THE IMPACT OF TECHNOLOGY ADOPTION ON CLIMATE ADAPTATION READINESS IN ASEAN: EVIDENCE FROM 2014–2023

A THESIS

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TITLE PAGE

The Impact of Technology Adoption on Climate Adaptation Readiness in ASEAN: Evidence From 2014–2023

BACHELOR THESIS

Written and filed to accomplish final exam requirements in order to obtain a bachelor's degree at the Economic Development International Program Faculty of Business and Economics, Universitas Islam Indonesia

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DECLARATION OF AUTHENTICITY

I declare that this thesis is my own original work. I have not used the work, ideas, or words of others without proper acknowledgment. All sources used in this thesis are cited and listed in the bibliography. If this statement is later found to be untrue, I am willing to accept any consequences in accordance with the applicable regulations.

Yogyakarta, 28 December 2025

Nayla Ilma Kauna

MOTTO

مَنْ لَمْ يَذُقْ ذُلَّ التَّعَلُّمِ سَاعَةً # تَجَرَّعَ ذُلَّ الْجَهْلِ طُوْلَ حَيَاتِـهِ

— Imam Syafi’i

“The most important thing we ever learn at school is the fact that the most important things can't be learned at school.”

— Haruki Murakami

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This thesis was written during a very short and overwhelming period of my life. A time when I spoke to ChatGPT more often compared to humans. From September to November, I went through repeated cycles of changing my research topic, constant revisions, and facing that my regression results were consistently invalid. But once my regression was finally validated and the topic was approved, everything shifted. With full focus, I completed this thesis in just 16 days, from 1 to 16 December 2025.

During those sixteen days, life continued relentlessly. I celebrated my birthday, taught English, prepared for my KKN, hosted International Day, assisted classes, taught taklim, witnessed devastating floods across Sumatera, and finally went to see a psychologist. There were moments when exhaustion, anxiety, and pressure felt heavier than I could carry. Many times, I questioned what I was doing and whether I could keep going. Yet, somehow, me & my ADHD finally made it.

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With heartfelt appreciation to all who are named and those remembered silently, I present the fruit of this research in the form of an undergraduate thesis entitled *"The Impact of Technology Adoption on Climate Adaptation Readiness in ASEAN: Evidence From 2014–2023."* I hope this work may serve as a source of insight for readers from various backgrounds and inspire reflection and dialogue beyond academic spaces.

As an author, I realized that this is not a perfect work and i also realized how much I still do not know after four years of studying economics. My understanding remains incomplete, and my questions are far from answered. For that reason, I do not see this thesis as the end of my learning, but as the beginning—a quiet declaration that I am ready to keep learning, questioning, and walking forward.

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Sleman, 28 December 2025

Nayla Ilma Kauna

ADVISORS' APPROVAL

THE IMPACT OF TECHNOLOGY ADOPTION ON CLIMATE ADAPTATION READINESS IN ASEAN: EVIDENCE FROM 2014–2023

A BACHELOR THESIS

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Bismillahirrahmanirrahim,

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THE IMPACT OF TECHNOLOGY ADOPTION ON CLIMATE ADAPTATION READINESS IN ASEAN: EVIDENCE FROM 2014–2023

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ABSTRACT

This study analyzes the effect of technological adoption on climate adaptation readiness in ASEAN Six and Non-ASEAN Six countries over the period 2014–2023, using dynamic panel data estimated with the System GMM approach. Technological adoption is proxied by secure internet services, while climate adaptation readiness is examined in total and across its social, governance, and economic dimensions, with economic size, innovation, and renewable energy consumption included as control variables. The findings show that technological adoption has a positive and significant impact on total climate adaptation readiness, particularly in ASEAN Six countries, indicating the importance of digital infrastructure in strengthening overall adaptive capacity. Technological adoption also significantly improves governance readiness, reflecting better institutional coordination and policy effectiveness. However, its effects on social and economic readiness are positive but statistically insignificant, suggesting that technology alone is insufficient without supportive social structures and economic institutions. Overall, the results highlight that climate adaptation readiness is persistent and cumulative, underscoring the need to integrate technological development with broader governance and structural reforms.

Keywords: *Technological Adoption, Climate Adaptation Readiness, ASEAN, Digital Infrastructure.*

DAMPAK ADOPSI TEKNOLOGI TERHADAP KESIAPAN ADAPTASI IKLIM DI ASEAN: STUDI EMPIRIS PERIODE 2014–2023

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ABSTRAK

Penelitian ini menganalisis pengaruh adopsi teknologi terhadap kesiapan adaptasi iklim di negara-negara ASEAN Six dan Non-ASEAN Six selama periode 2014–2023 dengan menggunakan data panel dinamis yang diestimasi melalui pendekatan System Generalized Method of Moments (System GMM). Adopsi teknologi diproksikan melalui *secure internet services* sedangkan kesiapan adaptasi iklim dianalisis secara total serta berdasarkan dimensi sosial, tata kelola pemerintahan, dan ekonomi. GDP, inovasi, dan konsumsi energi terbarukan digunakan sebagai variabel kontrol. Hasil penelitian menunjukkan bahwa adopsi teknologi berpengaruh positif dan signifikan terhadap kesiapan adaptasi iklim secara keseluruhan, terutama di negara-negara ASEAN Six, yang menegaskan pentingnya infrastruktur digital dalam memperkuat kapasitas adaptif secara menyeluruh. Adopsi teknologi juga secara signifikan meningkatkan kesiapan tata kelola, yang mencerminkan koordinasi kelembagaan dan efektivitas kebijakan yang lebih baik. Namun, pengaruhnya terhadap kesiapan sosial dan ekonomi bersifat positif tetapi tidak signifikan secara statistik, yang mengindikasikan bahwa teknologi saja tidak cukup tanpa dukungan struktur sosial dan institusi ekonomi yang memadai. Secara keseluruhan, hasil penelitian menegaskan bahwa kesiapan adaptasi iklim bersifat persisten dan kumulatif, sehingga diperlukan integrasi antara pengembangan teknologi dengan reformasi tata kelola dan struktural yang lebih luas.

Kata kunci: *Adopsi Teknologi, Kesiapan Adaptasi Iklim, ASEAN, Infrastruktur Digital.*

CHAPTER I

INTRODUCTION

1.1 Background

Climate change affects all regions, but ASEAN faces extremely high risks. Southeast Asia is identified as one of the most climate-vulnerable regions globally, especially due to dense coastal populations and rising sea levels (Putra 2024a) . Country-level assessments show Myanmar, the Philippines, and Thailand experiencing the highest climate-related risk and economic losses in the region (Ding & Beh, 2022). Regional analyses further reveal that several ASEAN economies rank among the world's most disaster-affected agricultural producers, with floods, storms, and extreme weather directly threatening food security (OECD, 2018). The range of hazards including El Niño, La Niña, earthquakes, tsunamis, floods, and tropical storms illustrates the region's multidimensional exposure (Indriawati & Prasetyani, 2021). These climate pressures also pose macroeconomic and financial risks, with potential GDP losses far exceeding global averages (Senga, 2010) and increased sovereign bond yields linked to climate vulnerability (Beirne et al., 2021), highlighting how climate change threatens long-term development stability across ASEAN.

In response to these escalating risks, ASEAN has strengthened its regional climate readiness agenda by updating Nationally Determined Contributions (NDCs) and developing long-term low-emission strategies (ASEAN, 2021b). ASEAN has coordinated climate measures through regional platforms such as the ASEAN Climate Change Initiative and the ASEAN Working Group on Climate Change (ASEAN, 2021b). ASEAN's official climate reports highlight progress in renewable energy, energy efficiency, coastal resilience, and regional joint statements at UNFCCC negotiations (ASEAN, 2021b). These initiatives reflect efforts to align national and regional strategies while promoting climate-focused knowledge-sharing and cooperation with dialogue partners.

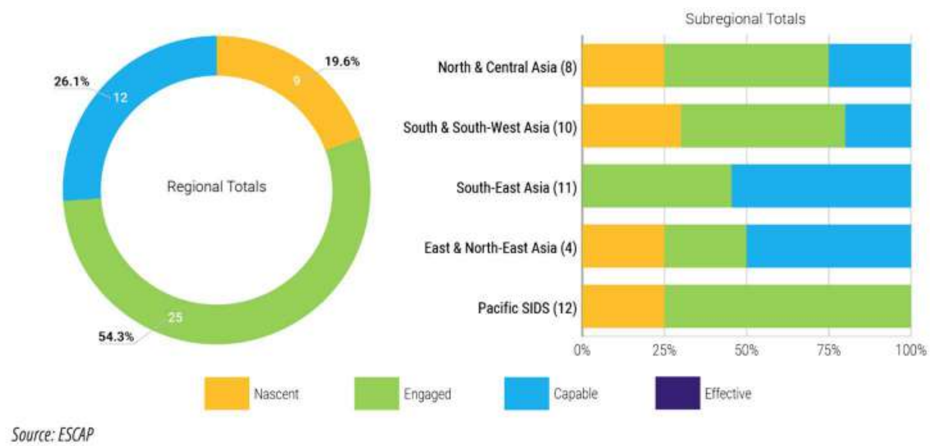

Figure 1.1 Regional and Subregional Assessment of Readiness on NDCs

Source: UN ESCAP

Despite these advancements, overall readiness remains uneven across ASEAN Member States (UN ESCAP, 2020). ASEAN countries continue to set relatively modest emissions-reduction targets, exhibit limited expansion in renewable energy deployment, and maintain significant reliance on fossil-fuel-based development pathways (Overland et al., 2021). This is rooted in economic pragmatism: despite framing climate change as a major threat, Southeast Asian governments still prioritize growth and investment over ambitious mitigation, resulting in slow progress and minimal renewable-energy expansion between 2005–2017 (Putra, 2024b).

Technological preparedness reflects similar disparities. While countries like Singapore possess strong systems for measurement, reporting, and verification, others lack robust climate data governance and modelling capacity (UN ESCAP, 2020). ASEAN is attempting to close this gap by linking climate goals with the *ASEAN Digital Masterplan 2025*, which emphasises integrated data systems and improved digital governance. Strengthening data infrastructure, transparency procedures, and early-warning capabilities is seen as essential to support evidence-based policy and regional climate resilience (ASEAN, 2021a).

Building on these technological readiness gaps, recent literature also underscores how technological innovation can advance climate action without constraining economic development. Green technologies have already delivered substantial emissions reductions globally, for instance: India's 62 GW solar expansion prevents 150 million metric tons of emissions annually, while Brazil's biofuel sector produces 35 billion litres of ethanol per year (Niu et al., 2023). Other emerging innovations, including drone-based forest surveillance (Elsayed et al., 2024), interactive air-quality monitoring systems (Tambo et al., 2016), and cross-border climate-technology transfer mechanisms (W.-J. Lee & Mwebaza, 2021), further demonstrate how technological solutions can reinforce both climate mitigation and adaptation efforts.

Technology adoption therefore emerges as a critical but still understudied dimension of climate readiness in ASEAN. Existing research has heavily emphasized policies, governance frameworks, and emissions-reduction commitments, yet far less attention has been given to whether technological progress actually strengthens climate adaptation capacity in developing regions (Fankhauser & Burton, 2011). This gap is especially relevant for ASEAN, where economic strategies increasingly prioritize digitalization, innovation, and technology-driven development.

Despite this potential, developing regions continue to face financial constraints, rising loss-and-damage costs, and limited economic buffers that restrict wide-scale technology adoption (ASEAN, 2021b). This leads to a critical research question: Does technology adoption significantly enhance climate adaptation readiness in ASEAN, or do structural limitations hinder its impact? This study addresses that question through the title: **"The Impact of Technology Adoption on Climate Adaptation Readiness in ASEAN: Evidence From 2014–2023"**

1.2 Problem Formulation

Based on the research background and previous studies concerning ASEAN vulnerability, technology adoption, and climate change, along with the varying findings this research formulates the following questions to address the central issue:

1. Is there any influence of technological adoption on the climate change adaptation readiness in South East Asian Countries?

2. Is there any difference in the effect of technological adoption on the climate change adaptation readiness in ASEAN Six Countries and Non-ASEAN Six Countries?

1.3 Research Objectives

Based on the issue that has been identified previously, the objectives of this research are as follows:

1. To investigate and analyze the influence of technological adoption on the climate change adaptation readiness in South East Asian Countries.
2. To compare and analyze the difference in the effect of technological adoption on the climate change adaptation readiness in ASEAN Six Countries and Non-ASEAN Six Countries.

1.4 Research Contributions

This research is expected to contribute to both academic understanding and practical policy development by deepening insights into how technology adoption influences climate change adaptation readiness across Southeast Asian countries, with a comparative focus between ASEAN-6 and non–ASEAN-6 economies. The expected contributions are as follows:

1. Policymakers: The results provide empirical evidence on the role of technological adoption in strengthening climate change adaptation readiness in Southeast Asia. These findings can support governments in designing digital transformation strategies and climate policies that are more targeted, data-driven,

and aligned with regional commitments such as the ASEAN Climate Change Strategic Action Plan.

2. Academics and Researchers: This study contributes to the growing literature on digitalization and climate resilience by offering cross-country evidence from Southeast Asia. By comparing ASEAN-6 and non–ASEAN-6 countries, the research also provides a basis for understanding structural disparities and heterogeneity in digital–climate linkages.
3. Regional and International Development Agencies: The findings offer insights for organizations working in adaptation planning, digital governance, and sustainable development. Evidence from this study may inform program design, capacity-building initiatives, and monitoring frameworks aimed at enhancing technological readiness as a component of climate resilience.

1.5 Systematic of Writings

The structure of the research is as outlined below:

CHAPTER I: INTRODUCTION

Chapter I of the thesis reveals an overview of the research, detailing the research background, problem formulation, research objectives, research contributions, and the arrangement of the writing structure.

CHAPTER II: THEORETICAL FRAMEWORK AND HYPOTHESIS DEVELOPMENT

Chapter II discusses the theory that forms the foundation of this research. It also discusses the basis of the definition concerning technological adoption and its effect on climate adaptation readiness. Moreover, it encompasses the development of a research framework and the formulation of proposed hypotheses in this research.

CHAPTER III: METHODOLOGY

Chapter III describes the operational definition of each variable, the methodologies and techniques adopted for collecting the data, the criteria for population and sample, and the data analysis methodology utilized in this research.

CHAPTER IV: DATA ANALYSIS AND DISCUSSION

Chapter IV describes the data processing results and provides a detailed analytical discussion of the findings obtained from the estimation results to achieve the optimal results.

CHAPTER V: CONCLUSION

Chapter V contains conclusions and suggestions for further research related to the topics examined in this study.

CHAPTER II

LITERATURE REVIEW

This chapter presents a review of relevant literature that forms the foundation of the current study. It discusses previous theories and research findings to build the conceptual framework and guide the study's direction. Additionally, this section outlines the hypotheses developed based on theoretical insights and prior empirical evidence.

2.1 Literature Review

Prior research shows that a country's climate adaptation readiness is shaped by the strength of its economic foundations, governance quality, social infrastructure, and technological capability. Sarkodie & Strezov (2019) found that developed countries including Norway, Switzerland, Canada, Sweden, and Germany are less vulnerable to climate change due to strong economic, governance, and social adaptation readiness. Edidin (2024) reinforced this by demonstrating that stable economies are better prepared for climate change, while less stable ones remain more vulnerable. Saeed et al., (2023) further showed that resource-endowed developed countries have successfully integrated adaptive and protective policies into their developmental agenda using human power, technology, and investment, making countries like Australia, Austria, Belgium, and the USA highly adaptive due to their readiness for adaptation.

Social infrastructure and human development further reinforce adaptation readiness. Epule et al., (2021) demonstrated that readiness has a positive correlation with literacy rates and an inverse relationship with poverty rates, highlighting how education and economic well-being directly influence a country's preparedness. Amegavi et al., (2021) confirmed that adaptation readiness has a significant negative effect on vulnerability to climate change, proving the importance of developing comprehensive adaptive capacity.

Technology emerges as a central factor distinguishing countries with strong readiness from those that remain highly vulnerable, particularly the developed from developing nations. Edidin et al., (2024) specifically highlighted the role of AI readiness in enhancing adaptation efforts, demonstrating how advanced technologies can strengthen a country's climate response capabilities. Saeed et al., (2023) noted that developing countries are more vulnerable to climate change because they lack adaptive capacity, suitable infrastructure, and technology, while developed countries leverage technology alongside human capital to build resilience. Hamwey (2021) suggested that developing countries can enhance their climate readiness through technological adaptation actions, underscoring technology's role as both a barrier for unprepared nations and an enabler for those with adequate technological capacity.

In the ASEAN context, technology adoption reflects substantial disparities across countries, reflecting broader differences in economic development and institutional capacity. Singapore consistently leads in multiple technology sectors, ranking highest in digital literacy levels (Kusumastuti & Nuryani, 2020), demonstrating mature Fintech development with high adoption rates (Huong et al., 2021), and showing advanced implementation of educational technologies including artificial intelligence applications (Machmud et al., 2021). Meanwhile, countries like Cambodia, Lao PDR, and Myanmar represent the lower tier of technological adoption, though they show positive improvements over time (Tran et al., 2022). The variation extends across sectors, with ICT adoption levels differing significantly among ASEAN logistics companies (Tongzon & Nguyen, 2013), and e-commerce adoption showing uneven patterns influenced by both individual characteristics and national cultural factors (Ayob, 2021).

These technological disparities carry significant implications for climate adaptation readiness across ASEAN. While several countries have made substantial progress in digital development, translating technological advancement into sustainable development outcomes remains challenging (Tran et al., 2022). The development of digital technology and innovation capabilities, as highlighted in the ASEAN Digital Masterplan 2025, is essential for addressing climate challenges, yet countries like Thailand still face gaps in maintaining competitiveness in this area (Wongwuttiwat et al., 2024). Furthermore, sustainable energy technology adoption across ASEAN is influenced by factors such as environmental awareness, cost considerations, and habitual energy-saving behaviors, suggesting that countries with stronger technological foundations may be better positioned to implement climate adaptation solutions (Lin et al., 2022).

Overall, the literature demonstrates that economic strength, governance quality, social development, and technological capability are deeply interconnected drivers of climate adaptation readiness. Across global and regional contexts, technology consistently emerges as a key enabler of resilience, improving information systems, decision-making, and adaptive capacity. However, persistent disparities in technological adoption especially within ASEAN suggest that countries with weaker digital and innovation infrastructures may struggle to achieve robust climate readiness. These gaps highlight the need for empirical research that not only assesses the impact of technology adoption on climate adaptation readiness in ASEAN but also compares differences between the ASEAN Six and the Non-ASEAN Six countries within the region. The present study responds to this need by evaluating how technology adoption influences adaptation readiness across ASEAN from 2014 to 2023, including a specific examination of readiness differentials between the ASEAN Six and Non–ASEAN Six subgroups.

2.2 Theoretical Background

This section presents an overview of the theoretical foundations that support this research, focusing primarily on how technology affects a country's development and the various factors that may influence it.

2.2.1 Classical Production Theory

The Cobb–Douglas production function explains how economic output is produced using capital and labor (Cobb & Douglas, 1928). The general form is:

$$Y = AK^{\alpha}L^{1-\alpha}$$

In this equation, Y represents output, K is capital, L is labor, and A captures overall productivity or efficiency. The function reflects key economic ideas, including how additional capital or labor increases output (marginal productivity), how output responds when all inputs increase together (returns to scale), and the ability to substitute capital for labor.

This framework is especially important for climate change analysis. Climate shocks such as floods, droughts, and storms can reduce productivity A by disrupting economic activities, damaging infrastructure, and lowering efficiency. Climate-related disasters may also destroy physical capital K and reduce the effective supply of labor L. As a result, overall output declines.

At the same time, technology adoption can improve productivity and strengthen economic resilience. By enhancing efficiency and reducing vulnerability to climate risks, technology effectively raises A, helping economies maintain output even under environmental stress.

2.2.2. Solow–Swan Neoclassical Growth Model

The Solow model explains long-term economic growth through capital accumulation, labour, and exogenous technological progress. In its simplest mathematical form, output per worker depends on capital per worker:

$$y = k^{\alpha}, \ 0 < \alpha < 1$$

Capital accumulation evolves according to the differential equation:

$$k = sk^{\alpha} – (n+\delta)k$$

where s is the savings rate, n is population growth, and δ is depreciation. This structure highlights two important ideas: diminishing returns to capital and convergence toward a steady-state level of income.

In the context of climate adaptation readiness, the Solow model is particularly relevant because climate shocks can damage infrastructure and physical assets, reducing capital K. Climate change can also slow technological progress A and increase capital depreciation δ through more frequent extreme weather events. Together, these effects lower long-run economic growth and weaken a country's capacity to adapt to climate risks.

2.2.3 Environmental Kuznets Curve

The Environmental Kuznets Curve is a modern theory describing an inverted-U relationship between economic growth and environmental degradation. It is commonly expressed as:

$$E = \beta_0 + \beta_1 Y + \beta_2 Y^2 + \epsilon$$

where E is environmental degradation and Y is income. At low income levels, pollution increases with growth; at higher income levels, countries reduce pollution due to better regulation, technology adoption, and institutional improvement.

This theory is relevant because it directly links economic development, technology, and environmental pressure as key components of climate adaptation readiness. The EKC suggests that as economies develop and adopt new technologies, environmental harm decreases. ASEAN countries tend to be on the "rising" or "turning point" of the curve, making technology adoption essential to accelerate the downward slope of environmental damage (Grossman & Krueger, 1995).

2.3 Conceptual Framework

Grounded in classical and modern economic theories that emphasize the role of technological progress, institutional quality, and environmental conditions in shaping long-run development, this study conceptualizes climate adaptation readiness as a multidimensional capacity that evolves dynamically over time. Climate adaptation readiness reflects the ability of a country to convert resources, institutions, and socio-economic structures into effective climate adaptation actions.

In this study, readiness is structured across four dimensions: economic readiness, governance readiness, and social readiness, alongside an aggregated total readiness index that combines these three pillars into an overarching assessment of adaptive capacity. A central feature of this framework is the recognition that readiness is path-dependent; that is, past levels of readiness shape current performance, which justifies the incorporation of lagged readiness indicators to capture persistence effects in adaptation capability.

Technology adoption functions as the principal explanatory factor within the conceptual model because technological infrastructure, digital capacity, and information systems underpin climate monitoring, early-warning mechanisms, and institutional coordination. Complementary determinants: economic performance, innovation capacity, and renewable energy consumption, provide additional structural foundations that influence how effectively countries can deploy resources, transition to sustainable systems, and enhance technological competitiveness. These factors collectively shape institutional preparedness and societal resilience, ultimately determining countries' ability to translate technological and economic capacity into adaptation outcomes. By integrating these determinants into a dynamic panel framework, the conceptual model highlights that climate adaptation readiness emerges from the interaction of technological capability, socioeconomic resources, and institutional systems, forming the analytical basis for assessing adaptation capacity across ASEAN countries.

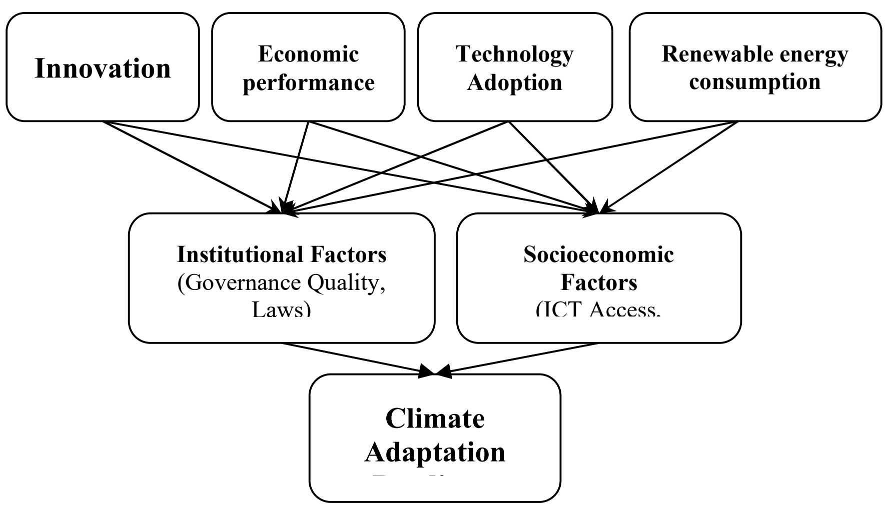

Figure 2.1 Conceptual Framework

2.4 Hypothesis Development

A hypothesis serves as a provisional explanation developed to address the research problem and guide the empirical investigation. In this study, the hypotheses are formulated to provide direction in examining how technological adoption and supporting economic and environmental factors influence climate adaptation readiness in ASEAN countries. These hypotheses outline the expected relationships among variables and act as the foundation for the empirical models presented as follows:

1. Technology adoption positively influences total readiness in ASEAN Six countries.
2. Technology adoption positively influences total readiness in Non-ASEAN Six countries.
3. Group classification (ASEAN Six vs Non–ASEAN Six) significantly affects total readiness.
4. The effect of technology adoption on total readiness differs between ASEAN Six and Non–ASEAN Six countries.
5. Technology adoption positively affects social readiness in ASEAN countries.
6. Technology adoption positively affects governance readiness in ASEAN countries.
7. Technology adoption positively affects economic readiness in ASEAN countries.

CHAPTER III

RESEARCH METHODOLOGY

This chapter describes the systematic approach employed in this research, including the process of sample selection, data categorization, and data collection techniques. It further presents the research model, detailing the operational definitions and measurement methods for each variable. In addition, this chapter explains the data analysis procedures and outlines the hypotheses that serve as the basis for interpreting the research findings.

3.1 Population and Sample

The population of this study comprises all Southeast Asian countries, reflecting the regional focus on climate adaptation readiness and technological capacity. From this population, a balanced panel of ASEAN Member States, including the newly admitted Timor-Leste, was constructed for the period 2014–2023. To enable comparative analysis consistent with the study's empirical framework, the sample is divided into two analytically meaningful groups: the "ASEAN Six," consisting of Indonesia, Malaysia, the Philippines, Singapore, Thailand, and Vietnam, countries widely recognized for relatively more advanced economic structures and data availability and the "Non-ASEAN Six," consisting of Brunei Darussalam, Cambodia, Lao PDR, Myanmar, and Timor-Leste. This grouping reflects heterogeneity in technological development, governance capacity, and economic structure, allowing the study to evaluate whether the effect of technological adoption on climate adaptation readiness differs across subregional development levels.

The final dataset is an unbalanced panel due to variation in data completeness across countries and years, particularly for Timor-Leste and Myanmar. Nevertheless, all countries were retained to preserve the representativeness of ASEAN as a regional system. The panel spans ten years, from 2014 to 2023, yielding a sufficiently rich dataset for estimating dynamic panel models. Each yearly observation contains measurements for the dependent variables: total readiness, social readiness, governance readiness, and economic readiness from the ND-GAIN Adaptation Readiness framework. Alongside the primary independent variable, technological adoption (measured as the log of secure internet servers), and three control variables: economic performance (log GDP), high-technology exports (innovation), and renewable energy consumption (environmental sustainability). This sampling structure ensures that the study can systematically assess both within-country dynamics over time and cross-country differences between ASEAN Six and Non-ASEAN Six groups.

3.2 Analytical Framework

This research aims to examine the influence of Technology Adoption on Climate Adaptation Readiness. Presented below are the research frameworks that constructed this study:

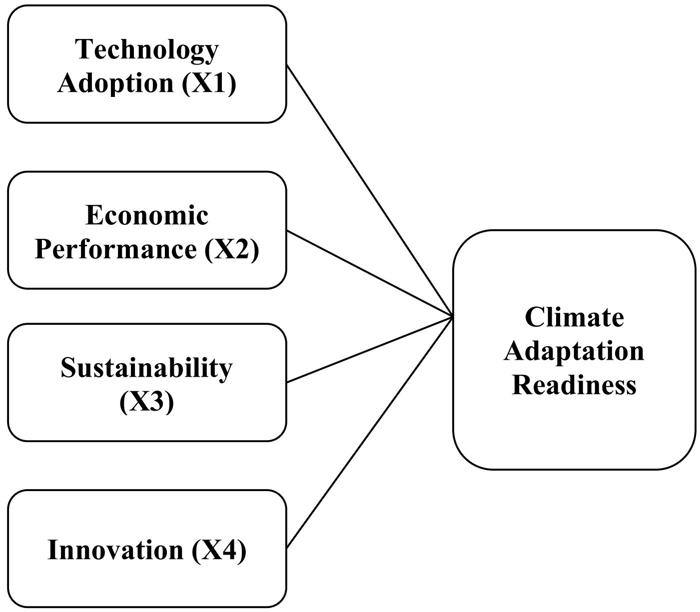

Figure 3.1 Research Framework

The figure 3.1 illustrates the conceptual framework linking technological adoption to climate change adaptation readiness in Southeast Asian countries. Climate change adaptation readiness (Y) represents a country's overall capacity to anticipate, prepare for, and respond to climate-related risks.

The main independent variable is technology adoption (X_1), measured using the number of secure internet servers, which indicates the extent of digital infrastructure development and technological capability. To provide a more comprehensive analysis, the framework includes three additional explanatory variables. Economic performance (X_2), represented by GDP, captures a country's financial capacity to support adaptation measures. Sustainability (X_3), measured through renewable energy consumption, reflects national commitment to environmental responsibility and long-term resilience.

Innovation (X_4), represented by high-technology exports, indicates the strength of a country's innovation ecosystem and technological competitiveness.

By examining each component separately, this framework captures the heterogeneity in how technology adoption and related factors influence distinct dimensions of adaptive capacity, namely social, governance, and economic readiness across the region. The comparison between ASEAN Six and Non-ASEAN Six countries further identifies whether these determinants operate differently across country groupings.

3.3 Data Collection Method

The study relies exclusively on secondary data sourced from internationally recognized and publicly accessible databases to ensure reliability, comparability, and transparency. Climate adaptation readiness indicators including total readiness, social readiness, governance readiness, and economic readiness that are obtained from the Notre Dame Global Adaptation Initiative (ND-GAIN) Country Index, which provides standardized annual scores reflecting countries' preparedness for climate-related risks.

Technological adoption is measured using the log transformation of Secure Internet Servers (SIS), collected from the World Bank's World Development Indicators (WDI). This variable serves as a proxy for digital and technological capacity frequently used in macro-technology and ICT-readiness studies. Economic performance is represented by the logarithm of Gross Domestic Product (GDP, constant 2015 US$), also taken from WDI, ensuring consistency with panel data requirements and cross-country comparability. Innovation capability is captured by high-technology exports as a percentage of manufactured exports, sourced from WDI, while renewable energy consumption refers to the share of total final energy consumption derived from renewable sources.

The study also constructs a country-group variable coded as one for ASEAN Six members and zero for other ASEAN countries including Timor-Leste. This variable is used to test moderating effects in the dummy and interaction models. All variables are collected on an annual basis for the period 2014 to 2023, enabling detailed longitudinal analysis and allowing the study to estimate dynamic effects through lagged dependent variables.

3.4 Operational Definition and Variable Measurement

Operational definitions specify how each variable in this research is conceptualized and measured to ensure consistency, reliability, and analytical clarity. This section outlines the dependent and independent variables used in the empirical models, supported by relevant academic literature that justifies their inclusion. All variables are operationalized using internationally recognized datasets with annual, cross-country comparability, allowing the analysis to accurately examine the relationship between technological development and climate adaptation readiness in ASEAN.

3.4.1 Dependent Variable

Climate adaptation readiness is measured using the ND-GAIN Readiness Index, which evaluates a country's capacity to leverage investments and convert them into effective climate adaptation actions (Chen et al., 2024). ND-GAIN divides readiness into three pillars: economic, governance, and social readiness, while also providing an aggregated total readiness score. Total readiness reflects the overall ability of institutions, economic systems, and society to support adaptation implementation. Social readiness measures social inequality, ICT access, and education; governance readiness assesses institutional quality and regulatory capacity; and economic readiness evaluates macroeconomic stability, business environment, and investment climate. According to Chen et al. (2024), readiness dimensions directly influence the success of climate adaptation by shaping a country's institutional and socioeconomic capacity to respond to climate risks. In the estimation, these variables are denoted as **TR**, **SR**, **GR**, and **ER**, respectively.

3.4.2 Independent Variable

This section describes how the researcher measured the independent variable in the study, which includes technology adoption, economics performance, renewable energy consumption, and innovation. The description of the measurement technique used will be condensed below.

3.4.2.1 Technology Adoption

Technological capacity is measured using the natural logarithm of the number of Secure Internet Servers (SIS) from the World Development Indicators. Secure servers are widely used in empirical work as a proxy for digital readiness, technological infrastructure, and the capacity to deploy advanced information systems. As noted by Niebel (2018), digital infrastructure significantly enhances productivity, innovation diffusion, and institutional capability, all of which are essential for climate adaptation processes that require data management, monitoring, and information flow. This variable is denoted as **LSIS**.

3.4.2.2 Economic Performance

Economic performance is measured using the natural logarithm of GDP (constant 2015 USD), sourced from the World Development Indicators. GDP reflects national economic capacity and the ability to fund adaptation investments, institutional development, and technological adoption. According to Tol and Yohe (2007), higher levels of economic development increase adaptive capacity because wealthier nations possess stronger fiscal, infrastructural, and technological resources. This variable is denoted as **LGDP**.

3.4.2.3 Innovation

Innovation is measured using high-technology exports, which reflect a country's ability to produce and commercialize advanced technologies. High-tech exports are widely used as an indicator of innovation capacity and technological sophistication. Lee and Malerba (2017) argued that national innovation systems, particularly high-tech industries, strengthen a country's competitiveness and resilience by fostering technological learning and capability accumulation. This variable is denoted as **Exp** in the estimation.

3.4.2.4 Environmental Sustainability

Environmental sustainability measured by the renewable energy consumption data are obtained from the World Development Indicators (WDI) published by the World Bank. This indicator measures the percentage share of renewable energy in total final energy consumption, including energy derived from hydro, solar, wind, geothermal, and modern bioenergy sources. Renewable energy reflects a country's progress toward environmental sustainability and its efforts to reduce ecological pressure while supporting economic development. According to Apergis and Payne (2010), renewable energy enhances energy security and reduces environmental degradation, contributing to more sustainable development pathways that align with adaptation goals. This variable is denoted as **RE** in the estimation.

3.5 Model Development

This study develops a series of dynamic panel data models to empirically assess how technology adoption, economic capacity, innovation, and renewable energy consumption influence climate adaptation readiness across ASEAN countries. The models are structured to capture both the persistence of readiness over time and the heterogeneity between ASEAN Six and Non-ASEAN Six groups. The first set of models examines total readiness under different sample specifications, followed by models that separately evaluate social, governance, and economic readiness dimensions.

3.5.1 Model 1: Total Readiness

3.5.1.1 ASEAN Six Countries

$$TR_{it} = \alpha + \beta_1 TR_{i,t\text{-}1} + \beta_2 LSIS_{it} + \beta_3 LGDP_{it} + \beta_4 Exp_{it} + \beta_5 RE_{it} + \varepsilon_{it}$$

where:

TR_{it} : Climate Adaptation Total Readiness for country *i* in year *t*
$TR_{i,t\text{-}1}$: Lagged Climate Adaptation Total Readiness (previous period)
SIS_{it} : Log of Technological Adoption (Secure Internet Services)
GDP_{it} : Log of Gross Domestic Product (constant 2015 US$)
Exp_{it} : Innovation (High-technology export)
RE_{it} : Renewable Energy Consumption
and the sample includes ASEAN Six countries only.

3.5.1.2 Non-ASEAN Six Countries

$$TR_{it} = \alpha + \beta_1 TR_{i,t\text{-}1} + \beta_2 LSIS_{it} + \beta_3 LGDP_{it} + \beta_4 Exp_{it} + \beta_5 RE_{it} + \varepsilon_{it}$$

where: the sample includes Non-ASEAN Six countries only.

3.5.1.3 General Model with Dummy and Intecation Variable

$$TR_{it} = \alpha + \beta_1 TR_{i,t\text{-}1} + \beta_2 LSIS_{it} + \beta_3 (LSIS_{it} \times Group_{it}) + \beta_4 Group_{it} + \beta_5 LGDP_{it} + \beta_6 Exp_{it} + \beta_7 RE_{it} + \varepsilon_{it}$$

where:

$Group_{it}$ = 1 if ASEAN Six, 0 otherwise.

3.5.2 Model 2: Social Readiness

$$SR_{it} = \alpha + \beta_1 SR_{i,t\text{-}1} + \beta_2 LSIS_{it} + \beta_3 LGDP_{it} + \beta_4 Exp_{it} + \beta_5 RE_{it} + \varepsilon_{it}$$

where:

SR_{it} : Climate Adaptation Social Readiness for country i in year t

$SR_{i,t\text{-}1}$: Lagged Climate Adaptation Social Readiness (previous period)

3.5.3 Model 3: Governance Readiness

$$GR_{it} = \alpha + \beta_1 GR_{i,t\text{-}1} + \beta_2 LSIS_{it} + \beta_3 LGDP_{it} + \beta_4 Exp_{it} + \beta_5 RE_{it} + \varepsilon_{it}$$

where:

GR_{it} : Climate Adaptation Governance Readiness for country i in year t

$GR_{i,t\text{-}1}$: Lagged Climate Adaptation Governance Readiness (previous period)

3.5.4 Model 4: Economic Readiness

$$ER_{it} = \alpha + \beta_1 ER_{i,t\text{-}1} + \beta_2 LSIS_{it} + \beta_3 LGDP_{it} + \beta_4 Exp_{it} + \beta_5 RE_{it} + \varepsilon_{it}$$

where:

ER_{it} : Climate Adaptation Economic Readiness for country i in year t

$ER_{i,t\text{-}1}$: Lagged Climate Adaptation Economic Readiness (previous period)

3.6 Data Analysis Method

This study applies a dynamic panel data approach to examine the determinants of climate adaptation readiness across ASEAN countries. Because readiness indicators exhibit persistence over time and several explanatory variables may be endogenous, a dynamic specification is required. The empirical model is estimated using the System Generalized Method of Moments (System GMM), which combines moment conditions in both levels and first differences to produce consistent estimates in the presence of endogeneity, autocorrelation, and unobserved country-specific effects.

3.6.1 Dynamic Panel Data Method

The empirical models are estimated using the System Generalized Method of Moments estimator developed by Arellano and Bover (1995) and Blundell and Bond (1998). System GMM is used to address three key empirical challenges commonly found in macro–panel data.

First, the inclusion of the lagged dependent variable introduces autocorrelation, making traditional fixed-effects or OLS estimators biased. System GMM resolves this by instrumenting the lagged dependent variable with deeper lags of itself.

Second, explanatory variables such as GDP, technology adoption, or innovation may be simultaneously determined with readiness. System GMM treats these variables as potentially endogenous and uses internally generated instruments to correct for simultaneity bias.

Third, unobserved heterogeneity across ASEAN countries is accounted for by transforming the data and allowing valid moment conditions to eliminate country-specific effects. This combination of first differences and level moments strengthens estimator efficiency and reduces finite-sample bias (Pugh, 2004).

3.6.2 Tool of Analysis

To ensure that the model estimation is valid and robust, several diagnostic tests specific to dynamic panel data models are conducted. These include the Arellano–Bond test for autocorrelation, the Sargan or Hansen test for instrument validity, and the Wald test for joint significance.

3.6.2.1 Consistency Test (Arellano–Bond)

The Arellano–Bond test is used to detect the presence of serial correlation in the residuals of the first-differenced equation. In the System GMM framework, first-order autocorrelation (AR(1)) is typically expected due to differencing, while the absence of second-order autocorrelation (AR(2)) indicates that the model is correctly specified (Pugh, 2004). The decision rule for this test is based on the p-value of the AR statistics:

- If the p-value for AR(1) is below 0.05, it indicates the expected first-order autocorrelation
- If the p-value for AR(2) greater than 0.05 confirms that no second-order autocorrelation is present.

3.6.2.2 Instrument Validity Test (Sargan)

The Sargan (Sargan, 1958) tests assess whether the instruments used in System GMM are valid, meaning they are uncorrelated with the error term and correctly excluded from the estimated equation. This test is fundamental because System GMM relies on internal lagged instruments.

- If the p-value > 0.05, the null hypothesis cannot be rejected, indicating that the instruments are valid and the model is correctly specified.

- If the p-value < 0.05, the instruments are invalid, suggesting problems of overidentification or correlation between instruments and the error term.

3.6.2.3 Unbiasedness Test

Estimator consistency is assessed by comparing the magnitude of System GMM coefficients with those from Pooled OLS and Fixed Effects estimations. System GMM is considered unbiased if its estimates fall between the upward-biased OLS estimator and the downward-biased Fixed Effects estimator (Pugh, 2004).

3.6.3 Regression Analysis

Regression analysis is conducted through the dynamic System GMM estimator to interpret the magnitude, direction, and statistical significance of the relationships between climate readiness and its determinants. Coefficients are evaluated based on t-statistics and p-values to determine their individual significance. A variable is significant if:

- If the p-value < 0.05 → the independent variable has a statistically significant effect.
- If the p-value > 0.05 → the effect is not statistically significant (Pugh, 2004).

CHAPTER IV

DATA ANALYSIS AND DISCUSSION

This chapter presents the results of the data analysis and discusses the findings of each estimated model. The analysis includes model estimation, diagnostic tests, instrument validity, and unbiasedness checks. The discussion focuses on interpreting the results in relation to the research objectives.

4.1 Data Analysis Result

This section reports the empirical results obtained from the dynamic panel data analysis. The results are presented systematically according to each model to provide a clear understanding of the estimated relationships.

4.1.1 Dynamic Panel Regression Result for Model 1

Model 1 examines the determinants of Climate Adaptation Total Readiness (TR). The estimation is conducted separately for ASEAN Six and Non-ASEAN Six countries to identify potential differences between the two groups. The model includes the lagged value of climate adaptation readiness, technological adoption (LSIS), economic size measured by GDP (LGDP), innovation (Exp), and renewable energy consumption (RE). The model is specified as follows:

$$TR_{it} = \alpha + \beta_1 TR_{i,t\text{-}1} + \beta_2 LSIS_{it} + \beta_3 LGDP_{it} + \beta_4 Exp_{it} + \beta_5 RE_{it} + \varepsilon_{it}$$

4.1.1.1 Dynamic Panel Regression Result for ASEAN Six Countries

This subsection presents the dynamic panel regression results for ASEAN Six countries. The model estimates the determinants of Climate Adaptation Total

Readiness using the SYS-GMM approach and focuses on the role of technological adoption alongside key control variables.

Table 4.1 Dynamic Panel Estimation Output

Variable	Coefficient	P-Value
L1.TR	0.8551264	0.000
LSIS	0.0022255	0.000
LGDP	0.0043081	0.001
EXP	0.0001626	0.480
RE	-0.0003895	0.228
_cons	0.0295004	0.520

Table 4.1 shows that total climate adaptation readiness in ASEAN Six Countries is highly persistent, as the lagged variable is positive and significant (L1.TR = 0.855, $p < 0.01$). This means that readiness in the previous year strongly affects readiness in the current year. Technological adoption (LSIS) also has a positive and significant effect (0.002, $p < 0.01$), indicating that better internet security infrastructure helps improve climate adaptation readiness. GDP has a positive and significant effect (0.004, $p < 0.01$), while innovation and renewable energy consumption are not statistically significant.

Table 4.2 Arellano–Bond Test Output

Test order	z-computed	Probability>z
1	-1.9677	0.0491

2	-0.92827	0.3533

The Arellano–Bond test results confirm the validity of the dynamic specification, with significant first-order serial correlation and insignificant second-order serial correlation ($p > 0.10$), indicating the absence of second-order autocorrelation.

Table 4.3 Sargan Test Output

chi2(27)	16.63071
Prob > chi2	0.9398

The Sargan test fails to reject the null hypothesis of valid instruments ($p > 0.10$), suggesting that the instruments employed in the System GMM estimation are appropriate.

Table 4.4 Unbiasedness Test Output

Variable	FEM	SYSGMM	PLS
L1.TR	0.7134	0.8551264	0.9792
LSIS	0.0027	0.0022255	0.0035
LGDP	0.0031	0.0043081	0.0047
EXP	0.0014	0.0001626	9.045e-06
RE	−0.0002	-0.0003895	0.0001
_cons	0.0416	0.0295004	−0.0452
(N)	40	40	40

The comparison across PLS, FEM, and System GMM shows that the coefficient of the lagged dependent variable under System GMM lies between the PLS and FEM estimates, indicating that System GMM effectively corrects for both upward bias in PLS and downward bias in FEM.

4.1.1.2 Dynamic Panel Regression Result for Non-ASEAN Six Countries

This subsection reports the dynamic panel regression results for Non-ASEAN Six countries. The estimation is conducted separately to compare the impact of technological adoption and other determinants of climate adaptation readiness across different country groups.

Table 4.5 Dynamic Panel Estimation Output

Variable	Coefficient	P-Value
L1.TR	0.8491	0.000
LSIS	0.0038	0.034
LGDP	−0.0031	0.775
EXP	0.0001	0.603
RE	−0.0003	0.342
_cons	0.0465	0.501

Table 4.5 shows the dynamic panel regression results for Non-ASEAN Six countries. The lagged dependent variable (L1.TR) has a positive and highly significant effect on total climate adaptation readiness ($\beta = 0.8491$, $p < 0.01$), indicating strong persistence over time. Technological adoption (LSIS) also has a positive and statistically significant impact ($\beta = 0.0038$, $p = 0.034$). However, when compared to ASEAN Six countries ($\beta = 0.0022$, $p < 0.01$), this effect is statistically weaker,

suggesting that technology plays a less robust role in enhancing climate adaptation readiness in Non-ASEAN Six countries. Other variables, including GDP, high-technology exports, and renewable energy consumption, are not statistically significant.

Table 4.6 Arellano–Bond Test Output

Test order	z-computed	Probability>z
1	-1.2635	0.2064
2	1.0863	0.2773

The Arellano–Bond test results confirm the validity of the dynamic specification, with significant first-order serial correlation and insignificant second-order serial correlation ($p > 0.10$), indicating the absence of second-order autocorrelation.

Table 4.7 Sargan Test Output

chi2(27)	22.88645
Prob > chi2	0.4674

The Sargan test fails to reject the null hypothesis of valid instruments ($p > 0.10$), suggesting that the instruments employed in the System GMM estimation are appropriate.

Table 4.8 Unbiasedness Test Output

Variable	FEM	SYSGMM	PLS
L1.TR	0.9680	0.8491	0.3947

LSIS	0.0006	0.0038	0.0052
LGDP	−0.0003	−0.0031	0.0143
EXP	−0.0001	0.0001	−0.0002
RE	−0.0002	−0.0003	−0.0001
_cons	0.0197	0.0465	0.1121
(N)	28	28	28

Consistent with the ASEAN Six results, the System GMM estimates for the lagged dependent variable fall between the PLS and FEM estimates. This further supports the use of System GMM as an appropriate estimator for dynamic panel analysis in both country groups.

4.1.1.3 Dynamic Panel Regression Result for General Model with Dummy & Interaction Variable

This subsection presents the results of the dummy and interaction models. The dummy model examines whether there are differences in climate adaptation readiness between ASEAN Six and Non-ASEAN Six countries, while the interaction model evaluates whether the effect of technological adoption differs between the two groups. The model is specified as follows:

$$TR_{it} = \alpha + \beta_1 TR_{i,t\text{-}1} + \beta_2 LSIS_{it} + \beta_3 (LSIS_{it} \times Group_{it}) + \beta_4 Group_{it} + \beta_5 LGDP_{it} + \beta_6 Exp_{it} + \beta_7 RE_{it} + \varepsilon_{it}$$

Table 4.9 Dynamic Panel Estimation Output

Variable	Coefficient	p-value

L1.TR	0.6690	0.000
LSIS	0.0032	0.338
(LSIS*Group)	−0.0016	0.671
Group	0.0420	0.317
LGDP	0.0026	0.149
EXP	−0.0002	0.686
RE	−0.0012	0.127
_cons	0.1173	0.215

Table 4.9 reports the results that the lagged dependent variable remains positive and highly significant ($\beta = 0.6690$, $p < 0.01$), indicating strong persistence in total readiness. In the dummy model, the ASEAN group variable is positive but not statistically insignificant ($\beta = 0.0420$, $p = 0.317$), suggesting no meaningful difference in aggregate readiness between ASEAN Six and Non-ASEAN Six countries. In the interaction model, the interaction term between technological adoption and the ASEAN group (LSIS × Group) is negative and not statistically significant ($\beta = -0.0016$, $p = 0.671$), indicating that the impact of technological adoption on aggregate climate adaptation readiness does not vary meaningfully across the two groups.

Table 4.10 Arellano–Bond Test Output

Test order	z-computed	Probability>z
1	-1.9144	0.0556
2	0.23637	0.8131

The model meets the key requirements of a dynamic panel regression. While first-order serial correlation is present, there is no second-order serial correlation, indicating that the SYS-GMM estimation is valid.

Table 4.11 Sargan Test Output

chi2(27)	26.22749
Prob > chi2	0.4507

The probability value of 0.4507 indicates that the null hypothesis cannot be rejected, suggesting that the instrumental variables used in the model are valid

Table 4.12 Unbiasedness Test Output

Variable	PLS	SYSGMM	FEM
L1.TR	0.9651	0.6690	0.5527
LSIS	0.0003	0.0032	0.0050
(LSIS*Group)	0.0030	−0.0016	−0.0010
Group	−0.0381	0.0420	Omitted
LGDP	0.0037	0.0026	0.0020
EXP	−0.0001	−0.0002	−0.0002
RE	−0.0002	−0.0012	−0.0001
_cons	0.0097	0.1173	0.1372
(N)	68	68	68

Table 4.12 compares the estimation results from Pooled Least Squares (PLS), Fixed Effects Model (FEM), and SYS-GMM to assess estimator consistency. The SYS-

GMM coefficients generally fall between the PLS and FEM estimates, particularly for the lagged dependent variable (0.5527 < 0.6690 < 0.9651). This pattern indicates that the SYS-GMM estimator is unbiased and consistent, making it appropriate for analyzing the dummy and interaction models.

4.1.2 Dynamic Panel Regression Results for Model 2

This subsection presents the dynamic panel regression results for Social Readiness, examining the effects of technological adoption, economic size, innovation, and renewable energy consumption while accounting for persistence through the lagged dependent variable. The model specification is given as follows:

$$SR_{it} = \alpha + \beta_1 SR_{i,t\text{-}1} + \beta_2 LSIS_{it} + \beta_3 LGDP_{it} + \beta_4 Exp_{it} + \beta_5 RE_{it} + \varepsilon_{it}$$

Table 4.13 Dynamic Panel Estimation Output

Variable	Coefficient	p-value
L1.SR	0.8989	0.0000
LSIS	0.0002	0.8150
LGDP	−0.0024	0.2690
EXP	0.0006	0.0980
RE	0.0001	0.6700
_cons	0.0291	0.5820

The regression results for Social Readiness indicate a strong persistence effect, as the lagged dependent variable (L1.sr) is positive and highly significant, suggesting that social readiness in the current period is strongly influenced by its previous level. Technological adoption (LSIS) does not show a statistically significant effect, indicating that higher technology use does not directly translate into improvements in social readiness. Economic size (GDP) and renewable energy consumption also do not have significant impacts. Innovation, measured by high-technology exports, shows a weak positive effect at the 10 percent significance level, suggesting a limited role in enhancing social readiness. Overall, the results imply that social readiness is mainly driven by its own past conditions rather than short-term changes in technology or economic factors.

Table 4.14 Arellano–Bond Test Output

Test order	z-computed	Probability>z
1	-1.1105	0.2668
2	1.0818	0.2794

The model meets the key requirements of a dynamic panel regression. While first-order serial correlation is present, there is no second-order serial correlation, indicating that the SYS-GMM estimation is valid.

Table 4.15 Sargan Test Output

chi2(27)	38.01273
Prob > chi2	0.0777

The Sargan test result shows a p-value of 0.077, indicating that the null hypothesis of instrument validity cannot be rejected at the 5 percent significance level but would be rejected at the 10 percent level. This suggests that the instruments used in the model are generally acceptable, although their validity is relatively weak.

Table 4.16 Unbiasedness Test Output

Variable	PLS	SYSGMM	FEM
L1.SR	1.0070	0.8989	0.6453
LSIS	0.0008	0.0002	0.0008
LGDP	0.0011	−0.0024	−0.0022
EXP	−0.0000	0.0006	−0.0004
RE	0.0002	0.0001	−0.0001
_cons	−0.0147	0.0291	0.1491
(N)	68	68	68

The unbiasedness test for Social Readiness confirms that the System GMM estimator provides reliable and consistent results. The System GMM coefficients lie between the PLS and FEM estimates, especially for the lagged Social Readiness variable, indicating that System GMM effectively corrects dynamic panel bias and is appropriate for this analysis.

4.1.3 Dynamic Panel Regression Result for Model 3

This subsection reports the dynamic panel regression results for Governance Readiness, focusing on how technological adoption and other key economic factors influence governance-related aspects of climate adaptation readiness over time. The model specification is given as follows:

$$GR_{it} = \alpha + \beta_1 GR_{i,t\text{-}1} + \beta_2 LSIS_{it} + \beta_3 LGDP_{it} + \beta_4 Exp_{it} + \beta_5 RE_{it} + \varepsilon_{it}$$

Table 4.17 Dynamic Panel Estimation Output

Variable	Coefficient	P-value
L1.GR	0.7725	0.000
LSIS	0.0050	0.003
LGDP	0.0108	0.024
EXP	−0.0009	0.187
RE	−0.0012	0.010
_cons	0.0562	0.208

The System GMM results for Governance Readiness show strong persistence, as the lagged governance readiness has a positive and highly significant effect, indicating that current governance readiness is strongly influenced by its past level. Technological adoption (LSIS) has a positive and significant impact, suggesting that greater use of secure internet services improves governance readiness. Economic size (LGDP) is also positive and significant, meaning that countries with larger economies tend to have better governance readiness for climate adaptation. Renewable energy consumption has a negative and significant coefficient, indicating that higher renewable energy use is associated with lower governance readiness in the short run, possibly due to adjustment or transition costs. In contrast, innovation measured by high-technology exports does not show a statistically significant effect on governance readiness.

Table 4.18 Arellano–Bond Test Output

Test order	z-computed	Probability>z
1	-1.9279	0.0539
2	0.18486	0.8533

The model meets the key requirements of a dynamic panel regression. While first-order serial correlation is present, there is no second-order serial correlation, indicating that the SYS-GMM estimation is valid.

Table 4.19 Sargan Test Output

chi2(27)	26.03673
Prob > chi2	0.5166

The Sargan test result shows a p-value of 0.5166, indicating that the null hypothesis of instrument validity can be rejected at the 5 percent significance level. This suggests that the instruments used in the model are valid.

Table 4.20 Unbiasedness Test Output

Variable	PLS	SYSGMM	FEM
L1.GR	0.9850	0.7725	0.5790
LSIS	0.0002	0.0050	0.0068
LGDP	0.0044	0.0108	0.0096
EXP	−0.0003	−0.0009	−0.0001
RE	−0.0005	−0.0012	−0.0002
_cons	0.0099	0.0562	0.0727

(N)	68	68	68

The unbiasedness test for Governance Readiness confirms that the System GMM estimator provides reliable and consistent results. The System GMM coefficients lie between the PLS and FEM estimates, especially for the lagged Social Readiness variable, indicating that System GMM effectively corrects dynamic panel bias and is appropriate for this analysis.

4.1.4 Dynamic Panel Regression Result for Model 4

This subsection presents the dynamic panel regression results for Economic Readiness, analyzing the role of technological adoption and macroeconomic factors in shaping the economic dimension of climate adaptation readiness. The model specification is given as follows:

$$ER_{it} = \alpha + \beta_1 ER_{i,t-1} + \beta_2 LSIS_{it} + \beta_3 LGDP_{it} + \beta_4 Exp_{it} + \beta_5 RE_{it} + \varepsilon_{it}$$

Table 4.21 Dynamic Panel Estimation Output

Variable	Coefficient	P-value
L1.ER	0.6927	0.0000
LSIS	0.0037	0.0850
LGDP	0.0016	0.7130
EXP	0.0001	0.8050
RE	−0.0015	0.2090
_cons	0.1407	0.1860

The System GMM results for Economic Readiness show strong persistence, as the lagged economic readiness variable is positive and statistically significant, indicating that past economic readiness strongly influences current readiness. Technological adoption (LSIS) has a positive effect and is weakly significant, suggesting that higher technology use tends to improve economic readiness, although the effect is not strong. Other control variables: economic performance (LGDP), innovation (Exp), and renewable energy consumption (RE) do not show statistically significant effects, implying that their direct impact on economic readiness is limited in this model. Overall, the results highlight the importance of existing economic conditions and suggest that technology adoption plays a supporting, but not dominant, role in shaping economic readiness.

Table 4.22 Arellano–Bond Test Output

Test order	z-computed	Probability>z
1	-2.1999	0.0278
2	-.99237	0.3210

The model meets the key requirements of a dynamic panel regression. While first-order serial correlation is present, there is no second-order serial correlation, indicating that the SYS-GMM estimation is valid.

Table 4.23 Sargan Test Output

chi2(27)	18.55754
Prob > chi2	0.8546

The Sargan test result shows a p-value of 0.8546, indicating that the null hypothesis of instrument validity can be rejected at the 5 percent significance level. This suggests that the instruments used in the model are valid.

Table 4.24 Unbiasedness Test Output

Variable	PLS	SYSGMM	FEM
L1.ER	0.9360	0.6927	0.6202
LSIS	0.0005	0.0037	0.0045
LGDP	0.0020	0.0016	0.0001
EXP	−0.0001	0.0001	−0.0000
RE	−0.0003	−0.0015	−0.0001
_cons	0.0316	0.1407	0.1366
N	68	68	68

The unbiasedness test for Economic Readiness confirms that the System GMM estimator provides reliable and consistent results. The System GMM coefficients lie between the PLS and FEM estimates, especially for the lagged Social Readiness variable, indicating that System GMM effectively corrects dynamic panel bias and is appropriate for this analysis.

4.2 Result Interpretation and Discussion

This section discusses the influence of technological adoption on different dimensions of climate adaptation readiness based on the empirical results from Models

1 to 4. The discussion is organized according to each readiness component to clearly address the research objectives.

4.2.1 The Influence of Technological Adoption on Total Readiness

Based on the empirical findings, technological adoption, proxied by secure internet services, shows a positive and statistically significant effect on total climate adaptation readiness, particularly in ASEAN Six countries. This indicates that improvements in technological infrastructure contribute to higher overall readiness to adapt to climate change. The significance of the coefficient suggests that technology plays an important role in strengthening countries' adaptive capacity by improving access to information, coordination, and policy implementation related to climate risks.

This result is consistent with previous studies emphasizing that digital technology enhances climate adaptation by supporting early warning systems, climate data management, and policy coordination (Sarkodie & Strezov, 2019). In ASEAN Six countries, where regional cooperation and institutional frameworks are relatively stronger, technological adoption appears to be more effectively translated into aggregate climate readiness. This implies that technology works best when it is supported by adequate institutional capacity.

In contrast, although technological adoption also shows a positive effect in Non-ASEAN Six countries, its influence is relatively weaker. This suggests that technology alone may not be sufficient to substantially improve climate adaptation readiness without strong governance structures and policy coherence. As highlighted by Bowen et al. (2014), the effectiveness of technology in climate adaptation depends not only on availability but also on how well it is integrated into national development and climate strategies. Additionally, variables such as renewable energy consumption and innovation often show mixed effects because they can reflect either progress in sustainability infrastructure or short-run transition costs and institutional adjustment challenges.

4.2.2 The Influence of Technological Adoption on Social Readiness

The results for Social Readiness (SR) reveal that technological adoption (LSIS) has a positive but statistically insignificant effect. This indicates that while improved internet infrastructure and digital tools are available, they do not automatically enhance social readiness for climate adaptation. Research suggests that social adaptation relies heavily on knowledge dissemination, active community engagement, and programs that foster behavioral change (Bowen & Friel, 2012).

Climate adaptation literature also indicates that social adaptation is shaped by complex socio-political and cultural factors, not just technological availability (de Sherbinin et al., 2021). Effective adaptation requires inclusive policy approaches that address social vulnerability, equity, and access to resources, rather than purely technocratic solutions (Kehler & Birchall, 2021). Moreover, adaptive capacity is a function of institutional learning and social capital, which evolve over time through education, community networks, and participatory governance (Adger, 2003; Field &

Barros, 2014). Thus, the insignificant result reflects deeper structural characteristics of societies that are not captured by technology indicators alone.

Control variables, such as GDP, innovation (high-technology exports), and renewable energy consumption, also show limited effects on social readiness. This underscores the fact that social adaptation is mediated by socio-political and cultural factors, including equity, institutional trust, and social capital, rather than purely by economic or technological inputs (Fankhauser & McDermott, 2014). Consequently, the insignificant effect of tech adoption reflects the deeper structural and institutional characteristics of societies in ASEAN, where social readiness depends on long-term education, community networks, and adaptive social institutions rather than short-term technological deployment.

4.2.3 The Influence of Technological Adoption on Governance Readiness

The results for Governance Readiness (GR) indicate that technological adoption has a positive and statistically significant effect. This suggests that improved digital infrastructure strengthens governance capacities by facilitating data sharing, policy coordination, and institutional responsiveness to climate risks. Digital tools such as early warning systems, geospatial data platforms, and secure internet services support governance networks in monitoring climate impacts and enabling rapid decision-making, consistent with research showing that technological integration enhances adaptive governance and disaster risk reduction (Zembe et al., 2024).

Moreover, adaptive governance literature emphasizes the importance of institutional flexibility, stakeholder collaboration, and polycentric decision-making structures in addressing environmental complexities (Yulianto et al., 2025). Such governance attributes are often reinforced by digital technologies that improve communication across levels of government and civil society, thereby strengthening climate adaptation strategies.

The positive role of economic performance (LGDP) suggests that larger economies are better equipped to invest in both technological infrastructure and governance systems. Empirical evidence indicates that higher GDP per capita enhances energy transition and environmental outcomes by providing the financial and institutional capacity needed for clean technology adoption and regulatory innovation (Lu et al., 2025). Similarly, higher income levels are associated with reduced climate vulnerability and stronger adaptation readiness across economic and governance dimensions, enabling countries to implement effective policies and coordinate climate actions more efficiently (Sarkodie et al., 2022). These findings support the notion that economic resources and institutional capacity are critical for leveraging technological adoption to strengthen governance and climate adaptation efforts.

At the same time, the negative coefficient on renewable energy consumption may reflect transitional governance challenges as countries adjust institutional frameworks to integrate new energy systems. Studies show that managing energy transitions involves navigating financing constraints, supply chain complexities, and policy coordination, highlighting the importance of governance systems in mitigating transitional risks (Fan et al., 2025). Robust digital infrastructure can help address these challenges by improving information flow, coordination, and monitoring, ensuring that renewable energy adoption complements rather than disrupts governance capacity. Together, these findings underscore that economic performance and effective institutional mechanisms are key enablers for maximizing the benefits of technological adoption and managing the complexities of energy transitions.

4.2.4 The Influence of Technological Adoption on Economic Readiness

The results for Economic Readiness (ER) reveal a positive but weakly significant effect of technological adoption (LSIS), suggesting that digital infrastructure supports economic adaptation, but its influence is conditional on broader structural and institutional factors. Technological adoption can enhance economic readiness by improving data-driven planning, market access, and climate-smart investment strategies. However, empirical evidence suggests that the economic benefits of adaptation-related investments are conditional on a country's level of climate adaptation readiness, which reflects institutional capacity and coordinated policy frameworks (Adom & Amoani, 2021).

Interestingly, GDP (LGDP) is not statistically significant in explaining economic readiness, which at first glance seems counterintuitive given the expectation that larger economies can invest more in adaptation measures. Empirical studies show that while economic size provides resources, its effect on adaptation is mediated by institutional quality, governance capacity, and the efficiency of investment in resilience

(Adom & Amoani, 2021). In other words, high GDP does not automatically translate into stronger economic readiness if the economy fails to channel its resources effectively toward adaptive measures, such as infrastructure, insurance mechanisms, or climate-resilient economic planning. Similarly, control variables such as innovation (high-technology exports) and renewable energy consumption show limited or negative effects in the short run, likely reflecting transitional challenges, adjustment costs, and policy or institutional constraints when adopting new technologies or energy systems (Lu et al., 2025).

Overall, the findings suggest that economic readiness is shaped by the interplay of technological adoption, institutional quality, and strategic use of economic resources rather than GDP alone. Countries with robust institutions, governance frameworks, and targeted policies are better able to leverage technology and resources for economic adaptation. This underscores the importance of a holistic approach in ASEAN, where technological adoption, economic capacity, and institutional effectiveness collectively determine the strength of economic readiness to climate change.

CHAPTER V

CONCLUSIONS AND IMPLICATIONS

5.1 Conclusions

This study examines the role of technological adoption in shaping climate adaptation readiness across countries, with a particular focus on ASEAN Six and Non-ASEAN Six countries from 2014-2023. Using dynamic panel data analysis with the System Generalized Method of Moments, the study analyzes how secure internet services, alongside key control variables—economic size (GDP), innovation (high-technology exports), and renewable energy consumption—influence total climate adaptation readiness and its four dimensions: social, governance, and economic readiness. The empirical findings provide important insights into the persistence, drivers, and limitations of technology-based adaptation across different institutional and regional contexts. The main conclusions are summarized as follows:

1. Technological adoption exerts a positive and statistically significant influence on total climate adaptation readiness, particularly in ASEAN Six countries. This finding indicates that improvements in digital infrastructure enhance overall adaptive capacity by strengthening information access, coordination mechanisms, and policy implementation related to climate risks. The results also reveal strong persistence in total readiness, as past levels of readiness significantly shape current outcomes. Economic performance, measured by GDP, further contributes positively in ASEAN Six countries, suggesting that larger economies are better positioned to mobilize resources for adaptation. In

contrast, although technological adoption also shows a positive effect in Non-ASEAN Six countries, its influence is relatively weaker, highlighting that technology alone is insufficient without supportive institutional capacity and policy coherence.

2. Technological adoption does not have a statistically significant effect on social climate adaptation readiness. While digital infrastructure improves connectivity and access to information, it does not automatically translate into higher social readiness. Social adaptation appears to be primarily driven by its own past conditions and deeper structural factors such as social capital, institutional learning, inclusiveness, and community engagement. Innovation shows only a weak positive effect, while GDP and renewable energy consumption remain insignificant. This result suggests that social readiness evolves gradually and depends more on long-term investments in education, participatory governance, and behavioral change rather than short-term technological improvements.
3. The findings indicate that technological adoption plays a significant and robust role in enhancing governance climate adaptation readiness. Secure internet services strengthen governance capacity by supporting data sharing, early warning systems, policy coordination, and institutional responsiveness to climate risks. Economic size also positively influences governance readiness, implying that stronger fiscal and administrative capacity supports better governance outcomes. Conversely, renewable energy consumption exhibits a negative short-run effect, which may reflect transitional governance challenges as countries

adjust regulatory and institutional frameworks to accommodate new energy systems. Overall, the results underscore that digital technologies are particularly effective in reinforcing governance-related dimensions of climate adaptation.

4. For economic climate adaptation readiness, technological adoption shows a positive but only weakly significant effect. This suggests that digital infrastructure supports economic adaptation by improving planning, investment efficiency, and market access, but its impact is conditional rather than dominant. Surprisingly, GDP does not have a statistically significant effect on economic readiness, indicating that higher income levels do not automatically translate into stronger economic preparedness for climate change. This finding implies that structural factors, such as; economic diversification, policy effectiveness, and institutional readiness, may matter more than economic size alone. Innovation and renewable energy consumption also remain insignificant, reinforcing the conclusion that economic readiness depends largely on accumulated adaptation capacity rather than short-term economic or technological changes.
5. Climate adaptation readiness is highly persistent over time. The consistently positive and significant lagged dependent variables across all models confirm that climate adaptation readiness is a cumulative and path-dependent process. Past adaptation capacity strongly shapes current readiness, underscoring the importance of sustained and long-term policy commitment.

5.2 Implications

Based on the empirical findings of this study, several policy implications can be drawn to support the strengthening of climate adaptation readiness in ASEAN and Non-ASEAN countries. These implications emphasize the importance of technological adoption while recognizing the critical role of institutional capacity, governance quality, and long-term structural readiness:

1. Governments should prioritize technological adoption as a strategic enabler of climate adaptation, particularly in governance-related functions. The results show that secure internet services significantly enhance total and governance climate adaptation readiness. Therefore, policymakers should invest in reliable digital infrastructure that supports climate data management, early warning systems, inter-agency coordination, and evidence-based policymaking. Strengthening digital governance platforms can improve institutional responsiveness to climate risks and enhance coordination across national and subnational levels of government.
2. Technological investments should be integrated with institutional and policy frameworks rather than implemented in isolation. Although technological adoption improves total and governance readiness, its impact on social and economic readiness is limited. This implies that digital infrastructure must be embedded within coherent adaptation strategies, supported by effective institutions and clear regulatory frameworks. Governments should ensure that

digital tools are aligned with national climate adaptation plans and sectoral policies to maximize their effectiveness.

3. Governments should strengthen governance capacity to fully leverage technological adoption for climate adaptation. The stronger effects observed in ASEAN Six countries indicate that technology yields greater benefits when institutional capacity is relatively robust. Policymakers should therefore focus on improving bureaucratic efficiency, regulatory quality, and inter-governmental coordination to ensure that digital technologies translate into tangible adaptation outcomes. Strengthening governance capacity will also help address short-term institutional challenges arising from structural transitions, such as renewable energy integration.
4. Economic growth alone is insufficient to guarantee stronger economic climate adaptation readiness. The insignificance of GDP in explaining economic readiness suggests that higher income levels do not automatically lead to better preparedness for climate-related economic risks. Governments should complement economic growth strategies with targeted adaptation policies, including economic diversification, climate-resilient infrastructure investment, and risk-informed fiscal planning. This approach ensures that economic resources are effectively translated into adaptive capacity.
5. Innovation policies should be redirected toward climate-oriented outcomes rather than export performance alone. The limited impact of high-technology exports on climate adaptation readiness indicates that innovation driven solely by export

markets may not directly contribute to domestic adaptation needs. Policymakers should promote climate-focused innovation by supporting research and development in adaptation technologies, encouraging public–private partnerships, and incentivizing innovation that directly addresses local climate vulnerabilities.

6. Renewable energy transitions should be accompanied by institutional and regulatory strengthening. While renewable energy consumption is essential for long-term climate mitigation, its short-run negative association with governance readiness suggests transitional challenges. Governments should strengthen regulatory frameworks, coordination mechanisms, and institutional capacity to manage the complexity of energy transitions effectively, ensuring that renewable energy deployment supports both mitigation and adaptation objectives.
7. Long-term and consistent adaptation policies are crucial due to the persistence of climate adaptation readiness. The strong persistence observed across all readiness dimensions indicates that adaptation is a cumulative process. Governments should adopt long-term policy commitments, maintain continuity in adaptation programs, and ensure sustained investment in institutions and capacity-building to avoid setbacks in climate preparedness.

5.3 Research Limitations

This study has several limitations that require improvement in further research. The following are the limitations related to this research:

1. The measurement of technological adoption using secure internet services (LSIS) may not fully capture the complexity of digital readiness for climate adaptation. While LSIS reflects the availability and security of digital infrastructure, it does not directly measure how technology is used for climate-specific purposes, such as early warning systems, climate risk modeling, or adaptation planning. As a result, the estimated effects of technological adoption may understate its broader role in climate adaptation processes.
2. The study is constrained by limited data availability across countries and time periods. The sample includes only 10 countries; some of them are incomplete, which restricts the observations and may affect the generalizability of the findings. Differences in data reporting standards across countries may also introduce measurement inconsistencies, particularly for variables such as renewable energy consumption and innovation.
3. Several control variables including GDP, innovation, and renewable energy consumption, do not exhibit statistically significant effects in some models, contrary to initial theoretical expectations. This discrepancy suggests the presence of unobserved factors such as institutional quality, policy effectiveness, or climate exposure that are not explicitly captured in the model but may influence climate adaptation readiness.
4. Although the System GMM estimator addresses endogeneity and dynamic panel bias, the validity of instruments in some models is relatively weak, as indicated

by marginal Sargan test results. This limitation may constrain the precision of the estimated coefficients and the depth of causal interpretation.

5.4 Recommendations

Based on the results that have been carried out, the researcher suggests the following recommendations for future researchers:

1. Future studies should consider using more climate-specific indicators of technological adoption, such as digital early warning systems, climate information platforms, or disaster risk management technologies. These indicators may better capture the direct role of technology in enhancing climate adaptation readiness.
2. Future research may expand the country coverage and observation period to improve the robustness and generalizability of the results. Including a broader set of developing and developed countries, as well as extending the time horizon, would allow for a more comprehensive analysis of long-term adaptation dynamics.
3. Researchers are encouraged to incorporate additional institutional and structural variables, such as governance quality, public sector effectiveness, climate vulnerability indices, or fiscal capacity. Including these variables may help explain why economic size and innovation do not consistently translate into higher climate adaptation readiness.

4. Future studies may explore interaction effects between technological adoption and institutional quality or governance indicators. This approach could provide deeper insights into the conditions under which technology effectively enhances climate adaptation readiness.

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APPENDICES

Appendix 1.1 Data of Research Samples

Country	Year	TR	SR	GR	ER	SIS	GDP	EXP	RE	Group
Brunei Darussalam	2014	0.466	0.323	0.546	0.528	99.0	$12,981,233,067.58	8.560	0	0
Brunei Darussalam	2015	0.458	0.305	0.548	0.520	238	$12,930,296,852.49	19.092	0	0
Brunei Darussalam	2016	0.465	0.303	0.547	0.545	257	$12,609,894,729.69	13.577	0	0
Brunei Darussalam	2017	0.471	0.286	0.580	0.547	688	$12,777,445,744.24	29.849	0	0
Brunei Darussalam	2018	0.500	0.346	0.600	0.552	853	$12,784,137,427.32	0.042	0	0
Brunei Darussalam	2019	0.495	0.282	0.602	0.600	4645	$13,278,735,782.13	8.094	0	0
Brunei Darussalam	2020	0.530	0.281	0.712	0.597	6890	$13,429,259,999.62	1.339	0	0
Brunei Darussalam	2021	0.524	0.269	0.705	0.597	6366	$13,215,632,370.10	1.361	0	0
Brunei Darussalam	2022	0.525	0.281	0.695	0.597	9606	$13,000,438,059.98	1.044		0
Brunei Darussalam	2023	0.536	0.291	0.719	0.597	4027	$13,147,036,744.65	1.019		0
Cambodia	2014	0.217	0.264	0.161	0.225	71	$22,549,052,336.93	0.506	63.7	0
Cambodia	2015	0.213	0.260	0.160	0.218	158	$24,174,170,369.07	1.535	60.6	0
Cambodia	2016	0.214	0.276	0.126	0.241	323	$26,085,259,688.34	1.859	58	0
Cambodia	2017	0.211	0.277	0.122	0.234	883	$28,191,654,621.95	1.742	56.3	0
Cambodia	2018	0.209	0.284	0.113	0.229	1318	$30,665,817,313.85	1.409	58.1	0
Cambodia	2019	0.213	0.292	0.121	0.225	2626	$33,099,747,942.81	1.194	53	0

Cambodia	2020	0.214	0.289	0.133	0.219	3152	$31,922,812,945.09	2.283	51.4	0
Cambodia	2021	0.220	0.292	0.150	0.219	2824	$32,909,177,695.68	2.981	52.4	0
Cambodia	2022	0.218	0.295	0.140	0.219	3156	$34,597,385,966.82	6.562		0
Cambodia	2023	0.215	0.300	0.126	0.219	3889	$36,329,791,405.13	12.960		0
Indonesia	2014	0.299	0.271	0.288	0.338	3006	$820,828,013,230.59	9.329	29.3	1
Indonesia	2015	0.308	0.277	0.306	0.340	4569	$860,854,232,686.21	8.890	26.6	1
Indonesia	2016	0.310	0.284	0.319	0.327	80094	$904,181,621,780.39	7.999	27.8	1
Indonesia	2017	0.340	0.295	0.355	0.369	338925	$950,021,694,164.00	8.446	25.2	1
Indonesia	2018	0.350	0.297	0.356	0.396	343412	$999,178,586,309.02	8.213	22	1
Indonesia	2019	0.337	0.311	0.316	0.384	455692	$1,049,330,233,997.45	8.092	19.8	1
Indonesia	2020	0.343	0.309	0.321	0.401	513564	$1,027,656,193,885.38	8.425	21.9	1
Indonesia	2021	0.347	0.318	0.322	0.401	605864	$1,065,709,127,396.86	7.204	20.2	1
Indonesia	2022	0.350	0.324	0.325	0.401	696075	$1,122,268,412,650.20	8.304		1
Indonesia	2023	0.348	0.329	0.313	0.401	765509	$1,178,932,006,499.50	9.083	58.2	1
Lao PDR	2014	0.243	0.248	0.229	0.252	22	$13,448,654,116.30	24.994	53.3	0
Lao PDR	2015	0.235	0.248	0.208	0.249	28	$14,426,380,125.65	35.180	51.7	0
Lao PDR	2016	0.246	0.252	0.198	0.290	57	$15,439,521,179.40	33.574	50.6	0

Lao PDR	2017	0.256	0.250	0.203	0.314	114	$16,503,694,943.29	37.950	50.2	0
Lao PDR	2018	0.263	0.256	0.196	0.337	144	$17,534,839,203.11	38.017	50.5	0
Lao PDR	2019	0.258	0.264	0.177	0.331	224	$18,491,844,275.71	20.609	50.6	0
Lao PDR	2020	0.260	0.267	0.176	0.336	384	$18,584,864,138.19	23.155	51.5	0
Lao PDR	2021	0.263	0.272	0.182	0.336	613	$19,054,754,737.38	7.286	49.2	0
Lao PDR	2022	0.271	0.274	0.203	0.336	2071	$19,570,648,221.69			0
Lao PDR	2023	0.271	0.277	0.201	0.336	2101	$20,303,702,352.30			0
Malaysia	2014	0.496	0.314	0.516	0.659	4513	$286,755,041,078.03	49.219	3	1
Malaysia	2015	0.489	0.323	0.467	0.675	7079	$301,355,266,964.95	48.485	3.4	1
Malaysia	2016	0.457	0.323	0.431	0.618	29017	$314,764,917,575.09	49.059	4.4	1
Malaysia	2017	0.442	0.322	0.424	0.579	152966	$333,061,328,477.27	51.124	5.2	1
Malaysia	2018	0.464	0.323	0.494	0.573	180124	$349,191,778,300.01	53.181	5.3	1
Malaysia	2019	0.471	0.320	0.479	0.614	214828	$364,602,265,936.14	51.593	5.7	1
Malaysia	2020	0.468	0.320	0.478	0.606	242565	$344,706,479,641.24	53.813	7	1
Malaysia	2021	0.462	0.320	0.459	0.606	274197	$356,134,704,342.14	51.679	7.5	1
Malaysia	2022	0.470	0.321	0.482	0.606	292023	$387,694,727,478.78	58.282		1
Malaysia	2023	0.474	0.323	0.493	0.606	283909	$401,479,163,711.43	59.416		1
Myanmar	2014	0.199	0.185	0.222	0.191	37	$55,711,475,876.25	0.627	72	0
Myanmar	2015	0.212	0.194	0.229	0.212	55	$59,607,290,407.62	0.470	70	0

Myanmar	2016	0.246	0.204	0.278	0.255	1087	$63,101,751,663.24	7.534	68.8	0
Myanmar	2017	0.256	0.217	0.289	0.263	529	$66,973,743,448.91	6.029	59.5	0
Myanmar	2018	0.260	0.228	0.284	0.267	494	$71,172,235,145.75	4.516	59.4	0
Myanmar	2019	0.259	0.238	0.277	0.263	663	$75,854,734,833.60	2.751	58.5	0
Myanmar	2020	0.272	0.250	0.269	0.297	765	$68,991,135,073.51	3.173	59.2	0
Myanmar	2021	0.249	0.265	0.184	0.297	676	$60,700,903,302.88	5.069	62.9	0
Myanmar	2022	0.242	0.267	0.160	0.297	797	$63,151,698,289.33	2.615		0
Myanmar	2023	0.237	0.270	0.145	0.297	1092	$63,756,973,610.30	2.946		0
Philippines	2014	0.309	0.258	0.324	0.345	1619	$288,153,024,771.70		32.4	1
Philippines	2015	0.304	0.263	0.314	0.334	2139	$306,445,871,242.32		30.8	1
Philippines	2016	0.296	0.267	0.306	0.314	4202	$328,355,086,268.98		28.6	1
Philippines	2017	0.297	0.262	0.308	0.321	9239	$351,113,338,965.58	60.318	27.8	1
Philippines	2018	0.289	0.257	0.293	0.317	9903	$373,379,140,695.82	61.346	27.6	1
Philippines	2019	0.287	0.261	0.286	0.314	12035	$396,224,439,236.64	62.247	26.9	1
Philippines	2020	0.301	0.271	0.308	0.325	12444	$358,510,629,276.39	67.045	29.1	1
Philippines	2021	0.304	0.284	0.303	0.325	15116	$378,998,554,988.86	64.225	28	1
Philippines	2022	0.307	0.295	0.301	0.325	11418	$407,730,367,707.39	66.611		1
Philippines	2023	0.312	0.308	0.301	0.325	35099	$430,232,801,525.65	63.978		1
Singapore	2014	0.817	0.705	0.901	0.845	13915	$299,095,084,828.98	50.640	0.6	1

Singapore	2015	0.811	0.705	0.897	0.832	19844	$307,998,545,269.40	52.217	0.7	1
Singapore	2016	0.790	0.712	0.895	0.764	106879	$319,541,032,495.05	52.233	0.7	1
Singapore	2017	0.798	0.710	0.905	0.777	329385	$333,846,562,289.75	53.098	0.7	1
Singapore	2018	0.805	0.722	0.916	0.778	477674	$345,370,865,382.87	51.572	0.8	1
Singapore	2019	0.805	0.726	0.913	0.775	698581	$349,888,458,531.09	51.817	0.9	1
Singapore	2020	0.807	0.733	0.912	0.774	729931	$336,541,232,520.50	55.262	0.9	1
Singapore	2021	0.813	0.746	0.917	0.774	963602	$369,376,902,514.87	54.972	1.1	1
Singapore	2022	0.810	0.748	0.907	0.774	1198709	$384,550,906,479.01	56.827		1
Singapore	2023	0.804	0.745	0.894	0.774	1353061	$391,555,143,381.89	56.138		1
Thailand	2014	0.412	0.315	0.315	0.605	3555	$389,101,609,925.93	22.644	24.4	1
Thailand	2015	0.405	0.319	0.297	0.600	4768	$401,296,238,228.08	23.908	22.6	1
Thailand	2016	0.403	0.326	0.321	0.563	10103	$415,081,396,923.29	24.153	22.4	1
Thailand	2017	0.404	0.329	0.323	0.561	40023	$432,422,173,710.33	25.095	22.2	1
Thailand	2018	0.416	0.328	0.320	0.600	66225	$450,682,801,200.34	23.701	23.7	1
Thailand	2019	0.419	0.332	0.317	0.609	97741	$460,212,749,509.63	24.146	23.9	1
Thailand	2020	0.429	0.337	0.314	0.636	133183	$432,369,701,127.28	27.648	20.9	1
Thailand	2021	0.432	0.345	0.315	0.636	153089	$439,080,796,986.82	24.664	19	1
Thailand	2022	0.434	0.346	0.321	0.636	197003	$450,410,744,554.86	25.838		1

Thailand	2023	0.432	0.349	0.313	0.636	215289	$459,498,911,646.80	26.051		1
Timor Leste	2014	0.393	0.370		0.416	7	$1,551,797,202.42		18.1	0
Timor Leste	2015	0.409	0.373		0.444	11	$1,590,282,400.00		18	0
Timor Leste	2016	0.404	0.378		0.431	14	$1,638,148,796.99		12.7	0
Timor Leste	2017	0.392	0.382		0.402	15	$1,586,016,100.27		13.2	0
Timor Leste	2018	0.389	0.387		0.390	37	$1,586,017,920.30		12.7	0
Timor Leste	2019	0.392	0.389		0.395	49	$1,957,336,651.25		11.7	0
Timor Leste	2020	0.380	0.395		0.366	119	$2,582,938,997.77		11.4	0
Timor Leste	2021	0.383	0.399		0.366	160	$2,720,236,115.58		12.1	0
Timor Leste	2022	0.383	0.401		0.366	290	$2,161,456,508.57		11.4	0
Timor Leste	2023	0.384	0.402		0.366	333	$1,769,697,034.78			0
Vietnam	2014	0.338	0.705	0.324	0.405	1864		32.055	36.7	1
Vietnam	2015	0.339	0.705	0.320	0.409	3033		36.369	27.8	1
Vietnam	2016	0.348	0.712	0.312	0.440	26098	$255,264,731,908.00	38.057	26.8	1
Vietnam	2017	0.342	0.710	0.281	0.448	127584	$272,980,590,259.00	41.738	28.3	1
Vietnam	2018	0.356	0.722	0.307	0.455	169056	$293,358,610,036.00	40.750	24.3	1
Vietnam	2019	0.362	0.726	0.300	0.481	250511	$314,947,640,805.00	40.433	20.4	1
Vietnam	2020	0.383	0.733	0.339	0.491	302313	$323,972,192,107.00	41.740	18.9	1
Vietnam	2021	0.393	0.746	0.354	0.491	380561	$332,245,562,394.00	41.540	24.2	1

Vietnam	2022	0.397	0.748	0.359	0.491	469839	$360,611,028,837.66	42.689		1
Vietnam	2023	0.388	0.745	0.330	0.491	527482	$378,876,063,686.80			1

Appendix 1.2 ASEAN Six Estimation Result

```
. estat sargan
Sargan test of overidentifying restrictions
H0: Overidentifying restrictions are valid

        chi2(27)     =  16.63071
        Prob > chi2  =    0.9398

. xtdpdsys ra lsis lgdp hte re, lags(1) vce(robust) artests(2)

System dynamic panel-data estimation          Number of obs     =        40
Group variable: country                       Number of groups  =         6
Time variable: year
                                              Obs per group:
                                                            min =         5
                                                            avg =  6.666667
                                                            max =         8

Number of instruments =     33                Wald chi2(5)      =   1219.56
                                              Prob > chi2       =    0.0000
One-step results
```

ra	Coefficient	Robust std. err.	z	P>|z|	[95% conf. interval]	
ra						
L1.	.8551264	.0943797	9.06	0.000	.6701457	1.040107
lsis	.0022255	.0005356	4.16	0.000	.0011757	.0032754
lgdp	.0043081	.0013176	3.27	0.001	.0017257	.0068904
hte	.0001626	.0002301	0.71	0.480	-.0002883	.0006136
re	-.0003895	.0003229	-1.21	0.228	-.0010224	.0002433
_cons	.0295004	.045867	0.64	0.520	-.0603973	.119398

```
Instruments for differenced equation
        GMM-type: L(2/.).ra
        Standard: D.lsis D.lgdp D.hte D.re
Instruments for level equation
        GMM-type: LD.ra
        Standard: _cons
```

```
. estat abond

Arellano-Bond test for zero autocorrelation in first-differenced errors
H0: No autocorrelation

Order          z   Prob > z
----------------------------
    1   -1.9677     0.0491
    2   -.92827     0.3533
----------------------------
```

```
. estimate table pls fem sysgmm
```

Variable	pls	fem	sysgmm
ra			
L1.	.97918034	.71344704	.85512643
lsis	.00350843	.00268923	.00222554
lgdp	.00467474	.00309754	.00430806
hte	9.045e-06	.00139843	.00016264
re	.00011025	-.00022209	-.00038952
_cons	-.04524276	.0415918	.02950036

Appendix 1.3 Non-ASEAN Six Estimation Result

```
. estat sargan
Sargan test of overidentifying restrictions
H0: Overidentifying restrictions are valid

        chi2(23)     =  22.88645
        Prob > chi2  =    0.4674

. xtdpdsys tr lsis lgdp exp re, lags(1) vce(robust) artests(2)

System dynamic panel-data estimation            Number of obs      =         28
Group variable: country                         Number of groups   =          4
Time variable: year
                                                Obs per group:
                                                              min =          7
                                                              avg =          7
                                                              max =          7

Number of instruments =      29                 Wald chi2(3)       =    1683.79
                                                Prob > chi2        =     0.0000
One-step results
```

tr	Coefficient	Robust std. err.	z	P>|z|	[95% conf. interval]	
tr						
L1.	.8490801	.111308	7.63	0.000	.6309204	1.06724
lsis	.0038106	.0017948	2.12	0.034	.0002929	.0073282
lgdp	-.0030743	.01077	-0.29	0.775	-.0241831	.0180344
exp	.0001458	.00028	0.52	0.603	-.000403	.0006945
re	-.0002984	.0003137	-0.95	0.342	-.0009132	.0003165
_cons	.0464688	.0690618	0.67	0.501	-.0888898	.1818275

```
Instruments for differenced equation
        GMM-type: L(2/.).tr
        Standard: D.lsis D.lgdp D.exp D.re
Instruments for level equation
        GMM-type: LD.tr
        Standard: _cons
```

. estat abond

```
Arellano-Bond test for zero autocorrelation in first-differenced errors
H0: No autocorrelation
```

Order	z	Prob > z
1	-1.2635	0.2064
2	1.0863	0.2773

. estimate table pls sysgmm fem, stat(N)

Variable	pls	sysgmm	fem
tr			
L1.	.96803994	.84908009	.39471849
lsis	.00063085	.00381057	.0051677
lgdp	-.00032371	-.00307433	.01431421
exp	-.00006846	.00014577	-.00023031
re	-.00018269	-.00029835	-.00008322
_cons	.01973501	.04646881	.11208765
N	28	28	28

Appendix 1.4 ASEAN Interaction & Dummy Variable Estimation Result

```
. estat sargan
Sargan test of overidentifying restrictions
H0: Overidentifying restrictions are valid

        chi2(26)     =  26.22749
        Prob > chi2  =    0.4507


. xtdpdsys tr lsis interaction group lgdp exp re, lags(1) vce(robust) artests(2)
note: group omitted from div() because of collinearity.

System dynamic panel-data estimation          Number of obs     =         68
Group variable: country                       Number of groups  =         10
Time variable: year
                                              Obs per group:
                                                           min =          5
                                                           avg =        6.8
                                                           max =          8

Number of instruments =     34                Wald chi2(7)      =     591.45
                                              Prob > chi2       =     0.0000
One-step results
```

tr	Coefficient	Robust std. err.	z	P>|z|	[95% conf. interval]	
tr						
L1.	.6689865	.1745256	3.83	0.000	.3269226	1.01105
lsis	.0032391	.0033804	0.96	0.338	-.0033863	.0098645
interaction	-.0016207	.0038127	-0.43	0.671	-.0090935	.005852
group	.0419815	.0419147	1.00	0.317	-.0401698	.1241328
lgdp	.0026386	.0018277	1.44	0.149	-.0009437	.006221
exp	-.0002355	.0005825	-0.40	0.686	-.0013772	.0009062
re	-.0011987	.000786	-1.53	0.127	-.0027392	.0003418
_cons	.1172536	.094467	1.24	0.215	-.0678984	.3024055

```
Instruments for differenced equation
        GMM-type: L(2/.).tr
        Standard: D.lsis D.interaction D.lgdp D.exp D.re
Instruments for level equation
        GMM-type: LD.tr
        Standard: _cons
```

```
. estat abond

Arellano-Bond test for zero autocorrelation in first-differenced errors
H0: No autocorrelation

Order          z   Prob > z
----------------------------
    1   -1.9144     0.0556
    2   .23637      0.8131
----------------------------

. estimate table pls_dummy sysgmm_dummy fem_dummy, stat(N)
```

Variable	pls_dummy	sysgmm_d~y	fem_dummy
tr			
L1.	.96513004	.66898649	.55267141
lsis	.00034796	.0032391	.0050326
interaction	.00298353	-.00162075	-.0010392
group	-.03805819	.04198152	(omitted)
lgdp	.00373976	.00263863	.00202675
exp	-.00006362	-.00023546	-.00017518
re	-.0002298	-.00119874	-.00012112
_cons	.00968199	.11725357	.13715505
N	68	68	68

Appendix 1.5 Model 2 Estimation Result

```
. estat abond

Arellano-Bond test for zero autocorrelation in first-differenced errors
H0: No autocorrelation

Order          z   Prob > z
----------------------------
    1   -1.1105     0.2668
    2   1.0818      0.2794
----------------------------
```

```
. estat sargan
Sargan test of overidentifying restrictions
H0: Overidentifying restrictions are valid

        chi2(27)     =  38.01273
        Prob > chi2  =    0.0777

. xtdpdsys sr lsis lgdp exp re, lags(1) vce(robust) artests(2)

System dynamic panel-data estimation             Number of obs     =         68
Group variable: country                          Number of groups  =         10
Time variable: year
                                                 Obs per group:
                                                              min =          5
                                                              avg =        6.8
                                                              max =          8

Number of instruments =     33                   Wald chi2(5)      =     252.62
                                                 Prob > chi2       =     0.0000
One-step results

------------------------------------------------------------------------------
             |               Robust
          sr | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
          sr |
         L1. |   .8989235   .1360049     6.61   0.000     .6323588    1.165488
             |
        lsis |   .0002203   .0009395     0.23   0.815     -.001621    .0020617
        lgdp |  -.0024465    .002211    -1.11   0.269      -.00678    .0018871
         exp |   .0006476   .0003917     1.65   0.098    -.0001202    .0014154
          re |    .000052    .000122     0.43   0.670    -.0001872    .0002911
       _cons |   .0291352   .0529829     0.55   0.582    -.0747094    .1329798
------------------------------------------------------------------------------
 Instruments for differenced equation
         GMM-type: L(2/.).sr
         Standard: D.lsis D.lgdp D.exp D.re
 Instruments for level equation
         GMM-type: LD.sr
         Standard: _cons
```

```
. estimate table pls_sr sysgmm_sr fem_sr
```

Variable	pls_sr	sysgmm_sr	fem_sr
sr			
L1.	1.007022	.89892347	.64533012
lsis	.00077901	.00022033	.00079375
lgdp	.00110846	-.00244645	-.00218178
exp	-.00002539	.00064761	-.00043328
re	.0001878	.00005197	-.0001009
_cons	-.01468309	.0291352	.14914971

Appendix 1.6 Model 3 Estimation Result

```
. estat sargan
Sargan test of overidentifying restrictions
H0: Overidentifying restrictions are valid

        chi2(27)     =  26.03673
        Prob > chi2  =    0.5166

. xtdpdsys gr lsis lgdp exp re, lags(1) vce(robust) artests(2)

System dynamic panel-data estimation            Number of obs      =         68
Group variable: country                         Number of groups   =         10
Time variable: year
                                                Obs per group:
                                                              min =          5
                                                              avg =        6.8
                                                              max =          8

Number of instruments =     33                  Wald chi2(5)       =     647.34
                                                Prob > chi2        =     0.0000
One-step results
```

gr	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
gr						
L1.	.7724679	.0899233	8.59	0.000	.5962216	.9487143
lsis	.0049986	.001684	2.97	0.003	.0016981	.0082991
lgdp	.0107908	.0047709	2.26	0.024	.00144	.0201416
exp	-.0008653	.0006564	-1.32	0.187	-.0021519	.0004212
re	-.0011539	.0004505	-2.56	0.010	-.0020368	-.0002711
_cons	.0561846	.0446425	1.26	0.208	-.0313131	.1436823

```
Instruments for differenced equation
        GMM-type: L(2/.).gr
        Standard: D.lsis D.lgdp D.exp D.re
Instruments for level equation
        GMM-type: LD.gr
        Standard: _cons
```

```
. estat abond
```

Arellano-Bond test for zero autocorrelation in first-differenced errors
H0: No autocorrelation

Order	z	Prob > z
1	-1.9279	0.0539
2	.18486	0.8533

Appendix 1.7 Model 4 Estimation Result

```
. estat sargan
Sargan test of overidentifying restrictions
H0: Overidentifying restrictions are valid

        chi2(26)     =  18.55754
        Prob > chi2  =    0.8546

. xtdpdsys er lsis lgdp exp re, lags(1) vce(robust) artests(2)

System dynamic panel-data estimation            Number of obs     =         68
Group variable: country                         Number of groups  =         10
Time variable: year
                                                Obs per group:
                                                              min =          5
                                                              avg =        6.8
                                                              max =          8

Number of instruments =     32                  Wald chi2(5)      =     559.73
                                                Prob > chi2       =     0.0000
One-step results

------------------------------------------------------------------------------
             |               Robust
          er | Coefficient  std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
          er |
         L1. |   .6926521   .1324333     5.23   0.000     .4330876    .9522166
             |
        lsis |   .0036955    .002147     1.72   0.085    -.0005125    .0079035
        lgdp |   .0016445    .004474     0.37   0.713    -.0071244    .0104134
         exp |   .0001023   .0004146     0.25   0.805    -.0007102    .0009148
          re |  -.0014836   .0011805    -1.26   0.209    -.0037973    .0008301
       _cons |   .1407183   .1064976     1.32   0.186    -.0680132    .3494498
------------------------------------------------------------------------------
Instruments for differenced equation
        GMM-type: L(2/.).er
        Standard: D.lsis D.lgdp D.exp D.re
Instruments for level equation
        GMM-type: LD.er
        Standard: _cons
```

```
. estat abond

Arellano-Bond test for zero autocorrelation in first-differenced errors
H0: No autocorrelation

Order          z   Prob > z
----------------------------
   1    -2.1999    0.0278
   2    -.99237    0.3210
----------------------------
```

```
. estimate table pls_re sysgmm_er fem_er, stat(N)
```

Variable	pls_re	sysgmm_er	fem_er
er			
L1.	.93602275	.69265209	.62016735
lsis	.0004939	.00369552	.00450431
lgdp	.00195741	.00164452	.00008308
exp	-.00009189	.00010231	-.00001625
re	-.00027676	-.00148362	-.00010152
_cons	.03161727	.1407183	.13660986
N	68	68	68