	5	125
PP - Fisher Chi-square	122.802	0.0000	5	130

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: ED
Date: 03/27/26 Time: 13:35
Sample: 1994 2020
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-0.68563	0.2465	5	125
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	0.85283	0.8031	5	125
ADF - Fisher Chi-square	7.41487	0.6858	5	125
PP - Fisher Chi-square	6.18978	0.7991	5	130

** Probabilities for Fisher tests are computed using an asymptotic Chi
-square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: URB
Date: 03/27/26 Time: 13:39
Sample: 1994 2020
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-2.75911	0.0029	5	125
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-2.21088	0.0135	5	125
ADF - Fisher Chi-square	28.4108	0.0016	5	125
PP - Fisher Chi-square	41.4078	0.0000	5	130

** Probabilities for Fisher tests are computed using an asymptotic Chi
-square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: TO
Date: 03/27/26 Time: 13:45
Sample: 1994 2020
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-0.44662	0.3276	5	125
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	0.63330	0.7367	5	125
ADF - Fisher Chi-square	6.34243	0.7857	5	125
PP - Fisher Chi-square	7.44166	0.6832	5	130

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Appendix 4.2.1: Panel Unit Root Test in Level with Intercept and Trend

Panel unit root test: Summary
Series: RUII
Date: 03/27/26 Time: 13:11
Sample: 1994 2020
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-0.15848	0.4370	5	125
Breitung t-stat	1.50783	0.9342	5	120
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	0.18292	0.5726	5	125
ADF - Fisher Chi-square	7.49535	0.6780	5	125
PP - Fisher Chi-square	13.2666	0.2091	5	130

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: FD
Date: 03/27/26 Time: 13:20
Sample: 1994 2020
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-0.38264	0.3510	5	125
Breitung t-stat	0.10658	0.5424	5	120
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-0.62352	0.2665	5	125
ADF - Fisher Chi-square	10.6869	0.3824	5	125
PP - Fisher Chi-square	24.5851	0.0062	5	130

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: DTD
Date: 03/27/26 Time: 13:29
Sample: 1994 2020
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-15.0260	0.0000	5	125
Breitung t-stat	0.86147	0.8055	5	120
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-13.0001	0.0000	5	125
ADF - Fisher Chi-square	336.868	0.0000	5	125
PP - Fisher Chi-square	312.637	0.0000	5	130

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: ED
Date: 03/27/26 Time: 13:36
Sample: 1994 2020
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	0.22618	0.5895	5	125
Breitung t-stat	1.40409	0.9199	5	120
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-0.39874	0.3450	5	125
ADF - Fisher Chi-square	12.2518	0.2686	5	125
PP - Fisher Chi-square	5.64367	0.8443	5	130

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: URB
Date: 03/27/26 Time: 13:40
Sample: 1994 2020
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-1.26536	0.1029	5	125
Breitung t-stat	-1.29530	0.0976	5	120
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	0.35283	0.6379	5	125
ADF - Fisher Chi-square	14.6884	0.1438	5	125
PP - Fisher Chi-square	15.6888	0.1089	5	130

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: TO
Date: 03/27/26 Time: 13:46
Sample: 1994 2020
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	1.18040	0.8811	5	125
Breitung t-stat	1.49223	0.9322	5	120
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	2.30700	0.9895	5	125
ADF - Fisher Chi-square	2.95490	0.9825	5	125
PP - Fisher Chi-square	3.42499	0.9696	5	130

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Appendix 4.2.2: Panel Unit Root Test in First Difference with Intercept

Panel unit root test: Summary
Series: D(RUII)
Date: 03/27/26 Time: 13:12
Sample: 1994 2020
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-0.54064	0.2944	5	120
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-3.52912	0.0002	5	120
ADF - Fisher Chi-square	32.5110	0.0003	5	120
PP - Fisher Chi-square	71.2270	0.0000	5	125

Panel unit root test: Summary
Series: D(FD)
Date: 03/27/26 Time: 13:21
Sample: 1994 2020
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-2.64095	0.0041	5	120
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-5.09365	0.0000	5	120
ADF - Fisher Chi-square	44.8480	0.0000	5	120
PP - Fisher Chi-square	71.8562	0.0000	5	125

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(DTD)
Date: 03/27/26 Time: 13:32
Sample: 1994 2020
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-4.98796	0.0000	5	120
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-4.48241	0.0000	5	120
ADF - Fisher Chi-square	42.3843	0.0000	5	120
PP - Fisher Chi-square	46.2260	0.0000	5	125

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(ED)
Date: 03/27/26 Time: 13:37
Sample: 1994 2020
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-4.26096	0.0000	5	120
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-4.90030	0.0000	5	120
ADF - Fisher Chi-square	43.5346	0.0000	5	120
PP - Fisher Chi-square	56.1971	0.0000	5	125

** Probabilities for Fisher tests are computed using an asymptotic Chi
-square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(URB)
Date: 03/27/26 Time: 13:41
Sample: 1994 2020
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-1.18372	0.1183	5	120
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-0.18775	0.4255	5	120
ADF - Fisher Chi-square	9.50037	0.4854	5	120
PP - Fisher Chi-square	17.4023	0.0659	5	125

** Probabilities for Fisher tests are computed using an asymptotic Chi
-square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(TO)
Date: 03/27/26 Time: 13:48
Sample: 1994 2020
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-3.60634	0.0002	5	120
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-3.55043	0.0002	5	120
ADF - Fisher Chi-square	30.9123	0.0006	5	120
PP - Fisher Chi-square	61.7517	0.0000	5	125

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Table 4.2.2: Panel Unit Root Test in First Difference with Intercept and Trend

Panel unit root test: Summary
Series: D(RUII)
Date: 03/27/26 Time: 13:13
Sample: 1994 2020
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-0.19913	0.4211	5	120
Breitung t-stat	-1.92596	0.0271	5	115
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-3.22036	0.0006	5	120
ADF - Fisher Chi-square	28.1533	0.0017	5	120
PP - Fisher Chi-square	63.2032	0.0000	5	125

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(FD)
Date: 03/27/26 Time: 13:23
Sample: 1994 2020
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-2.78625	0.0027	5	120
Breitung t-stat	-1.47246	0.0704	5	115
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-4.10421	0.0000	5	120
ADF - Fisher Chi-square	34.8029	0.0001	5	120
PP - Fisher Chi-square	304.521	0.0000	5	125

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(DTD)
Date: 03/27/26 Time: 13:34
Sample: 1994 2020
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	0.66821	0.7480	5	120
Breitung t-stat	-0.33292	0.3696	5	115
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-1.66035	0.0484	5	120
ADF - Fisher Chi-square	17.9641	0.0556	5	120
PP - Fisher Chi-square	98.9185	0.0000	5	125

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(ED)
Date: 03/27/26 Time: 13:38
Sample: 1994 2020
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-3.04493	0.0012	5	120
Breitung t-stat	-3.84145	0.0001	5	115
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-3.35188	0.0004	5	120
ADF - Fisher Chi-square	29.6268	0.0010	5	120
PP - Fisher Chi-square	40.1884	0.0000	5	125

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(URB)
Date: 03/27/26 Time: 13:42
Sample: 1994 2020
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-2.86252	0.0021	5	120
Breitung t-stat	-0.75611	0.2248	5	115
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-3.34375	0.0004	5	120
ADF - Fisher Chi-square	31.9293	0.0004	5	120
PP - Fisher Chi-square	27.7805	0.0020	5	125

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(TO)
Date: 03/27/26 Time: 13:49
Sample: 1994 2020
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-3.66291	0.0001	5	120
Breitung t-stat	-3.97730	0.0000	5	115
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-3.33872	0.0004	5	120
ADF - Fisher Chi-square	28.0905	0.0017	5	120
PP - Fisher Chi-square	56.4325	0.0000	5	125

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Table 4.3.1: Pedroni (Engle-Grander Based) with individual intercept

Pedroni Residual Cointegration Test
Series: RUII FD DTD ED URB TO
Date: 04/29/26 Time: 13:39
Sample: 1994 2020
Included observations: 135
Cross-sections included: 5
Null Hypothesis: No cointegration
Trend assumption: No deterministic trend
User-specified lag length: 1
Newey-West automatic bandwidth selection and Bartlett kernel

Alternative hypothesis: common AR coefs. (within-dimension)

	Statistic	Prob.	Weighted Statistic	Prob.
Panel v-Statistic	0.182773	0.4275	0.249353	0.4015
Panel rho-Statistic	0.498124	0.6908	0.471780	0.6815
Panel PP-Statistic	-1.179744	0.1191	-1.124332	0.1304
Panel ADF-Statistic	-0.795250	0.2132	-0.956789	0.1693

Alternative hypothesis: individual AR coefs. (between-dimension)

	Statistic	Prob.
Group rho-Statistic	1.535562	0.9377
Group PP-Statistic	-0.288918	0.3863
Group ADF-Statistic	-0.416709	0.3384

Cross section specific results

Phillips-Peron results (non-parametric)

Cross ID	AR(1)	Variance	HAC	Bandwidth	Obs
1	0.546	0.654098	0.645550	3.00	26
2	0.115	1.109609	1.059156	1.00	26
3	0.222	3.427110	3.427110	0.00	26
4	0.348	4.455056	4.455056	0.00	26
5	0.436	2.061779	2.165315	2.00	26

Augmented Dickey-Fuller results (parametric)

Cross ID	AR(1)	Variance	Lag	Max lag	Obs
1	0.345	0.617688	1	--	25
2	-0.003	0.958405	1	--	25
3	0.100	2.838386	1	--	25
4	0.355	4.025295	1	--	25
5	0.167	1.769713	1	--	25

Table 4.3.1: Pedroni (Engle-Grander Based) with individual intercept and individual trend

Pedroni Residual Cointegration Test
Series: RUII FD DTD ED URB TO
Date: 04/29/26 Time: 13:43
Sample: 1994 2020
Included observations: 135
Cross-sections included: 5
Null Hypothesis: No cointegration
Trend assumption: Deterministic intercept and trend
User-specified lag length: 1
Newey-West automatic bandwidth selection and Bartlett kernel

Alternative hypothesis: common AR coefs. (within-dimension)

	Statistic	Prob.	Weighted Statistic	Prob.
Panel v-Statistic	-0.728359	0.7668	-0.758744	0.7760
Panel rho-Statistic	1.229104	0.8905	1.064526	0.8565
Panel PP-Statistic	-0.916171	0.1798	-1.210649	0.1130
Panel ADF-Statistic	-0.892449	0.1861	-0.965812	0.1671

Alternative hypothesis: individual AR coefs. (between-dimension)

	Statistic	Prob.
Group rho-Statistic	2.001885	0.9774
Group PP-Statistic	-0.447395	0.3273
Group ADF-Statistic	-0.432788	0.3326

Cross section specific results

Phillips-Peron results (non-parametric)

Cross ID	AR(1)	Variance	HAC	Bandwidth	Obs
1	0.297	0.677470	0.678715	2.00	26
2	0.060	1.055548	0.962429	2.00	26
3	0.182	3.081401	3.081401	0.00	26
4	0.335	3.808757	3.808757	0.00	26
5	0.410	2.088769	1.688006	3.00	26

Augmented Dickey-Fuller results (parametric)

Cross ID	AR(1)	Variance	Lag	Max lag	Obs
1	0.160	0.652079	1	--	25
2	-0.085	0.924113	1	--	25
3	0.058	2.516255	1	--	25
4	0.257	3.460182	1	--	25
5	0.131	1.767278	1	--	25

Table 4.3.2: Kao (Engle-Grander Based) with individual intercept

Kao Residual Cointegration Test
Series: RUII FD DTD ED URB TO
Date: 04/29/26 Time: 13:45
Sample: 1994 2020
Included observations: 135
Null Hypothesis: No cointegration
Trend assumption: No deterministic trend
User-specified lag length: 1
Newey-West automatic bandwidth selection and Bartlett kernel

	t-Statistic	Prob.
ADF	-2.245995	0.0124
Residual variance	3.646861	
HAC variance	3.709391	

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(RESID)
Method: Least Squares
Date: 04/29/26 Time: 13:45
Sample (adjusted): 1996 2020
Included observations: 125 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RESID(-1)	-0.291761	0.064331	-4.535317	0.0000
D(RESID(-1))	0.033578	0.087408	0.384152	0.7015

R-squared	0.150705	Mean dependent var	0.072311
Adjusted R-squared	0.143800	S.D. dependent var	1.966458
S.E. of regression	1.819584	Akaike info criterion	4.050964
Sum squared resid	407.2391	Schwarz criterion	4.096217
Log likelihood	-251.1852	Hannan-Quinn criter.	4.069348
Durbin-Watson stat	1.935772		

Table 4.4.1 & Table 4.4.2: Panel ARDL Test

Dependent Variable: D(RUII)
Method: ARDL
Date: 03/25/26 Time: 16:50
Sample: 1997 2020
Included observations: 120
Dependent lags: 2 (Fixed)
Dynamic regressors (3 lags, fixed): FD DTD ED URB TO
Fixed regressors: C

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
	Long Run Equation			
FD	-0.734480	0.088962	-8.256077	0.0000
DTD	0.091010	0.012340	7.374890	0.0000
ED	0.293476	0.013591	21.59388	0.0000
URB	-6.633513	0.303997	-21.82102	0.0000
TO	0.306439	0.052723	5.812231	0.0000
	Short Run Equation			
COINTEQ01	-0.828881	0.458562	-1.807568	0.0782
D(RUII(-1))	0.455769	0.265779	1.714841	0.0941
D(FD)	-0.188827	0.502766	-0.375577	0.7092
D(FD(-1))	-0.639886	0.654234	-0.978069	0.3339
D(FD(-2))	-0.281832	0.576883	-0.488543	0.6278
D(DTD)	-0.001569	0.052129	-0.030107	0.9761
D(DTD(-1))	0.002424	0.047833	0.050667	0.9598
D(DTD(-2))	-0.066685	0.128048	-0.520778	0.6054
D(ED)	-0.250535	0.184079	-1.361023	0.1811
D(ED(-1))	-0.181317	0.067531	-2.684952	0.0105
D(ED(-2))	-0.076185	0.175622	-0.433803	0.6668
D(URB)	-18.38396	29.66698	-0.619678	0.5390
D(URB(-1))	23.55194	51.12863	0.460641	0.6476
D(URB(-2))	-38.70397	60.66921	-0.637951	0.5271
D(TO)	-0.062123	0.164698	-0.377192	0.7080
D(TO(-1))	-0.013244	0.103786	-0.127613	0.8991
D(TO(-2))	-0.131138	0.052698	-2.488455	0.0171
C	23.34423	12.81758	1.821267	0.0761

Root MSE	0.014803	Mean dependent var	-0.003875
S.D. dependent var	0.059864	S.E. of regression	0.027194
Akaike info criterion	-3.980257	Sum squared resid	0.029581
Schwarz criterion	-1.935804	Log likelihood	363.6673
Hannan-Quinn criter.	-3.149448		

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This chapter provides an overview of the study, including the definition, significance, and trends of rural–urban income inequality, financial development, and digital technology development. The analysis focuses on five Asian countries—China, India, Malaysia, Japan, and South Korea—with particular attention to the impact of financial development and digital technology development on rural–urban income inequality. The chapter also outlines the problem statement, research objectives, research questions, and the significance of the study. Furthermore, it reviews the relevant literature, including theoretical review, empirical evidence, hypothesis development, and identifies literature gaps. In addition, the chapter discusses the methodological framework, covering data sources, data collection methods, research design, and analytical approaches.

This research will focus on the role of financial development and digital technology development in rural-urban income inequality and will mainly focus on five Asian countries, which include China, India, Malaysia, Japan, and South Korea. To suggest whether financial development and digital technology development widen or narrow the urban and rural income gap from 1994 to 2020 by using the Panel ARDL approach. Due to a large population in China and India, increasing inequality in China and India strongly shapes income distribution in Asia. Additionally, Japan and South Korea are technology and finance leaders, while Malaysia represents a middle- income country in Southeast Asia, which balances emerging and advanced economies in the region. Rural-urban income inequality is represented by a difference in income levels, living standards, and access to opportunities between individuals living in urban and in rural areas. It is an important factor affecting social stability and equal opportunities within a country, and it has a significant impact on socioeconomic development across Asian economies (Zou et al., 2025). Many economists argue that rising inequality can be a key driver of economic instability and financial crises (Stiglitz, 2009).

China's income inequality is characterized by rural-urban inequality, but the inequality within rural and urban areas has constantly increased. Urban households typically enjoy higher income, better educational opportunities, and superior infrastructure, while rural populations often depend on agriculture, informal labor, and have limited access to essential services like financial institutions or the financial market in most Asian countries. China and India, because of their substantial population sizes, have a significant influence on the overall patterns of regional inequality. In China, income inequality is largely shaped by the rural-urban gap, yet differences within rural and urban areas have also been impacted alongside China's rapid economic growth. (Imai & Malaeb, 2018).

Other than that, Imai and Malaeb (2018) find that faster non-agricultural or industrial growth tends to widen the rural–urban income gap over time, whereas agricultural growth shows little direct effect on this gap. Moreover, while accelerated agricultural growth significantly reduces inequality within rural areas, rapid industrial growth has the opposite effect, increasing rural inequality over time. Figure 1.1 presents rural–urban income inequality across the five selected countries. Rural-urban income inequality (RUII) is proxied by comparing the value added per worker in agriculture to that in the industrial sector, expressed as a ratio. A value above 100 indicates that rural income is growing faster than urban income. In contrast, a value below 100 suggests that urban income levels remain higher than those in rural areas (Gollin et al., 2013; Sehrawat & Gini, 2015). According to Figure 1.1, the overall range of rural-urban income inequality for China, India, Malaysia, South Korea, and Japan is between 17 and 58 from 1994 to 2020. Across all five countries, the values remain well below 100 and involve a stable trend, confirming that industrial or urban workers consistently earn more than agricultural or rural workers throughout the period. If the value of the rural-urban INQ ratio increases over time, which means the country's income gap is reducing since the rural workers are catching up with urban workers, however, if the rural-urban INQ ratio decreases over time, urban workers' earnings grow faster, which widens the country's income gap. Compared among countries, Malaysia records the highest rural-urban INQ ratio, with values ranging from 43 to 55, which the rural-urban income inequality is better than others. China's rural-urban income inequality ratio is quite moderate after 2002, with a range is in between 18 and 25, the lowest among the other five countries, which means there is a huge income gap between urban and rural areas. The rural-urban INQ ratio for India, Japan, and South Korea is quite moderate which in a ranging between 20 to 39 for these three countries from 1994 to 2020.

Furthermore, financial development represents the advancements of financial institutions, markets, and instruments that support the efficient allocation of resources, encourage savings, and expand access to credit. It involves improvement in the financial system, including the pooling of savings, channeling capital to efficient investment, spreading risks, and enabling the exchange of goods and services. These developments play a crucial role in shaping savings and investment behavior as well as enhancing the effectiveness of how funds are distributed (Svirydzenka, 2016). Financial development is a key factor in promoting a country's economic growth. A well-functioning financial system enables households to save, access credit, invest in opportunities, and generate income. Across Asia, many countries experienced substantial financial development characterized by improvements in financial inclusion, deepening capital markets, and enhanced regional financial integration, which can boost economic growth, reduce reliance on the traditional banking system (Teo et al., 2006).

Based on the graph, the level of financial development among the five selected Asian countries, including Malaysia, Japan, South Korea, China, and India, shows an overall upward trend from 1994 to 2020, even though the level of development varies greatly among countries.

Firstly, Japan consistently records the highest level of financial development among the five countries. The index increased steadily from 0.576 in 1994 to 0.925 in 2020, which indicates a highly mature financial system. This reflects Japan's involvement in a stable banking sector, developed capital markets, and strong financial infrastructure compared to others. Japan's long history of banking, advanced market mechanisms, and post-crisis reforms has reinforced financial stability and efficiency, enabling the country to maintain its position as one of the most financially developed economies in Asia (Bank of Japan, 2020). Similar to Japan, Korea demonstrates a relatively high level of financial development over the study period. The index rose from approximately 0.6 in 1994 to about 0.832 in 2020. Despite minor fluctuations over time, the overall trend indicates a steady upward movement. The graph observe that Korea's financial development mainly increased in 1997 and 1998 to become more stable and efficient. One of the main reasons was the financial restructuring that occurred after the Asian Financial Crisis. Korea implemented major reforms to stabilize and modernize its financial system. These reforms included strengthening bank supervision, improving corporate governance, and restricting weak financial institutions (Shabsigh, G., 2013). Thirdly, Malaysia shows moderate but stable financial development. The index gradually increased from 0.39 in 1994 to 0.725 by 2020. This steady improvement suggests ongoing financial sector reforms, expansion of banking services, and development of financial markets in Malaysia. Malaysia's financial system is still developing, but it has shown consistent progress over time. Other than that, China has made significant improvements in financial development. The index rose from 0.35 in 1994 to 0.672 by 2020. Indicating that it is a rapid expansion of China's financial sector, financial liberalization policies, and the rise of digital finance platforms. Financial reforms and the transition toward a more market-based financial system can increase financial institutions and markets, while the rapid growth of fintech and digital payment systems further improved financial access and efficiency (Zhang, L., 2021). Lastly, India indicates the lowest financial development index among the five countries, although there is a gradual improvement, the index fluctuates between 0.35 and 0.5 over 1994 to 2020. This is attributed to restricted access to financial services in rural areas. Despite improvements in access to bank accounts, still many people, especially in rural or low-income populations do not use financial services actively. Moreover, India's financial system faced a lot of problem including high non-performing loans, inefficient credit allocation, and others, which may limit the efficiency and stability of financial development (Schipke, A., et al, 2023).

Last but not least, Digital Technology Development (DTD) represents a central aspect of a nation's digital economy, highlighting the progress made in building and utilizing digital infrastructure, platforms, and innovations. It involves the expansion of technologies like artificial intelligence (AI), big data, cloud computing, the Internet of Things (IoT), and blockchain. These technologies streamline production, logistics, and financial services, which boost productivity and competitiveness. A country that invests in DTD strengthens its position in the global economy and attracts foreign investments, trade opportunities, and innovation ecosystems. DTD is a foundation for sustainable economic growth, reducing inequality, and improving governance. Asia has seen a growth in e-commerce and digital payments, driven by widespread internet and smartphone adoption. Additionally, digital payment solutions have gained a lot of adoption, with mobile payments, contactless payments, and digital banking platforms becoming more popular, secure, and convenient financial services (Lugtu, 2023).

From 1994 to 2020, the percentage of individuals using the internet increased significantly in China, India, Malaysia, Japan, and South Korea. This reflects the rapid expansion of digital infrastructure, increasing smartphone penetration, and broader access to online services over time. However, the five countries show different patterns of digital adoption depending on their economic development, technology infrastructure, and government digital policies.

South Korea experienced the highest level of internet usage, which increased from 0.31% to 96.51%. A particularly sharp increase from 1998 to 2001, which rose from 6.78% to 56.6%. This rapid growth can be attributed to the widespread adoption of high-speed internet services, as South Korea maintains some of the fastest and most affordable residential internet connections in the world (Bang & Choi, 2011). Consequently, South Korea has maintained one of the highest internet penetration rates globally, driven by strong government investment in broadband and advanced ICT infrastructure.

Besides that, Japan also shows a significant increase in internet usage, rising from 0.8% to 90.22% during the study period. This high internet penetration may be due to its advanced technological infrastructure and high-income economy. Commercial internet services became available in Japan in the early 1990s, and the country experienced rapid broadband expansion in the early 2000s due to the strong competition and technological development in the telecommunications sector. Therefore, Japan represents a mature digital economy, where internet adoption occurred early and eventually stabilized at high levels as the market approached saturation (Sunada et al, 2011).

In contrast, India was the lowest and slowest growth among these selected countries. India's internet usage kept remained below 1% of its population from 1994 to 2001. Although the internet growth was slow initially. India experienced faster growth after around 2015, which increased from 14.9 in 2015 to 43.41 in 2020. Despite this improvement, India still lags behind other countries. This may be due to limited telecommunications infrastructure, especially in rural areas. A large share of India's population resides in rural areas, slowing the overall national growth rate of internet usage. In addition, India is a developing economy with lower average income levels, which reduces purchasing power and slows the adoption of internet technologies such as computers, smartphones, and internet subscriptions (Singh, 2010).

Malaysia and China also experienced substantial growth in internet usage from 1994 to 2020. However, the growth patterns differ slightly between the two countries. In China, internet usage remained relatively low and increased slowly during the early years, but it began to rise rapidly after around 2007, reflecting the rapid expansion of digital infrastructure, broadband services, and smartphone adoption. In contrast, Malaysia experienced a more gradual and consistent increase in internet penetration, supported by government initiatives to improve digital connectivity and information and communication (ICT) infrastructure (Hilbert, 2016).

Rural-urban income inequality has remained one of the most pressing socio-economic challenges in Asia, particularly in emerging economies such as India, China, and Malaysia, as well as in advanced nations like Japan and South Korea.

Even though substantial economic growth, structural transformation, and poverty alleviation have been achieved over the last several decades, rural areas often lag significantly behind urban regions in household income, access to services, and economic opportunities. For example, China's urban per capita disposable income yielded a rural-urban income ratio in 2023 is 2.39:1 (NBOSOC, 2024). The rural-urban income ratio in India is 2.1:1, meaning that urban incomes are significantly higher than rural incomes (Liao et al., 2025). Similar trends are shown by Malaysia in 2022, the rural-urban income ratio is 1.83:1 (DOSM, 2023). Although advanced economies such as Japan and South Korea show narrow gaps due to stronger social protection systems and more balanced regional development, income inequality between urban and rural areas remains observable (İşcan & Lim, 2021; Chakraborty et al., 2020). This ongoing inequality continues to limit inclusive development and creates obstacles to achieving the Sustainable Development Goals (SDGs), especially Goal 10, which focuses on reducing inequality (Bhandari, 2024).

Financial development and digital technology are widely recognized as potential equalizers of opportunity. Financial development can enhance access to credit, payments, savings, and investment to rural households (Yang et al., 2024), while digital technology development, such as e-commerce platforms and mobile banking, enables individuals in rural areas to connect to urban markets by bridging geographical barriers (Zhang & Li, 2024). However, their actual effects on narrowing or widening the rural-urban income gap are unclear and remain underexplored, especially in the context of Asia-Pacific countries (Vo et al., 2023). On one hand, some studies argue that financial deepening and digital access reduce inequality by empowering rural households and enabling income mobility (Li et al, 2024; Shen et al., 2025). On the other hand, research also highlights that limited financial inclusion or inadequate digital infrastructure in rural households could exacerbate inequality instead of reducing it (Peng et al, 2023). Therefore, it remains unclear whether, and under what conditions, financial development and digital technology development mitigate or exacerbate the rural-urban income gap in Asia-Pacific contexts.

This discrepancy highlights some critical research gaps, such as the lack of comparative cross-country evidence in Asia that integrates the consequences of financial development and digital technology in shaping rural-urban income inequality. It is crucial to analyze them collectively because each nation has a unique background, including technology inclusion, policy, digital penetration rates, and rural-urban structural characteristics. Few studies have looked into how these factors affect both emerging and advanced Asian economies, whereas most studies have looked at them separately. Furthermore, most of the studies employ the conventional regression method instead of panel unit root tests and the panel ARDL approach. Given the socio-economic importance of reducing inequality in Asia, clarifying whether financial development and digital technology mitigate or exacerbate the rural-urban income gap is both urgent and valuable. A clearer understanding will not only contribute to academic debates on inequality and development but also provide policymakers with evidence-based guidance for designing financial and digital technologies strategies tailored to national contexts.

Each country have implemented policy initiatives aimed at reducing rural–urban income inequality. For instance, the Chinese government has introduced targeted poverty alleviation strategies, including substantial investment in rural infrastructure and the implementation of the "New Socialist Countryside" program (Li & Sicular, 2014). In India, the Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA) was introduced to expand job opportunities in rural areas and strengthen infrastructure development. (Dutta et al., 2014). Similarly, South Korea introduced the "New Village Movement" to improve rural living conditions and enhance the quality of life of rural residents (Wen et al., 2025). Japan employs the Chiho Sosei policy, which funds rural revitalization projects such as agriculture subsidies and infrastructure development in depopulated areas (Kitagawa, 2024). Under the New Economic Policy (NEP), Malaysia has promoted rural infrastructure (roads, electricity), FELDA land development schemes, and income support for farmers (Tey et al., 2019). However, rural–urban income disparities remain remarkably persistent even after decades of extensive policy interventions across Asia. This implies that policy interventions may continue to fail without a deeper understanding of how financial development and digital technology interact with structural and institutional conditions. Therefore, addressing this gap is not only important from an academic perspective but also essential for designing more effective and context-specific strategies to achieve inclusive growth in the Asia-Pacific.

1. Does financial development have a significant impact on rural–urban income inequality in selected Asian countries?
2. Does digital technology have a significant effect on urban–rural income inequality in selected Asian countries?

The main objective of this study is to investigate the relationship between financial development and digital technology development on rural-urban income inequality in selected Asian countries, including India, China, Japan, South Korea, and Malaysia.

1. To investigate whether financial development has a significant impact on rural–urban income inequality in selected Asian countries.

2. To examine whether digital technology development is significant in rural–urban income inequality in selected Asian countries.

This study seeks to examine how financial development and digital technology development influence rural–urban income inequality in five selected Asian countries. This study examines five countries with distinct characteristics, all of which experience rural–urban income inequality. The objective is to explore the underlying causes of these disparities. By considering these differing contexts, the study looks into the impact of financial development and digital technology development on income inequality. Rural-urban income inequality is closely linked with the objectives of Sustainable Development Goal 10 (SDG 10), which emphasizes reducing income inequality and ensuring equality of opportunity for everyone, regardless of religion, origin, or economic status within countries. Disparities between rural and urban areas in terms of income highlight structural imbalances that hinder inclusive growth. To sum up, addressing these inequalities is essential for establishing SDG 10, as narrowing the rural-urban gap contributes to social cohesion, balanced economic development, and greater equity in opportunities and outcomes.

Firstly, by focusing on five Asian countries, current research offers and provides a clear perspective and understanding of how financial development and digital technology development can impact income disparities between rural and urban areas. This contributes to academic literature by offering insights into the mechanisms that increase or decrease financial development and digital technology development, either exacerbating or reducing inequality.

Secondly, this paper provides a comparative analysis on five Asian countries—China, India, Malaysia, Japan, and South Korea, over the period from 1994 to 2020. Previous research has rarely examined this specific combination of countries, and particularly in relation to the joint effects of financial development and digital technology development on rural–urban income inequality. So, by addressing these gaps, this study enhances the understanding of how financial development and digital technology shape the rural– urban income gap across these five countries.

Lastly, the findings of this study will provide useful insights for governments and policymakers in reducing rural-urban income inequality, which is important for ensuring sustainable economic prospects in the five selected Asian countries. It allows governments to better understand how financial development and digital technology development influence rural–urban income inequality, thereby supporting the formulation of appropriate policies to reduce the income gap between rural and urban areas.

This study investigates the relationship between financial development and rural-urban income inequality by applying the Financial Development Theory, particularly the inequality-widening and inequality-narrowing hypotheses, to explain how financial development influences income disparities between urban and rural areas. The inequality-widening hypothesis suggests that credit allocation tends to favor urban and wealthier individuals, who are more likely to provide collateral and demonstrate higher repayment capacity. As a result, individuals with limited funding frequently struggle to secure loans, even in developed financial markets, deepening the country's income inequality. In contrast, the inequality-narrowing hypothesis argues that the expansion of the financial sector can improve access to credit for previously excluded low-income groups, thereby promoting more inclusive financial participation.

This study investigates the relationship between financial development and rural-urban income inequality by applying the Financial Development Theory, particularly the inequality-widening and inequality-narrowing hypotheses, to describe how financial development affects income gaps between urban and rural areas. The inequality-widening hypothesis suggests that credit allocation tends to favor urban and wealthier individuals, who are more likely to provide collateral and demonstrate higher repayment capacity. As a result, individuals with limited financial resources often face difficulties in obtaining loans, even in well-developed financial markets, which can worsen income inequality within a country. In contrast, the inequality-reducing hypothesis suggests that the growth of the financial sector can enhance credit access for low-income groups that were previously excluded, thereby promoting more inclusive financial participation.

The Inequality-Widening Hypothesis argues that economic growth, structural changes, technology and skill disparities, financial development, and globalization may contribute to an expansion of the rural-urban income gap. This study focuses specifically on the role of financial development in shaping rural-urban income inequality. As financial development develops, disparities between urban and rural incomes may increase. This growing gap can be attributed to various challenges in financial markets, such as transaction costs, information asymmetry, insufficient collateral, and limited credit history, all of which can limit credit access for low-income groups (Beck et al., 2007). It limits rural households' access to benefits, leaving them dependent only on their restricted savings and income. This hypothesis indicates that financial development may tend to favor wealthier groups or urban areas. Additionally, urban households with a substantial income can provide collateral and are more likely to repay loans, whereas rural households with a lower income may find it difficult to acquire loans (Zal Yıldırım & Yüncü, 2025). Furthermore, Financial markets, such as stocks, bonds, and mutual funds, create opportunities. Wealthy households can invest and earn returns, whereas households with low incomes are excluded (Clarke et al., 2006). Since urban and educated populations have more financial knowledge, they make use of complex financial tools. Rural households may not benefit equally because of a lack of awareness or sense of financial expertise. (Greenwood & Jovanovic, 1990).

On the other hand, the inequality-narrowing hypothesis argues that improvements in financial development can lessen and reduce the inequality in income between urban and rural areas. When there is a financial development, this hypothesis indicates that rural households gain easier access to banking, credit, and insurance, and they can invest in education or small business. This helps to raise the rural areas' productivity and income, gradually narrowing the rural-urban income inequality (Zal Yildirim & Yüncü, 2025). Furthermore, microfinance, mobile banking, and rural credit schemes reduce barriers that traditionally solely favoured urban areas. When the financial system is inclusive for rural households, they may have easier access to credit and capital (Burgess & Pande, 2005). Other than that, savings and investment opportunities increase since they can participate in formal savings schemes such as banks, pension funds, insurance companies, and others to make rural income more stable and predictable (Omar & Kazuo Inaba, 2020). Other than that, financial development encourages small and medium enterprises (SMEs) in rural areas by giving them loans, which involves job creation and business growth, so it spreads resources more evenly, supporting rural populations and reducing reliance on agriculture, which increases the income for rural populations (Seven et al., 2016).

To understand the impact of digital technology on rural-urban income inequality, it is important to draw upon established economic and technological theories. This theory discusses how digital technologies spread across regions and also why their impact on income distribution may differ between urban and rural areas. The study applies the Digital Divide Theory.

Digital Divide Theory (DDT) explains how unequal access to digital technologies leads to differences in individuals' opportunities and outcomes. This reflects entrenched socio-economic structures rather than temporary gaps (Van Dijk, 2006). At its foundation, the theory should incorporate three key dimensions, which are access, usage, and outcomes. Digital access plays an essential role in narrowing the digital divide; it highlights the differences in the availability of digital infrastructure, such as internet connectivity, devices, and stable electricity. The second dimension, usage, emphasizes individuals' digital skills and the ability to effectively leverage technology for meaningful purposes. This level explores how digital engagement impacts real-world outcomes and opportunities for individuals and groups (Reddick et. al., 2024). Building on the traditional three-dimensional framework of access, usage, and outcomes, later scholars refined the model by distinguishing access into four sub-dimensions, which are motivation, material, skills, and usage access (Lamberti et al., 2020). Importantly, the divide is dynamic, shifting with technological evolution and adoption rates, yet it also risks becoming stratified, where disadvantaged groups remain persistently behind.

Applied to rural-urban inequality, urban populations generally benefit from better infrastructure and digital literacy programs, which enhance their human capital and productivity. Conversely, rural populations often face poor connectivity, fewer resources, and limited exposure to digital training, reinforcing cycles of poverty and exclusion (Saleminl et al., 2017; OECD, 2021). Socio-economic and cultural factors influence both Internet access and usage, which represents the first-level digital divide. Importantly, the theory suggests that even when physical access barriers are reduced, skills and usage divided may persist, leading to a 'second-level divide', and this can affect individuals' life prospects and the opportunities available to them (third-level divide) (DiMaggio & Hargittai, 2001). Thus, DDT underscores the possibility of entrenched inequality unless targeted interventions are implemented. In this way, DDT provides a structural lens, explaining why the benefits of digital learning and technology adoption may be unevenly distributed, thereby widening the rural–urban income gap unless equity- focused policies are enacted.

This study incorporates three control variables: economic development, urbanization, and trade openness. The Kuznets Hypothesis is used to explain the relationship between economic development and rural–urban income inequality, while the Lewis Dual-Sector Model is applied to describe the link between urbanization and rural–urban income inequality. Furthermore, the Stolper-Samuelson theorem describes how trade openness is linked to rural–urban income inequality.

This study adopts the Kuznets hypothesis to explain the relationship between economic development and rural-urban income inequality. This hypothesis suggests an inverted U-shaped relationship, where rural–urban income inequality first rises in the early phase of economic development due to structural information and rural-urban migration, but decreases at later stages as income distribution improves (Kuznets, S., 1995). This is because in the early phase of development, the transition from an agriculture-driven economy to one based on industry and urban development creates income disparities between rural and urban populations. However, as development progresses, factors such as improved education, institutional development, and redistributive policies reduce inequality (Deininger & Squire, 1998; Ravillion, 2001).

To understand the impact of urbanization on rural-urban income inequality, it is important to consider structural transformation theories. This study applies to the Lewis Dual-Sector Model, developed by Arthur Lewis (1954), which describes the transfer of labour from low-productivity rural areas to more productive urban sectors. Rural areas often experience surplus labor with low marginal productivity, while urban industrial sectors offer higher wages and better employment opportunities. As labor migrates to urban areas, overall productivity and income levels increase, contributing to economic growth and structural transformation. This process may help reduce rural-urban income inequality over time, as rural workers gain access to higher-paying urban employment opportunities.

Lastly, The Stolper-Samuelson theorem is applied to describe how trade openness relates to rural–urban income inequality. It is derived from the Heckscher-Ohlin model; this theory presents how trade openness affects income distribution by altering the returns to factors of production (Stolper & Samuelson, 1941). In developing economies such as China, India, and Malaysia, where low-skilled labour is relatively abundant, trade liberalization raises the demand for goods that are labour-intensive, which in turn raises wages for low-skilled workers. So, rural incomes are expected to increase, leading to a reduction in rural-urban income inequality. However, in economies where capital or skilled labour is relatively abundant, trade openness may widen income inequality (Heckscher & Ohlin, 1991).

Many empirical studies have examined the rural-urban income inequality using various econometric models. Empirical studies show an insignificant effect in narrowing rural-urban income inequality. Law and Tan (2009), using quarterly data for Malaysia from 1980 to 2000 and applying the ARDL bounds testing approach, find that financial development, whether measured through banking sector indicators, stock market capitalization, or financial aggregates, is statistically insignificant in narrowing rural-urban income inequality in Malaysia. Sehrawat and Giri (2015) report that financial development does not help to reduce rural-urban income inequality. In order to prevent inequality from getting worse, they recommend policies that encourage financial growth, such as expanding access to financing.

Some empirical shows a mixed effect, such as Turkish researchers using panel data for 31 emerging and developing economies over the period 2000 to 2019 with a system GMM model, the study finds that banking development widens income inequality between rural and urban, while stock market development and financial openness help reduce it. The results highlight that the structure of the financial system matters more than its size in shaping inequality outcomes (Zal Yıldırım & Yüncü, 2025). Based on past findings, Zhang and Chen (2015), using annual data for China over the period 1978 to 2013 and employing a structural vector auto-regression (SVAR) model, find that financial scale (FIR) and efficiency (FER) raise rural–urban income inequality in the short term but lower it in the long term. Results also show that urbanization initially narrows the gap before turning positive, while fiscal expenditures widen inequality in the short run but help reduce it over time.

Moreover, Demirgüç-Kunt and Levine (2009) mentioned that financial development that enhances financial services and runs on an intensive margin could widen the distribution of income. Ang (2010) investigates the factors that influence the Gini coefficient in an autoregressive distributed lag model and, using the ARDL limits technique and the ECM cointegration test, concludes that the financial system's underdevelopment impacts the poor more than the rich, leading to wider income inequality between rural and urban. Perugini and Tekin (2022) indicate that, across the 48 middle- and high-income nations, Financial development is generally associated with higher income inequality, but this effect weakens as the quality of governance-related institutions improves.

However, Nokulunga Mbona (2022) reports that the overall financial sector development, including institutional development and market development, helps to reduce rural–urban income inequality. Kappel (2010) states that financial development lowers income inequality while promoting economic growth; however, the development of the stock market has a less significant but still significant impact than that of the credit market, illustrating that both markets contribute to the help of low-income households in high-income nations. Bittencourt (2006) demonstrates that expanded access to credit and financial markets reduces income disparity and enhances economic well-being in Brazil. Moreover, Liang's (2006) empirical result indicates that China's financial development significantly helps to reduce rural-urban income inequality. Lastly, Shahbaz and Islam (2011) suggest that inequality in income is reduced by financial development and made worse by financial instability. The results also showed that the distribution of income in Pakistan has greatly improved due to the poor's easy access to financial markets and effective credit funding.

Numerous empirical studies have examined how digital technology influences rural-urban income inequality and produced mixed findings. Some studies show positive effects in narrowing inequality. For instance, Wang et al. (2021), using provincial panel data, find that internet development combined with FDI and urbanization alleviates provincial rural-urban income disparities. Furthermore, Zhang et al. (2024), using panel data, also reach a similar conclusion, which is that digital economic development significantly narrows rural-urban income gaps, particularly in regions with lower human capital endowments. Similarly, Su and Ren (2025) apply a two-way fixed effects model using multi-country data and find that rural e-commerce helps narrow the income gap, with internet usage levels acting as a partial mediator.

Conversely, some studies caution that digital technology may widen income inequality between rural and urban. Peng and Dan (2023), applying the entropy value method, reveal a U-shaped relationship in China. Digital economy development initially narrows and later widens the rural-urban income gap. Deng et al. (2023), using city-level data, similarly highlight that although both urban and rural incomes increase with digitalization, the gains are disproportionately larger for urban residents, resulting in a widening of the rural-urban income gap. Beyond China, Mwansa et al. (2025) document in rural South Africa that over half of the population lacked reliable internet, leading to restricted access to education, healthcare, and economic participation. This reinforces existing rural–urban inequalities and limits the transformative potential of digital technology.

Overall, these findings indicate that the relationship between digital technology and rural-urban income inequality remains inconclusive but highly dependent upon national contexts. Factors such as institutional capacity, infrastructure, and digital literacy play a decisive role in shaping whether digitalization acts as an equalizer or an amplifier of inequality.

The use of control variables in this study is crucial for capturing the more significant rural-urban income gap in five Asian nations. By accounting for relevant effects, the research gives a more accurate and realistic view of the income disparity between rural and urban areas. Control factors such as Economic Development (ED), Urbanization (URB), and Trade Openness (TO) are included for their possible influence on rural-urban income inequality, resulting in a more intensive and thorough analysis.

Firstly, ED refers to a qualitative measure of how that growth improves lives and society, which plays an important role in rural-urban income inequality since it can strongly influence income distribution. Studies consistently find that higher ED narrows the rural-urban income gap, which is significantly negative at 1% significance level in China (Deng, X. et al, 2023). A country's income level contributes to reducing income inequality in the Asia-Pacific region (Koh et al., 2022). However, Economic growth can widen the rural-urban income gap in India (Tiwari et al 2010), and ED significantly affects the efficiency of income allocation, thereby impacting the disparity between urban and rural incomes (Yan, D. et al, 2025).

Urbanization is the process by which an increasing of the population lives in urban areas, leading to the expansion and development of cities. It reflects population migration and structural transformation, which may influence the income distribution between rural and urban areas. It is essential to include urbanization as a control variable in this study since it allows the model to account for structural demographic changes that may independently impact rural-urban income inequality, ensuring the estimated impacts on financial development and digital technology are more accurate (Zhao & Liu, 2022). Empirical studies indicate that higher urbanization levels can contribute to narrowing the rural-urban income gap. For example, Xia et al (2024) and Liang & Liu (2026) promote that regions with advancing urbanization experience greater labor mobility and better integration into the labor market, which narrows the rural-urban income gaps. Similarly, Sun & Kuang (2023), Jiang & Han (2023), and Yan et al (2024) also point out that the rural-urban income gap will gradually decrease as urbanization, partly due to the diffusion of technology and capital from urban to rural areas.

Trade openness refers to how freely a country permits the movement of goods, services, and capital across its borders, reflecting its involvement in the global trading system. Trade openness is included as control variables since it can influence regional income differences since urban areas often benefit more from trade and also affect employment and industrial system (Perez & Krivonos, 2021). Historical studies show that trade openness can affect the rural-urban income gap through several channels. For instance, Koh et al (2022), Liu et al (2023) reveal that increasing trade openness contributes to reducing income inequality through industrial development and labor mobility. In contrast, Wan et al (2007) and Zhang et al (2011) reported that trade openness may widen the rural-urban income gap, as export-oriented industries are mainly concentrated in urban regions. These differing results suggest that the impact of trade openness on urban–rural income inequality may depend on a country's stage of economic development and its regional structural features.

The conceptual framework illustrates the hypothesized relationships among the study variables. In this framework, financial development and digital technology serve as independent variables, while the urban–rural income inequality gap is the dependent variable. In addition, several control variables, including GDP per capita, urbanization rate, and trade openness, are incorporated to account for potential confounding effects and to ensure a more accurate estimation of the relationships. As shown in Figure 2.3, the model proposes that financial development and digital technology influence the rural-urban income inequality either positively (widening) or negatively (reducing), alongside the effects of the control variables.

Although existing studies report inconsistent results regarding the link between financial development and income inequality, financial resources are typically concentrated in urban regions where financial institutions are more developed, which can lead to unequal access for rural populations. According to Credit Rationing

Theory, proposed by Joseph Stiglitz and Andrew Weiss (1981), financial markets may allocate credit inefficiently due to information asymmetry. Banks prefer to lend to lower-risk borrowers, such as urban residents or high-income households, resulting in limited access to finance for rural households. As a result, financial development may reinforce existing inequalities when financial resources are disproportionately concentrated in urban areas, thereby widening the rural–urban gap (Wang et al., 2023; Zhang et al., 2025). Furthermore, financial development does not necessarily lead to improvement in financial inclusion, as it may disproportionately benefit urban populations where financial institutions are concentrated (Ozili, 2018). Therefore, although financial development has the potential to reduce inequality, its effect may not be evenly distributed. Hence, this study expects that improvement in financial development will increase rural-urban income inequality.

Although some studies suggest that digital technology development may widen inequality due to unequal access and differences in digital skills, it is generally recognized as a key driver of inclusive and sustainable economic growth. By reducing transaction costs and lowering information barriers, digital platforms enhance rural residents' access to markets, financial services, and employment opportunities (Wen et al. 2024). Digital technology in rural communities facilitates the acquisition of agricultural information and allows involvement in a range of online economic activities. Furthermore, the digital economy can empower disadvantaged groups by providing timely access to job information and flexible engagement in non-agricultural employment, thereby enhancing household earnings, diversifying income sources, and gradually narrowing the income gap between rural and urban residents (Zhang & Li, 2024). Nevertheless, as digital technologies become more widely diffused and accessible across regions, the digital divide is expected to narrow gradually, allowing rural populations to increasingly benefit from digital opportunities. Therefore, this study assumes that an increase in digital technology development will reduce rural–urban income inequality.

Economic development plays a significant role in shaping income distribution. While the early stages of development may be associated with rising inequality, Simon

Kuznets (1995) proposed that economic development may reduce income inequality in the long term. Empirical studies show that the stabilization of currency and fiscal policy, and open markets and other liberalized financial policies may increase the rural resident income. The income will increase until the same level as other families' income in society. They emphasize there is not a 'trickle-down' effect, even though wealthier groups benefit first and any advantages are later expected to spread to lower-income groups (Dollar & Kraay, 2002). Therefore, economic development is expected to decrease rural-urban income inequality in this study.

Urbanization reflects the movement of labor from low-productivity rural sectors to high-productivity urban sectors. When urbanization increases, it facilitates job opportunities, improves accessibility to education and public services, and enhances the income-generating capacity for rural migrants. As more rural residents transition to urban areas for work, the income gap between rural and urban populations is expected to narrow. Previous empirical studies show that urbanization promotes labor mobility and structural transformation, which will reduce income inequality (Wan et al., 2022; Nguyen, 2019). As a result, this study shows urbanization is expected to reduce rural-urban income inequality.

Trade openness captures a country's level of participation in the global economy and influences the distribution of income. While some studies highlight uneven benefits, others suggest that trade can enhance rural income through increased agricultural exports, improved market access, and greater participation in global value chains. Through trade liberalization, rural producers can access larger markets, benefit from higher demand for agricultural goods, and obtain better prices for their products. In addition, trade openness encourages investment in rural infrastructure and productivity, which further supports income growth in less developed regions (Winters et al., 2004; Dollar & Kraay, 2004). In conclusion, trade openness is expected to contribute to a reduction in rural-urban income inequality in this study.

H0: Financial development does not have a significant effect on rural–urban income inequality in the selected Asian countries.

H1: Financial development has a significant effect on rural–urban income inequality in the selected Asian countries.

H0: Digital technology development does not have a significant effect on rural–urban income inequality in the selected Asian countries.

H1: Digital technology development has a significant effect on rural–urban income inequality in the selected Asian countries.

Despite extensive research on the effects of financial development and digital technology on rural–urban income inequality, several gaps remain. Firstly, many previous studies concentrate on developed economies or single-country contexts, such as studies confined to Chinese provinces. There is a lack of comparative cross-country evidence within Asian countries that simultaneously examines the variables, including financial development and digital technology development in influencing rural-urban income inequality. It is significant since each country involves different characteristics, including different levels of financial market development, technology adoption, digital inclusion, and government policy framework. Secondly, most existing research focuses on either financial development or digital technology development, with a limitation on the integration of both factors in explaining rural-urban income inequality. Thirdly, much of the existing research relies on conventional regression methods, including pooled OLS, Fixed Effects (FE), and Random Effects (RE), which may not adequately capture dynamic adjustments across countries. To address this limitation, this study employs panel unit root tests together with the panel ARDL approach, allowing for the estimation of both short-run and long-run effects while accommodating differences in adjustment speeds across countries. Finally, findings remain inconclusive, while some studies argue that financial development and digital technology development promote inclusive growth, others highlight their tendency to reinforce inequalities, particularly when resources are disproportionately concentrated in urban areas.

Addressing these gaps, the study contributes new empirical evidence by examining both factors simultaneously, thereby contributing to a more holistic and policy-relevant understanding of inequality in selected Asian countries.

This study adopts a quantitative approach, which involves analyzing numerical data to measure variables and test hypotheses. The research focuses on five Asian countries, including China, India, Malaysia, Japan, and South Korea over the period from 1994 to 2020. The choice of these countries is based on their diverse levels of economic development, financial development, and technological advancement, which provide a comprehensive perspective on the dynamics of rural-urban inequality. The study relies on secondary data, and the data is compiled into a balanced panel dataset covering 27 years. This study uses data from 1994 to 2020 because the mid-1990s mark the beginning of widespread internet diffusion and digital technology development in many Asian countries. The World Wide Web became publicly accessible during this period, and the internet infrastructure began expanding rapidly (Comin & Hobijin, 2010). Other than that, one of the reasons is that complete and consistent data for all variables are only available up to 2020. Some indicators, particularly the financial development index and certain rural-urban income indicators, are not consistently available for all selected countries after 2020. The use of incomplete data may result in an unbalanced panel dataset, which may reduce the reliability and comparability of the empirical results. Therefore, this study focuses on the period from 1994 to 2020 to maintain a balanced panel for econometric analysis (Baltagi, 2008 & Wooldridge, 2010).

The target population of this study comprises rural and urban household incomes in five Asian countries, namely China, India, Malaysia, Japan, and South Korea. These countries were purposively selected as representing different stages of financial and digital technology development. China and India, as large emerging economies with substantial populations, reflect rapid growth alongside persistent inequality. Malaysia represents a middle-income economy undergoing transition, while Japan and South Korea are advanced economies with highly developed financial systems and widespread digital adoption. This variation provides a meaningful basis for comparison, allowing the study to examine both commonalities and differences in how financial and digital development influence rural-urban income inequality. The dataset consists of annual observations spanning the period from 1994 to 2020.

This study examines the effects of financial development and digital technology development on rural–urban income inequality. To better understand the role of financial and digital technology development toward rural- urban income inequality among five Asian countries, a panel of selected countries with a period from 1994 to 2020 is chosen for this research.

Rural–urban income inequality (RUII), the dependent variable of this study, is measured using the rural–urban income quotient (INQ). Due to the limited availability of consistent income data across countries, a proxy based on sectoral productivity is employed. In this approach, the rural sector is represented by agricultural value-added per worker, while the urban sector is proxied by industrial value-added per worker. The rural–urban INQ is calculated as the ratio of agricultural to industrial value-added per worker, multiplied by 100. This ratio provides an indirect measure of the relative development gap between rural and urban areas. The RUII variable is constructed by the authors using data obtained from the World Bank's World Development Indicators (WDI) database. Although this proxy may not fully capture all dimensions of income inequality, it provides a reasonable approximation of rural–urban economic disparities due to data limitations across countries. Previous studies have suggested that differences in productivity between agriculture and industry are a key determinant of the urban-rural income gap (Wang & Du, 2026; Liu et al.,2024; Liao et al., 2025).

Financial Development (FD), the independent variable, is measured by the Financial Development Index, which is sourced from the International Monetary Fund (IMF). Financial development refers to the improvements in financial institutions, markets, and instruments that facilitate the allocation of resources, the mobilization of savings, and the provision of credit. Financial development refers to improvements in the financial system, including the pooling of savings, allocation of capital to productive investments, monitoring of investment activities, risk diversification, and the facilitation of the exchange of goods and services. These functions may affect savings and investment decisions as well as the efficiency of capital allocation (Katsiaryna Svirydzenka, 2016). The financial development index typically ranges between 0 and 1, where higher values indicate a more advanced level of financial development, while lower values represent weaker financial development. It offers a comprehensive measure by incorporating multiple dimensions of the financial system, including depth, access, and efficiency (IMF, 2025). While previous empirical studies have often proxied financial development using single indicators such as the ratio of private credit to GDP or stock market capitalization to GDP. However, these indicators do not capture the multidimensional nature of financial development. By employing FDI, the study captures the extent to which financial development contributes to narrowing or widening income gaps across the selected countries.

The independent variables, Digital Technology Development (DTD), is proxied by the indicator of individuals using the internet (% of population), with data obtained from the World Bank. This indicator reflects the level of digital connectivity and the diffusion of digital technologies across the population. This measure has been commonly applied in empirical research on the effects of digitalization on economic outcomes (Oloyede et al., 2023). Previous research suggests that internet development can improve access to information, enhance labor market efficiency, and create new opportunities for employment and entrepreneurship, thereby influencing income distribution between urban and rural areas (Li et. al., 2024). However, this indicator may not fully capture the nature of digital technology development, which also includes advanced technologies such as artificial intelligence, cloud computing, and big data. Additionally, internet penetration measures access rather than the quality of digital infrastructure or the effective use of digital technologies. Despite these limitations, it remains a commonly adopted proxy for digital development due to its availability and comparability across countries (Shuai & Li, 2025).

To account for macroeconomic and demographic influences, this study introduces three control variables. First, economic development (ED) is measured by GDP per capita, which reflects the level of development in each country. Second, urbanization (URB), defined as the increase in the concentration of population in urban areas, is proxied by the proportion of urban population as a share of total population, and it may have implications for rural–urban income inequality. Third, trade openness (TO) is measured by the ratio of the total trade to GDP, calculated as the sum of exports and imports relative to total GDP. This indicator reflects the degree of a country's integration into the global economy and the intensity of cross-border flows of goods, services, and capital, which may subsequently influence rural-urban income inequality. All data are obtained from the World Development Indicators (World Bank).

This study employs panel data analysis to investigate the effects of financial development, digital technology, and selected control variables on rural–urban income inequality across five Asian countries. To avoid omitted variable bias, several control variables are included, which are economic development, urbanization, and trade openness. The empirical specification is presented as follows:

To capture potential nonlinear relationships and ensure robustness, the log-linear specification is adopted. Following prior studies, this study adopts a log-linear (double-log) specification. The log transformation not only stabilizes variance and mitigates heteroskedasticity but also enables coefficient estimates to be interpreted as elasticities, which provides more meaningful insights into the proportional effects of financial development and digital technology on rural–urban income inequality (Liang, 2023; Zhong et al., 2022). Therefore, the log-linear model is specified as:

Based on the empirical discussions in Chapter 2, the expected signs of the coefficients are that Financial Development (FD) is expected to have a significant negative relationship with rural-urban income inequality (RUII), suggesting that higher financial development may widen the income gap. For Digital technology development (DTD), economic development (ED), urbanization (URB), and trade openness (TO) are expected to have positive relationships with RUII, suggesting that increases in these variables may help to narrow the rural-urban income gap.

It is important to determine whether the series is stationary or non-stationary in order to avoid the problem of spurious regression. Therefore, unit root tests are conducted for this purpose. A panel unit root test extends the standard unit root test to panel data, providing higher statistical power than individual time series unit root tests. It examines whether variables across multiple cross-sections and time periods are stationary, while improving test efficiency and accounting for heterogeneity. Panel unit root tests are employed to assess whether variables are stationary and determine their order of integration, typically classified as I(0) or I(1). A variable is classified as I(0) if it is stationary at level, meaning its mean and variance remain constant over time, whereas an I(1) variable is non-stationary in level but becomes stationary after first differencing (Engle & Granger, 1987). This distinction is important because the panel autoregressive distributed lag (ARDL) models requires variables to be I(0) or I(1), while excluding I(2) series (Pesaran et al., 1999). I(2) variables refer to the variable that becomes stationary only after second differencing, and they are excluded because excessive differencing may destroy or eliminate the long-run relationship.

To ensure robustness, this study employs several panel unit root tests. The Levin-Lin-Chu (LLC) test assumes a common unit root process across all cross-sections, implying homogeneity in the autoregressive coefficient among individuals. However, the LLC framework still allows heterogeneity in individual intercepts, time trends, error variances, and serial correlation structures (Levin et al., 2002). In contrast, the Im-Pesaran-Shin (IPS) test relaxes the assumption of homogeneity by allowing the autoregressive coefficient to vary across cross-sections, making it more suitable for panels with diverse units (Im et al., 2003). The Fisher-type test, proposed by Maddala and Wu (1999) and extended using the Phillips-Perron (PP) approach, aggregates individual unit root test statistics from each cross- sectional unit, providing greater flexibility in handling unbalanced panels. Since these tests have varying power and underlying assumptions, applying multiple tests (LLC, IPS, and Fisher-PP) enhances consistency and robustness in identifying the integration order (Breitung & Pesaran, 2008).

The hypotheses are defined as follows:

$H_0 = \mathit{The\ variable\ contains\ a\ unit\ root}\ (\mathit{non-stationary})$.
$H_1 = \mathit{The\ variable\ did\ not\ contain\ a\ unit\ root}\ (\mathit{stationary})$.

Before applying the ARDL approach, it is important to test whether a long-run equilibrium relationship exists among the variables. This is important because the ARDL model requires cointegration to ensure meaningful long-run estimates. In this study, the Pedroni and Kao cointegration tests are applied to examine the presence of a long-run equilibrium relationship among the variables. The Pedroni (2004) cointegration test allows for heterogeneity across panel members while assessing cointegration in panel data settings, meaning that each cross-sectional unit may have different intercepts and dynamic structures. Despite this heterogeneity, the test is capable of evaluating the presence of a long-run relationship using pooled statistics. In addition, the Kao Cointegration Test (Kao, 1999) is also applied as a complementary approach. Similar to the Pedroni test, it is a residual-based approach used to examine whether a long-run equilibrium relationship exists among variables in panel data. However, it assumes homogeneous slope coefficients across cross-sectional units.

The hypotheses are defined as follows:

$H_0 = \mathit{There\ is\ no\ cointegration\ in\ the\ models}$.
$H_1 = \mathit{There\ is\ cointegration\ in\ the\ models}$.

This study utilises the Panel Autoregressive Distributed Lag (Panel ARDL) model to examine dynamic relationships among the variables. The Panel ARDL approach is suitable for datasets containing a mix of I(0) and I(1) variables, while excluding I(2) series. It is commonly used to analyse both short-run and long-run relationships among economic variables (Pesaran et al 1999). The Panel ARDL approach includes lagged values of both dependent and independent variables, enabling it to capture dynamic adjustments over time. Since the dependent variable (Rural-Urban INQ_{it}), such as rural-urban income inequality, depends not only on the current independent variables, such as financial development and digital development, but also on its past values. This study incorporates lags because economic and social processes take time to adjust, and past values of variables influence current outcomes. Without lags, the model may misrepresent or underestimate effects. Behavioral adjustments, such as delayed responses by households and firms, and institutional factors like policy implementation, also justify the inclusion of lags (Gujarati et al., 2009).

Furthermore, the model can be reformulated into an Error Correction Model (ECM), which separates between short-run dynamics and long-run equilibrium relationships. The ECM incorporates an error correction term (ECT) that reflects the speed of adjustment back to long-run equilibrium following short-run deviations. A negative and statistically significant ECT coefficient indicates the existence of cointegration among the variables.

Cointegration refers to a situation in which a linear combination of non-stationary variables becomes stationary, indicating that the variables move together in the long-run despite short-run deviations. Although temporary disequilibrium may occur, the variables tend to converge back to their long-run equilibrium over time. To estimate both short-run and long-run effects simultaneously, this study employs the Pooled Mean Group (PMG) estimator developed by Pesaran, Shin, and Smith (1999), which is suitable for small samples (Haug, 2002 & Alimi, 2002). The PMG approach restricts long-run coefficients to be homogeneous across countries while permitting heterogeneity in short-run dynamics, intercepts, and error variances, thereby capturing both common long-run relationships and country-specific adjustments.

Although diagnostic tests are important in econometric analysis, this study focuses on estimating long-run relationships using the Panel ARDL framework. In particular, the ARDL model is implemented through the Pooled Mean Group (PMG) estimator developed by Pesaran et al (1999), which incorporates lagged variables that help address issues such as autocorrelation and endogeneity. Furthermore, the primary focus of this study is on the long-run equilibrium relationship and the error-correction dynamics result. This study conducts limited diagnostic testing and focuses primarily on key estimation and model selection procedures, including unit roots, cointegration test, ECM analysis, and optimal lag selection. Previous studies including Garidzirai & Muzindutsi, and Mestiri, applying Panel ARDL have emphasized the importance of establishing long-run relationships and selecting appropriate estimators, while placing less emphasis on extensive residual diagnostic testing (Menegaki, A. N. 2019).

This chapter presents the empirical results and findings derived from the models introduced in the previous chapter. The analysis is organized into two main sections. The first part presents the descriptive statistics and correlation analysis, providing an overview of the data distribution and the relationships between the independent variables and dependent variables. The second part focuses on the regression results, which examine the relationship between rural–urban income inequality (RUII) and the explanatory variables, namely financial development (FD), digital technology development (DTD), economic development (ED), urbanization (URB), and trade openness (TO).

Table 4.1.1 presents the descriptive results for five countries from 1994 to 2020, totaling 135 observations. The mean value of rural-urban income inequality (RUII) is 31.2931, with a standard deviation of 9.6406, resulting in a coefficient of variation of 0.3081. This indicates moderate variation in income inequality across the selected countries. The minimum and maximum values of 17.5191 and 58.2267 suggest that income disparities vary notably across countries and over time. Furthermore, the range-to-mean ratio of 1.3 implies that some extreme values exist in the sample. The positive skewness (0.8771) indicates that the distribution of RUII is moderately right-skewed.

Financial Development (FD) has a mean of 0.6099 and a standard deviation of 0.1653, resulting in a coefficient of variation of 0.2710, which suggests relatively low variation. Combined with a range-to-mean ratio of 0.9559, this indicates an overall moderate variation across countries. The skewness of 0.1049 is close to zero, indicating an approximately symmetric distribution. Digital Technology Development (DTD) records a mean of 40.3675 and a standard deviation of 34.0891, which indicates high volatility across the countries. The maximum and minimum values are 96.5051 and 0.0011, further highlighting the substantial differences in digital development levels. The skewness value (0.149) is close to zero, suggesting a relatively symmetric distribution.

For the control variable economic development (ED), the mean is 14603.57, with a relatively large standard deviation of 14902.18, indicating substantial income disparities across China, India, Malaysia, Japan, and Korea. The skewness value of 0.8036 suggests a moderately right-skewed distribution, implying that a small number of countries record relatively high GDP per capita. Urbanization records a mean of 61.9688 and a standard deviation of 22.1308, with minimum and maximum values of 26.3710 and 91.7810, respectively. The coefficient of variation (0.35) and range-to-mean ratio (1.056) indicate moderate variation in urbanization levels. The negative skewness value (-0.3693) suggests a slight concentration of observations above the mean. Lastly, the mean value and standard deviation of trade openness (TO) are 70.2573 and 55.8161, indicating considerable variation in countries' integration into the global economy. The high positive skewness (1.3922) suggests that some countries are much more open to trade than others.

The Jarque-Bera test results show that all variables are not normally distributed, as their probabilities are below 0.05, leading to the rejection of the null hypothesis of normality. These deviations are common in macroeconomic and cross-country datasets due to heterogeneity across observations (Gujarati & Porter, 2021). Overall, the descriptive statistics reveal substantial cross-country heterogeneity, particularly in economic development, digital development, and trade openness.

Table 4.1.2 shows the correlation matrix among the variables. Financial Development (FD), Digital Technology Development (DTD), and Economic Development (ED) have a negative correlation with Rural-Urban Income Inequality (RUII), although the relationships are relatively weak. In contrast, Trade Openness (TO) shows a strong positive correlation with RUII (0.7254), indicating that higher trade openness is associated with greater income inequality. Urbanization demonstrates only a very weak positive relationship with RUII. Furthermore, the relatively high correlation among independent variables, particularly FD, URB, and DTD, indicates possible multicollinearity, which may distort the magnitude and direction of the estimated coefficients in the regression model.

A panel unit root test is conducted to determine whether variables in panel data are stationary or non-stationary. A stationary series is a time series where its statistical features do not change over time. However, non-stationary data may result in misleading or spurious regression outcomes, as stochastic trends among variables may produce misleading interpretations. The test is used to detect or identify whether a time series contains a unit root, which helps determine if it is stationary or needs differencing to become stationary. Ensuring stationarity enhances the reliability of the long-run regression model and supports a more explicit understanding of each variable, including rural–urban income inequality, financial development, digital technology development, economic development, urbanization, and trade openness. This study employs four panel unit root tests, which are the Levin-Lin-Chu (LLC) test, the Im, Pesaran and Shin (IPS) test, the ADF-Fisher Chi-square, and PP-Fisher Chi-square tests. These tests are performed under both constant and constant-with-trend specifications, each of which is based on different assumptions and has its own limitations.

Table 4.2.1 shows the results of the panel unit root tests for the logarithmic levels of the variables, which include lnRUII, lnFD, lnDTD, lnED, lnURB, and lnTO. However, Table 4.2.2 presents the results for the first-differenced form of the logged variables. Since it stabilizes the variance and normalizes the distribution of the data, all variables are transformed into natural logarithms to enhance consistency and comparability across the dataset.

The results in Table 4.2.1 indicate that only the Digital Technology Development variable is stationary, as it does not contain a unit root in level form. In addition, the PP test rejects the null hypothesis for the Financial Development variable at the 1% and 5% significance levels under both constant and constant-with-trend specifications, respectively, which the variable is considered stationary. Moreover, the control variable, Urbanization, is found to be stationary under the constant (intercept) specification. The remaining variables are non-stationary.

Economic Development, and Trade Openness become stationary across all panel unit root tests at the 1% significance level under both intercept and intercept-with-trend models. The Rural-Urban Income Inequality variable is also stationary at the 1% significance level, except under the LLC test. In contrast, the Digital Technology Development variable is found to be stationary at the 1% significance level across all panel unit root tests under the constant specification. However, the Urbanization variable remains non-stationary at first difference under the LLC, IPS, and ADF tests with constant specification.

The stationary results indicate that all variables are either integrated of order I(0), or I(1). This is an important requirement for long-run regression analysis, particularly for the Panel ARDL approach, as it permits the use of a mixture of I(0) and I(1) variables. So, the variables can be included in both levels and first difference forms, to make sure the validity and reliability of the estimated long-run and short-run relationships.

Table 4.3.1 reports the results of the Pedroni residual cointegration test used to examine the long-run relationship among the variables. The findings show that both panel and group statistics, including PP-statistic and ADF-statistic, are insignificant at the 10% significance level. Since the p-values are greater than the significance level under both individual intercept and the individual intercept with trend specifications, the null hypothesis cannot be rejected. This suggests that no cointegration exists among the variables, implying the absence of a long-run relationship based on the Pedroni test.

After taking the first difference, Table 4.2.2 indicates that Financial Development, Economic Development, and Trade Openness become stationary across all panel unit root tests at the 1% significance level under both intercept and intercept-with-trend models. The Rural-Urban Income Inequality variable is also stationary at the 1% significance level, except under the LLC test. In contrast, the Digital Technology Development variable is found to be stationary at the 1% significance level across all panel unit root tests under the constant specification. However, the Urbanization variable remains non-stationary at first difference under the LLC, IPS, and ADF tests with constant specification.

The stationary results indicate that all variables are either integrated of order I(0), or I(1). This is an important requirement for long-run regression analysis, particularly for the Panel ARDL approach, as it permits the use of a mixture of I(0) and I(1) variables. So, the variables can be included in both levels and first difference forms, to make sure the validity and reliability of the estimated long-run and short-run relationships.

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cointegration exists among the variables, implying the absence of a long-run relationship based on the Pedroni test.

Table 4.3.2 reports that the Kao residual cointegration test shows significant ADF statistics at the 5% level of significance. The null hypothesis of no cointegration is rejected since the P-Value is less than the significance level under the individual intercept. So, there is cointegration among the variables, suggesting the existence of a long-run relationship among the variables for the Kao cointegration test.

In summary, the Pedroni cointegration test does not reject the null hypothesis of no cointegration, suggesting the absence of a long-run relationship. However, the Kao test shows statistically significant results, suggesting the presence of cointegration. The conflicting findings may be due to differences in model assumptions, particularly regarding cross-sectional heterogeneity. Therefore, the Panel ARDL model is estimated, and the significance of the error correction term (ECT) is used as further evidence of a long-run relationship among the variables.

Table 4.4.1 presents the long-run estimation results. It indicates that all explanatory variables are statistically significant, as their probability values are close to zero, which rejects the null hypothesis. This result indicates a stable long-run relationship between rural-urban income inequality (RUII) and the explanatory variables. In this study, RUII is measured as the ratio of agriculture value-added per worker to industrial value-added per worker. Hence, a higher RUII indicates a narrowing rural-urban income gap, while a lower RUII reflects a wider gap. Financial Development (FD) and Urbanization (URB) show a negative relationship with RUII, suggesting that improvements in financial development and urbanization will decrease the value of RUII, which widens the income inequality in the long run. Specifically, as 1% increase in FD will reduce the value of RUII by 0.7345%, ceteris paribus. In contrast, Digital Technology Development (DTD), Economic Development (ED), and Trade Openness (TO) have a positive relationship with RUII, when these factors increase may contribute to reducing the income disparities over time.

Table 4.4.2 reports the short-run dynamics derived from the Error Correlation Model (ECM). The error correction term (ECT) is negative (-0.8289) and significant at the 10% level (p=0.0782), providing evidence of a long-run equilibrium relationship among the variables. The coefficient implies that approximately 82.95% of the short-run disequilibrium is corrected in each period, indicating a relatively fast adjustment towards the long-run equilibrium. In the short run, most explanatory variables are statistically insignificant, suggesting these variables do not have a significant impact on rural-urban income inequality (RUII) in the short-run period. However, the significant ECT indicates that deviations from the long-run equilibrium are gradually corrected over time, thereby supporting the long-run results reported in Table 4.4.1. ED is significant at the first lag (ln ED(-1)) at the 5% significant level. Since a higher RUII indicates a narrower income gap, the negative coefficient of (ln ED(-1)) implies that a 1% increase in ED in the previous period will widen the rural-urban income gap in the short run. Similarly, TO also exhibits a negative relationship at the second lag (ln TO(-2)) at 5% significance level. The negative coefficient indicates that 1% increase in TO may reduce 0.1311% in the value of RUII, which will widen the income gap in the short run. The lagged dependent variable, ln(RUII)(-1), is marginally significant at the 10% level ($p = 0.0941$), suggesting some persistence in income inequality over time.

Since this study employed rural-urban income inequality, the rural sector is represented by agricultural value-added per worker, while the urban sector is represented by industrial value-added per worker, which used the ratio of agricultural value-added per worker to industrial value-added per worker as a proxy. Meant that if there is an increase in the value of RUII, there is a narrowing in rural-urban income inequality. In contrast, if there is a decrease in the value of RUII, it means there is a widening in rural-urban income inequality.

Table 4.4 presents a comparison between the expected relationship and research findings. FD has a negative relationship with expected and research findings. This suggests that higher FD is associated with a larger rural-urban income inequality. In the case of digital technology development, a significant positive relationship was expected and is supported by the results. Improvements in digital technology development contribute to reducing the rural–urban income disparity.

Other than that, for control variables, economic development shows a significant positive relationship in both expected and research findings, which suggests that ED narrows the rural-urban income inequality. Urbanization was expected to narrow the rural-urban income gap. However, the results suggest that it contributes to a widening of the gap. This outcome can be explained by the concentration of economic activities and resources in urban areas, which reinforces regional development. (Henderson, 2003). Additionally, according to the Harris–Todaro Model, migration is driven by expected income differences between rural and urban areas. Although many individuals migrate in search of better opportunities, only a portion secure high-paying jobs, while others remain unemployed or work in low-wage informal sectors. As a result, this situation widens the income disparity between rural and urban areas. (Harris & Todaro, 1970). Lastly, trade openness shows a significantly positive relationship, as expected. Trade openness tends to narrow the rural-urban income gap, which matches the research findings by Winter (2004) and Dollar & Kraay (2004).

This study finds a significant negative relationship between financial development and rural–urban income inequality, implying that higher financial development is associated with a wider income gap between rural and urban areas. This may be attributed to the unequal distribution of financial resources, where financial institutions tend to lend to lower-risk borrowers, such as urban residents or high-income households, rather than rural households. In addition, financial institutions are more developed in urban areas than in rural areas, which supports the inequality-widening hypothesis (Wang et al., 2023; Zhang et al., 2025).

In contrast, digital technology development shows a significant positive relationship with RUII, suggesting that an increase in digital technology development helps to narrow the rural–urban income gap. The expansion of digital technologies in rural areas improves access to information and job opportunities and boosts income diversification, thereby reducing rural–urban income inequality (Zhang & Li, 2024).

Overall, the findings highlight the different roles of financial development and digital technology development in shaping rural–urban income inequality.

Despite decades of policy interventions across Asia, rural–urban income inequality remains persistent. This suggests that existing policies may be insufficient without a deeper understanding of how financial development and digital technology interact with underlying structural and institutional factors. So, filling this gap is important for creating more effective, suited policies that support inclusive growth in the Asia-Pacific region.

Based on the findings in the previous chapter, financial development is found to have a significant negative relationship with rural-urban income inequality across the five Asian countries, indicating that higher financial development is associated with a widening income gap between rural and urban areas. This is because financial institutions generally prefer to lend to low-risk borrowers, such as urban residents or individuals with higher incomes, rather than to those in rural areas. Moreover, financial services are more advanced and accessible in urban regions compared to rural areas. Therefore, governments should implement policies that improve rural access to financial services, such as expanding microfinance institutions, digital banking, and other services targeted at rural households and small-scale farmers. This would help ensure the financial development benefits both rural and urban populations equally and may reduce the rural-urban income inequality.

Furthermore, the results indicate a significant relationship between digital technology development and rural–urban income inequality, suggesting that higher levels of digital technology development are associated with a reduction in the income gap between rural and urban areas. When rural areas gain access to digital tools such as internet connectivity, mobile applications, and e-learning platforms, they are able to improve access to information and employment opportunities. This enables rural individuals to explore multiple sources of income, thereby promoting income diversification. So, policymakers should treat digital technology not just as a tool for economic growth, but as a strategy to reduce countries' income disparities by empowering rural areas individually. They can expand rural digital infrastructure, such as investing in high-speed internet, mobile networks, and affordable digital devices for rural communities.

Last but not least, the control variable includes economic development, urbanization, and trade openness, which all show a significant to rural-urban income inequality, indicating that macroeconomic factors play an important role in income distribution. The positive effect of economic development, which narrows rural-urban income inequality. Suggest that policymakers should promote sustainable and inclusive growth to ensure a balance of rural and urban income inequality. However, the study finds that urbanization widens rural-urban income inequality, implying that the government can reduce the concentration of resources in urban areas and create more job opportunities in rural areas. Furthermore, the significance of trade openness and the narrowing of rural-urban income inequality indicate that policymakers should continue to support international trade while ensuring that rural sectors benefit through improved market access and export opportunities.

This research on rural-urban income inequality is subject to several limitations. Firstly, this study adopts a macro-level approach using country-level data, which focuses on overall trends but may not capture micro-level variations within countries. Differences across regions, households, and individuals are not considered, which may limit a deeper understanding of rural-urban income inequality.

Secondly, this study adopts a static framework that focuses on the average relationship between each variable over the sample period. As a result, it may not fully capture the dynamic changes in the relationship between financial development, digital technology development, and rural-urban income inequality over time. In particular, potential dynamic changes arising from economic shocks, policy shifts, or technological transitions are not explicitly examined.

Future research can adopt a micro-level approach by using household or individual-level data to better capture variations in income distribution between rural and urban areas. Additionally, future studies may incorporate regional or state-level data to examine spatial disparities within countries, which provide deeper insights. The use of more advanced methodologies and higher-frequency data is also recommended to improve the robustness of the results.

Furthermore, future studies may consider using dynamic models, such as Generalized Method of Moments (GMM) approach or time-varying techniques, to better capture changes in relationships over time. Moreover, incorporating structural break analysis and higher-frequency data can help examine the impact of economic shocks, policy changes, and technological transitions on rural-urban income inequality.

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