UCLouvain NHH LOUVAIN School of Management

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Assessing Renewable Energy Investments in Sub-Saharan Africa

The Influence of Financial Development and the Moderating Role of Institutional Quality

Elise Naalsund

Master's thesis for the dual degrees:

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Supervisor: Prof. Bertrand Candelon

Reader: Prof. Paul Pelzl

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Declaration of the use of AI tools

During the preparation of this master's thesis, the author utilized Chat GPT 4.0 for the following purpose:

Purpose: The purpose of using Chat GPT has been to streamline administrative tasks, such as making literature searches and help with the coding process more productive, including concretization of recurring themes and summary sentences. Additionally, the tool has supported the structuring of sub-chapters and refinement of specific arguments.

After using the AI tool, the author diligently reviewed and edited the content produced by the tool. I take full responsibility for the final content presented in this thesis.

By signing this declaration, I affirm that the content of this master's thesis reflects my original work, augmented by the responsible use of AI.

Elise Naalsund

Abstract

This study examines the relationship between financial development and renewable energy investment in Sub-Saharan Africa and analyzes whether institutional quality serves as a moderating factor. The study uses a panel dataset of 46 Sub-Saharan African countries over the period 2000 to 2020 and applies multiple panel regression estimators, including pooled OLS, Fixed Effects, and Random Effects, with PCSE used for robustness check. The findings show that financial development is positively associated with renewable energy investment when comparing across countries, but the effect becomes statistically insignificant once within-country-variation is considered. Moreover, no significant moderating effect of institutional quality is found. However, each institutional dimension, regulatory quality, political stability and control of corruption, independently shows a strong association with renewable energy investment. These findings suggest that financial development alone is not sufficient to drive renewable energy investment, but strong governance and institutional frameworks are also required to scale up renewable energy investment in the region.

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My academic track combined majors in Energy, Natural Resources and the Environment and International Finance. With this in mind, I wanted to write a thesis that brought together these two fields, both to build new competencies and to explore an area I find meaningful. I am especially thankful for the opportunity to dive into a topic of personal interest and challenge myself to define and investigate a research question independently.

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1. Introduction

Renewable energy investment have in recent years gained global attention as a key driver for sustainable economic development and an accelerator for green transition (UN, 2023). From 2019 to 2024, global renewable energy investments nearly doubled, but despite this shift, major regional imbalances persist. For instance, in 2024, Africa accounted for only about 3% of global renewable energy investments, compared to 6% in Latin America, 5.6% in India, and 2.3% in Southeast Asia (IEA, 2024). While Africa does not receive the lowest share, it consistently falls behind other developing regions when attracting renewable energy financing. Moreover, between 2000 and 2020, Sub-Saharan Africa (SSA) received less than 1.5 % of the USD 2.8 trillion invested in renewable energy projects globally (IRENA, 2024a). This underscores both their experience with historical underinvestment and their ongoing struggle to mobilize renewable energy capital.

To better understand what contributes to this uneven distribution, it is important to define what renewable energy investments entail. Renewable energy investments refer to capital flows allocated to the development, expansion, and maintenance of renewable energy infrastructure (L. He et al., 2019), including solar farms, wind turbines, hydropower plants, and geothermal energy (IRENA, 2024a). These investments often have high upfront costs and need long-term financing to be developed. Therefore, energy projects need to have access to well-developed financial markets in order to grow (Cai et al., 2024; Steffen, 2018). Besides, SSA has struggled to attract sufficient private investments to expand their renewable energy infrastructure, despite having high access to renewable resources. Conversely, public investments have been the most prominent source for investment flows for such projects. This is largely due the region's high institutional risks such as political instability, weak legal systems, and regulatory uncertainty, which discourage private sector financing (Asongu & Odhiambo, 2020; IRENA, 2024b).

The overall state of financial development in a country is a crucial factor influencing the level of renewable energy investment flows. A strong and robust financial system facilitates capital mobilization, reduces investment risks, and provides credit access for firms (Levine, 2005) looking to develop renewable energy projects. Additionally, financial development encompasses a broad range of elements, including banking system depth, capital market efficiency, financial inclusion, and credit availability (King & Levine, 1993). Therefore, countries with advanced financial systems typically attract greater investments in energy infrastructure, whereas countries with underdeveloped financial systems encounter capital constraints that hinder the green transition (AfDB, 2022; Timmons et al., 2014). This pattern is apparent in SSA, where insufficient financial development hinders capital mobilization for renewable energy, frequently leading to uneven distribution of investments across the region. Consequently, countries with more advanced financial sectors and regulatory systems tend to attract a greater share of the region's renewable energy investments (Asongu & Odhiambo, 2020; IRENA, 2024a).

In addition to these financial barriers, SSA expects to face rapidly growing energy demand the coming decade due to a fast-growing population, industrialization, increased energy access and rising living standards (IRENA, 2024b). Thus, to meet this growing demand it will necessitate significant expansion of energy infrastructure. Fortunately, Africa possesses significant potential for renewable energy that is well distributed throughout the continent. In a recent report (IRENA, 2024b) on the energy transition in Africa, IRENA states that the renewable energy potential is 1000 times greater than the expected energy demand for electricity in 2040. This represents a significant possibility for enhanced access to renewable energy. Despite this huge potential, SSA's financial sector remains one of the least developed globally (Allen et al., 2011), which may counteract the advantages provided by the region's immense renewable energy resources. Therefore, since limited access to investments remain a key barrier to scaling renewable infrastructure, it is particularly relevant for SSA to enhance their understanding of this relationship.

Recent studies have explored the relationship between financial development and renewable energy consumption in SSA. For instance, Osman et al. (2025) examined how financial development interacted with natural resources, and how its impact influenced renewable energy consumption. They found that the interaction plays a significant role in determining consumption patterns, especially by mitigating the negative effects of resource dependence. Similarly, Asongu & Oshiambo (2020) assessed the relationship between financial development, income inequality, and renewable energy consumption across 39 SSA countries. They determined that while financial development enhances renewable energy consumption, its impact is partially offset by inequality.

While these studies focus on consumption rather than investment as their dependent variable, both highlight a broader connection between financial development and renewable energy outcomes. Financial development appears to enhance access to and utilization of renewable energy, although the methods vary. While renewable energy consumption indicates demand-side improvements such as cost or accessibility in a country, investment emphasizes the capital mobilization that is required to expand infrastructure.

Thus, although the importance of financial systems for renewable energy consumption is evident, the question of whether well-developed financial systems attract greater renewable energy investments remains largely unexplored. This distinction is crucial because higher consumption does not necessarily imply more investments, which is vital for SSA to meet its future energy demand and scale up its renewable energy supply.

The consequences of this disparity between a growing demand and insufficient investments are already evident in SSA. Evidence indicates that the region encounters a substantial gap in renewable energy supply as well as a persistent electricity access deficit (Zahonogo, 2025). As of 2022, IEA reported that 600 million people still lacks access to electricity in SSA (IEA, 2022), representing 43% of the population. This underscores the importance of understanding the extent to which financial development influences investment mobilization in the region.

Given these gaps in both infrastructure and research, this study shifts the focus from renewable energy consumption to investments. The study analyzes how financial development influences renewable energy investment in SSA based on historical data of public renewable energy investments. To guide this inquiry, the thesis will address the following research question:

How does financial development influence renewable energy investments in Sub-Saharan Africa?

The aim off this study is to empirically assess whether countries with stronger financial development attract greater renewable energy investment, by looking at data from the period 2000 to 2020. In addition, the study investigates whether institutional quality moderates this relationship and recognizes that governance and institutional conditions may either enable or constrain the effectiveness of financial systems in supporting renewable investments. Thus, the study seeks to contribute to both academic understanding and policy discussions in three main ways when addressing this research question.

First, the study contributes to the literature by addressing an underexplored area assessing the relationship between financial development and renewable energy and focuses on investment flows rather than consumption. Prior research mainly focuses on the relationship between financial development and renewable energy consumption, whereas there is a limited amount of studies investigating its effect on investment, particularly within the SSA context.

Therefore, this paper addresses a regional research gap by analyzing the historical role of financial development on renewable energy investments and offers new insight into how financial systems influence the supply side of the energy sector.

Second, this contribution is especially important considering SSA's ongoing energy access challenges and objectives for climate resilience. Given that over 600 million people lack access to electricity (IEA, 2022), it is imperative to accelerate renewable energy investments to achieve inclusive economic growth, ensure energy security, and meet global climate objectives such as Sustainable Development Goal 7. A recent report by IRENA (2024) highlight that addressing the funding gap in SSA requires considerable improvements in the efficiency of the financial sector. In contrast to consumption, investments reflect capital mobilization and infrastructure development, both essential components when addressing the rising energy demand and climate goals. Thus, understanding the financial determinants of renewable energy investments can help review national policy and international support frameworks.

Third, the study develops an empirical approach by constructing a multidimensional proxy for financial development. The proxy combines three indicators of financial systems: private credit to GDP (representing market depth), broad money to GDP (representing monetary credibility), and credit-to-deposit ratio (representing banking efficiency). In addition, the study examines whether institutional quality moderates the impact of financial development on renewable energy investment. The dimension of institutional quality is disaggregated into regulatory quality, political stability, and control of corruption. This allows for a more detailed understanding of how financial and institutional dynamics interact, contributing both methodologically and empirically to the field.

The remainder of this thesis is organized as follows: Chapter 2 presents the literature review, outlining relevant theoretical foundations and empirical studies that inform the study's research question. Chapter 3 outlines the methodology and data used in the analysis. Chapter 4 describes the empirical results and analysis, followed by Chapter 5, which discusses the findings. Chapter 6 outlines the study's limitation and direction for future research, and finally, Chapter 7 concludes the study.

2. Literature Review

This chapter reviews the theoretical and empirical literature about the relationship between financial development, institutional quality, and renewable energy investment, specifically in SSA. Most prior research examines renewable energy consumption, but only a limited number explore how financial development affects renewable energy investments, and even fewer focus on SSA. The review is structured as follows: Section 2.1 explores both theoretical, global and regional findings on financial development and renewable energy investment. Section 2.2 reviews literature about institutional quality and its potential moderating effect. Lastly, section 2.3 presents the conceptual model and key hypotheses for the study.

2.1 Financial Development and Renewable Energy Investment

2.1.1 Theoretical Foundations

Economic theory has long acknowledged the correlation between financial development and investment. Schumpeter (1911) stressed the importance of financial intermediaries in fostering innovation by mobilizing capital. According to King and Levine (1993) and Levine (2005) efficient financial institutions lower transaction costs, pool savings, and direct resources to the most profitable investments, which leads to enhanced economic growth. These strategies are particularly important for renewable energy projects, as they entail substantial initial capital and long investment horizons. Solar farms, wind parks, and hydroelectric plants all require substantial initial investment prior to generating revenue, making access to initial funding crucial for success.

The pecking order theory (Myers & Majluf, 1984) claims that enterprises prefer internal over external financing due to asymmetric information and capital costs. Managers possess more information about firm prospects than outside investors, so they will issue equity when they believe the firm is overvalued and debt when undervalued. Thus, this can lead to adverse selection problems and higher external capital costs. However, for renewable energy projects, that are capital intensive, both external and public financing becomes crucial as they require significant upfront capital exceeding most firms' internal resources.

Green bonds, project finance, and sustainability-linked loans help overcome initial investment barriers (Y. He & Yoo, 2024; Steffen, 2018). Financial markets also reduce risk premiums through increased credit access and specialized instruments (Kim & Park, 2016; Wang &

Zhao, 2022). So, financial development can reduce the cost of capital in renewable projects and make them more viable for investors.

Despite a theoretical understanding of financial development and how it can affect investment, much of the empirical literature focus on renewable energy consumption, not investment. This distinction is important, because while consumption reflects usage and affordability, investment reflects capital mobilization for infrastructure. Accordingly, this study shifts the attention to the supply-side drivers of energy development, a relatively underexplored area in the SSA context, and focus on renewable energy investments instead.

2.1.2 Global and Cross-Regional Evidence

A growing number of studies in both developed and emerging markets show how financial development help facilitate renewable energy investment, specifically by expanding credit access and reducing financing costs. Kim and Park (2016) find that banking sector efficiency and capital market liquidity significantly promote investment in renewable energy across both OECD and non-OECD countries. They highlight that financial sector maturity plays an important role in reducing risk premiums and extending long-term credit. Similarly, Sun et al. (2023) show that improved financial systems accelerate renewable energy investments through better credit allocation, particularly when combined with stable regulatory support and targeted climate finance policies.

In high-income countries, Le et al. (2020) document that financial development is strongly associated with renewable energy investment, partly due to the availability of advanced financial instruments and better macroeconomic management. Such environments tend to be most supportive when they combine diversified capital markets with credible governance structures, as this combination plays a key role in strengthening investor confidence and lowering perceived risks. Financial innovation, especially in the form of green bonds and renewable-focused investment vehicles, has further contributed to lowering the cost of capital for clean energy projects (Kim & Park, 2016; Steffen, 2018; Timmons et al., 2014).

However, the effect of financial development on renewable energy investments are highly context-dependent. In countries with weak institutional environments or regulatory gaps, financial liberalization may lead to capital misallocation toward conventional energy sectors, which are often perceived as less risky and with faster returns (L. He et al., 2019; Jiang & Ma, 2019; Sun et al., 2023). For example, Jiang and Ma (2019) emphasize that a well-developed financial sector in emerging economies might be counterintuitive and will negatively affect environmental outcomes unless the systems are accompanied by sound policy frameworks. So, these studies show that funding alone does not always lead to a green transition. Instead, it requires effective policy alignment and complementary institutional reforms.

Moreover, in situations marked by limited investor confidence and project risk, development finance institutions (DFIs) and blended finance instruments play a central role. Steffen (2018) and IEA (2024) highlight that FDIs often act as anchor investors, absorbing early-stage risks and thereby mobilizing private capital. Blended finance and public-private partnerships are particularly useful in fragile financial environments, where they can help align the risk-return expectations of different investor types. These arrangements also address issues such as high upfront costs and long payback periods.

In sum, while financial development is shown to support renewable energy investment in many settings, few studies examine this connection in the SSA context. In addition, many existing studies rely on narrow indicators and thereby overlooks the complexity of financial systems. To address this gap, this study uses a multidimensional index that captures market depth, monetary credibility, and banking efficiency, and offers a more comprehensive view of how financial systems has historically shaped renewable investment in the region.

2.1.3 Sub-Saharan-Africa Specific Cases

The link between financial development and renewable energy outcomes in SSA is affected by a mix of both structural and institutional barriers. Some studies imply that more developed financial systems will help support green development (Mugume & Bulime, 2023). On the other hand, they suggest that in countries with persistent constraints, like underdeveloped banking infrastructure, shallow capital markets, and high interest rates, it still limit the effectiveness of capital allocation (Allen et al., 2011; Soumaré et al., 2021). For instance, short-term government securities still make up a substantial part of the capital markets in SSA, and only a few economies that are relatively more advanced tend to acquire long-term loans.

Additionally, broader socioeconomic factors also frequently limit how effective financial development is in promoting renewable energy outcomes. Osman et al. (2025) shows how inequality and the "resource curse" weaken the positive benefits derived from a strong financial development on renewable energy consumption. For instance, in Nigeria fossil fuel subsidies are still high and their oil revenues make up most of the government's income. Therefore, investment in renewable energy has been relatively low in the country. Similarly, Asongu and Odhiambo (2020) presents a Gini coefficient threshold beyond which financial development does not help renewable energy consumption, pointing to how important it is to have inclusive financial institutions.

A growing body of policy literature underscores the importance of green finance frameworks tailored to SSA's growth and institutional needs. Shipalana (2020) supports that African governments should prioritize green bonds, environmental funds, and targeted fiscal incentives to receive both private and public capital for the contribution to build clean infrastructure. The African Development Bank (AfDB, 2022) agrees with these assertions. They stress the need for concessional finance, risk-sharing tools, and technical assistance to strengthen African countries' domestic financial institutions and attract international investors. These tools are especially important in a region where problems with governance and macroeconomic instability can deter long-term investment.

However, existing research usually focus more on the consumption of renewable energy or the general policy designs, than looking at investment flows. Studies frequently stop short of quantifying how financial development has affected renewable energy investment in SSA over time, leaving an important gap in evidence-based policies. Therefore, this study tries to fill this gap by analyzing historical data over the period of 2000 to 2020 and empirically analyzing the relationship between financial development and renewable energy investments in the region. In doing so, it tries to give new insights about how structural conditions and financial systems interact to affect the results of renewable investment outcomes.

2.2 Institutional Quality and Renewable Energy Investment

Institutional quality refers to the set of formal and informal standards, enforcement procedures, and governance structures that regulate economic activity and help reduce uncertainty (Richter, 2005). Robust institutions help ensure transparency, regulatory predictability, and secure the protection of investor rights, and will be beneficial for renewable energy investments. So, these factors are crucial for attracting long-term capital to the renewable energy sector. Especially, these attributes are critical in high-risk contexts such as SSA, where infrastructure gaps and political volatility often deter private investment.

Empirical evidence strongly supports the enabling role of institutional quality in shaping renewable energy investment outcomes. Alinsato et al. (2023) and Dossou et al. (2023) find that higher levels of both regulatory quality, political stability, and control of corruption are associated with increased investment in renewables. With the focus on SSA, Nyeadi (2023) identifies persistent institutional shortages, such as weak regulatory enforcement, political fragmentation, and limited transparency, as major barriers to obtain effective clean energy finance. Conversely, case studies looking at stable governance environments, such as China, demonstrate how structured institutional support can intensely accelerate renewable energy deployment (Chang et al., 2019).

Institutional quality is often treated as a direct driver of renewable energy investment, but recent literature also emphasizes its moderating role in scaling the effectiveness of financial development. Foundational studies by Beck and Levine (2002) and La Porta et al. (1998) underscore how strong institutions make financial reforms work better by mobilizing capital more effectively, as well as lowering the risks of misallocation. Osman et al. (2025) and Mugume & Bulime (2023) say that without strong institutional foundations, the effect of financial development on green investment are often weakened or redirected, making it particularly relevant for the SSA context.

Recent studies call for a disaggregated approach to institutional quality in order to better understand these dynamics. Rather than using a composite index, this method allows for individual analysis of specific governance dimensions. Regulatory quality, for instance, determines the clarity and enforcement of finance and energy policy frameworks. Alinsato et al. (2023) show that improved regulatory quality significantly strengthens the relationship between financial development and renewable energy consumption across African countries. Political stability, on the other hand, reduces perceptions of investment risk and increases the likelihood of banking sector resilience. Dossou et al. (2023) and Mlachila & Ouedraogo (2020) provide evidence that instability can trigger financial crises, thereby undermining investment climates. Finally, control of corruption is crucial to guarantee that financial resources are allocated to the intended sectors. Brunnschweiler (2009) and Sharma & Paramati (2021) assert that corruption skews capital distribution and undermines the integrity of environmental finance tools, especially in emerging and transitional countries.

While these aspects are interconnected, analyzing them separately facilitates for a more detailed understanding of their unique moderating impacts. In SSA, where institutional performance significantly varies among nations, this approach can help identify the governance enhancements that are most critical and effective for the region. Therefore, this study follows this disaggregated approach by examining each of the three dimensions (regulatory quality, political stability, and control of corruption) as potential moderators of the relationship between financial development and renewable energy investments. In doing so, this contributes to a growing body of literature aimed at aligning financial sector reform with broader institutional development to achieve a sustainable energy transition in SSA.

2.3 Conceptual Model and Hypotheses

Despite the growing academic interest in the link between financial development and renewable energy, there are important gaps that remain when it comes to understanding investment flows in SSA. First, much of the existing research focus on the consumption of renewable energy. Though these studies reflect the usage patterns in countries, they overlook renewable energy investments, which is essential for developing more infrastructure and long-term progress (Mugume & Bulime, 2023). Second, while both financial development and institutional quality are widely recognized as important drivers of investment, their interplay remains insufficiently studied. This gap is relevant in low-income countries, where weak governance structures often constrain the effectiveness of financial systems and limit their ability to support investment (Sun et al., 2023). Third, much of the existing literature tends to rely on a single indicator, such as banking depth or credit access, to represent financial development. While these measures offer useful insights, this narrow focus risks overlooking their ability to capture the complex nature of financial systems and how they contribute more broadly to facilitating investment (Alshagri et al., 2024).

The study addresses these gaps by developing a conceptual framework that looks at the main independent variable, financial development, and how it influences the dependent variable, renewable energy investments. In addition, the study develops a composite index to reflect financial development more comprehensively, and combines indicators for market depth, monetary credibility, and banking efficiency. This approach enables a more nuanced examination of how financial systems support renewable investments across a broader context of the term. The conceptual model is illustrated in Figure 1.

The study also includes institutional quality as a moderating factor, reflecting the idea that financial development is more effective in environments with stronger institutions. This dimension is disaggregated into three distinct dimensions: regulatory quality (IQ1), political stability (IQ2), and control of corruption (IQ3). By dividing the institutional quality dimension, the study thereby acknowledges that different aspects of governance may influence investment dynamics in distinct ways. For instance, effective regulatory systems can enhance transparency and reduce investor uncertainty (Alinsato et al., 2023), political stability may ensure policy continuity, and control of corruption can strengthen the credibility of financial and legal institutions (Brunnschweiler, 2009; Pan et al., 2022). Hence, the study gains a more nuanced understanding of what institutional quality index influences this relationship the most.

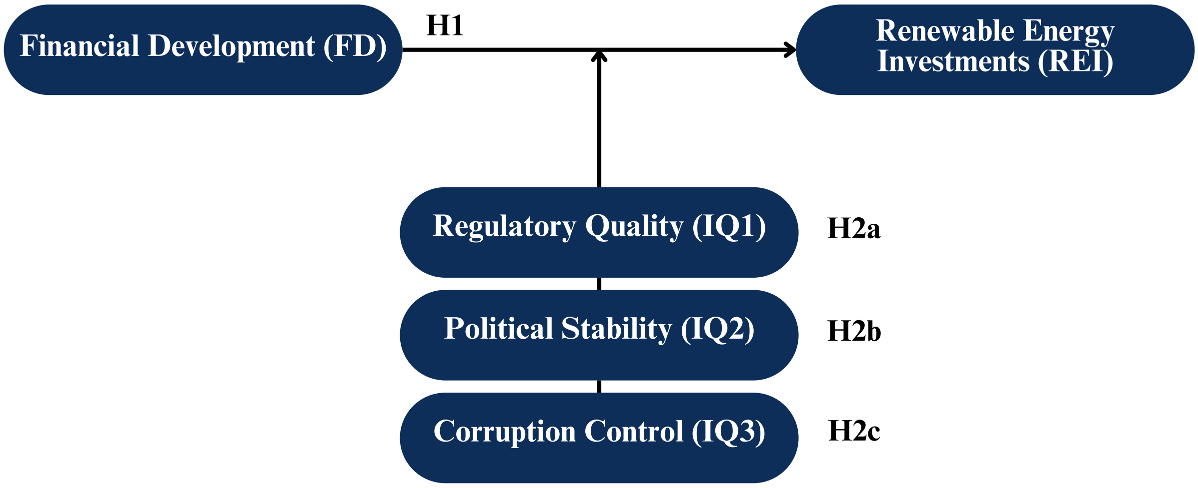


Figure 1: Conceptual Model

Furthermore, the model includes macroeconomic and structural control variables to isolate the effect of financial and institutional variables on renewable energy investments. These include GDP per capita, which captures the countries' income level and their capacity to fund infrastructure (Sadorsky, 2010). Trade openness is a sign of financial integration and the spread of technology (Ben Jebli et al., 2016). CO2 emissions per capita, show how environmental problems might lead to green investment (Salahuddin et al., 2018). Electricity access indicates current baseline infrastructure, often a precondition for new investment to the sector in the future (IRENA, 2024a). Inflation reflects macroeconomic stability and investment uncertainty (AfDB, 2022). Lastly, renewable electricity consumption control for historical investment patterns (Safarzyńska & van den Bergh, 2017).

Based on this framework, the first hypothesis is the following:

Hypotheses 1 (H1): Financial development positively affects renewable energy investment in SSA.

The literature further suggests that financial development may be more effective when supported by sound institutions. Regulatory quality, in particular, plays a central role in shaping financial and investment policy coherence. Studies have shown that countries with higher regulatory quality are more likely to attract long-term capital to renewable energy projects (Alinsato et al., 2023; Dossou et al., 2023). Accordingly, the second hypothesis is:

Hypothesis 2a (H2a): Regulatory quality positively moderates the relationship between financial development and renewable energy investment.

Another dimension is political stability, which is believed to influence financial sector performance. Instability can increase investor uncertainty and weaken the financial system's ability to support long-term projects (Jha, 2019; Mlachila & Ouedraogo, 2020). Thus, stable political environments may strengthen the link between financial development and REI:

Hypothesis 2b (H2b): Political stability positively moderates the relationship between financial development and renewable energy investment.

Finally, corruption is well-documented as an obstacle to effective financial intermediation. High levels of corruption reduce the transparency of project selection, distort credit allocation, and increase transaction costs (Ondoa & Seabrook, 2022; Sharma & Paramati, 2021). Consequently, with stronger control of corruption it may instead enhance the efficiency of financial systems in mobilizing capital for renewable energy:

Hypothesis 2c (H2c): Control of corruption positively moderates the relationship between financial development and renewable energy investment.

By integrating these dimensions into a unified framework, this study aims to provide a more comprehensive understanding of how financial and institutional structures jointly shape investment in renewable energy across SSA.

3. Methodology

The following chapter outlines the methodology used in the analysis to examine how financial development influences renewable energy investments in SSA, and how this relationship is moderated by institutional quality. Section 3.1 introduces the research design. Section 3.2 presents the empirical model, variable construction, and data sources. And lastly, section 3.3 describes the estimation techniques and describes measures to ensure validity.

3.1 Research Design

To examine the dynamic relationship between financial development, institutional quality, and renewable energy investments in SSA, this study adopts a panel data research design. This approach leverages the combination of cross-sectional and time-series dimensions, allowing for more robust control of unobserved heterogeneity across 46 SSA countries over the period 2000-2020 (Baltagi, 2005; Hsiao, 2014). The unit of analysis is country-year. This empirical analysis is conducted using RStudio (v2024.12.1), with the full code available in appendix 9.6.

Panel regression techniques are used to estimate how financial development influences renewable energy investments, conditional on institutional and macroeconomic conditions. This framework allows for the simultaneous estimation of multiple explanatory variables while accounting for unobserved heterogeneity across countries and time, particularly relevant given SSA's diverse financial systems, governance structures, and energy infrastructures (Levine, 2005; Wooldridge, 2010). By controlling for both country- and time-fixed effects, the model isolates structural variation and global shocks relevant to the hypotheses developed in Chapter 2.

Specifically, the analysis tests whether financial development positively influences renewable energy investment (H1), and whether this relationship is moderated by institutional quality, namely regulatory quality (H2a), political stability (H2b), and control of corruption (H2c).

3.2 Model Specification and Data

This study extends the methodological framework proposed by Osman et al. (2025), who applied panel regression to assess how financial development and natural resources interact to shape renewable energy consumption in SSA. Building on their approach, this study introduces a composite index of financial development and examines how its effect on renewable energy investment is moderated by institutional quality. Interaction terms are included to capture this moderating relationship, along with control variables reflecting key macroeconomic and structural factors. The model is specified as follows:

$$\log(REI_{it} + 1) = \alpha + \beta_1 FD_{it} + \beta_2 IQ_{it} + \beta_3 (FD_{it} \times IQ_{it}) + \gamma X_{it} + \mu_i + \lambda_t + \epsilon_{it}$$

where μ_i captures time-invariant, country-specific heterogeneity and λ_t is a full set of year dummies that absorb common shocks.

Here, $\log(REI_{it} + 1)$ is the log-transformed measure of public renewable energy investment in country i at time t, expressed in millions of USD. The variable is collected from the International Renewable Energy Agency (IRENA), which provides annual data for 46 SSA countries over the period 2000 to 2020.

FD_{it} represents the independent variable and is the indicator for financial development for each country (i) for the year (t). The variable is proxied by three complementary indicators: Private Credit to GDP, Broad Money (M2) to GDP, and the Bank Credit to Bank Deposits (%). All three variables are sourced from the World Bank's Worldwide Development Indicators (WDI). Following best practices in index construction, each of the three indicators was first standardized using z-scores to ensure comparability. The composite index was then calculated as the simple arithmetic mean of these standardized scores, as implemented in the R script (Appendix 9.6). This approach reflects a broader, multidimensional view of financial development in line with King and Levine (1993) and Allen et al. (2011). The first two indicators were log-transformed before standardization due to significant right-skewness.

Institutional quality, IQ_{it}, is included to capture governance conditions that may influence the effectiveness of financial development. Three institutional dimensions are used and gathered from the World Bank's Worldwide Governance Indicators (WGI): Regulatory Quality (IQ1), Political Stability (IQ2), and Control of Corruption (IQ3). These are treated independently in the empirical analysis to enable a disaggregated assessment of their moderating effects. Each is scaled from -2.5 to +2.5, with higher scores reflecting better institutional performance. Interaction terms between FD_{it} and each of the three institutional indicators ($FD_{it} \times IQ_{it},$) are included to test whether financial development is more effective in countries with stronger institutional frameworks.

The vector of control variables, X_{it}, includes several macroeconomic and environmental variables characterized expected to influence renewable energy investments. *GDP per capita* (log-transformed) is included to capture income effects and the investment capacity of individual countries. *Trade openness* measures the sum of exports and imports as a percentage of GDP (also log-transformed) and reflects a country's market integration and access to technology transfer. *CO2 emissions per capita,* sources from the Global Carbon Project, serve as a proxy for environmental pressure and the structure of energy systems (log-transformed). Two infrastructure-related indicators are included in their raw form. *Access to electricity* (measured as the percentage of the population with access) and *renewable energy consumption* (as a percentage of the total final energy use), both of which describe the baseline energy environment. Finally, *inflation* is incorporated as an indicator of macroeconomic stability. This variable is log-transformed only for positive values due to the presence of deflationary observations in some country-years combinations.

All variables were assessed for skewness prior to estimation, and log-transformations were applied where necessary to improve normality and reduce heteroskedasticity. This included *REI*, *private credit, broad money, GDP per capita, trade,* CO_2 *emissions*, and *inflation*. A constant of +1 was added to zero values prior to transformation. Variables unsuited to log-transformation, such as inflation with non-positive values, were log-transformed only where valid. Justifications and diagnostic plots are provided in Appendix 9.2. Following best practice for macro-panels (Baltagi, 2005; Wooldridge, 2010), we add a full set of year dummies (λ_t) to every baseline regression. The fixed-effects estimator removes μ_i via the within transformation, while the random-effects model treats μ_i as a random draw. The pooled OLS specification implicitly sets $\mu_i = 0$.

Prior to estimation, the dataset underwent extensive preprocessing to enhance internal validity and fulfill econometric assumptions. Following Dong & Peng (2013) and Newman (2014), countries with more than 50% missing values across the 21-year period were excluded to avoid biased estimates. Based on this threshold, Somalia and South Sudan were removed, yielding a panel of 46 SSA countries (see Appendix 9.3). Additionally, institutional quality variables were linearly interpolated for the year 2001 due to missing data across countries in that year. Given their bounded scale and limited volatility year-on-year, this interpolation is methodologically defensible and avoids unnecessary sample loss (Baltagi, 2005; Kaufmann et al., 2010).

3.3 Estimation Techniques

3.3.1 Estimation Strategy

This study employs a panel data estimation strategy designed to address key econometric challenges associated with macroeconomic panels. As a baseline, a pooled ordinary least squares (POLS) model is estimated, augmented with a full set of year dummies to absorb common shocks. Because the pooled approach still assumes homogeneity across countries and does not control for country-specific effects ($\mu_i = 0$), it remains unsuitable for drawing causal inference in a macro-panel context (Baltagi, 2005).

The main estimation method is a two-way Fixed Effects (FE) model, which controls for both time-invariant unobserved country characteristics and time-specific shocks. Country fixed effects capture structural differences across countries, such as geographic, institutional, or historical factors, while year fixed effects account for shared external events, such as global policy shifts or oil price fluctuations. This method is well-suited to contexts like SSA, where national contexts vary widely in terms of governance, infrastructure, and financial development. To test whether the assumptions of the FE model hold, a Random Effects (RE) model is also estimated. A Hausman test with year dummies included is used to evaluate whether the country effects are correlated with the regressors. The test result is reported in § 4.3.4 and informs the choice between FE and RE.

To address issues specific to macro-panel data, such as heteroskedasticity, contemporaneous correlation, and autocorrelation, a Panel-Corrected Standard Errors (PCSE) estimator is employed. This approach, developed by Beck and Katz (1995), corrects for non-spherical error structures that are common in panels with interdependent units, such as regional datasets. Because PCSE requires sufficient within-country variation over time, countries with fewer than five valid annual observations were excluded from this specification to ensure the robustness of the estimates.

In addition, an attempt was made to apply Generalized Method of Moments (GMM) estimator to address potential endogeneity between renewable energy investment and its predictors. However, due to the limited cross-sectional dimension and data loss from differencing and lagging, the instrument was weak and the estimates unstable. This aligns with existing cautionary literature (Roodman, 2009), which notes that GMM can be inappropriate in short panels with missing data. Therefore, the PCSE model is retained as the primary robustness estimator in this analysis. This limitation reinforces the choice to use PCSE as the main estimator, particularly for testing the moderating role of institutional quality.

3.3.2 Model Diagnostics

To ensure the validity of the estimation results, the study implements different diagnostic checks. First, to test for potential multicollinearity the Variance Inflation Factors (VIF) test is used. Multicollinearity was assessed using these VIF scores, flagging any values above 10 as potentially problematic (Gujarati & Porter, 2009).

Then, to assess potential cross-sectional dependence, the study applies the Pesaran's (2007) CD test, which tests the null hypothesis of no contemporaneous correlation among residuals. This test informs us whether standard errors should be adjusted, for instance by applying PCSE. Due to software and data limitations, second-generation panel unit root tests (such as Pesaran's CIPS test) could not be implemented. However, given the moderate time dimension in the panel, and efforts to reduce missingness during preprocessing, concerns about non-stationarity are considered limited.

Additionally, a series of residual diagnostics are also performed to verify classical regression assumptions. Normality is assessed visually through histograms and Q-Q plots and formally using the Shapiro-Wilk test. Heteroskedasticity is tested using the Breusch-Pagan test, while first-order serial correlation is evaluated by using the Baltagi-Wu BG(1) test (Wooldridge-type). These tests inform whether strong standard errors are needed for addressing misspecification and test results are provided in appendix 9.5.

Together, these diagnostic checks contribute to the internal validity of the empirical analysis. They ensure that key statistical assumptions are met.

4. Empirical Results and Analysis

This section presents the empirical results of the analysis. It starts with the univariate analysis (descriptive statistics and correlation analysis), followed by the pre-estimation diagnostics assessing key model assumptions (multicollinearity and cross-sectional dependence). Subsequently, the multivariate analysis is presented, consisting of the pooled OLS, FE and RE model, and PCSE model for the robustness of these findings.

4.1 Univariate Analysis

This section presents a statistical overview of the dataset by presenting key descriptive statistics and pairwise correlation.

4.1.1 Descriptive Statistics

Table 1 presents summary statistics for all variables used in the empirical analysis. Variables are shown in their final transformed forms (see §3.2 and Appendix 9.2 for details). The table includes the mean, median, standard deviation, and observed ranges.

The financial development (*FD*) variable is a single proxy capturing key aspects of financial sector depth, credibility, and efficiency. As shown in Table 1, *FD* has a mean of 0.002 and a standard deviation of 0.646, with values ranging from -2.07 to 1.85. This broad range underscores the disparities in financial development among SSA nations, possibly indicative of differences in access to credit, liquidity, and banking infrastructure.

The three institutional quality proxies, reg_quality (*QI1*), pol_stability (*IQ2*), and corruption_indx (*IQ3*), each show averages near -0.6. This underscores weak governance performance in the region. Their ranges are constrained by the bounded scale of -2.5 to +2.5, but they display variation within the range. For instance, *IQ1* spans from -2.23 to +1.20, suggesting that there are countries with both fragile and relatively stronger regulatory environments. This applies to *IQ2* and *IQ3* as well, ranging from -2.70 to +1.20 and -1.64 to +1.39, respectively.

Table 1: Descriptive Statistics

Descriptive Statistics						
Variable	**Mean**	**Median**	**Std. Dev.**	**Min**	**Max**	**N**
Log_REI	2.384	2.258	2.133	0.000	8.902	689
FD	0.002	0.036	0.646	−2.073	1.853	859
IQ1	−0.665	−0.682	0.597	−2.227	1.197	966
IQ2	−0.465	−0.344	0.841	−2.699	1.283	966
IQ3	−0.597	−0.710	0.620	−1.646	1.389	966
FD × IQ1	0.189	0.018	0.607	−2.099	3.562	859
FD × IQ2	0.134	0.001	0.664	−1.793	4.718	859
FD × IQ3	0.175	0.037	0.533	−1.350	3.016	859
Log_GDP	7.119	6.941	0.952	5.537	9.877	944
Log_Trade	4.153	4.098	0.468	2.903	5.855	814
Log_CO2	0.466	0.260	0.515	0.021	2.368	966
REC	65.338	76.200	26.466	0.700	98.300	966
Elec_Access	39.022	35.400	25.901	1.300	100.000	957
Log_Inflation	1.855	1.851	0.831	0.036	6.325	836

Note. Log_-prefixed variables are natural logarithms. REC is renewable-energy consumption expressed as a percent of total final energy use, and Elec_Access is access to electricity expressed as a percent of population. IQ1–IQ3 are governance-quality indices ranging from –2.5 (weak) to +2.5 (strong). Sample sizes (*N*) differ across variables; see final column.

The macroeconomic control variables also show interesting patterns. *Log_GDP* averages 7.119, which corresponds to an arithmetic average of approximately USD 2,109 in the original (unlogged) scale. This indicates a sample with a lower-middle-income profile. *Log_Inflation*, despite being logged, still shows considerable dispersion (SD=0.831, range from log 0.036 to 6.325), that can reflect regional instability and perhaps underlying variation in price levels. Trade openness (*Log_Trade*) also shows large variation (SD=0.468), with values ranging from log 2.903 to 5.855. This indicates different degrees of global integration and economic openness across countries. As for electricity access (*Elec_access*) it ranges from 1.3% to nearly 100%, while renewable energy consumption (*REC*) varies from under 5% to over 90%. This captures distinct cross-country differences in access and dependence on energy.

Overall, these descriptive statistics shows the diversity of the SSA region and support the need to control for both time-invariant country characteristics and time dynamics in the analysis.

4.1.2 Correlation Analysis

The correlation matrix presented in Table 2 presents pairwise correlation between *Log_REI* and the explanatory and control variables. *Log_REI* have a statistically significant positive correlation with *FD* (r = 0.15, ***), that indicates that financial development is positively associated with renewable energy investments across countries and time. On the other hand, the institutional indicators show mixed patterns. First, *IQ1* is positively correlated with *Log_REI* (r = 0.08, **), whereas *IQ2* and *IQ3* exhibit significant negative correlations (r = –0.21, *** and r = –0.10, **, respectively). These findings suggest that governance dimensions related to regulatory quality may support renewable energy investment, whereas instability and corruption may hinder it.

Table 2: Correlation Matrix

Correlation Matrix														
Variable	**Log_REI**	**FD**	**IQ1**	**IQ2**	**IQ3**	**FD × IQ1**	**FD × IQ2**	**FD × IQ3**	**Log_GDP**	**Log_Trade**	**Log_CO2**	**REC**	**Elec_Access**	**Log_Inflation**
Log_REI	1	0.15***	0.08**	-0.21***	-0.1**	-0.04	-0.09**	-0.1**	-0.01	-0.09**	-0.01	0.04	0.08**	0.01
FD	0.15***	1	0.5***	0.25***	0.44***	-0.57***	-0.42***	-0.64***	0.35***	0.1***	0.36***	-0.44***	0.42***	-0.24***
IQ1	0.08**	0.5***	1	0.59***	0.75***	-0.08**	-0.1***	-0.14***	0.44***	0.23***	0.41***	-0.49***	0.36***	-0.11***
IQ2	-0.21***	0.25***	0.59***	1	0.68***	-0.07**	-0.1***	-0.04	0.52***	0.4***	0.46***	-0.6***	0.44***	-0.13***
IQ3	-0.1**	0.44***	0.75***	0.68***	1	-0.12***	-0.05	-0.07**	0.42***	0.31***	0.39***	-0.57***	0.41***	-0.07*
FD × IQ1	-0.04	-0.57***	-0.08**	-0.07**	-0.12***	1	0.75***	0.9***	0.07*	0.05	0.15***	-0.01	0	0.23***
FD × IQ2	-0.09**	-0.42***	-0.1***	-0.1***	-0.05	0.75***	1	0.78***	0	0.13***	-0.01	0.02	0	0.22***
FD × IQ3	-0.1**	-0.64***	-0.14***	-0.04	-0.07**	0.9***	0.78***	1	0.03	0.08**	0.07**	0.02	-0.02	0.21***
Log_GDP	-0.01	0.35***	0.44***	0.52***	0.42***	0.07*	0	0.03	1	0.61***	0.89***	-0.78***	0.83***	-0.15***
Log_Trade	-0.09**	0.1***	0.23***	0.4***	0.31***	0.05	0.13***	0.08**	0.61***	1	0.53***	-0.6***	0.47***	-0.06
Log_CO2	-0.01	0.36***	0.41***	0.46***	0.39***	0.15***	-0.01	0.07**	0.89***	0.53***	1	-0.76***	0.72***	-0.14***
REC	0.04	-0.44***	-0.49***	-0.6***	-0.57***	-0.01	0.02	0.02	-0.78***	-0.6***	-0.76***	1	-0.72***	0.18***
Elec_Access	0.08**	0.42***	0.36***	0.44***	0.41***	0	0	-0.02	0.83***	0.47***	0.72***	-0.72***	1	-0.22***
Log_Inflation	0.01	-0.24***	-0.11***	-0.13***	-0.07*	0.23***	0.22***	0.21***	-0.15***	-0.06	-0.14***	0.18***	-0.22***	1

Note. Coefficients are Pearson correlations. Two-tailed significance levels: $p < 0.10$ = *, $p < 0.05$ = **, $p < 0.01$ = ***. Based on 859 country-year observations; pairwise deletion for missing values.

Among macroeconomic controls, *Log_Trade* and *Log_GDP* both have weak negative correlations with *Log_REI,* though only *Log_Trade* is statistically significant (r = –0.09, ***). *Log_CO2* and *Log_Inflation* show no significant correlation, suggesting that their influence on REI may be nonlinear or dependent on interaction with other factors. For the environmental variables we observe a positive relationship with *Elec_Access* (r = 0.08, **), suggesting that countries with good electricity infrastructure may facilitate more investment in energy projects as well. Moreover, neither *REC* nor the interaction terms between *FD* and *IQ* dimensions show significant bivariate relationships with the dependent variable.

These correlations highlight the need for multivariate estimation techniques to account for confounding factors, omitted variable bias, and unobserved country-specific heterogeneity, concerns that are addressed in the following analysis.

4.2 Diagnostic Tests for Model Assumptions

Before estimating the regression models, a set of diagnostic tests is conducted to assess key assumptions, including multicollinearity and cross-sectional dependence.

4.2.1 Multicollinearity Diagnosis: Variance Inflation Factor (VIF)

The Variance Inflation Factor (VIF) test was conducted, to assess multicollinearity among the independent variables. The results from this test are presented in Appendix 9.4 (Table 10) and shows that all but one variable have VIF values below 5. This indicates low collinearity and remains well within acceptable thresholds (Gujarati & Porter, 2009). The only exception is the variable *Log_GDP*, with a VIF of 8.43. Hence, indicating moderate multicollinearity. However, since it remains below the conventional cut-off of 10, it is retained in the analysis with caution. From the results it is confirmed that multicollinearity is not a significant concern for this sample, and all variables can be included in the regression without adjustments.

4.2.2 Cross-Sectional Dependence (CD) Test

The presence of cross-sectional dependence was tested using Pesaran's (2007) CD test, given the regional integration of SSA economies and potential policy spillovers, particularly in energy and financial markets (Osman et al., 2025). The results from this test are presented in Table 3. The CD test assesses the null hypothesis of cross-sectional independence (no correlation across countries) against the alternative of cross-sectional dependence. A p-value close to zero leads to rejection of the null, indicating cross-country correlation (Pesaran, 2007).

As shown in Table 3, the variables *Log_REI, FD, IQ1, Log_GDP, Log_Trade, Log_CO2, REC, Elec_access,* and *Log_Inflation* all have highly significant p-values ($p < 0.01$), leading to a strong rejection of the null hypothesis. This supports the view that economic and institutional developments in one SSA country are likely influenced by those in others. This is theoretically reasonable given shared regional economic dynamics, climate initiatives, and institutional frameworks.

In contrast, the variables *IQ2* ($p = 0.948$) and *IQ3* ($p = 0.343$) display high p-values. Therefore, these do not reject the null hypothesis, suggesting greater independence in these governance indicators across countries.

Table 3: Cross-Sectional Dependence (CD) Test (Pesaran, 2007)

Results of Cross-Sectional Dependence Test		
Variable	**CD Statistic**	**p-value**
Log_REI	7.716	0.000
FD	26.722	0.000
IQ1	5.881	0.000
IQ2	0.065	0.948
IQ3	0.949	0.343
Log_GDP	61.565	0.000
Log_Trade	14.468	0.000
Log_CO2	30.025	0.000
REC	45.158	0.000
Elec_Access	128.405	0.000
Log_Inflation	22.362	0.000

Note. Pesaran's CD test (2007) examines the null hypothesis of cross-sectional independence. Small *p*-values ($p < 0.10$) reject H_0 and indicate significant cross-sectional dependence. In this sample, $N = 37$ countries and $T = 23$ years (859 country-year observations).

4.3 Multivariate Analysis

This section presents the multivariate regression results examining the relationship between financial development, institutional quality, and renewable energy investment in SSA. First, this section starts by presenting three baseline estimation techniques in sections 4.3.1-4.3.3 (Pooled OLS, FE Model, and RE Model). Then it presents the Hausman specification test in 4.3.4, which guides the model selection. Finally, section 4.3.5 summarizes the main findings from the different estimators.

4.3.1 Pooled OLS Model

The first estimation uses the pooled OLS model, supplemented with a full set of year dummies that absorb common shocks, but still assumes $\mu_i = 0$ (no country-specific effects). As shown in Table 4, *FD* has a positive and statistically significant association with log-transformed *REI* at the 10% level ($\beta = 0.577, p < 0.1$). Since both variables are log-transformed, this coefficient can be interpreted semi-elastically. A 1-unit increase in the *FD* index is associated with approximately a 57.7% increase in *REI*, on average. This result reinforces the idea that countries with more advanced financial systems are generally better positioned to support greater public investment in renewable energy, as they offer the financial infrastructure and stability needed to mobilize such funding effectively.

Among the institutional quality indicators, *IQ1* is positively and significantly correlated with *REI* ($\beta = 1.204, p < 0.01$). This is consistent with the expectation that stronger institutional frameworks support investment environments. *IQ2*, on the other hand, shows a negatively and significantly association ($\beta = -0.579, p < 0.01$). This can potentially reflect investor hesitation in countries and environments undergoing political transitions or volatility. Lastly, from these indicators, *IQ3* is negative but statistically significant in this specification ($\beta = -0.968, p < 0.01$).

Moreover, analyzing the interaction terms between *FD* and *IQ*, only *FD* × *IQ2* is statistically significant ($\beta = -0.595, p < 0.05$). This suggests that in more politically stable countries, the effect of *FD* on *REI* will be weaker compared to more volatile nations. One possible explanation is that politically stable systems experience less urgency to mobilize green finance, as policy continuity and institutional strength already offer a reliable foundation for investment. As a result, investment may be less dependent on additional financial system development in such contexts. This signifies that when political stability is low the benefits of financial development on renewable energy investments is absent, contrary to what theory suggests.

Among the control variables, only *Elec_access* and *Log_Inflation is* statistically significant ($\beta = 0.028, p < 0.01, and\ \beta = 0.263, p < 0.05$, respectively), whereas the remaining controls are statistically insignificant. Furthermore, the model has an R-squared value of 0.143, which represent a moderate explanatory power and captures only 14.3% of the variation in renewable energy investments across countries and years without accounting for country-specific effects.

These findings provide some initial support for the proposed relationship. However, the pooled OLS model has important limitations. Specifically, it does not control for unobserved country-specific characteristics, which may lead to omitted variable bias. Therefore, these estimates should be interpreted primarily as descriptive and indicative. More reliable insights are offered in the subsequent analysis using fixed and random effects models, which better account for cross-country heterogeneity.

4.3.2 Fixed Effects Model

To better account for both country-specific and time-specific factors, a two-way fixed effects model is estimated. This approach controls for unobserved heterogeneity across countries and years, allowing the analysis to focus on within-country variation in financial and institutional conditions and their association with renewable energy investment.

Once fixed effects are included, the results change notably. In the FE model *FD* is no longer significantly associated with *REI* ($\beta = 0.159, p > 0.1$), which suggests that the within-country variation in *FD* over time does not have a strong impact. Therefore, this weakens the support for Hypothesis 1 and likely reflects that most of the variation in financial systems actually lies between countries, and not within them over time.

Similarly, the three institutional quality indicators (*IQ1, IQ2, IQ3*) and their interaction terms (*FD × IQ1, FD × IQ2, FD × IQ3)* all become statistically insignificant in the FE model. This shift implies that the moderating effect observed in the pooled model does not hold once fixed effects are included. While this weakens support for Hypothesis 2, it may also reflect limited within-country variation in institutional quality over the sample period.

Among the control variables, *REC* is the only variable that remains statistically significant ($\beta = -0.079, p < 0.05$), and shows a negative association with *REI*. This somewhat counterintuitive finding may suggest a substitution effect, where countries with already high levels of renewable energy consumption allocate fewer resources toward expanding the capacity further, as the existing demand is already met. However, this result should be interpreted cautiously.

The R-squared (≈ 0.106) indicates limited explanatory power, which again is not uncommon in macro-panel settings where many structural drivers of investment are unobservable.

4.3.3 Random Effects Model

The random effects model serves as a middle ground, capturing both within- and between-country variation. It relies on the assumption that unobserved country-specific factors are uncorrelated with the explanatory variables. Like the other models, year dummies are included to account for common shocks over time.

In this model, *FD* also shows a positive association but is not statistically significant with *REI* ($\beta = 0.423, p > 0.1$). The results indicate that countries with more developed financial systems generally exhibit higher levels of renewable energy investment. However, this cannot be concluded with confidence, as the effect is not statistically significant and may be driven by unobserved factors or noise in the data.

IQ1 is again positive and significant ($\beta = 1.135, p < 0.05$), while *IQ2* and *IQ3* shows negative and significant associations with *REI* ($\beta = -0.545, p < 0.05, \beta = -1.041, p < 0.05$, respectively). These results are in line with the pooled OLS model, and suggest that stronger regulatory environments encourage investment, while political instability and less control of corruption discourages it.

All interaction terms show no statistical significance and can therefore not support Hypothesis 2. The findings even show that both *FD* × *IQ1* and *FD* × *IQ2* have negative coefficients. Thus, the interaction terms suggest a potential negative moderating effect, but the relationship is not statistically significant and should therefore be interpreted with caution.

Like the pooled OLS, *Elec_access* remains positively and significantly associated with *REI* ($\beta = 0.026, p < 0.01$). This indicates a clear positive relationship between electricity access and renewable energy investments. The remaining control variables are not statistically significant. Also, the R-squared accounts for even less of the variation in renewable energy investment across countries and years, with an explanatory power of ≈ 0.07.

4.3.4 Model Selection: Hausman Test

To determine whether the fixed effects or random effects estimator is more appropriate, a Hausman test was conducted. The test result ($\chi^2 = 21.92$, df=33, $p < 0.93$), indicates that the null hypothesis of RE consistency cannot be rejected. Despite this statistical outcome, the two-way fixed effects model remains the preferred specification, as unobserved country characteristics, such as resource endowments and legal origins, are theoretically likely to correlate with financial development (T. Beck & Levine, 2002). The random effects estimates are therefore included as a robustness check.

4.3.5 Summary of Baseline Regression Results

Overall, the baseline regressions, each including year fixed effects, point to a complex and context-dependent relationship between financial development and renewable energy investment in SSA. The Hausman test does not reject the null hypothesis, indicating that the RE estimator may be consistent. Still, the two-way fixed effects specification is retained as the main model on theoretical grounds. While the pooled OLS model suggests a positive, but weak, association between financial development and renewable energy investment, this relationship does not hold in the fixed effects model. This implies that financial development may help explain cross-country differences in investment levels, but not within-country changes over time.

Institutional quality shows a similar pattern. Independently, the indicators are statistically significant in the pooled and RE model, but lose significance in the FE model, which better isolates within-country changes. This suggests that their influence is mainly driven by cross-country differences rather than by changes within countries over time. All interaction terms are also not statistically significant in the FE model. This limits the evidence that supports all hypotheses, and we cannot conclude that institutional quality moderates the relationship between financial development and renewable energy investment.

Across all three models, electricity access is the most consistent control variable that is positively associated with investment in renewable energy. However, the link is only statistically significant in the pooled OLS and RE model. This association may indicate that countries investing in renewable energy also experience improvements in infrastructure, suggesting a mutually reinforcing relationship between investment and electricity access.

The results show that both financial development and institutional quality are important for shaping the investment landscape in SSA countries. Nevertheless, they also suggest that many of the factors are relatively stable over time and therefore do not fully account for short-term variation within countries. The findings underscore the need for individually tailored financial and governance reforms, especially in countries where weak institutions may be limiting the potential for green investment.

Table 4: Regression Baseline Models (Pooled OLS, Fixed and Random Effects)

Regression results: REI–FD–IQ relationship in SSA			
Variable	**POLS**	**FEM**	**REM**
FD	0.577* (0.323)	0.159 (0.562)	0.423 (0.389)
IQ1	1.204*** (0.407)	0.753 (0.742)	1.135** (0.493)
IQ2	-0.579*** (0.193)	-0.369 (0.272)	-0.545** (0.225)
IQ3	-0.968*** (0.344)	-0.993 (0.613)	-1.041** (0.413)
FD × IQ1	-0.073 (0.479)	-0.752 (0.748)	-0.14 (0.561)
FD × IQ2	-0.595** (0.29)	-0.213 (0.401)	-0.504 (0.319)
FD × IQ3	0.77 (0.56)	0.743 (0.762)	0.538 (0.62)
Log_GDP	-0.308 (0.307)	1.621 (1.187)	-0.232 (0.439)
Log_Trade	-0.118 (0.278)	0.311 (0.527)	-0.127 (0.347)
Log_CO2	-0.494 (0.476)	-0.372 (2.309)	-0.619 (0.677)
REC	-0.003 (0.008)	-0.079** (0.032)	-0.01 (0.011)
Elec_Access	0.028*** (0.007)	0.005 (0.015)	0.026*** (0.01)
Log_Inflation	0.263** (0.129)	0.076 (0.174)	0.111 (0.147)
R-squared	0.143	0.106	0.07
Observations (N)	450	450	450

Note. Robust standard errors clustered by country are reported in parentheses. Two-tailed significance levels: *** p < 0.01, ** p < 0.05, * p < 0.10. All models include year fixed effects; FEM includes country fixed effects, REM includes country random effects.

4.4 Robustness Check

Following evidence of both heteroskedasticity and cross-sectional dependence in the baseline model diagnostics that was performed (see Section 4.2.2 and appendix 9.5), the study conducts a PCSE estimation, as recommended by Beck and Katz (1995). This method adjusts for such issues by correcting the standard errors. This makes it particularly useful for datasets where countries are regionally clustered and may experience similar shocks or structural features over time. Given these characteristics, the study uses the PCSE model as an important robustness check to validate the consistency of the baseline results.

Before running the model, all country-year observations with fewer than five valid entries were excluded from the model, to improve the reliability of standard error estimates. After filtering, the dataset had a final sample of 438 observations. This still preserved some moderate variation over time within each country, but the study recognizes this as a limitation.

The results from the PCSE are presented in Table 5. The model is consistent with the baseline models, as *FD* remains positively associated with *REI* and is statistically significant at the 10 percent level $(\beta = 0.4558, p < 0.1)$. *IQ1* is also positively strong and significant $(\beta = 1.2816, p < 0.01)$ and reinforces the role of sound institutions when enabling green investment. In contrast, *IQ2* $(\beta = -0.6623, p < 0.01)$ and *IQ3* $(\beta = -0.7787, p < 0.05)$ both have significant negative coefficients. This suggests that not all institutional dimensions support *REI* equally. In some settings, political stability may signal resistance to change or a lack of reform momentum, while high levels of corruption can weaken the functioning of financial systems and hinder effective policy implementation.

Similarly to the baseline specifications, the interaction terms (*FD × IQ1, FD × IQ2, FD × IQ3)* are not statistically significant in the PCSE. This indicates that institutional quality does not systematically moderate the relationship between financial development and renewable energy investments in the model. Furthermore, among the control variables, electricity access stays consistent and remains statistically significant $(\beta = 0.0326, p < 0.01)$, as most other models. Other control variables are not significant.

As a comparative specification, the PCSE model confirms that the main results remain consistent. This strengthens the robustness of the analysis and suggests that the observed relationships are not overly sensitive to model choice.

Table 5: The Panel-Corrected Standard Errors (PCSE) Model Results

Robustness Check: PCSE Model Results

Variable	Estimate	PCSE
FD	0.4558*	0.2678
IQ1	1.2816***	0.4036
IQ2	-0.6623***	0.1779
IQ3	-0.7787**	0.3314
FD × IQ1	-0.1839	0.3722
FD × IQ2	-0.2939	0.3120
FD × IQ3	0.3963	0.5676
Log_GDP	-0.4088	0.2949
Log_Trade	-0.1327	0.2838
Log_CO2	-0.4034	0.3506
REC	3e-04	0.0067
Elec_Access	0.0326***	0.0067
Log_Inflation	0.2374	0.1556
R-squared	0.153	NA
Observations (N)	438	NA

Note. Panel-corrected standard errors (PCSE) following Beck & Katz (1995) are reported in the **PCSE** column; they are robust to heteroskedasticity and contemporaneous cross-sectional correlation. Two-tailed significance levels: *** p < 0.01, ** p < 0.05, * p < 0.10. The specification includes country and year fixed effects.

5. Discussion on Findings

This section interprets the main findings from the analysis, linking them to the theoretical framework and hypotheses outlined in Chapter 2. The discussion is structured to answer the two hypotheses: (1) the effect of financial development on renewable energy investments in SSA, and (2) the moderating role of institutional quality on this relationship. Lastly, the section discusses the broader theoretical and policy implications of the findings in light of the existing literature.

5.1 The Role of Financial Development in Renewable Energy Investment

The multidimensional index for financial development, that combines banking depth, monetary credibility, and efficiency, explores the broader influence of financial development. The analysis reveals that only the pooled OLS model shows a statistically significant positive association between financial development and renewable energy investment. This supports Hypothesis 1 and is consistent with findings from the literature review, that emphasizes how well-developed financial systems reduce borrowing costs, mobilize capital, and improve access to long-term financing for renewable energy projects (Alshagri et al., 2024; Cai et al., 2024). Similarly, credit access and financial intermediation are key drivers to foster green investment in both developing and emerging economies (Le et al., 2020; Steffen, 2018), supporting what the finding in the pooled OLS model implies.

However, this relationship gets weaker and becomes statistically insignificant in both the FE and RE models. First, in the FE model, this likely reflects the limited within-country variation over time in financial development. It also implies that the observations in the pooled OLS and PCSE models can potentially be driven by structural differences across countries, rather than the short-term changes. This could be structural differences such as financial system maturity or historical institutional structures that still influence today's investment conditions. Second, the RE model, on the other hand, incorporates both within- and between-country variation, and again does not find a significant relationship. This reinforces the view that cross-sectional patterns in the pooled OLS may not capture causal effects.

These findings align with earlier concerns raised in literature by Safarzyńska and van den Bergh (2017), that addressed the warning that panel regressions without adequate controls might overemphasize the causal effect of financial development. The lack of significance in both the FE and RE models may therefore reflect precisely this issue. Especially if unobserved structural factors are driving the association observed in the pooled model.

At the same time, the financial development variable remains positively signed across all specifications. This aligns with theoretical expectations and prior studies, despite the lack of statistical significance. Therefore, it suggests that financial systems potentially play an influencing role in renewable investments. The robustness check through the PCSE model adds further influence on this view. After correcting for heteroskedasticity and cross-sectional dependence, financial development is once again positively and significantly associated with renewable energy investments ($\beta = 0.4458, p < 0.1$).

This strengthens arguments made by Kim and Park (2016) and Le et al. (2020), that both found that financial depth and intermediation can facilitate capital flows to the renewable energy sector. Particularly in environments with stable macroeconomic and institutional conditions. The effect varies in strength across models, but the consistently positive relationship suggests that financial development remains a potentially important factor for expanding renewable energy investments in SSA.

5.2 The Moderating Role of Institutional Quality

The results offer little support for the idea that institutional quality moderates the relationship between financial development and renewable energy investment, as proposed in Hypothesis 2. Across all models, except for a weakly significant FD × IQ2 interaction in the pooled OLS, the interaction terms are statistically insignificant. Importantly, this one significant finding appears in a model that does not control for unobserved heterogeneity and is therefore not robust for inference. The PCSE model, which accounts for both heteroskedasticity and cross-sectional dependence, shows no significant moderating effects. Taken together, the results suggest that institutional quality does not systematically alter the impact of financial development on renewable energy investment within this sample.

Looking at the interaction between financial development and regulatory quality (FD × IQ1), the sign is consistently negative and contrary to what was expected. This contradicts studies such as Alinsato et al. (2023), which suggest that clear and effective regulatory frameworks should strengthen the role of finance by reducing uncertainty and transaction costs. One plausible explanation is that, in many SSA countries, regulatory institutions may still be underdeveloped or poorly enforced, making it difficult for financial systems to function as intended. Still, regulatory quality on its own is strongly and positively associated with renewable energy investment across multiple models, reinforcing its independent importance.

A similar pattern emerges for political stability (FD × IQ2). While this interaction is weakly significant and negative in the pooled OLS model, it loses significance once more appropriate controls are applied. The negative sign runs counter to expectations but may reflect the role of external capital. As noted by Nyeadi (2023), countries with more stable institutions often attract concessional finance and donor funding, reducing the need to rely on domestic financial markets. In that case, institutional stability may still encourage renewable energy investment, just not through financial development.

The final interaction term (FD × IQ3), which examines the role of control of corruption, shows a positive sign across models, aligning with theoretical expectations from Brunnschweiler (2009) and Shah and Yasmeen (2023). However, the effect is not statistically significant in any specifications. It is possible that the influence of corruption control, like other institutional mechanisms, works more directly than through financial development. It may also be that its effects vary significantly across countries and contexts.

Although the interaction effects are not supported, the direct effects of institutional quality are much clearer. All three institutional indicators, namely regulatory quality, political stability, and control of corruption, show significant associations with renewable energy investments in at least two of the three baseline models. This suggests that institutions matter, even if they do not consistently amplify the role of financial systems. In line with the broader literature, including IEA (IEA, 2024) and Le et al. (2020), stronger institutions are likely to increase investor confidence, improve policy credibility, and reduce perceived risk, thereby attracting more renewable energy investments directly.

In sum, while the moderating role of institutions is not empirically supported, institutional quality itself still appears to play a key role in shaping renewable energy investment patterns across SSA. This reinforces the idea that financial and institutional reforms may not act independently but may need to be sequenced or coordinated in more targeted ways. Studies such as Alinsato et al. (2023) and Shah and Yasmeen (2023) support this view. Future research may benefit from exploring these complementarities further, perhaps using country-level case studies or threshold-based approaches.

5.3 Theoretical and Policy Implications

This study contributes to the literature on renewable energy finance by offering both theoretical insight and policy-relevant findings. Theoretically, the study confirms that financial development can help foster investment in the renewable sector, but it is not significant on its own. The lack of significance in the FE model suggests that much of this relationship is tied to structural, country-specific characteristics that do not change over time. This supports arguments by Brunnschweiler (2009) and Mugume and Bulime (2023), who emphasize the importance of institutional context when shaping finance-led energy transitions.

A central contribution in the study lies in the disaggregated use of institutional quality. Here, regulatory quality consistently shows a positive link with renewable energy investment, resonating with findings from Alinsato et al. (2023) and Dossou et al. (2023). However, the coefficients of political stability and control of corruption appear in some cases even counterintuitive, particularly in models that emphasize cross-country differences. This highlights the value of examining them individually, as treating them as a single construct may obscure important differences in how they relate to investment. These results indicate that improving institutions does not always lead to more renewable energy investments right away. It may be that a basic level of governance needs to be in place before these improvements have a real impact. This highlights the importance of understanding how financial and institutional reforms interact, and in what order they should be introduced, especially in countries with limited administrative capacity, where early reforms may not work as intended.

On the other hand, from a policy perspective, financial development seems most effective in countries that also have sound institutions and adequate infrastructure. For instance, the strong and consistent role of electricity access highlights grid connectivity as an important basic condition for scaling up renewables. This suggests that infrastructure development should go hand in hand with financial sector reforms. Instead of trying to change entire institutions at once, more focused efforts, like cutting red tape, protecting investors, and making approval processes easier, could lead to quicker results. Although institutional quality did not clearly strengthen the link between finance and investment in this study, it still plays an important role. One way forward could be to connect financial support, such as concessional loans or blended finance, to clear improvements in how regulations work and how transparent the system is.

6. Limitations and Future Research

Despite a structured and well-grounded empirical approach, this study faced several limitations. First, an important constraint for the study was missing data that reduced the effective sample size, particularly for renewable energy investments. In addition, foreign direct investment was initially considered as a control variable, but due to the large number of zeros and negative values preventing log transformation, it was therefore excluded. While this helped maintain model consistency, it may have narrowed the scope of macroeconomic control.

Second, for all data in 2001 for the institutional quality indicators, missing values were filled using linear interpolation. Since institutional change tends to occur gradually, this was considered reasonable. Though, it introduces a small degree of estimation uncertainty.

Third, although Pesaran's test confirmed cross-country dependence, the second-generation unit root tests, like CIPS, were not run due to technical and data limitations. Similarly, the models did not account for spatial spillovers, which may exist across countries in SSA, especially in the energy sector. This might mean that some regional dynamics were not fully captured.

Fourth, establishing clear causality remains difficult in most panel data studies, including this study. Because, while fixed effects and robustness checks improve the validity of the findings, they do not rule out reverse causality or omitted variable bias.

Finally, the analysis reflects broader data challenges common in SSA. These include inconsistent reporting and limited access to detailed data. Despite careful cleaning and validation, these constraints may limit generalizability.

Looking ahead, future research could apply methods that better address endogeneity and missing data. This could be multiple imputation or dynamic panel models like system GMM, assuming a better data coverage. Access to proprietary or project-level data could improve measurement accuracy of the data coverage. In addition, spatial econometric techniques could capture regional spillovers in investment and policy. Further studies might also focus on specific renewable energy technologies, as financial and institutional drivers likely differ across solar, wind, hydro, and biomass across SSA. Finally, future work could explore threshold or nonlinear effects to better understand under which conditions institutional quality strengthens the link between finance and green investment.

7. Conclusion

This study set out to examine whether financial development influences renewable energy investments in SSA, and whether this relationship is moderated by institutional quality. Using panel data covering 46 SSA countries over the period 2000 to 2020, and several estimation methods, the findings offer a nuanced understanding of the finance–energy–institutional nexus in the region.

The first hypothesis receives only partial support regarding the influence of financial development on renewable energy investment. In the pooled OLS and PCSE estimator the study observes a positive and significant association. However, the relationship becomes statistically insignificant once country-specific effects are controlled for but remains positively signed. This suggests that financial development explains differences between countries but not changes within them over time.

The second hypothesis is not supported, and the study cannot conclude that institutional quality moderates this relationship. Interaction terms between financial development and institutional dimensions do not show significant effects in the main models. However, institutional quality dimensions appear important when analyzed individually. Regulatory quality is consistently associated with higher renewable energy investments, while political stability and control of corruption show significant, but negative associations.

These findings may indicate that political stability does not always translate into active support for reform, particularly in sectors requiring structural change. Similarly, high levels of corruption may not prevent investment entirely, but could influence how effectively resources are allocated, thereby affecting the quality rather than the quantity of investment. The findings therefore support the idea that individual institutional factors influence investment directly, but not through moderation. This points to a more complex relationship than theory often assumes.

Overall, the study reinforces the idea that financial development alone cannot drive the energy transition in SSA. Instead, supportive institutions, clear regulations, and access to electricity infrastructure emerge as crucial enablers. Thus, improving governance may be just as important as expanding financial markets.

In sum, aligning financial development with institutional and infrastructure reforms appears essential for scaling renewable energy investment in SSA. With nearly a third of the population still lacking access to electricity, and energy demand expected to rise sharply due to rapid population growth, the need for coordinated reform is pressing. Future research should explore how finance and governance interact, using more detailed data that captures reform timing and sequencing. These findings suggest that actors such as the AfDB, national energy regulators, and international donors could support targeted reforms. These should focus on strengthening institutional capacity and reducing regulatory uncertainty. Ultimately, bridging the financial and institutional gap is essential to convert investment potential into energy access and unlocking the region’s renewable energy potential.

8. Bibliography

AfDB. (2022). *Financing a Just Transition in Africa: Challenges and Opportunities*. African Development Bank Group. https://www.afdb.org/sites/default/files/2022/12/09/financing_a_just_transition_in_africa-challenges_and_opportunities_final_1_2.pdf

Alinsato, A. S., Dossou, T. A. M., Dossou, P. K., Kambaye, E. N., & Asongu, S. A. (2023). The financial development and renewable energy consumption nexus in Africa: Does the quality of governance matter? *Natural Resources Forum*, 1–24. https://doi.org/10.1111/1477-8947.12512

Alisanto. (2023).

Allen, F., Otchere, I., & Senbet, L. W. (2011). African financial systems: A review. *Review of Development Finance*, *1*(2), 79–113. https://doi.org/10.1016/j.rdf.2011.03.003

Alshagri, R., Alsabhan, T. H., & Binsuwadan, J. (2024). Investigating the Role of Financial Development in Encouraging the Transition to Renewable Energy: A Fractional Response Model Approach. *Sustainability*, *16*(18), 8153. https://doi.org/10.3390/su16188153

Asongu, S., & Odhiambo, N. M. (2020). *Inequality, Finance, and Renewable Energy Consumption in Sub-Saharan Africa* (AGDI Working Paper No. WP/20/084). African Governance and Development Institute (AGDI). https://www.econstor.eu/handle/10419/228061

Baltagi, B. H. (2005). *Econometric Analysis of Panel Data* (3rd Edition). Wiley.

Beck, N., & Katz, J. N. (1995). What to do (and not to do) with time-series cross-section data. *American Political Science Review*, *89*(3), 634–647. https://doi.org/10.2307/2082979

Beck, T., & Levine, R. (2002). Industry growth and capital allocation: Does having a market- or bank-based system matter? *Journal of Financial Economics*, *64*(2), 147–180. https://doi.org/10.1016/S0304-405X(02)00074-0

Ben Jebli, M., Ben Youssef, S., & Ozturk, I. (2016). Testing environmental Kuznets curve hypothesis: The role of renewable and non-renewable energy consumption and trade in OECD countries. *Ecological Indicators*, *60*, 824–831. https://doi.org/10.1016/j.ecolind.2015.08.031

Brunnschweiler, C. N. (2009). Finance for renewable energy: An empirical analysis of developing and transition economies. *Environment and Development Economics*, *15*, 241–274. https://doi.org/doi:10.1017/S1355770X1000001X

Cai, K., Lemaire, T., Medici, A., Melina, G., Schwerhoff, G., & Thube, S. (2024). Harnessing Renewables in Sub-Saharan Africa: Barriers, Reforms, and Economic Prospects. *International Monetary Fund*, *2024*(005), 42. https://doi.org/10.5089/9798400290107.066

Chang, K., Zeng, Y., Wang, W., & Wu, X. (2019). The effects of credit policy and financial constraints on tangible and research & development investment: Firm-level evidence from China's renewable energy industry. *Energy Policy*, *130*, 438–447. https://doi.org/10.1016/j.enpol.2019.04.005

Dong, Y., & Peng, C.-Y. J. (2013). Principled missing data methods for researchers. *SpringerPlus*, *2*(1), 222. https://doi.org/10.1186/2193-1801-2-222

Dossou, T. A. M., Kambaye, E. N., Asongu, S. A., Alinsato, A. S., Berhe, M. W., & Dossou, P. K. (2023). Foreign direct investment and renewable energy development in sub-saharan Africa: Does governance quality matter? *Renewable Energy*, 119403. https://doi.org/10.1016/j.renene.2023.119403

Gujarati, D. N., & Porter, D. C. (2009). *Basic Econometrics* (5th Edition). McGraw-Hill Education. https://www.mheducation.com/search.html?searchQuery=9780073375779

He, L., Liu, R., Zhong, Z., Wang, D., & Xia, Y. (2019). Can green financial development promote renewable energy investment efficiency? A consideration of bank credit. *Renewable Energy*, *143*, 974–984. https://doi.org/10.1016/j.renene.2019.05.059

He, Y., & Yoo, T. H. (2024). Financial Development Impact on Domestic Investment: Does Income Level Matter? *Cogent Economics & Finance*, *12*(1), 2321811. https://doi.org/10.1080/23322039.2024.2321811

Hsiao, C. (2014). *Analysis of Panel Data* (3rd Edition). Cambridge University Press. https://doi.org/10.1017/CBO9781139839327

IEA. (2022). *Africa Energy Outlook 2022*. International Energy Agency. https://iea.blob.core.windows.net/assets/220b2862-33a6-47bd-81e9-00e586f4d384/AfricaEnergyOutlook2022.pdf

IEA. (2024). *World Energy Investment 2024*. International Energy Agency. https://iea.blob.core.windows.net/assets/60fcd1dd-d112-469b-87de-20d39227df3d/WorldEnergyInvestment2024.pdf

IRENA. (2024a). *Sub-Saharan Africa: Policies and Finance for Renewable Energy Deployment*. International Renewable Energy Agency. https://www.sipotra.it/wp-content/uploads/2024/07/SUB-SAHARAN-AFRICA-POLICIES-AND-FINANCE-FOR-RENEWABLE-ENERGY-DEPLOYMENT.pdf

IRENA. (2024b). *The energy transition in Africa: Opportunities for international collaboration with a focus on the G7*. International Renewable Energy Agency. https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2024/Apr/IRENA_G7_Energy_transition_Africa_2024.pdf

Jha, C. K. (2019). Financial reforms and corruption: Evidence using GMM estimation. *International Review of Economics and Finance*, *62*, 66–78. https://doi.org/10.1016/j.iref.2019.03.003

Jiang, C., & Ma, X. (2019). The Impact of Financial Development on Carbon Emissions: A Global Perspective. *Sustainability*, *11*(19), 5241. https://doi.org/doi:10.3390/su11195241

Kaufmann, D., Kraay, A., & Mastruzzi, M. (2010). The Worldwide Governance Indicators: Methodology and Analytical Issues. *World Bank Policy Research Working Paper No. 5430*. https://doi.org/10.1596/1813-9450-5430

Kim, J., & Park, K. (2016). Financial Development and Deployment of Renewable Energy Technologies. *Energy Economics*, *59*, 238–250. https://doi.org/DOI: 10.1016/j.eneco.2016.08.012

King, R. G., & Levine, R. (1993). Finance and Growth: Schumpeter Might be Right. *The Quarterly Journal of Economics*, *108*(3), 717–737. https://doi.org/10.2307/2118406

LaPorta, Rafael, Florencio Lopez-de-Silanes, Andrei Shleifer, & Robert W Vishny. (1998). Law and Finance. *Journal of Political Economy*, *106*(6), 1113–1155.

Le, T.-H., Nguyen, P., & Park, D. (2020). Financing Renewable Energy Development: Insights from 55 Countries. *Energy Research & Social Science*, *68*, 101537. https://doi.org/10.1016/j.erss.2020.101537

Levine, R. (2005). Finance and Growth: Theory and Evidence. In P. Aghion & S. Durlauf (Eds.), *Handbook of Economic Growth* (1st ed., Vol. 1, pp. 865–934). Elsevier. https://www.nber.org/papers/w10766

Mlachila, M., & Ouedraogo, R. (2020). Financial development curse in resource-rich countries: The role of commodity price shocks. *Journal of Comparative Economics*, *76*, 84–96.

Mugume, R., & Bulime, E. (2023). Financial Development and Renewable Energy Transition: Evidence from Sub-Saharan Africa. *SSRN*, *Preprint*. http://dx.doi.org/10.2139/ssrn.4569168

Myers, S. C., & Majluf, N. S. (1984). Corporate financing and investment decisions when firms have information that investors do not have☆. *Journal of Financial Economics*, *12*(2), 187–221. https://doi.org/10.1016/0304-405X(84)90023-0

Newman, D. A. (2014). Missing data: Five practical guidelines. *Organizational Research Methods*, *17*(4), 372–411. https://doi.org/10.1177/1094428114548590

Nyeadi, J. D. (2023). The impact of financial development and foreign direct investment on environmental sustainability in Sub-Saharan Africa: Using PMG-ARDL approach. *Economic Research-Ekonomska Istraživanja,* *36*(2), 2106270. https://doi.org/DOI: 10.1080/1331677X.2022.2106270

Ondoa, A., & Seabrook, A. M. (2022). Governance and financial development: Evidence from a global sample of 120 countries. *International Journal of Finance and Economics*, *27*(3), 3405–3420. https://doi.org/10.1002/ijfe.2327

Osman, A., Afjal, M., Alharthi, M., Elheddad, M., Djellouli, N., & He, Z. (2025). Green Growth Dynamics: Unraveling the Complex Role of Financial Development and Natural Resources in Shaping Renewable Energy in Sub-Saharan Africa. *Humanities & Social Sciences Communications*, *12*(64), 1–11.

Pan, X., Dossou, T. A. M., Berhe, M. W., & Kambaye, E. N. (2022). Towards efforts to promote renewable energy development in Africa: Does governance quality matter? *Energy & Environment*, *555*, 3039–3054. https://doi.org/10.1177/

Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross-section dependence. *Journal of Applied Econometrics*, *22*(2), 265–312.

Richter, R. (2005). The New Institutional Economics: Its Start, Its Meaning, Its Prospects. *European Business Organization Law Review*, *6*(2), 161–200. https://doi.org/DOI:10.1017/S1566752905001618

Roodman, D. (2009). How to do Xtabond2: An Introduction to Difference and System GMM in Stata. *The Stata Journal*, *9*(1), 86–136. https://doi.org/10.1177/1536867X0900900106

Sadorsky, P. (2010). The impact of financial development on energy consumption in emerging economies. *Energy Policy*, *38*(5), 2528–2535. https://doi.org/10.1016/j.enpol.2009.12.048

Safarzyńska, K., & van den Bergh, J. C. J. M. (2017). Financial stability at risk due to investing rapidly in renewable energy. *Energy Policy*, *108*, 12–20. http://dx.doi.org/10.1016/j.enpol.2017.05.042

Salahuddin, M., Alam, K., Ozturk, I., & Sohag, K. (2018). The effects of electricity consumption, economic growth, financial development and foreign direct investment on CO_2 emissions in Kuwait. *Renewable and Sustainable Energy Reviews*, *81*, 2002–2010. https://doi.org/10.1016/j.rser.2017.06.011

Shah, W. U. H., & Yasmeen, Y. (2023). Evaluating the role of banking efficiency, institutions and financial development for sustainable development: Implications for Belt and Road Initiative (BRI). *PLoS ONE*, *18*(10). https://doi.org/10.1371/journal.pone.0290780

Sharma, C., & Paramati, S. R. (2021). Does financial development reduce the level of corruption? Evidence from a global sample of 140 countries. *International Journal of Finance and Economics*, *26*(4), 5093–5109. https://doi.org/10.1002/ijfe

Shipalana, P. (2020). *Green Finance Mechanisms in Developing Countries: Emerging Practice*. South African Institute of International Affairs. https://cer.org.za/wp-content/uploads/2021/07/Shipalana-Policy-Briefing-.pdf

Soumaré, I., Kanga, D., Tyson, J., & Raga, S. (2021). Capital market development in sub-Saharan Africa: Progress, challenges and innovations. *Joint FSD Africa and ODI Working Paper. London: Overseas Development Institute.*

Steffen, B. (2018). The importance of project finance for renewable energy projects. *Energy Economics*, *69*, 280–294. https://doi.org/10.1016/j.eneco.2017.11.006

Sun, Z., Zhang, X., & Gao, Y. (2023). The Impact of Financial Development on Renewable Energy Consumption: A Multidimensional Analysis Based on Global Panel Data. *Int. J. Environ. Res. Public Health*, *20*(4), 3124. https://doi.org/10.3390/ijerph20043124

Timmons, D., Harris, J. M., & Roach, B. (2014). *The Economics of Renewable Energy*. Global Development and Environment Institute, Tufts University. https://www.bu.edu/eci/files/2019/06/RenewableEnergyEcon.pdf

UN Environment Programme. (2023, September). *Climate change undermines nearly all Sustainable Development Goals*. https://www.unep.org/news-and-stories/press-release/climate-change-undermines-nearly-all-sustainable-development-goals

Wang, B., & Zhao, W. (2022). Interplay of Renewable Energy Investment Efficiency, Shareholder Control, and Green Financial Development in China. *Renewable Energy*, *199*, 192–203. https://doi.org/10.1016/j.renene.2022.08.122

Wooldridge, J. M. (2010). *Econometric Analysis of Cross Section and Panel Data* (2nd Edition). The MIT Press.

Zahonogo, W. A. (2025). Do tariff reductions alleviate energy poverty? Evidence for Sub-Saharan African countries. *Energy Policy*, *197*, 114431. https://doi.org/10.1016/j.enpol.2024.114431

9. Appendix

9.1 Appendix 1: Variable Description and Sources

Table 6: Variable Description and Sources

Code	Definition	Source
REI_USD	Public renewable energy investment as a percentage of GDP	International Renewable Energy Agency (IRENA)
Private_Credit_GDP	Domestic credit to private sector as % of GDP. Includes loans, trade credits, and claims on private entities.	World Bank – WDI
M2_GDP	Broad money (M2) as % of GDP. Reflects the total liquidity available in the financial system.	World Bank – WDI
Credit_Deposit_Ratio	Bank credit as % of bank deposits. Captures banking sector efficiency in financial intermediation.	World Bank – WDI
Reg_Quality	Regulatory quality index (-2.5 to + 2.5). Measure's ability of governments to implement policies.	World Bank – WGI
Pol_Stability	Political stability and absence of violence index (-2.5 to + 2.5).	World Bank – WGI
Corruption_indx	Control of corruption index (-2.5 to + 2.5).	World Bank – WGI
GDP_pc	GDP per capita (constant 2017 USD).	World Bank – WDI
Trade_GDP	Trade (% of GDP). Sum of exports and imports as a share of GDP.	World Bank – WDI
FDI_GDP	Foreign direct investment net inflows as % of GDP.	World Bank – WDI
REC	Renewable energy consumption (% of total final energy consumption).	World Bank – WDI
Elec_access	Access to electricity (% of population).	World Bank – WDI
CO2	CO2 emissions per capita (metric tons).	Our World in Data (Global Carbon Project)
Inflation	Annual inflation rate (%). Consumer price index.	World Bank – WDI

9.2 Appendix 2: Variable Transformation Diagnostic

Table 7: Overview of Variable Transformations Used in the Empirical Analysis

Variable	Transformation	Used in Model AS
REI_USD	Log-transformed	log(REI_USD + 1)
Private_Credit_GDP	Log-transformed	log(Private_Credit_GDP + 1)
M2_GDP	Log-transformed	log(M2_GDP + 1)

Credit_Deposit_Ratio	No transformation (used raw)	Credit_Deposit_Ratio
Reg_Quality	None (standardized WGI Index)	Reg_Quality
Pol_Stability	None (standardized WGI Index)	Pol_Stability
Corruption_indx	None (standardized WGI Index)	Corruption_indx
GDP_pc	Log-transformed	log(GDP_pc + 1)
Trade_GDP	Log-transformed	log(Trade_GDP + 1)
FDI_GDP	Log-transformed (if > 0 only)	log_FDI
REC	No transformation (bounded %)	REC
Elec_access	No transformation (bounded %)	Elec_access
CO2	Log-transformed	log(CO2_pc + 1)
Inflation	Log-transformed (if > 0 only)	Log_Inflation

9.2.1 Skewness Distribution and Transformation: REI_USD

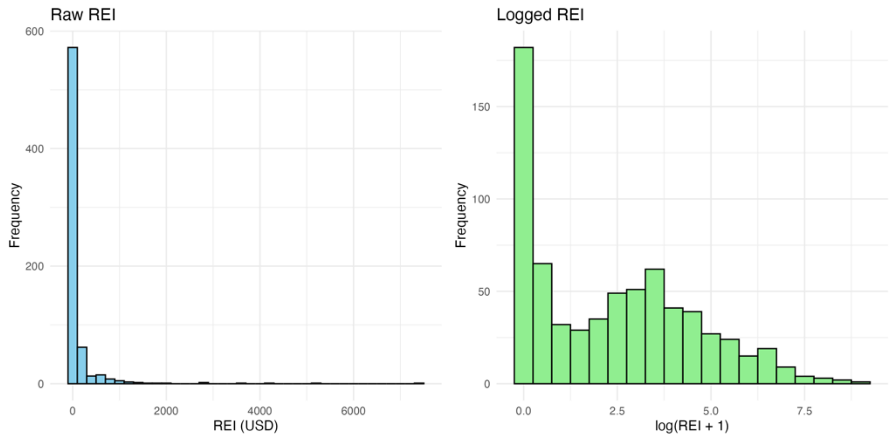


Figure 2: Distribution of Public REI Before and After Log Transformation

Figure 2 shows the distribution of the dependent variable, REI, measured in millions of USD. The original distribution is heavily right-skewed (skewness = 9.43), with extreme values far above the median. To reduce skewness and improve the distributional properties of the variable, log transformation was applied. The transformed variable, log(REI + 1), has a much lower skewness (0.56) and a more symmetric shape. Based on these results, the regression models use the logged version of the variable.

9.2.2 Skewness Distribution and Transformation: Private_Credit_GDP

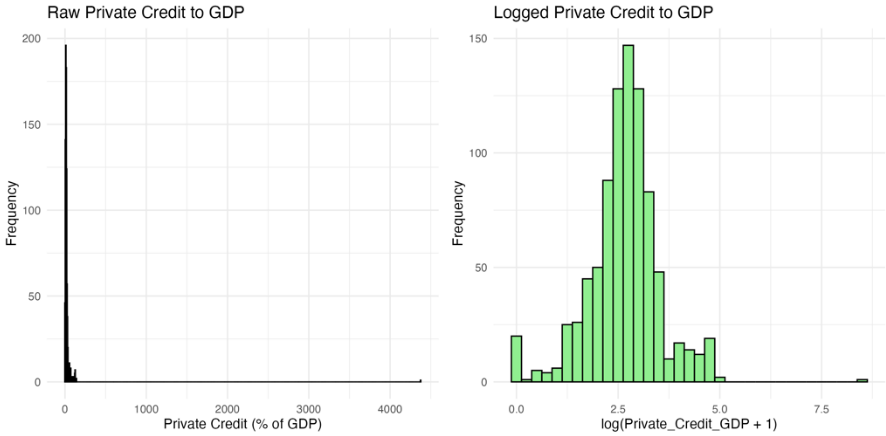


Figure 3: Distribution of Private Credit to GDP Before and After Log Transformation

Figure 3 presents the distribution of domestic credit to the private sector as a percentage of GDP. The normal data are extremely right-skewed (skewness = 28.64), with a small number of extreme outliers. Again, this variable is log transformed. The transformed variable, log(Private_Credit_GDP + 1), exhibits near-zero skewness (-0.02) and has a highly symmetric distribution.

9.2.3 Skewness Distribution and Transformation: M2_GDP

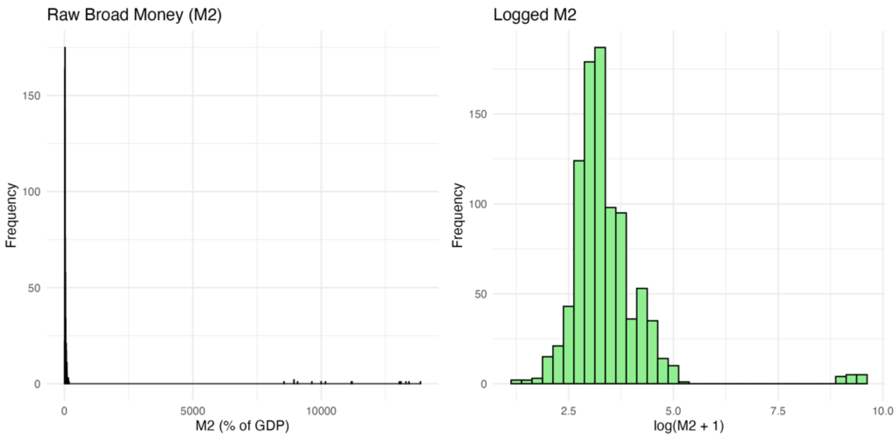


Figure 4: Distribution of Broad Money (M2, % of GDP) Before and After Log Transformation

Figure 4 shows the distribution of broad money (M2) as a share of GDP. The raw distribution is highly skewed (skewness = 8.33), with several extreme values, including an outlier exceeding 13,800% of GDP. To correct for this extreme skewness and facilitate more stable parameter estimation, here again, a log transformation was applied to the variable. While the logged version still exhibits moderate skew (3.57), the distribution is markedly improved and concentrated.

9.2.4 Skewness Distribution and Transformation: GDP_pc

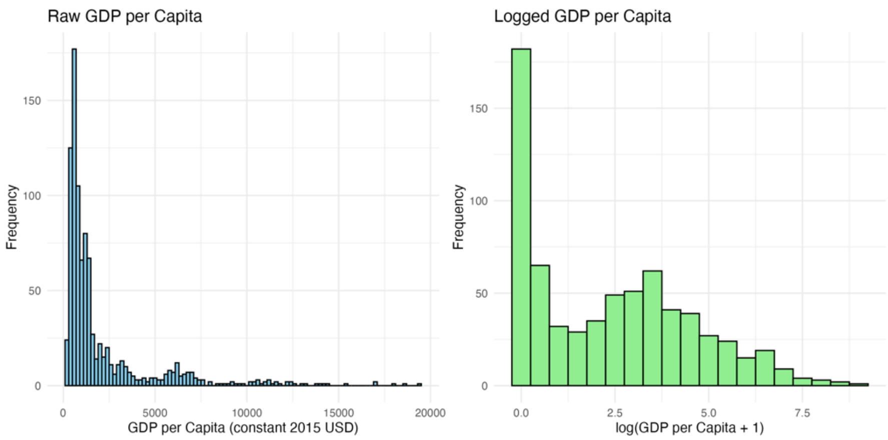


Figure 5: Distribution of GDP per Capita Before and After Log Transformation

Figure 5 presents the distribution of GDP per capita (constant 2015 USD). The raw distribution is also significantly right-skewed (skewness = 2.78), with a mean of 2,109 and a maximum value nearing 20,000. To address this skewness and reduce heteroscedasticity, this variable is also log transformed. The transformed variable, log(GDP per capita + 1), displays a much lower skewness (0.78) and a more balanced distribution.

9.2.5 Skewness Distribution and Transformation: Trade_GDP

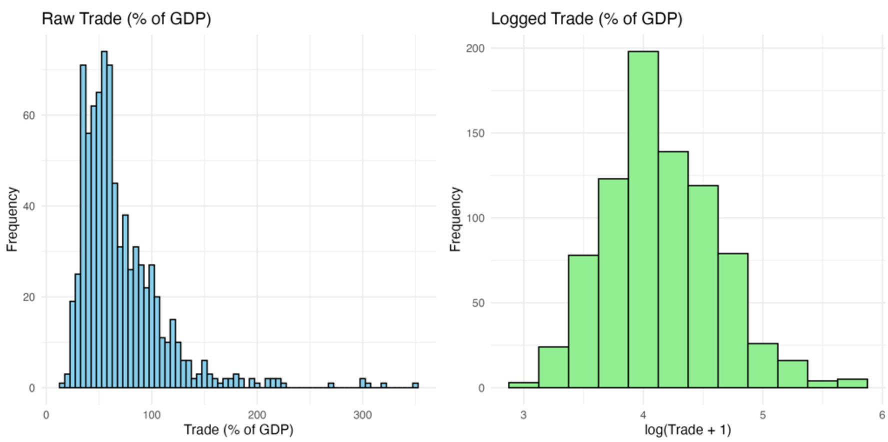


Figure 6: Distribution of Trade Openness (% of GDP) Before and After Log Transformation

Figure 6 displays the distribution of trade openness, measured as the sum of exports and imports as a percentage of GDP. The raw variable exhibits a considerable right skew (skewness = 2.46), with values ranging up to 348% of GDP. To mitigate skewness and achieve a more symmetric distribution, a log transformation was applied. The resulting variable, log(Trade_GDP + 1), exhibits a substantially reduced skewness (0.47) and a near-normal shape.

9.2.6 Skewness Distribution and Transformation: FDI_GDP

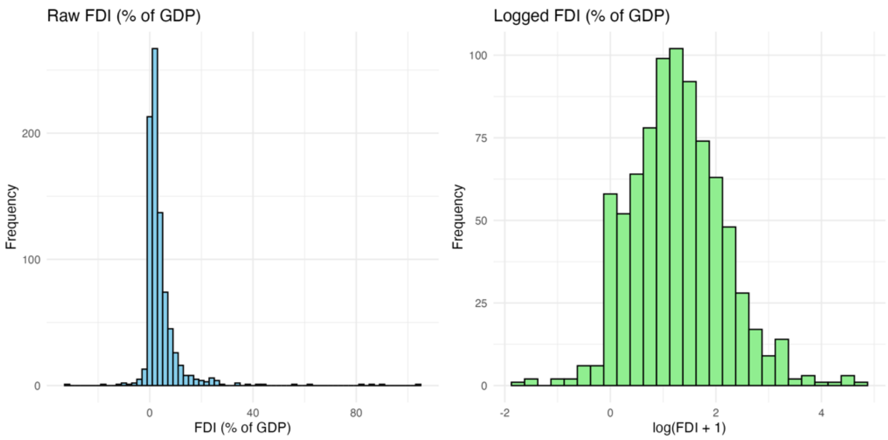


Figure 7: Distribution of FDI Inflows (% of GDP) Before and After Log Transformation

Figure 7 illustrates the distribution of foreign direct investment inflows (as a percentage of GDP). The raw distribution is highly right-skewed (skewness = 6.09), with extreme outliers and a small set of negative values. To improve the statistical properties of the variable and interpret coefficients more meaningfully in elasticity terms, a log transformation was applied. However, since the logarithm is undefined for non-positive values, the transformation was tried applied only to strictly positive FDI values. The resulting variable, log(FDI_GDP), has a much lower skewness (0.38) and a more symmetric shape.

However, due to a high number of zero and negative observations in the *FDI_GDP* variable, it complicated log transformation and significantly reduced the available sample size. Therefore, I decided to exclude this variable from the final regression analysis. Retaining *FDI_GDP* would have introduced substantial missingness and potential bias, thus undermining the consistency and robustness of the estimations.

9.2.7 Skewness Distribution and Transformation: CO2_pc

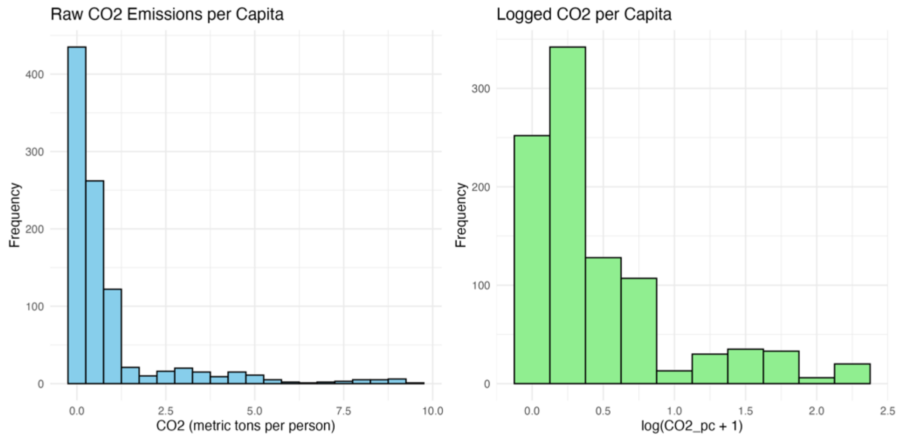


Figure 8: Distribution of CO2 Emissions per Capita Before and After Log Transformation

Figure 8 shows the distribution of CO_2 emissions per capita (measured in metric tons per person). The raw variable is moderately right-skewed (skewness = 3.09), with a long tail of high emitters. To reduce this skew and ensure more normally distributed residuals, a log transformation was applied. The transformed variable, log(CO2_pc + 1), reduces skewness to 1.78 and presents a more compact distribution while preserving the cross-country variation. Although some skewness remains, the transformation enhances statistical robustness and interpretability.

9.2.8 Skewness Distribution and Transformation: Inflation

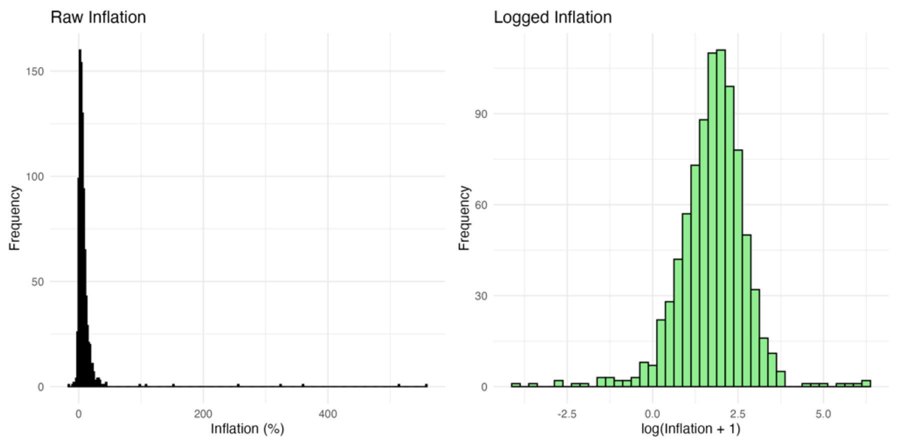


Figure 9: Distribution of Inflation Rates (%) Before and After Log Transformation

Figure 9 illustrates the distribution of annual inflation rates. The raw data are extremely right-skewed (skewness = 13.10), with a long tail driven by hyperinflation episodes in select countries and years. To correct for this skewness and achieve a more symmetric distribution, a log transformation was applied. However, the presence of negative inflation values (i.e., deflation) caused the transformation to return undefined values (NaN). To resolve this, the log transformation was only applied to positive inflation values. The transformed variable, log(Inflation + 1), substantially improves the distribution (skewness = -0.55), yielding a near-normal shape. Observations with non-positive values were excluded from the transformed variable.

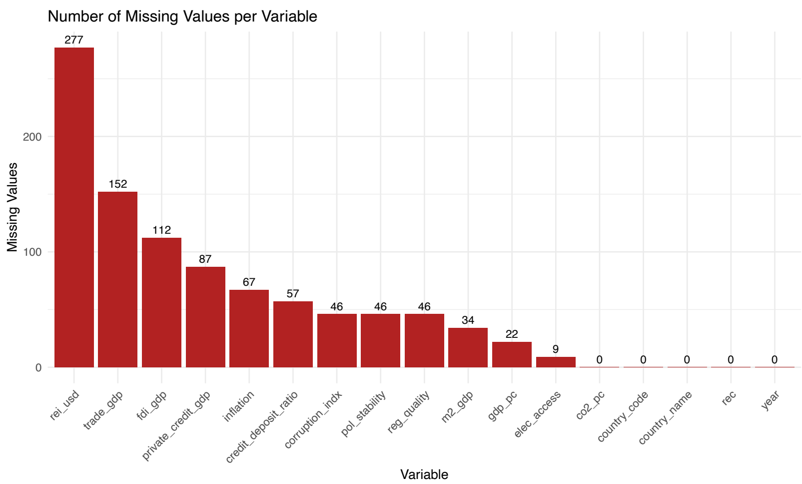
9.3 Appendix 3: Data Cleaning & Missing Data Handling

The following outlines the procedures undertaken to identify, visualize, and address missing data within the panel dataset prior to regression analysis.

9.3.1 Overview of Missing Data

An initial assessment revealed varying degrees of missingness across variables. Notably, the dependent variable, *rei_usd*, exhibited 277 missing observations. Other variables, such as *fdi_gdp* and *inflation*, also presented gaps. A comprehensive summary of missing values per variable is provided in Table 8.

Table 8: Summary of Missing Values per Variable



To visualize the pattern of missing data across the dataset, a heatmap was generated using the VIM package in R. This visualization aids in identifying any systematic missingness that could bias the analysis (Figure 10: Heatmap of Missing Data Patterns

Figure 10: Heatmap of Missing Data Patterns

Due to extensive data deficiencies, particularly in key variables, Somalia and South Sudan were excluded from the analysis. Their exclusion ensures a more balanced and reliable panel dataset, enhancing the robustness of the regression results.

To assess the distribution of missing REI data, a frequency table was constructed, detailing the number of missing observations per country. This analysis is crucial for understanding potential biases in the dataset and whether the missingness is concentrated to some countries or spread out. This is presented in **Error! Reference source not found.**.

Table 9: Frequency of Missing REI Observations by Country

AGO	BDI	BEN	BFA	BWA	CAF	CIV	CMR	COD	COG	COM	CPV	DJI	ERI	GAB	GIN	GMB	GNB	GNQ	KEN
8	7	5	2	6	10	8	3	4	8	12	8	6	11	12	7	11	6	14	2

LBR	LSO	MDG	MRT	MUS	MWI	NAM	NER	NGA	RWA	SEN	SLE	STP	SWZ	SYC	TCD	TGO	ZAF	ZMB	ZWE
7	5	4	5	12	3	1	7	2	4	1	7	7	17	16	10	9	1	3	6

9.3.2 Treatment of Missing Values

Institutional Quality Indicators:

The variables representing institutional quality (*reg_quality, pol_stability,* and *corruption_indx*) had missing values exclusively for the year 2001 across all countries. Given that institutional characteristics typically evolve gradually over time, linear interpolation was deemed appropriate to estimate the missing values for this single year. This approach aligns with standard practices in panel data analysis, where interpolation is acceptable for variables exhibiting temporal stability (Baltagi, 2005).

Other Variables:

For variables such as *fdi_GDP*, *Inflation*, and *rei_usd*, interpolation was not applied due to their inherent volatility and the potential for introducing bias. Instead, observations with missing values in these variables were omitted from the regression analysis through listwise deletion. This method maintains the integrity of the dataset by ensuring that only complete cases are analyzed (Baltagi, 2005).

9.4 Appendix 4: VIF Test Results for Multicollinearity

Table 10: VIF Test Results

Variance Inflation Factor (VIF) Test Results

Variable	VIF
Log_Private_Credit	3.66
Log_M2	1.23
Credit_Deposit_Ratio	2.16
IQ1	4.67
IQ2	2.49
IQ3	3.92
Log_GDP	8.43
Log_Trade	1.86
Log_CO2	5.33
REC	4.37
Elec_Access	4.28
Log_Inflation	1.21

9.5 Appendix 5: Model-Diagnostic & Normality tests

This appendix reports residual-based diagnostics that verify the classical regression assumptions for the preferred fixed-effects specification. Following best-practice guidelines for panel-data analysis (Wooldridge, 2010, ch. 10).

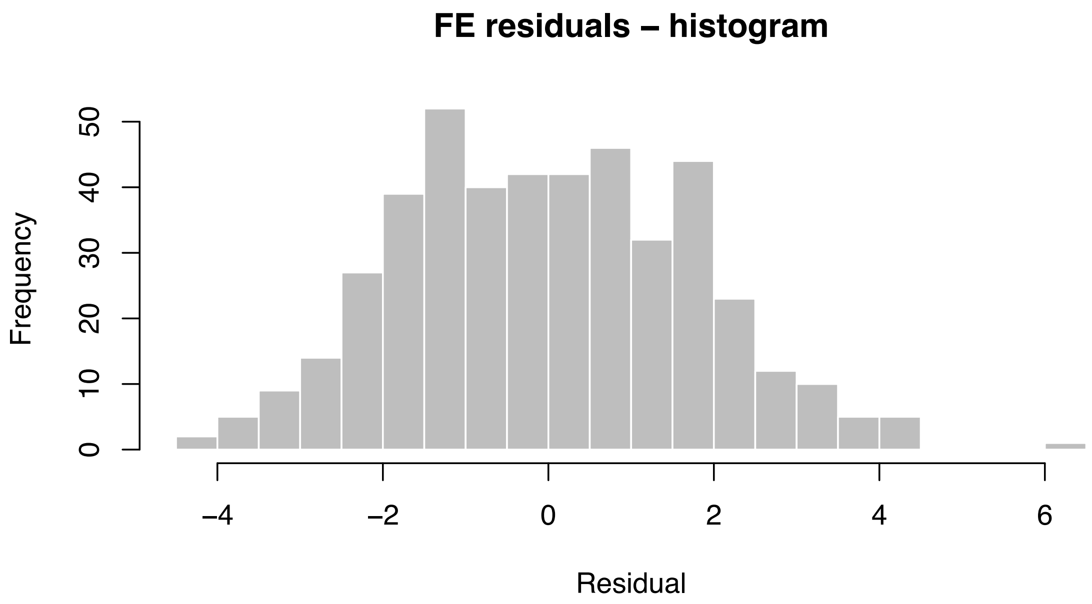


Figure 11: Histogram of Fixed-Effects Residuals

The histogram shows an approximately symmetric bell-shaped distribution centered around zero showed in Figure 11. The figure shows no extreme outliers. This visual impression supports the assumptions that the idiosyncratic errors are roughly normally distributed, after the data cleaning.

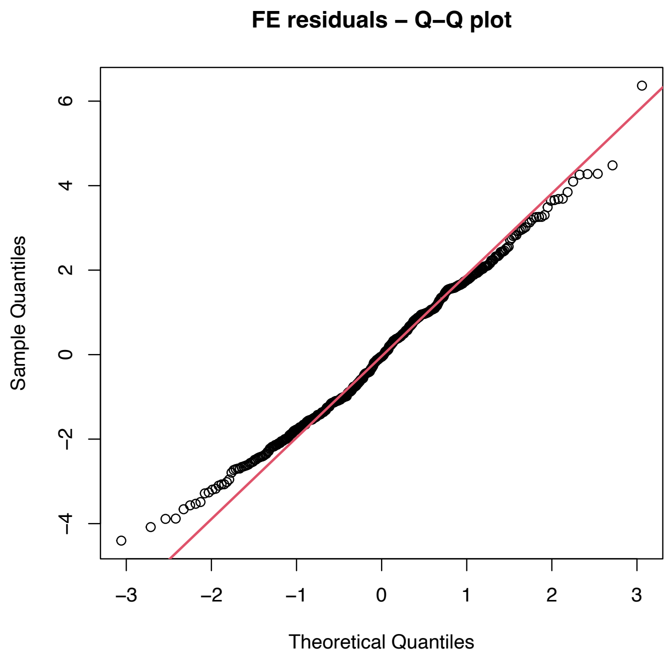


Figure 12: Q-Q Plot of Fixed-Effects Residuals

Figure 12 presents the Q-Q plot of the FE residuals. Here we see that most residual quantiles lie close to the 45-degree line. And only the extreme tails depart slightly from this. Together with the histogram in Figure 11, this suggests that departures from normality, if any, are modest and unlikely to bias coefficient estimates.

Table 11: Diagnostic Tests for the Fixed-Effects Model

Diagnostic tests – Fixed-Effects model		
Test	**Test stat**	**p-value**
Shapiro-Wilk	0.993	0.037
Breusch-Pagan	48.930	0.000
Wooldridge BG(1)	0.765	0.382

Overall, the numeric tests confirm that the residuals are acceptably normal, but they do exhibit heteroskedasticity and first-order serial correlation. The thesis, therefore, reports PCSE, which are robust to both issues.

9.6 Appendix 6: R Script for Empirical Analysis

This appendix contains the full R script used in the empirical analysis of the thesis. Code is provided in a readable and annotated form to ensure transparency and replicability.

```
############################################################################
# MASTER THESIS 2025: R SCRIPT FOR EMPIRICAL ANALYSIS
# Title: The influence of Financial Development on Renewable Energy
Investments
# in Sub-Saharan Africa
# Author: Elise Naalsund
# Insitution: NHH / UCL
#Appendix Reference: Appendix 9.7 - R Script for Panel Data Analysis
############################################################################
============================================================================
# LOAD REQUIRED PACKAGES
============================================================================

# INSTALL
install.packages(c("tidyverse", "plm", "lmtest", "sandwich",
                   "psych", "car", "stargazer", "moments")) # etc.

# LOAD
library(tidyverse)    # Data wrangling and visualization
library(plm)          # Panel data models
library(lmtest)       # Diagnostic tests (e.g., Hausman test)
library(sandwich)     # Robust standard errors
library(psych)        # Descriptive statistics
```

```
library(car)          # VIF and multicollinearity tests
library(stargazer)    # Regression output tables
library(moments)      # Skewness for transformation diagnostics

===========================================================================
# LOAD AND PREPARE DATA
===========================================================================
setwd("~/Desktop/LSM/Master thesis/Data Analysis")

# Load your cleaned panel dataset
panel_data <- read.csv("~/Desktop/LSM/Master thesis/Data
Analysis/zFULL_Panel/aCSV/Clean_Subset_Panel_REI.csv")

# Standardize column names
names(panel_data) <- tolower(names(panel_data))   # Makes all lowercase

===========================================================================
# PANEL STRUCTURE CHECK
===========================================================================
# To view dataset
str(panel_data)                  # Quick look at variable names and types
summary(panel_data)             # Summary statistics of raw data

# Check number of unique countries and years
length(unique(panel_data$country_code))    # Should return 46 (SSA
countries)
length(unique(panel_data$year))            # Should return 21 (2000-2020)

# Convert dataset to panel data structure using plm package
panel_data <- pdata.frame(panel_data, index = c("country_code", "year"))
panel_data$key <- NULL

# After conversion:
# Use pdim() to check if your panel is balanced and consistent:
pdim(panel_data)

# Expected output:
# Balanced Panel: n = 46, T = 21, N = 966

===========================================================================
# MISSING VALUE CHECK & HANDLING
===========================================================================

# Count total missing values per column
na_counts <- colSums(is.na(panel_data))
print(na_counts)

# Create summary of missing values per variable
missing_summary <- panel_data %>%
  summarise(across(everything(), ~sum(is.na(.)))) %>%
  pivot_longer(cols = everything(), names_to = "Variable", values_to =
"Missing_Count")

# Plot missing values
missing_plot <- ggplot(missing_summary, aes(x = reorder(Variable, -
Missing_Count), y = Missing_Count)) +
  geom_bar(stat = "identity", fill = "firebrick") +
```

```
  geom_text(aes(label = Missing_Count), vjust = -0.5, size = 3.5) +  #
Value labels on bars
  labs(title = "Number of Missing Values per Variable", x = "Variable", y
= "Missing Values") +
  theme_minimal(base_size = 12) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))

# Save as PDF
pdf("Figures/Missing_Values_Barplot_Labeled.pdf", width = 10, height = 6)
print(missing_plot)
dev.off()

# Visualize missing data pattern and save as PNG
library(VIM)

pdf("Figures/Missing_Data_Heatmap.pdf", width = 16, height = 8)
matrixplot(panel_data, main = "Missing Data Pattern", sortby =
"country_code", las = 2)
dev.off()

# Note: South Sudan and Somalia were removed earlier due to excessive
missingness

# Interpolate IQ variables (Regulatory Quality, Political Stability,
Corruption)
# Assumes variables are named 'reg_quality', 'pol_stability',
'corruption_indx'

library(dplyr)
library(zoo)

panel_data <- panel_data %>%
  group_by(country_code) %>%
  mutate(
    reg_quality = na.approx(reg_quality, year, na.rm = FALSE),
    pol_stability = na.approx(pol_stability, year, na.rm = FALSE),
    corruption_indx = na.approx(corruption_indx, year, na.rm = FALSE)
  ) %>%
  ungroup()

# Confirm interpolation worked
summary(panel_data$reg_quality)

# Count missing REI observations per country
rei_missing <- panel_data %>%
  filter(is.na(rei_usd)) %>%
  count(country_code, name = "Missing_REI_Count") %>%
  arrange(country_code)    # alphabetical order

# Split into two halves (alphabetically)
half <- ceiling(nrow(rei_missing) / 2)
rei_top <- rei_missing[1:half, ]
rei_bottom <- rei_missing[(half + 1):nrow(rei_missing), ]

# Pivot each to horizontal layout
```

```r
rei_top_wide <- t(rei_top$Missing_REI_Count)
colnames(rei_top_wide) <- rei_top$country_code
rei_bottom_wide <- t(rei_bottom$Missing_REI_Count)
colnames(rei_bottom_wide) <- rei_bottom$country_code

==========================================================================
# TRANSFORMATION PREP - CHECK FOR NEGATIVES BEFORE LOGGING
==========================================================================
# Count negative or zero values in log-sensitive variables
sum(panel_data$fdi_gdp <= 0, na.rm = TRUE)
sum(panel_data$inflation <= 0, na.rm = TRUE)

==========================================================================
# CREATE LOGGED VARIABLES (WHERE APPLICABLE)
==========================================================================
# Log-transform variables (handling negatives where necessary)
panel_data <- panel_data %>%
  mutate(
    # Log-transform dependent variable (public RE investment)
    log_REI = log(rei_usd + 1),

    # Financial Development Indicators
    log_Private_Credit = log(private_credit_gdp + 1),
    log_M2 = log(m2_gdp + 1),
    Credit_Deposit_Ratio = credit_deposit_ratio,  # Kept raw (not
transformed)

    # Institutional Quality Indicators (raw, not logged)
    reg_quality = reg_quality,
    pol_stability = pol_stability,
    corruption_indx = corruption_indx,

    # Macroeconomic Control Variables
    log_GDP_pc = log(gdp_pc + 1),
    log_Trade = log(trade_gdp + 1),

    # Environmental Controls
    log_CO2 = log(co2_pc + 1),
    REC = rec,  # Raw percentage
    Elec_access = elec_access,  # Raw percentage

    # Log FDI and Inflation using case_when to avoid warnings from log()
    log_FDI = case_when(
      !is.na(fdi_gdp) & fdi_gdp > 0 ~ log(fdi_gdp),
      TRUE ~ NA_real_
    ),
    log_Inflation = case_when(
      !is.na(inflation) & inflation > 0 ~ log(inflation + 1),
      TRUE ~ NA_real_
    )
  )

sum(is.na(panel_data$log_FDI))  # Count how many NA values remain

==========================================================================
# CREATE INDEX VARIABLES AND INTERACTION TERMS
```

```
==============================================================================
# Create Financial Development Index and interaction terms with
Institutional Quality
panel_data <- panel_data %>%
  mutate(
    FD_Index = (scale(log_Private_Credit) + scale(log_M2) +
scale(credit_deposit_ratio)) / 3,
    FDxIQ1 = FD_Index * reg_quality,
    FDxIQ2 = FD_Index * pol_stability,
    FDxIQ3 = FD_Index * corruption_indx
  )

==============================================================================
# SAVE CLEANED DATA
==============================================================================
# To save the transformed dataset

write.csv(panel_data, "Panel_Cleaned_Logged.csv", row.names = FALSE)

# ============================================================
# 1. UNIVARIATE ANALYSIS OF PANEL DATA
# ============================================================
# Load required libraries
library(tidyverse)      # Data wrangling and visualization
library(psych)          # Descriptive statistics
library(stargazer)      # Exporting tables
library(gt)             # Pretty tables
library(webshot2)       # Saving gt tables as PDFs
library(knitr)          #
library(kableExtra)     # For nicer tables
library(dplyr)
library(tibble)

# ------------------------------------------------------------
# 1.1 Load Cleaned and Logged Dataset
# ------------------------------------------------------------
panel_data <- read.csv("~/Desktop/LSM/Master thesis/Data
Analysis/Panel_Cleaned_Logged.csv")

# Preview the structure
glimpse(panel_data)

# ------------------------------------------------------------
# 1.2 Descriptive Statistics of Panel Data
# ------------------------------------------------------------
# Select variables for descriptive statistics
descriptive_vars <- panel_data %>%
  select(
    log_REI,
    FD_Index,
    reg_quality,
    pol_stability,
    corruption_indx,
    FDxIQ1,
    FDxIQ2,
```

```
    FDxIQ3,
    log_GDP_pc,
    log_Trade,
    log_CO2,
    rec,
    elec_access,
    log_Inflation
  )

# Create a simplified descriptive statistics function
descriptive_panel <- function(varname) {
  x <- panel_data[[varname]]
  if (!is.numeric(x)) {
    warning(paste("Skipping", varname, "- not numeric."))
    return(NULL)
  }

  # Calculate core stats
  overall_mean   <- mean(x, na.rm = TRUE)
  overall_median <- median(x, na.rm = TRUE)
  overall_sd     <- sd(x, na.rm = TRUE)
  min_val        <- min(x, na.rm = TRUE)
  max_val        <- max(x, na.rm = TRUE)
  n_total        <- sum(!is.na(x))

  data.frame(
    Variable = varname,
    Mean = round(overall_mean, 3),
    Median = round(overall_median, 3),
    SD = round(overall_sd, 3),
    Min = round(min_val, 3),
    Max = round(max_val, 3),
    N = n_total
  )
}

# List of variables to include
vars <- c("log_REI", "FD_Index", "reg_quality", "pol_stability",
"corruption_indx",
          "FDxIQ1", "FDxIQ2", "FDxIQ3",
          "log_GDP_pc", "log_Trade", "log_CO2", "rec", "elec_access",
"log_Inflation")

# Run and bind results
descriptive_df <- do.call(rbind, lapply(vars, descriptive_panel))

# View the table
print(descriptive_df)

# Export Tables
# -------------------------------------------------------------

clean_names <- c(
  "Log_REI",       # log_REI
  "FD",            # FD_Index
  "IQ1",   # reg_quality
  "IQ2",# pol_stability
```

```
  "IQ3",    # corruption_indx
  "FD × IQ1",       # FDxIQ
  "FD × IQ2",      # FDxIQ2
  "FD × IQ3",      # FDxIQ3
  "Log_GDP",    # log_GDP_pc
  "Log_Trade", # log_Trade
  "Log_CO2",     # log_CO2
  "REC", # rec
  "Elec_Access", # elec_access
  "Log_Inflation"          # log_Inflation
)

# Assign the 'nice names' to your Variable column
descriptive_df$Variable <- clean_names

desc_note <- md("*Note.* `Log_`-prefixed variables are natural logarithms.
\
REC and Elec_Access are reported in percent. \
IQ1–IQ3 are governance-quality indices ranging from −2.5 (weak) to +2.5
(strong). \
Sample sizes (*N*) differ across variables; see final column.")

# Create GT table
descriptive_table <- descriptive_df %>%
  gt() %>%
  tab_header(title = "Descriptive Statistics") %>%
  fmt_number(
    columns = c("Mean", "Median", "SD", "Min", "Max"),  # Specify manually
    decimals = 3
  ) %>%
  fmt_number(
    columns = "N",  # Format N separately
    decimals = 0
  ) %>%
  cols_label(
    Variable = "Variable",
    Mean = "Mean",
    Median = "Median",
    SD = "Std. Dev.",
    Min = "Min",
    Max = "Max",
    N = "N"
  ) %>%
  tab_style(
    style = cell_text(
      font = "Times New Roman",
      weight = "bold"
    ),
    locations = cells_column_labels(everything())
  ) %>%
  tab_style(
    style = cell_text(
      font = "Times New Roman"
    ),
```

```
    locations = cells_body()
  ) %>%
  tab_source_note(source_note = desc_note) %>%
  tab_style(
    style     = cell_text(font = "Times New Roman"),
    locations = cells_source_notes()
  ) %>%
  tab_options(
    table.font.size = 12,
    data_row.padding = px(4),
    table.layout = "fixed",
    table.width = pct(100)
  )

# Save as PDF
library(webshot2)

tempfile_desc <- tempfile(fileext = ".html")
gtsave(descriptive_table, filename = tempfile_desc)
webshot2::webshot(tempfile_desc, file =
"Figures/Descriptive_Statistics_Cleaned.pdf", vwidth = 700, vheight =
1000)

# --------------------------------------------------------------
# 1.3 Correlation Matrix
# --------------------------------------------------------------
library(GGally)
library(Hmisc)  # For rcorr to get p-values

# Calculate correlation matrix with significance levels
cor_results <- rcorr(as.matrix(descriptive_vars))
cor_matrix <- cor_results$r
p_matrix <- cor_results$P

# Create matrix with stars for significance
get_stars <- function(p) {
  ifelse(p < 0.01, "***",
         ifelse(p < 0.05, "**",
                ifelse(p < 0.1, "*", "")))
}

# Combine correlation values with stars
cor_with_stars <- matrix(NA, nrow = nrow(cor_matrix), ncol =
ncol(cor_matrix))
for (i in 1:nrow(cor_matrix)) {
  for (j in 1:ncol(cor_matrix)) {
    if (i == j) {
      cor_with_stars[i, j] <- "1"
    } else {
      cor_with_stars[i, j] <- paste0(round(cor_matrix[i, j], 2),
get_stars(p_matrix[i, j]))
    }
  }
}

# Apply clean names
colnames(cor_with_stars) <- clean_names
```

```
rownames(cor_with_stars) <- clean_names

# Convert to data frame
cor_df <- as.data.frame(cor_with_stars)
cor_df <- tibble::rownames_to_column(cor_df, var = "Variable")

star_note <- md("*Note:* *p* < 0.10 = *,  *p* < 0.05 = **,  *p* < 0.01 =
***")

# Create GT table
correlation_table <- cor_df %>%
  gt() %>%
  tab_header(title = md("**Correlation Matrix**")) %>%
  fmt_markdown(columns = everything()) %>%  # Make stars appear correctly
  tab_style(
    style = cell_text(font = "Times New Roman", weight = "bold"),
    locations = cells_column_labels(everything())
  ) %>%
  tab_style(
    style = cell_text(font = "Times New Roman"),
    locations = cells_body()
  ) %>%
  opt_row_striping() %>%
  tab_options(
    table.font.size = 10,
    data_row.padding = px(4),
    table.layout = "fixed",
    container.width = px(1100),
    container.height = px(1500)
  ) %>%
  tab_source_nore(source_note = star_note) %>%
  tab_style(
    style = cell_text(font = “Times New Roman”),
    location = cells_source_notes()
)

# Save table as PDF
cor_temp <- tempfile(fileext = ".html")
gtsave(correlation_table, filename = cor_temp)
webshot2::webshot(cor_temp, file =
"Figures/Correlation_Matrix_Cleaned.pdf", vwidth = 1000, vheight = 2000)

# Optional: also create a heatmap plot
pdf("Figures/Correlation_Plot_Cleaned.pdf", width = 12, height = 10)  #
Units are in inches
ggcorr(
  descriptive_vars,
  label = TRUE,
  label_size = 3,
  hjust = 0.9,
  size = 2.5
)
dev.off()

# ---------------------------------------------------------------
```

```
# 1.4 Multicollinearity Check (VIF Test)
# ---------------------------------------------------------------
# Load required package
library(car)

# Run a pooled OLS regression to get VIFs
vif_model <- lm(
  log_REI ~ log_Private_Credit + log_M2 + credit_deposit_ratio +
    reg_quality + pol_stability + corruption_indx +
    log_GDP_pc + log_Trade + log_CO2 + rec + elec_access + log_Inflation,
  data = panel_data
)

# Calculate VIF values
vif_values <- vif(vif_model)
vif_df <- data.frame(Variable = names(vif_values), VIF = round(vif_values,
2))

# Now apply your existing clean names (shortened selection)
clean_names_vif <- c(
  "Log_Private_Credit",
  "Log_M2",
  "Credit_Deposit_Ratio",
  "IQ1",
  "IQ2",
  "IQ3",
  "Log_GDP",
  "Log_Trade",
  "Log_CO2",
  "REC",
  "Elec_Access",
  "Log_Inflation"
)

# Assign clean names
vif_df$Variable <- clean_names_vif

# Create the GT table
vif_table <- vif_df %>%
  gt() %>%
  tab_header(title = "Variance Inflation Factor (VIF) Test Results") %>%
  fmt_number(columns = "VIF", decimals = 2) %>%
  cols_label(
    Variable = "Variable",
    VIF = "VIF"
  ) %>%
  tab_style(
    style = cell_text(font = "Times New Roman", weight = "bold"),
    locations = cells_column_labels(everything())
  ) %>%
  tab_style(
    style = cell_text(font = "Times New Roman"),
    locations = cells_body()
  ) %>%
  tab_options(
    table.font.size = 12,
    data_row.padding = px(4),
```

```
    table.width = pct(50)
  )

# Save the table as PDF
tempfile_vif <- tempfile(fileext = ".html")
gtsave(vif_table, filename = tempfile_vif)
webshot2::webshot(tempfile_vif, file =
"Figures/VIF_Test_Results_Cleaned.pdf", vwidth = 250, vheight = 400)

# Save raw VIF results as CSV
write.csv(vif_df, "Tables/VIF_Test_Results_Cleaned.csv", row.names =
FALSE)

# ---------------------------------------------------------------
# 1.5 Cross-Sectional Dependence and Panel Unit Root Tests
# ---------------------------------------------------------------
# Load necessary libraries
library(pcse)
library(plm)
library(tidyverse)
library(tseries)
library(metatest)  # For the Pesaran CD test
library(urca)
library(purtest)
library(panelvar)
library(gt)
library(webshot2)

# Define panel data structure if not already done
panel_data <- pdata.frame(panel_data, index = c("country_code", "year"))

# Variables to test (use your cleaned variables)
vars_to_test <- c(
  "log_REI", "FD_Index", "reg_quality", "pol_stability",
"corruption_indx",
  "log_GDP_pc", "log_Trade", "log_CO2", "rec", "elec_access",
"log_Inflation"
)

# Create empty results table
cd_results <- data.frame(Variable = character(), CD_stat = numeric(),
p_value = numeric())

# Run Pesaran CD test for each variable
for (v in vars_to_test) {
  f <- as.formula(paste(v, "~ 1"))
  model <- plm(f, data = panel_data, model = "pooling")
  test <- pcdtest(model, test = "cd")
  cd_results <- rbind(cd_results, data.frame(
    Variable = v,
    CD_stat = round(test$statistic[[1]], 3),
    p_value = round(test$p.value, 3)
  ))
}
```

```
# Clean up variable names for the output table
clean_names_cd <- c(
  "Log_REI", "FD",
  "IQ1", "IQ2", "IQ3",
  "Log_GDP", "Log_Trade", "Log_CO2",
  "REC", "Elec_Access", "Log_Inflation"
)

cd_results$Variable <- clean_names_cd

# Create GT table for the results
cd_table <- cd_results %>%
  gt() %>%
  tab_header(
    title = md("**Results of Cross-Sectional Dependence Test**")
  ) %>%
  fmt_number(
    columns = c("CD_stat", "p_value"),
    decimals = 3
  ) %>%
  cols_label(
    Variable = "Variable",
    CD_stat = "CD Statistic",
    p_value = "p-value"
  ) %>%
  tab_style(
    style = cell_text(font = "Times New Roman", weight = "bold"),
    locations = cells_column_labels(everything())
  ) %>%
  tab_style(
    style = cell_text(font = "Times New Roman"),
    locations = cells_body()
  ) %>%
  tab_footnote(
    footnote = "Note: Null hypothesis is cross-sectional independence. p-
values close to zero suggest significant cross-sectional dependence
(Pesaran, 2007).",
    locations = cells_title(groups = "title")
  ) %>%
  tab_options(
    table.font.size = 11,
    data_row.padding = px(4),
    table.layout = "fixed",
    container.width = px(300),
    container.height = px(600)
  )

# Save table as PDF
tempfile_cd <- tempfile(fileext = ".html")
gtsave(cd_table, filename = tempfile_cd)
webshot2::webshot(tempfile_cd, file =
"Figures/CD_Test_Results_Cleaned.pdf", vwidth = 600, vheight = 800)

# ============================================================
# 2. MULTIVARIATE REGRESSION ANALYSIS
# ============================================================
# ------------------------------------------------------------
```

```
# 2.0 Load required libraries
# -------------------------------------------------------------
library(plm)
library(lmtest)
library(sandwich)
library(dplyr)
library(gt)
library(webshot2)
library(broom)
library(pcse)
library(stargazer)

# -------------------------------------------------------------
# 2.1 Prepare dataset structure
# -------------------------------------------------------------
# Remove duplicates (country_code, year)
panel_data <- panel_data[!duplicated(panel_data[, c("country_code",
"year")]), ]

# Remove rows with missing values in key variables
panel_data <- panel_data %>%
  filter(!is.na(log_REI), !is.na(FD_Index), !is.na(reg_quality),
         !is.na(pol_stability), !is.na(corruption_indx),
         !is.na(log_GDP_pc), !is.na(log_Trade), !is.na(log_CO2),
         !is.na(rec), !is.na(elec_access), !is.na(log_Inflation))

# Re-define as panel structure
panel_data <- pdata.frame(panel_data, index = c("country_code", "year"))

# -------------------------------------------------------------
# 2.2 Baseline Models: Pooled OLS, Fixed Effects (FEM), Random Effects
(REM)
# -------------------------------------------------------------
# Pooled OLS Model
pooled_model <- plm(
  log_REI ~ FD_Index + reg_quality + pol_stability + corruption_indx +
    FDxIQ1 + FDxIQ2 + FDxIQ3 +
    log_GDP_pc + log_Trade + log_CO2 + rec + elec_access + log_Inflation,
  data = panel_data,
  model = "pooling"
)

summary(pooled_model)

# Fixed Effects Model (FEM)
fixed_model <- plm(
  log_REI ~ FD_Index + reg_quality + pol_stability + corruption_indx +
    FDxIQ1 + FDxIQ2 + FDxIQ3 +
    log_GDP_pc + log_Trade + log_CO2 + rec + elec_access + log_Inflation,
  data = panel_data,
  model = "within"
)

summary(fixed_model)
```

```
# Random Effects Model (REM)
random_model <- plm(
  log_REI ~ FD_Index + reg_quality + pol_stability + corruption_indx +
    FDxIQ1 + FDxIQ2 + FDxIQ3 +
    log_GDP_pc + log_Trade + log_CO2 + rec + elec_access + log_Inflation,
  data = panel_data,
  model = "random"
)

summary(random_model)

# -------------------------------------------------------------
# 2.3 Hausman Test: FEM vs REM
# -------------------------------------------------------------

hausman_test <- phtest(fixed_model, random_model)
print(hausman_test)

# -------------------------------------------------------------
# 2.4 Create Baseline Regression Tables
# -------------------------------------------------------------
# GT Table

# Load necessary libraries
library(dplyr)
library(broom)
library(gt)
library(webshot2)

# Remove intercepts
pooled_coefs <- tidy(pooled_model) %>% filter(term != "(Intercept)")
fixed_coefs  <- tidy(fixed_model) %>% filter(term != "(Intercept)")
random_coefs <- tidy(random_model) %>% filter(term != "(Intercept)")

# Add stars based on significance
add_stars <- function(coef, pval) {
  stars <- ifelse(pval < 0.01, "***",
                ifelse(pval < 0.05, "**",
                       ifelse(pval < 0.1, "*", "")))
  return(paste0(round(coef, 3), stars))
}

pooled_est <- add_stars(pooled_coefs$estimate, pooled_coefs$p.value)
fixed_est  <- add_stars(fixed_coefs$estimate, fixed_coefs$p.value)
random_est <- add_stars(random_coefs$estimate, random_coefs$p.value)

pooled_se <- paste0("(", round(pooled_coefs$std.error, 3), ")")
fixed_se  <- paste0("(", round(fixed_coefs$std.error, 3), ")")
random_se <- paste0("(", round(random_coefs$std.error, 3), ")")

# Create Regression Names

regression_names <- c(
  "FD",              # FD_Index
  "IQ1",             # reg_quality
  "IQ2",             # pol_stability
  "IQ3",             # corruption_indx
```

```
  "FD × IQ1",       # FDxIQ1
  "FD × IQ2",       # FDxIQ2
  "FD × IQ3",       # FDxIQ3
  "Log_GDP",        # log_GDP_pc
  "Log_Trade",      # log_Trade
  "Log_CO2",        # log_CO2
  "REC",            # rec
  "Elec_Access",    # elec_access
  "Log_Inflation"   # log_Inflation
)

# Create combined table
baseline_table <- data.frame(
  Variable = regression_names,
  POLS = paste0(pooled_est, " ", pooled_se),
  FEM = paste0(fixed_est, " ", fixed_se),
  REM = paste0(random_est, " ", random_se)
)

# Add R-squared and N manually
r_squared_row <- data.frame(
  Variable = "R-squared",
  POLS = as.character(round(summary(pooled_model)$r.squared[1], 3)),
  FEM = as.character(round(summary(fixed_model)$r.squared[1], 3)),
  REM = as.character(round(summary(random_model)$r.squared[1], 3))
)

n_obs_row <- data.frame(
  Variable = "Observations (N)",
  POLS = as.character(nobs(pooled_model)),
  FEM = as.character(nobs(fixed_model)),
  REM = as.character(nobs(random_model))
)

# Final table binding
baseline_final_table <- bind_rows(baseline_table, r_squared_row,
n_obs_row)

# Create GT Table

baseline_gt <- baseline_final_table %>%
  gt() %>%
  tab_header(
    title = md("**REI-FD-IQ relationship in SSA: Regression Models**")
  ) %>%
  cols_label(
    Variable = "Variable",
    POLS = "POLS",
    FEM = "FEM",
    REM = "REM"
  ) %>%
  tab_style(
    style = cell_text(font = "Times New Roman", weight = "bold"),
    locations = cells_column_labels(everything())
  ) %>%
```

```
  tab_style(
    style = cell_text(font = "Times New Roman"),
    locations = cells_body()
  ) %>%
  tab_options(
    table.font.size = 11,
    data_row.padding = px(4),
    table.width = pct(75),
    column_labels.hidden = FALSE
  ) %>%
  cols_align(
    align = "right",
    columns = c(POLS, FEM, REM)
  ) %>%
  cols_align(
    align = "left",
    columns = "Variable"
  ) %>%
  tab_footnote(
    footnote = "Standard errors in parentheses. ***p<0.01; **p<0.05;
*p<0.1.",
    locations = cells_title(groups = "title")
  )

# Save table as PDF
tempfile_baseline <- tempfile(fileext = ".html")
gtsave(baseline_gt, filename = tempfile_baseline)
webshot2::webshot(tempfile_baseline, file =
"Figures/Baseline_Regression_Table_FINAL.pdf", vwidth = 1400, vheight =
1000)

# ============================================================
# 3. ROBUSTNESS CHECK: PCSE Model
# ============================================================
# ------------------------------------------------------------
# 3.1 Correct Panel Data for PCSE (Filter)
# ------------------------------------------------------------

library(dplyr)
library(gt)
library(webshot2)
library(pcse)

# Check number of observations per country
country_counts <- panel_data %>%
  group_by(country_code) %>%
  summarise(obs_count = n())

# Filter: keep countries with at least 5 observations
good_countries <- country_counts %>%
  filter(obs_count >= 5) %>%
  pull(country_code)

# Subset panel_data
panel_data_pcse <- panel_data %>%
  filter(country_code %in% good_countries)
```

```r
# ------------------------------------------------------------
# 3.2 Re-Run PCSE on cleaned data
# ------------------------------------------------------------

# New pooled model
pooled_pcse_model <- lm(
  log_REI ~ FD_Index + reg_quality + pol_stability + corruption_indx +
    FDxIQ1 + FDxIQ2 + FDxIQ3 +
    log_GDP_pc + log_Trade + log_CO2 + rec + elec_access + log_Inflation,
  data = panel_data_pcse
)

# Run PCSE correcting for panel structure
pcse_model <- pcse(
  pooled_pcse_model,
  groupN = panel_data_pcse$country_code,
  groupT = panel_data_pcse$year,
  pairwise = TRUE
)

# ------------------------------------------------------------
# 3.3 Extract and Present PCSE Results in GT Table
# ------------------------------------------------------------

# Create data.frame manually from pcse_model list
pcse_results <- data.frame(
  Estimate = pcse_model$b,
  PCSE = pcse_model$pcse,
  p_value = pcse_model$pval
)

# Remove Intercept (first row)
pcse_results <- pcse_results[-1, ]

# Add variable names
regression_names <- c(
  "FD", "IQ1", "IQ2", "IQ3",
  "FD × IQ1", "FD × IQ2", "FD × IQ3",
  "Log_GDP", "Log_Trade", "Log_CO2", "REC", "Elec_Access", "Log_Inflation"
)

pcse_results$Variable <- regression_names

# Rearrange columns
pcse_results <- pcse_results %>%
  select(Variable, everything())

# Add significance stars
add_stars <- function(est, p) {
  if (p < 0.01) {
    paste0(round(est, 4), "***")
  } else if (p < 0.05) {
    paste0(round(est, 4), "**")
  } else if (p < 0.1) {
    paste0(round(est, 4), "*")
```

```
  } else {
    round(est, 4)
  }
}

# Apply stars
pcse_results$Estimate_Starred <- mapply(add_stars, pcse_results$Estimate,
pcse_results$p_value)

# -------------------------------------------------------------
# 3.4 Build and Export GT Table
# -------------------------------------------------------------

# Calculate Observations (N) and "Pseudo" R-squared manually
pcse_N <- panel_data_pcse %>% nrow()
pcse_R2 <- summary(lm(
  log_REI ~ FD_Index + reg_quality + pol_stability + corruption_indx +
    FDxIQ1 + FDxIQ2 + FDxIQ3 +
    log_GDP_pc + log_Trade + log_CO2 + rec + elec_access + log_Inflation,
  data = panel_data_pcse
))$r.squared

# Prepare the main PCSE results table
pcse_main_table <- pcse_results %>%
  select(Variable, Estimate_Starred, PCSE) %>%
  rename(
    "Estimate" = Estimate_Starred,
    "PCSE" = PCSE
  )

# Create additional bottom rows for N and R-squared
additional_rows <- data.frame(
  Variable = c("R-squared", "Observations (N)"),
  Estimate = as.character(c(round(pcse_R2, 3), pcse_N)),
  PCSE = c(NA, NA)
)

# Bind them together
pcse_final_table <- bind_rows(pcse_main_table, additional_rows)

# Build GT Table
pcse_gt_table <- pcse_final_table %>%
  gt() %>%
  tab_header(title = "Robustness Check: PCSE Model Results") %>%
  fmt_number(
    columns = c(PCSE),
    decimals = 4
  ) %>%
  tab_style(
    style = cell_text(font = "Times New Roman", weight = "bold"),
    locations = cells_column_labels(everything())
  ) %>%
  tab_style(
    style = cell_text(font = "Times New Roman"),
    locations = cells_body()
  ) %>%
  tab_options(
```

```
    table.font.size = 11,
    data_row.padding = px(4),
    table.width = pct(50)
  ) %>%
  tab_footnote(
    footnote = "Panel-corrected standard errors (PCSE) in parentheses.
***p<0.01; **p<0.05; *p<0.1",
    locations = cells_title()
  )

# Save the table
tempfile_pcse <- tempfile(fileext = ".html")
gtsave(pcse_gt_table, filename = tempfile_pcse)
webshot2::webshot(tempfile_pcse, file = "Figures/PCSE_Model_Results.pdf",
vwidth = 1000, vheight = 800)


# ================================================================
# 4.  MODEL-DIAGNOSTIC & NORMALITY TESTS ——  Appendix 7
#     (run right after you estimate `fixed_model`)
# ================================================================

suppressPackageStartupMessages({
  library(plm)          # panel tools
  library(lmtest)       # bptest(), pbgtest()
  library(nortest)      # Shapiro
  library(tseries)      # Jarque-Bera
  library(gt); library(webshot2); library(dplyr)
})

# ---------------------------------------------------------------
# 1.  Normality of residuals (plots + test)
# ---------------------------------------------------------------
res_FE <- residuals(fixed_model)

if(length(res_FE) <= 5000){
  norm_FE   <- shapiro.test(res_FE)
  norm_name <- "Shapiro-Wilk"
} else {
  norm_FE   <- jarque.bera.test(res_FE)
  norm_name <- "Jarque-Bera"
}

pdf("Figures/FE_Residual_Hist.pdf", 7, 4)
hist(res_FE, 30, main = "FE residuals – histogram",
     xlab = "Residual", col = "grey", border = "white")
dev.off()

pdf("Figures/FE_Residual_QQ.pdf", 6, 6)
qqnorm(res_FE, main = "FE residuals – Q-Q plot")
qqline(res_FE, col = 2, lwd = 2)
dev.off()

# ---------------------------------------------------------------
# 2.  Heteroskedasticity  (Breusch-Pagan)
```

```
# ---------------------------------------------------------------
bp_FE <- bptest(fixed_model)

# ---------------------------------------------------------------
# 3.  Serial correlation (Wooldridge / Baltagi-Wu BG(1))
# ---------------------------------------------------------------
pbg_FE <- pbgtest(fixed_model, order = 1)

# ---------------------------------------------------------------
# 4.  Wrap results into a table + export
# ---------------------------------------------------------------
diag_tbl <- tibble(
  Test      = c(norm_name, "Breusch-Pagan", "Wooldridge BG(1)"),
  Statistic = round(c(norm_FE$statistic,
                      bp_FE$statistic,
                      pbg_FE$statistic), 3),
  p_value   = signif(c(norm_FE$p.value,
                       bp_FE$p.value,
                       pbg_FE$p.value), 3)
)

diag_gt <- diag_tbl %>%
  gt() %>%
  tab_header(title = md("**Diagnostic tests - Fixed-Effects model**")) %>%
  cols_label(Statistic = "Test stat", p_value = "p-value") %>%
  fmt_number(columns = where(is.numeric), decimals = 3) %>%
  tab_style(style = cell_text(weight = "bold"),
            locations = cells_column_labels(everything()))

tmp_html <- tempfile(fileext = ".html")
gtsave(diag_gt, tmp_html)
webshot2::webshot(tmp_html, "Figures/FE_Diagnostic_Tests.pdf",
                  vwidth = 1000, vheight = 600)

write.csv(diag_tbl, "Tables/FE_Diagnostic_Tests.csv", row.names = FALSE)

# END OF SCRIPT
```

UNIVERSITÉ CATHOLIQUE DE LOUVAIN
Louvain School of Management
Place des Doyens, 1 bte L2.01.01, 1348 Louvain-la-Neuve, Belgique | **www.uclouvain.be/lsm**