DISSERTATION

# THREE ESSAYS ON CLIMATE POLICY AND GREEN FINANCE


Submitted by

Vedanshi Nevatia

Department of Economics


In partial fulfillment of the requirements

For the Degree of Doctor of Philosophy

Colorado State University

Fort Collins, Colorado

Summer 2025

Doctoral Committee:

Advisor: Daniele Tavani
Co-Advisor: Ramaa Vasudevan

Ray Miller
Robert Schwebach

ABSTRACT

THREE ESSAYS ON CLIMATE POLICY AND GREEN FINANCE

This dissertation contains three chapters that empirically explore the intricate dynamics between state climate policy and financial market risk perception of clean energy investments. The first chapter examines the systematic regional differences in the cost of climate debt measured by green-labeled sovereign bond pricing. It applies the coarsened exact matching technique on a bond-level panel data obtained from Bloomberg, spanning 44 countries between 2017 and 2023. Findings reveal that while the absolute price of sovereign green bonds is higher for emerging economies, it is substantially discounted relative to conventional bonds, particularly in volatile conditions. The study prescribes the suitability of sovereign green bonds as a public green finance instrument for emerging economies. The second chapter uses the 2022 Inflation Reduction Act (IRA) as a natural experiment to assess how a major climate policy shapes climate transition risk. It analyzes extended equity price reactions of U.S. based renewable energy firms to the IRA, using financial news from 2022 to 2023 and natural language processing for sentiment analysis. A dynamic difference-in-differences model reveals an initial stock price surge followed by a gradual reversion, indicating investor reassessment due to implementation frictions and policy uncertainties. The study highlights adaptive market behavior in response to climate policy signals and evolving investor expectations. The third chapter examines drivers of compositional shift in public-private partnerships (PPPs) towards renewable energy from 1996 to 2023 across 72 developing countries. Using a novel dataset combining World Bank PPP data with institutional and policy indicators, it applies a static Tobit and a dynamic GMM model. Results show that renewable PPP uptake is shaped by integrated policy environments. However, public investment, international support, and targeted policy tools consistently promote renewable adoption. While middle-income countries benefit from market and regulatory instruments, low-income countries face the problem of inadequate public finance to support

high risk projects. The transition is path-dependent, highlighting the need for sustained and targeted government strategies.

ACKNOWLEDGEMENTS

This dissertation has reached fruition today due to the effort and support of several people. I thank the Department of Economics at Colorado State University for providing a stimulating academic environment throughout my graduate degree, marking the beginning of a journey that doesn't end with the submission of this dissertation. I am extremely grateful to my advisor, Dr. Daniele Tavani, for his continuous guidance and support, and to my co-advisor Dr. Ramaa Vasudevan for being an invaluable source of inspiration. I am also thankful to Dr. Robert Schwebach and Dr Ray Miller for their insightful comments and essential feedback. I express my appreciation to the Department of Finance and Real Estate for sharing resources vital for the success of this research. It is with deep gratitude that I acknowledge the faculty and fellow graduate students for their teachings, contributions, shared experiences, and friendships. Specifically, I would like to thank Elene, Lackson, Adam, Debora, Apurva, Kamini, Kartik, Emily, Siddharth, Mostafa, Namita, Garima, Saloni, Mridula, Sanchari, Saniya, Amy, Pratiksha and many others for memorable times. I am particularly grateful to Ashish for his invaluable friendship, motivation and support. I am also extremely thankful to my friend Devanshi Jain, for simply existing. Further, I extend my immense gratitude to the wonderful people from Jawaharlal Nehru University that I had the opportunity to learn and work with. Especially, Dr Jayati Ghosh, who inspired my passion for economic inquiry in climate change. I am profoundly grateful to my husband, Pratyoosh Kashyap, for the beautiful partnership we share. Thank you for being my cheerleader, my mentor, and my home. Your love, joy, and patience has made this journey meaningful and fun, with so much more to look forward to. To my father, Sameer Nevatia, I dedicate my dissertation to you who instilled in me the dream to pursue a PhD. To my brother, Soham Nevatia, I thank you with all my heart for making sure I fulfil this dream. To my mother, Aparna Nevatia, I revere you for your constant love and for giving this journey a spiritual direction. Lastly, to Him who is the reason for all knowledge, love and joy, I dedicate my journey to You.

TABLE OF CONTENTS

# Introduction

Achieving global climate goals consistent with the Paris Agreement and subsequent net-zero pledges requires a massive scale-up of investments in clean energy, sustainable infrastructure, and adaptation measures. The central role of climate finance in enabling this transition cannot be overstated. Finance is not merely a supporting component of climate policy but a determining factor of its success. The concept of "*green finance*" encompasses the flows of capital – public and private, domestic and international – that are directed toward climate mitigation and adaptation projects (Falconer & Stadelmann, 2014). Recent estimates underscore the magnitude of the challenge: annual climate investment must reach into the trillions of dollars by the end of this decade to limit global warming to below 2°C, far above the roughly $600 billion per year currently flowing into climate-related projects (Climate Policy Initiative, 2021).

Mobilizing sufficient financing is especially critical in emerging and developing economies (EMDEs), where both the marginal cost of abatement and the vulnerability to climate impacts are high (Kerr & Hu, 2025a) . However, research indicates that climate-vulnerable developing countries often face a climate investment trap, wherein high financing costs deter adequate green investment, which in turn perpetuates higher future costs and climate vulnerabilities (Ameli et al., 2021). Consequently, clean energy projects in low-income countries can face prohibitive interest rates or required returns that are several percentage points higher than similar projects in advanced economies. Such disparities make it difficult for EMDEs to compete for international private capital to fund renewable energy, sustainable transport, or adaptation infrastructure. Currently, almost 80% of energy transition in EMDEs is financed through public sources, especially Development Finance Institutions (DFIs). Additionally, 61% of it is raised in debt (Climate Policy Initiative, 2021). The fact necessitates restructuring of the green finance market to support more risk-mitigated debt instruments viable for developing countries.

In this light, using green-labeled sovereign bonds as benchmark securities, Chapter 1 of this dissertation investigates regional variations in the cost of climate debt between developmentally segregated economies. It also assesses the viability of sovereign green bonds as risk-mitigating public instruments for climate finance through the estimation of discounted pricing associated with green-labeled bonds or "*greenium*." To achieve this, the study employs the coarsened exact matching technique to identify the closest counterfactual bond. This research is particularly timely, given the urgent need for direct government participation in green finance and the growing share of sovereign-issued bonds in the green bond market (Ando et al., 2023). The findings demonstrate that the green labeling of sovereign bonds significantly reduces climate capital costs in emerging markets by lowering perceived risk and informational asymmetry, especially for riskier countries, speculative-grade bonds, and during periods of financial volatility.

The dissertation then shifts focus from green finance instruments to interlinkages between climate policy and financial markets. While the availability of resources for climate transition is a fundamental need, the effectiveness of policy depends on its absorption by public and private institutions. Climate transition risk arises from the economic and regulatory adjustments required to shift toward reduced greenhouse gas emissions and transition to renewable energy (Di Febo & Angelini, 2025). As governments implement climate policies (such as carbon pricing, coal phase-out plans, or large green subsidies), these actions can create winners and losers in the market: firms in high-carbon industries may face asset stranding or higher compliance costs, while firms in clean tech sectors may gain competitive advantage. This in turn drives the *ex-ante* valuation of climate risk in private capital assets that finance transition (Engle et al., 2020).

Chapter 2 leverages the 2022 Inflation Reduction Act (IRA), a landmark climate policy aimed at accelerating clean energy transition passed by the Biden administration in the U.S. to examine the renewable energy financial market response to realized transition risk. Using a multi-method empirical approach, this study analyzes both immediate and intertemporal market reactions of renewable energy firms to the policy's announcement and implementation. To capture informational dynamics, Natural

Language Processing (NLP) tools are employed, including Latent Dirichlet Allocation (LDA) for topic modeling and the ClimateBERT model for sentiment scoring of climate-related news occurring between 2021 and 2023. Immediate response event study demonstrates statistically significant cumulative abnormal returns (CARs) of up to 17% following the IRA's announcement, with media narratives playing a critical role in amplifying investor sentiments. Extended term dynamics from a staggered difference-in-differences study, however, reveal that these effects were not uniformly sustained. There was a gradual reversion in both cumulative abnormal returns and trading volumes in the year following the associated IRA policy announcement, suggesting investor reassessment as implementation frictions and policy uncertainties emerged. These patterns are indicative of adaptive market behavior, wherein initial optimism is tempered by evolving information and institutional bottlenecks. By integrating financial econometrics with behavioral finance and climate news analytics, this chapter contributes novel insights into the equity market pricing dynamics of transition risk.

The dissertation then brings together all dimensions of climate policy landscape in the EMDEs by addressing the larger question of institutional and infrastructural constraints that drive long-term public private partnerships in energy transition. Effective mobilization of climate finance requires robust domestic institutions – clear regulatory frameworks, credible climate strategies, and capable financial intermediaries (Kerr & Hu, 2025a). Additionally, institutional investors and global banks often have limited presence in smaller emerging markets, which leads to informational asymmetries and higher due diligence costs. These issues are compounded by underdeveloped local capital markets that offer few green financial products, meaning EMDE projects often rely on foreign currency debt that carries exchange rate risk (Ameli et al., 2021).

Even where funding is potentially available, many EMDEs lack a pipeline of "bankable" green projects – projects that are well-prepared with feasibility studies, risk mitigation measures, and clear revenue streams (Basílio & Basílio, 2022). Building renewable energy plants or electric mass transit in developing countries frequently involves addressing land acquisition, grid integration, and social and environmental safeguards, requiring upfront technical expertise and planning (Alloisio & Carraro, 2015a). This gap in project development capacity means that viable climate projects often do not reach financial close, or face long delays, thereby slowing the pace of green investment. Ciplet et al. (2022) argue that in many ways climate finance reproduces historical dependency: countries with stronger institutions and lower climate vulnerability attract the bulk of funds, whereas fragile states or climate-vulnerable small economies remain underserved. Private investors naturally gravitate toward lower-risk, more familiar markets – for example, large emerging economies like China or Brazil attract orders of magnitude more clean energy investment than least-developed countries in Sub-Saharan Africa.

Prior research highlights the need for innovative mechanisms (blended finance, green banks, etc.) to mobilize private investment alongside public funds (Falconer & Stadelmann, 2014; Pauw, 2017). At the same time, there is an increasing emphasis on aligning climate finance with development priorities: for instance, ensuring climate projects also advance energy access, poverty reduction, and resilience (Roy et al., 2018).

Mobilizing private capital through public-private partnerships (PPPs) has become a key strategy to finance large infrastructure projects, including in the energy sector. PPPs involve collaboration where private investors finance, build, and operate projects with public sector support or guarantees. There is burgeoning literature on determinants of PPPs in renewable infrastructure finance that suggest the formation of strong legal frameworks, government credibility, and risk-sharing arrangements as imperative for project uptake (Abba et al., 2022; Kim, 2020). Researchers have started examining how PPPs contribute to renewable energy deployment. Renewable energy PPP projects – such as solar or wind farms built with private participation – offer a way to leverage private expertise and funding, but they depend on an enabling environment (Hossin et al., 2024).

However, systematic evidence on what leads to a compositional shift in PPP infrastructure portfolios from conventional to renewable energy is still rare. Chapter 3 of this dissertation contributes to the literature by quantitatively analyzing the determinants of energy transition within PPP investment portfolios across

EMDEs. Despite growing global investment in clean infrastructure, renewable energy PPPs remain unevenly distributed, particularly in lower-income countries where energy access gaps persist. The study constructs a novel panel dataset of 72 countries from 1996 to 2023, combining project-level data from the World Bank's PPI database with institutional, macroeconomic, and policy indicators. Using a mixed-method approach, it first conducts a probit analysis to identify project-level characteristics that distinguish renewable from conventional PPPs. It then estimates static Tobit and dynamic GMM model specifications to assess how energy access, regulatory quality, investment incentives, and market-based instruments influence the share of renewable PPPs by volume and investment.

The results show that renewable energy PPPs are shaped by multi-dimensional policy environments rather than isolated interventions. Quantifiable actions like public investment, international financial support, and project-based policy tool adoption are consistently associated with greater renewable participation. Investment policies are favored in low-income economies while market and regulatory instruments are more responsive in upper-middle-income contexts. Dynamic GMM findings confirm that the transition is path-dependent, with prior renewable PPP engagement predicting current outcomes. This study is the first to analyze renewable energy transition in PPPs using a dynamic, share-based framework. It highlights the importance of bundled policy approaches and public finance continuity in mobilizing private investment for clean energy, offering actionable insights for sustainable infrastructure planning in emerging markets.

While each chapter of this dissertation addresses a distinct aspect of climate finance and policy, together they form a cohesive narrative about how policies, financial instruments, and investor behavior interact to shape climate outcomes. By addressing both high-level financial market dynamics and ground-level project implementation, the dissertation aims to contribute to academic debates and provide actionable insights for policymakers and investors striving to align financial flows with shared climate objectives.

# 1. Sovereign Green Bonds: Reducing Climate Capital Costs in Emerging Markets

## 1.1. Introduction

Rapidly transforming the global energy sector toward predominantly renewable and clean technologies requires substantial investment, particularly in developing countries where the impacts of climate change are more severe (Adom, 2024). However, volatile macroeconomic conditions, a lack of business confidence, and opacity in regulatory frameworks pose significant barriers to accessing financing for low-carbon projects in these regions (Ameli et al. 2021; Bilir, Chor, and Manova 2019; Egli, Steffen, and Schmidt 2019; Ragosa and Warren 2019). Although international investment in renewable energy nearly tripled after 2015, most of this growth was concentrated in developed countries. Emerging economies, which require approximately USD 1.7 trillion annually for renewable energy investments, attracted only USD 544 billion in 2022 (UNCTAD 2022)1. This disparity illustrates the "climate investment trap" in emerging economies, where underdeveloped financial markets lead to high country-risk premiums, increasing the cost of debt, slowing climate mitigation investments, and exacerbating climate impacts (Ameli et al. 2021).

In response to these challenges, the past decade has seen the emergence and exponential growth of the sovereign *green* bond market ( Ando et al. 2023; Doronzo, Siracusa, and Antonelli 2021; G. Cheng, Ehlers, and Packer 2022; R. Cheng, Gupta, and Rajan 2023; Xiao, n.d.). A sovereign green bond is a fixed-income debt instrument issued by the government to finance verified environmental projects. Since their first issuance by France and Poland in 2017, the cumulative amount issued through sovereign green bonds has grown to 366 billion USD globally as of 2023 (see **Error! Reference source not found.**.1). As part of governments' green fiscal policy, sovereign green bonds are an innovative tool that can potentially

[1] Retrieved from UNCTAD World Investment Report 2022: Accessed using: https://unctad.org/system/files/official-document/wir2022_en.pdf. Last access: 2 August 2024.

finance mitigation costs, increase welfare, and promote intra- and intergenerational equity through fair climate transition (Doronzo et al., 2021). For emerging economies, sovereign green bonds can not only advance national environmental agendas but also reduce the perceived risk in their financial sector by reducing informational asymmetry through improved reporting standards (R. Cheng et al., 2023). The evidence also suggests that sovereign green bonds have positive spillover effects on the issuance size and pricing of green bonds in the private sector (Xiao, n.d.). Given their pivotal role, it is essential to study the pricing dynamics of sovereign green bonds to assess their viability as a climate financing tool, particularly in emerging markets.

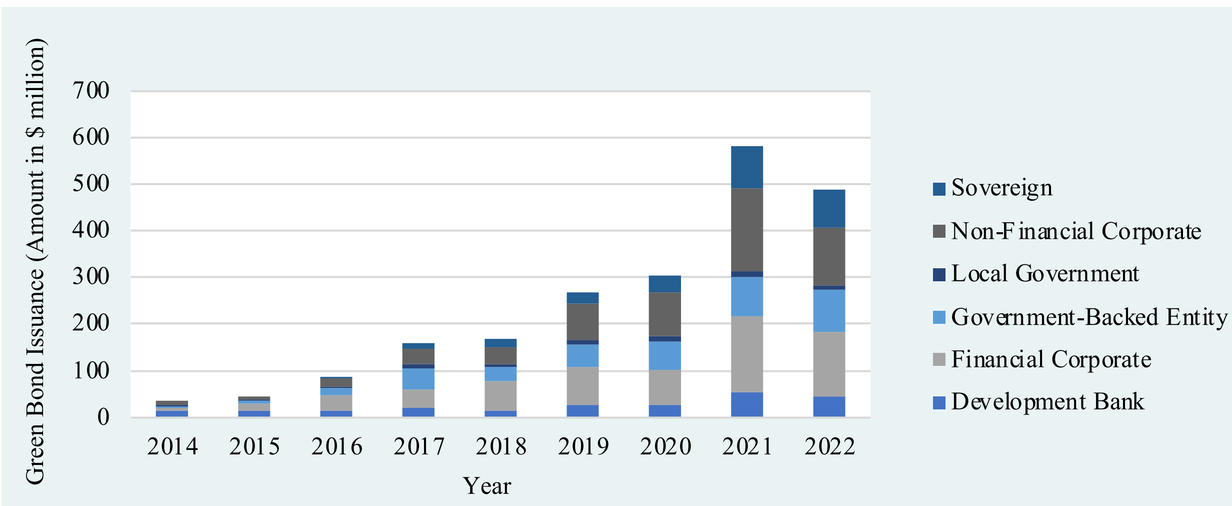



*Figure 1.1. Growth of green bond issuance by issuer type. Retrieved from Climate Bonds Initiative.*

Building on the distinctive characteristics of sovereign bonds as benchmark macro securities (Dittmar & Yuan, 2008; Presbitero et al., 2016), this research analyzes the green finance risk-mitigating properties of sovereign green bonds in developed and emerging markets. This study is the first to systematically estimate regional differences in the cost of climate debt, measured through sovereign green bond yields. Additionally, it provides an estimate of the cost of debt associated with sovereign green, social, and sustainability (GSS) bonds, a rapidly growing category not labeled explicitly green. The findings aim to offer policy insights into the utility of sovereign green bonds as instruments for financing climate transitions in diverse economic contexts.

In this study, I specifically investigate the presence, magnitude, and volatility of sovereign "*greenium*" in the secondary market—a lower yield premium on green bonds, which reflects their climate financing potential (Arat et al. 2023; Baker et al. 2022; Banga 2019; Dorfleitner, Utz, and Zhang 2022; Fatica, Panzica, and Rancan 2021; Grishunin et al. 2023; Leitao, Ferreira, and Santibanez-Gonzalez 2021; Löffler, Petreski, and Stephan 2021; Zerbib 2019). G*reenium* is mostly attributed to the nonpecuniary incentive for investors to invest in climate instruments and transparency in the use of proceeds of such bonds (MacAskill et al., 2021). The presence of *greenium* indicates a lower cost of capital for the issuer and a higher probability of investment opportunity due to high investor demand driving up green bond prices (or driving down yields). While the existence of *greenium* has been debated (Baker et al., 2022; Zerbib, 2019), studies consistently show its presence in green bonds issued by government entities, particularly in the secondary market (Bachelet et al., 2019). However, research on sovereign *greenium* remains limited (Ando et al., 2023).

Additionally, the study addresses the regional variation in green bond pricing dynamics (Doronzo et al., 2021; Ivashkovskaya & Mikhaylova, 2020), a gap attributed to the scarcity and heterogeneity of firm-level data, policies, and taxonomies in emerging economies (Grishunin et al., 2023). Most green bond studies analyze either global issuances or limit them to only the largest markets, such as the U.S., Europe or China. This research contributes to the literature by utilizing the homogeneity and transparency of sovereign bond data to explore regional variations in *greenium.*

I utilize data from Bloomberg and identify sovereign sustainability bonds issued between 2017 and 2023 across 42 countries. Given the caveat that any 2 bonds, even from the same issuer, may not be perfectly comparable, the distinguishing feature of a sovereign bond is that it is not affected by microeconomic firm-level heterogeneity. Leveraging this simplification, I employ coarsened exact matching (CEM) to identify the closest possible counterfactuals for each green bond analyzed. Subsequently, I use a two-way fixed effects model to draw causal inferences on the effect of green labeling on sovereign bond yields at the global and regional levels. Finally, I use a fixed effects panel data model to establish a direct relationship between country risk and sovereign *greenium.*

I find a statistically significant sovereign *greenium* of -10.2 basis points for emerging economies, which is in stark contrast to a positive and statistically significant yield premium of 42.5 basis points for sovereign green bonds in advanced economies. These findings have substantial policy implications: green-labeling of sovereign bonds reduces climate capital costs in emerging markets by lowering perceived risk, especially for speculative-grade bonds and during periods of financial volatility. The results are further strengthened by a significant positive premium on nonlabelled GSS bonds in emerging economies, indicating the importance of reporting standards. Conversely, this risk mitigation through green labeling does not extend to advanced economies, where conventional bonds might act as safe havens.

This research makes several contributions to literature: it is one of the few studies investigating regional and temporal variations in sovereign *greenium,* the first to compare yield differentials between sovereign GSSs and conventional bonds, and the first to use CEMs to form precise bond pairs for estimating average treatment effects for sovereign green bonds. Additionally, it explores how sovereign green bonds mitigate country risk, identifying the groups most likely to benefit from their issuance.

The remainder of this chapter is structured as follows: Section 1.2 outlines the theoretical framework underpinning the study. Section 1.3 provides a comprehensive overview of green bonds, sovereign green and sustainability bonds and the literature on *greenium*. Section 1.4 and 1.5 detail the data and methodology. Section 1.6 presents the model estimation results and various specifications. Section 1.7 and 1.8 conclude with a discussion of the findings, policy implications, and avenues for future research.

## 1.2. Theoretical Framework

Several notable studies have made theoretical predictions about how environmental concerns influence asset pricing and investment (Baker et al. 2022; Fama and French 2007; Heinkel, Kraus, and Zechner 2001; Idzorek, Kaplan, and Ibbotson 2023; Oehmke and Opp 2024; Pastor, Stambaugh, and Taylor 2021;

Pedersen, Fitzgibbons, and Pomorski 2021). The highly acclaimed Fama and French (2007) model uses a modified version of the capital asset pricing model (CAPM) to analyze the effect of taste-based investor biases on equity pricing. In this framework, a security's expected return accounts for the traditional CAPM beta for systematic risk and a second term that captures the agents' tastes for an asset's environmental attributes. However, the above models are designed for equity pricing.

The standard exponential affine function to determine bond prices posits that the logarithm of bond prices can be determined by macroeconomic risk factors and bond-specific characteristics (Dittmar & Yuan, 2008). This study therefore combines the standard function with the taste-based CAPM model to include additional bond price determinants: the use of proceeds indicating investors' preferences for environmental assets, and green labeling to demonstrate bias towards symmetrical reporting standards. Figure 1.2 demonstrates that the sovereign bond price is a function of a set of macroeconomic risk factors, and bond characteristics, including greenness of the asset. However, evidence shows that country risk is a significant determinant of bond characteristics (Damodaran, 2012). The three hypotheses developed in Section 1.3 therefore test for the direction and magnitude of corresponding factors, by controlling for other confounding variables and studies the synergies between country risk and greenness of the bond.

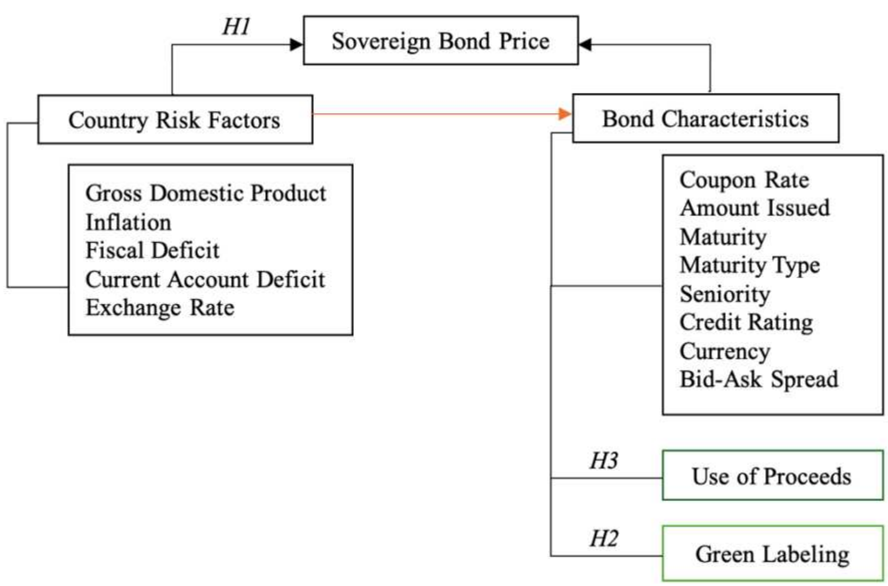



*Figure 1.2: Theoretical Framework*

## 1.3. Background and Review of Literature

### 1.3.1. Green Bonds and the Case for Sovereign Green Bonds

Green bonds, or bonds explicitly labeled "green," are fixed-income securities designated to finance projects that address climate and environmental challenges. These typically include investments in clean and renewable energy, energy efficiency, green infrastructure, or electrified transportation[2]. The first green bond was issued in 2007 by the World Bank in cooperation with the Swedish National Bank[2]. Since then, the market has grown significantly, from USD 11 billion in 2013 to USD 2.15 trillion in 2023 (see Figure 1.1). Demands for green bonds consistently surpass supply in both primary markets, where new bonds are issued, and secondary markets, where issued bonds are freely traded (MacAskill et al., 2021).

Although green bonds still represent a small percentage of the cumulative bond market (S&P Global)[3], they account for 58% of the total sustainability bonds issued (CBI 2022)[4]. Green bonds can be issued by various entities, including governments, municipalities, financial and nonfinancial corporations, and development banks. As of 2023, approximately 67% of green bond issuance originates from advanced economies, with approximately 50% issued by public corporations. European issuers have been the most prevalent, followed by US, Chinese, and supranational issuers. European issuers dominate the market, followed by those in the U.S., China, and supranational entities. The average issuance size of green bonds is generally smaller than that of conventional bonds, with approximately 88% of deals being less than USD 500 million. Short- to medium-term tenors, typically under five years, are most common.

Currently, the certification of green bonds lacks a universal global regulatory framework. Instead, it is generally aligned with the Green Bond Principles (GBPs) published by the International Capital Markets Association (ICMA)[4] in 2014. The ICMA also designates third-party verifiers for the green labeling and

[2] Retrieved from Climate Bonds Database. Accessed using:https://www.climatebonds.net/market/explaining-green-bonds.
[3] Retrieved from S&P Global, "Measuring the Impact of Green Bonds". Accessed using:https://www.spglobal.com/esg/insights/blog/measuring-the-impact-of-green-bonds. Last access: 2 August 2024.
[4] Retrieved from ICMA Group, "Green Bonds Principles", June 2023. Accessed using: https://www.icmagroup.org/assets/documents/Sustainable-finance/2022-updates/Green-Bond-Principles-June-2022-060623.pdf. Last access: 2 August 2024.

documentation of bond proceeds, including Climate Bonds Initiative (CBI), Bloomberg, Dealogic, and Environmental Finance[5]. Of these, only CBI and Bloomberg require alignment with GBP principles to be listed as a green bond, and CBI does not provide information on bond pricing dynamics. This study, therefore, leverages Bloomberg's well-documented green bond database for replicability. However, the process of green bond certification entails substantial administrative and transaction costs. Additionally, since issuers are not mandated to adhere to GBP guidelines, approximately 20% of corporate green bonds are self-labeled as green without external review, contributing to the ambiguity in corporate green bond pricing (MacAskill et al., 2021). This issue, compounded by underdeveloped capital bond markets with limited private participation, remains a significant barrier to the growth of green bonds in emerging economies (Banga, 2019; Jain et al., 2022; Magale, 2021; Mankata et al., 2022).

Sovereign bonds hold a unique position in that they can be treated as benchmark securities for the country under analysis (Dittmar & Yuan, 2008), in that they embody only macroeconomic country risk, not firm-specific microeconomic risk. Hence, combinations of sovereign bond rates and equity premiums are generally used as proxies for country risk measurement (Ameli et al., 2021; Gautam et al., n.d.). Sovereign bonds are also found to have strong positive spillover effects on corporate bond markets (Bevilaqua, Hale, and Tallman 2020; Presbitero et al. 2016). Evidence shows that their issuance promotes market completeness and price informativeness in emerging economy financial markets (Dittmar & Yuan, 2008).

It can therefore be reasonably assumed that sovereign green bond issuance would perform a similar function. A recent study by (Xiao, n.d.) revealed that sustainable corporate green bond issuance increased, with evidence of greater liquidity and reduced yield spreads following sovereign green issuance. Sovereign green bonds have also facilitated the development of standardized verification standards for the green bond market (Xiao, n.d.). In fact, all emerging economies, apart from India and Nigeria, issued

5 Retrieved from ICMA Group, "Summary of Green Bond Database Providers", May 2017. Accessed using: https://www.icmagroup.org/assets/documents/Regulatory/Green-Bonds/Green-Bond-Databases-Summary-Document-190617.pdf. Last access: 2 August 2024.

other green bonds only after the first sovereign green issuance. G. Cheng, Ehlers, and Packer (2022) note that *all* sovereign issuers are endorsed by at least one, and often multiple, third-party verifiers.

Owing to this increased transparency, sovereign green bonds can issue larger amounts with longer maturities, thereby reducing refinancing risk (G. Cheng et al., 2022). The public sector accounts for 80% of bonds with the longest tenors (20 years and above), with sovereigns representing 39%. The financial literature indicates that issue size is positively related to the coupon rate, credit rating, and financial health of issuers, with internationally denominated bonds being larger (Steckel and Jakob 2018). Given that climate mitigation is a global goal, sovereign green issuances can promote international financial pooling through established channels because of their risk-bearing capacity (Oman, n.d.; Zettelmeyer, n.d.). Doronzo, Siracusa, and Antonelli (2021) reported that Poland's sovereign green bond issuance attracted new green investors, accounting for 61% of its investor base. Therefore, sovereign green bonds can facilitate a smoother transition into the bond market and are better positioned to manage green certification costs.

Given that sovereigns act as benchmark securities, they are useful tools to estimate a country's cost of debt and draw regional comparisons. The same applies to sovereign green bonds. However, in structurally underdeveloped markets, the elevated cost of debt financing may also extend to climate-related debt instruments, potentially reflecting broader market inefficiencies. Building on the existing literature and the theoretical framework outlined above, I propose the following hypothesis:

*H1: There is a systematic difference in the yields of sovereign green bonds between advanced and emerging markets.*

### 1.3.2. The Greenium

The *"greenium"* or green bond premium refers to the yield differential at which green bonds are priced compared with comparable traditional bonds. Generally, expressed in basis points (bps), *greenium* is calculated as the spread between the yield of a green bond (GB) and a matched conventional bond (CB) yield, as given by equation 1.1:

$$Greenium = (Yield_{GB} - Yield_{CB}) \times 100 \qquad (1.1)$$

The presence of *greenium* across primary and secondary markets and among various issuers has been a heavily researched topic in the green bond literature, with inconclusive results. Some studies suggest a small positive, albeit significant, green bond premium, whereas others report a negative or negligible premium (Agliardi and Agliardi 2021; Ando et al. 2023; Bachelet, Becchetti, and Manfredonia 2019; Baker et al. 2022; Fatica, Panzica, and Rancan 2021; Gianfrate and Peri 2019; Grishunin et al. 2023; Hachenberg and Schiereck 2018; Hu et al. 2024; Ivashkovskaya and Mikhaylova 2020; Karpf and Mandel 2018; Liaw 2020; Löffler, Petreski, and Stephan 2021; Nanayakkara and Colombage 2019; Tang et al. 2023; Zerbib 2019). The variability in results is often attributed to differences in dependent variables, matching methods, analytical and econometric models, and the scope of analysis, ranging from corporate issuers to municipalities and from individual countries to regional groupings.

For example, Zerbib (2019) uses a synthetic matched conventional bond to analyze 110 green bonds in the secondary market, finding a low negative premium of -2 bps. Gianfrate and Peri (2019) employ propensity score matching (PSM) and identify an 18-bps premium among 121 European green bonds, with corporate issuers benefiting the most. Grishunin et al. (2023), on the other hand, reported a greenium of approximately -3 bps in the European market. Baker et al. (2022), utilizing the Fama and French (2007) technique, and Karpf and Mandel (2018), using the synthetic bond matching method, study the pricing of municipal green bonds in the U.S. and both report a negative *greenium*, although the latter attributes it observable bond characteristics. Tang et al. (2023) analyzes global corporate green bonds and finds a positive stock market reaction to green bond issuance but no statistically significant premium. Fatica, Panzica, and Rancan (2021) do not find a premium for financial institutions. (Hu et al., 2024) find that greenium is attributed to corporate issuers' greenness in the Chinese market.

Löffler, Petreski, and Stephan (2021) are the only ones to use CEM to test for the yield premium, finding a negative and statistically significant *greenium* in both primary and secondary markets. Nanayakkara and Colombage (2019) apply the natural logarithm of OAS to analyze yield differences between daily yields of conventional bonds and green bonds in a sample of 125 bonds from 2016–2017 and find that green bonds traded at a premium of 63 bps compared with comparable corporate bonds. MacAskill et al. (2021) provide a meta-analysis concluding that green premiums are identified in 56% of primary and 70% of secondary market studies, particularly for publicly issued, investment-grade, certified bonds with stronger reporting procedures. Recently, it has been suggested that *greenium*, especially in the private sector, may gradually disappear as the market matures (Kanamura 2020, Duguid 2022[6])

Studies on the determinants of green premia identify four key areas: (1) investors' preference for environmentally sound instruments; (2) greater liquidity of green bonds; (3) government incentives and tax breaks; and (4) compliance with GBP and the assignment of green certificates (Hyun, Park, and Tian 2021; 2023; Ivashkovskaya and Mikhaylova 2020; MacAskill et al. 2021). Flammer (2021) find stronger positive abnormal stock price reactions to the announcement of green bonds certified by independent third parties and first-time issuers. Among the few regional studies, Caramichael and Rapp (2024) find that while green bond governance significantly influences *greenium*, the credibility of the underlying projects does not have a substantial effect. Instead, *greenium* is unevenly distributed among large, investment-grade issuers, primarily in the banking sector and developed economies. (Dorfleitner et al., 2022; Fatica et al., 2021; Kapraun et al., 2021) demonstrate that external certification of "greenness" is a crucial driver of green bond premia in the U.S. and international bond markets. Ivashkovskaya and Mikhaylova (2020) use OAS spread to show that *greenium* is significant and more pronounced in developed economies (27.2 bps) than in emerging economies (18.3 bps). The authors emphasize the heteroskedasticity of the market and the policy and goodwill of the issuer when studying emerging economies. Moreover, they find that *greenium* is related to a higher level of liquidity associated with green bonds. Fatica, Panzica, and Rancan

[6] Retrieved from Financial Times, "Rising green bond issuance erodes premiums", July 18, 2022. Accessed using: https://www.ft.com/content/32dbf37c-8ff5-436b-88f3-9873fc864a7b. Last access: 2 August 2024.

(2021) also find significant *greenium* in developed country primary markets for all green bond types but a positive premium of 20.61 bps for emerging economies.

The literature on sovereign green bonds is growing, although most studies explore different market aspects rather than *greenium* (G. Cheng et al., 2022; R. Cheng et al., 2023; Doronzo et al., 2021; Oman, n.d.). (Xiao, n.d.) makes significant contributions by empirically demonstrating the spillover effects of sovereign green bond issuance on private *greenium.* They show that sovereign issuance not only increases the size and maturity of private green bonds but also solidifies green bond verification standards within a country. To date, only one preliminary study by Ando et al. (2023) has examined the yield dynamics of the sovereign green market. This study constructs a synthetic bond, as in (Zerbib, 2019), to compare Z-spreads between sovereign green bonds and conventional bonds, finding significant *greenium* for both advanced (4 bps) and emerging (11 bps) economies. However, the study is limited in scope, as it excludes bonds issued after mid-2022 and therefore considers only 23 matched sovereign, green-labeled bonds out of the 113 issued. Moreover, critical factors such as bond credit ratings, market tickers and varying macroeconomic risk measures are not accounted for in the study (see Section 1.5).

### 1.3.3. Twin Bonds Case Study

To establish a benchmark *greenium* for government securities in the Euro green finance market, Germany issued four pairs of twin "bunds" in 2020, comprising one green-labeled bond and one conventional bond (German Finance Agency, 2022). These paired bonds were designed with identical maturity dates and coupon rates but differed in issuance size. Figure 1.3a illustrates the yields and *greenium* for one such twin bond pair maturing in 2030. The green bond consistently traded at a *greenium* of -5--20 bps in the secondary market. However, the conventional bond was issued with a size of €30 billion, whereas the green bond was issued with a size of €6 billion, potentially leading the *greenium* to be biased downwards.

The established financial literature suggests that the issuance size is positively related to the bond yield to compensate investors for potential liquidity losses (Chiesa & Barua, 2019).

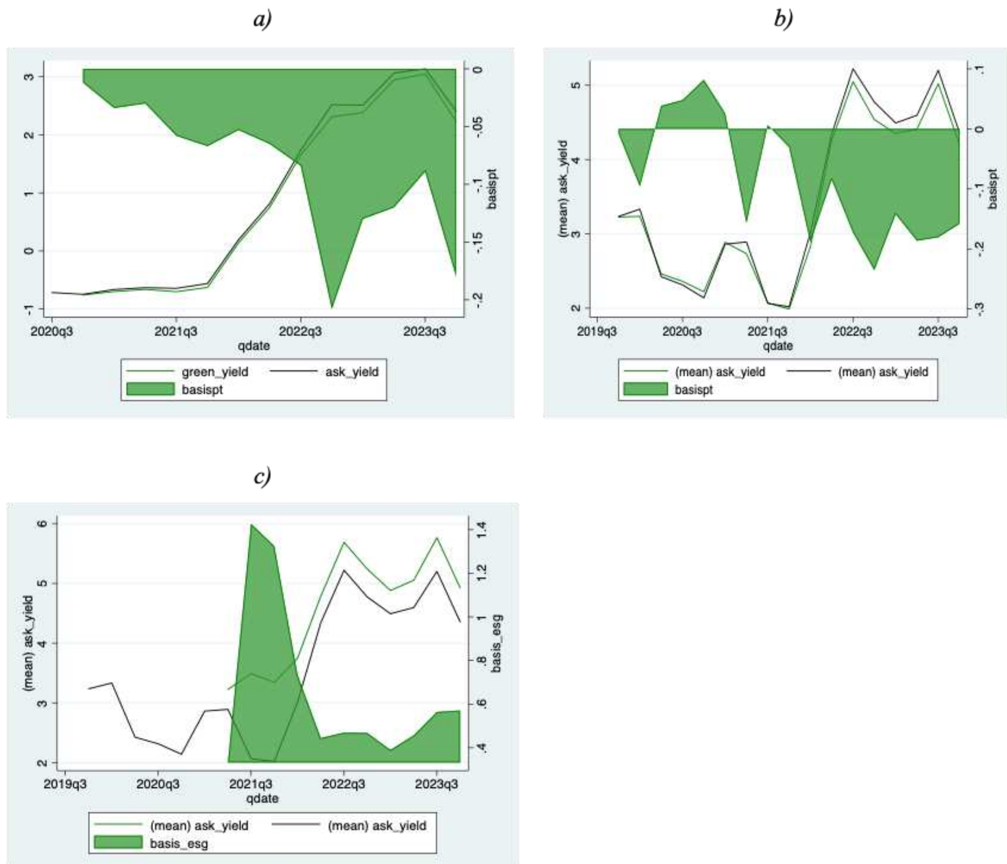



*Figure 1.3: Greenium for German twin bonds (a) and Chile twin bonds (b) and yield premium for Chile's non-labeled sustainability bond over the matched conventional bond.*

An example from Chile is illustrated in Figure 1.3b for a green bond pair. In 2018, the Chilean Ministry of Finance (MoF) issued its first sovereign green bonds to promote sustainable finance and development toward a low-carbon economy. The bond is found to be trading at a lower yield than matched conventional bond in the secondary market, with the *greenium* reaching -25 bps over time. Based on the literature and the twin-bond case study, I propose the following hypothesis:

*H2: The difference between the yields of sovereign green bonds and their conventional counterparts (i.e., greenium) is negative, significant, and more pronounced for emerging economies.*

Bonds that are not explicitly labeled green but are allocated to sustainable (green and social) activities are categorized as GSS bonds by CBI (and environmental, social, governance (ESG) bonds by Bloomberg). Sovereign issuers contributed 20 billion USD in 2022 to this category. Sovereign issuers contributed 20 billion USD to this category in 2022. Because GSS bonds are not subject to stringent financial documentation and labeling costs, they can be more easily issued by countries with less developed financial institutions (CBI, 2022)[7]. For example, the Philippines has historically relied heavily on developed economies for climate finance and technology. In 2021, the country established a sustainable financing framework and issued its first sustainability bond in 2022 (CBI, 2022)[7]. The academic literature on social and sustainability bonds is more limited, primarily due to fewer issuances. Emerging evidence suggests either a nonexistent or minimal sustainability premium (Torricelli & Pellati, 2022).

An intriguing case was provided by a pair of sovereign bonds issued by Chile: a green-labeled bond (ISIN: US168863DL94) and a non-labeled GSS bond (ISIN: XS2327851874). Although not intentionally issued under the twin-bond criteria, both bonds share similar characteristics, differing only in the amount issued (USD denominated, A- rated, 3.5% coupon rate, issued in 2021 with a 30-year maturity). The project details for both mention "Solar Wind Hydro Digital energy and energy efficiency BREEAM or other building and energy efficient infrastructure Electric Public Rail Sustainable infrastructure for clean and/or drinking water", but the nongreen GSS bond also includes health care (Bloomberg). Over the 11 quarters since issuance, the yields of the two bonds have varied within 5 bps of each other, with no consistent appearance of *greenium* (see Appendix A). However, the issuance size of the green bond is USD 2.3 billion, whereas that of the GSS bond is USD 1.5 billion. This example indicates the possibility that green labeling sustainability loans *allow* countries to issue larger amounts because of their reporting standards, provided that 100% of their proceeds are used only for climate purposes. Figure 1.3c here illustrates the case of a Chilean sovereign non-labeled GSS bond paired with a conventional bond. In

[7] Retrieved from Climate Bonds Initiative, "Sustainable debt, Global state of the market". Accessed using: https://www.climatebonds.net/files/reports/cbi_sotm_2022_03e.pdf. Last access: 2 August 2024

contrast to Figure 1.3b, the GSS bond is selling at a yield premium reaching a maximum of 140 bps. Based on this pattern, I propose the following hypothesis:

*H3: Yields of sovereign GSS bonds that are not labeled green are substantially different from those of green-labeled bonds.*

## 1.4. Data

To conduct the analysis, I constructed a novel dataset of 2,150 sovereign bond yields spanning 42 countries, beginning with the first global issuance of sovereign green bonds by Poland in January 2017. The data for each country start from the date its first sovereign green or GSS bond was issued, resulting in an unbalanced panel. I selected the quarterly frequency of bond yields because it offers greater granularity and sensitivity to macroeconomic factors and market-risk perceptions (Gopinath et al., n.d.). This approach also efficiently captures seasonal volatility, particularly during the timeframe considered, which includes significant events such as the COVID-19 pandemic and the Ukraine War. While many financial studies use bond-day panels to gauge microeconomic costs and benefits for issuers and investors through *greenium* (Baker et al. 2022; Karpf and Mandel 2018), this study aims to offer macroeconomic policy prescriptions for developed and emerging economies over the long run. As such, daily frequencies may capture excessive idiosyncratic volatilities arising more from market fluctuations than from broad trends, making quarterly data more appropriate for controlling country-level risk factors, which are typically available no more frequently than quarterly data (Gopinath et al., n.d.).

I categorized the countries into advanced economies (AEs) and emerging and developing economies (EMDEs) according to the IMF World Economic Outlook Classification (April 2023)[8]. Figure 1.4 presents a map of the amount issued through sovereign green bonds across countries. While AEs generally issue higher amounts (indicative of healthier credit ratings), there is fair representation of

[8]IMF World Economic Outlook 2023 classification of countries conforms with the World Bank Classification by Income-level 2022-23, except for Hungary, which is classified as High-Income by the latter.

EMDEs among issuers. For each country, the dataset includes quarterly time series data on bond-ask yields to maturity, as well as other bond-level and country-level characteristics. Next, I discuss the data sources, the steps taken to create the dataset, and the summary statistics of the study variables.

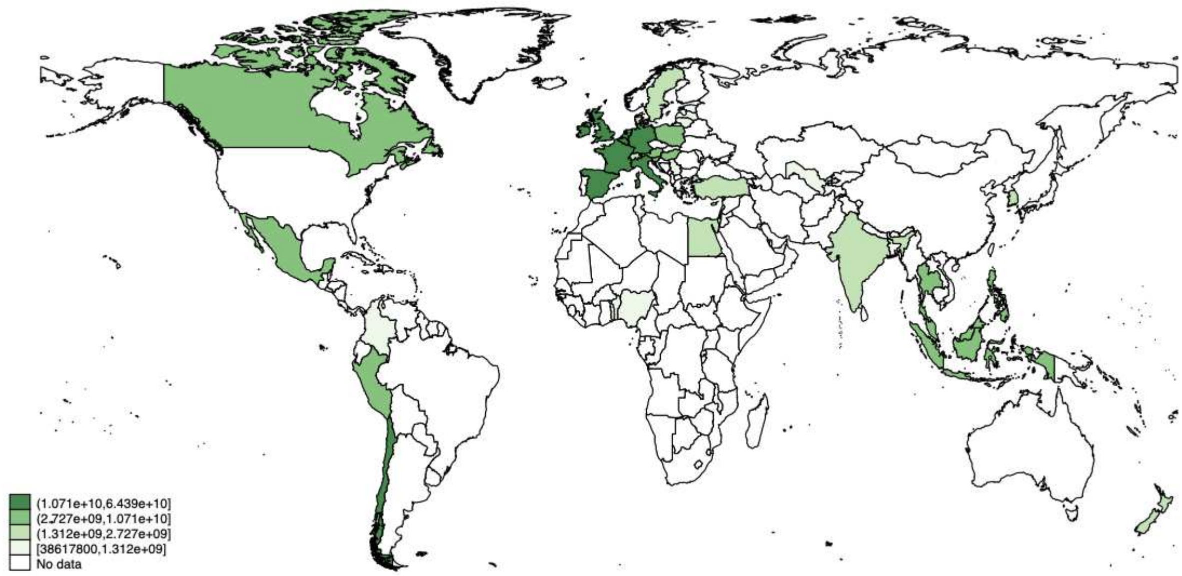


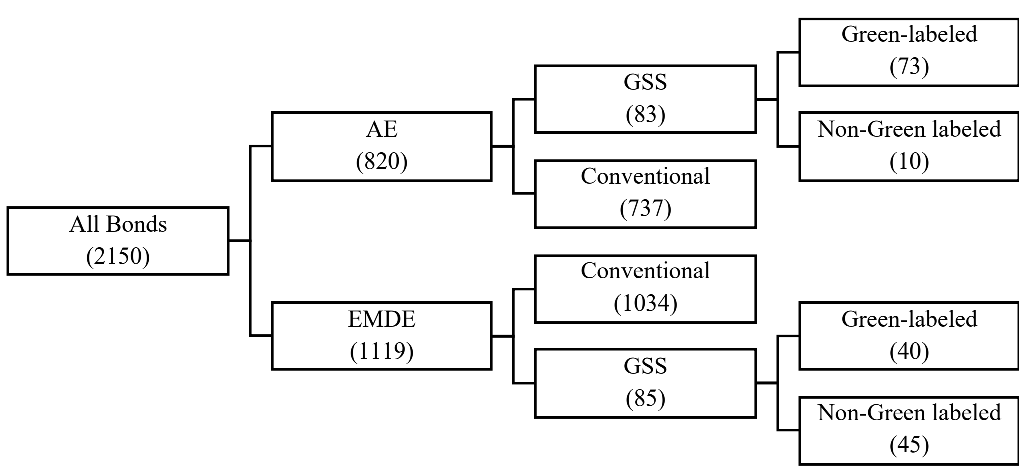

*Figure 1.4: Representation of the amount issued (in USD) through sovereign green bonds by country.*

I created the dataset by first extracting the entire sample of 171 sovereign GSS bonds indexed by Bloomberg as of December 31, 2023, using a 'Green/Sustainability' filter on the 'Use of Proceeds' criteria for bonds classified as sovereign under the Bloomberg Industry Classification Standard (BICS) Level 2. Of these, 113 bonds were identified as green-labeled by complying with the GBP guidelines and third-party verification. Note that all the GSS bonds are issued primarily for projects related to renewable energy deployment or energy efficiency, and no green bonds are outside the GSS category[9]; however, only 65.45% of the GSS bonds, mostly from developed economies, are labeled with green. This indicates that green labeling has substantial administrative and transaction costs, which, to be feasible, must not surpass the benefit from the country's *greenium,* if any. This is because green labeling involves substantial administrative and transaction costs, which must not surpass the benefits from the country's *greenium*, if any. Eleven countries, including Benin, Luxembourg, Mexico, Malaysia, Slovenia, Spain,

[9] See Appendix Table A2 for a detailed description of the use of proceeds and projects for which each GSS bond is issued.

Uzbekistan, Latvia, Peru, the UAE, and Cyprus, have issued only GSS bonds. All other countries have issued a combination of both categories of bonds.

Next, I extracted data for all conventional sovereign bonds (CBs) for those countries that have issued at least one GSS bond. Unlike GSS bonds, 96% of conventional sovereign bond issuances do not explicitly state the purpose of their issuance, highlighting the nonmandatory nature of reporting the use of proceeds. Subsequently, I obtained bond and issuer characteristics, including the currency and country of the issuer, amount issued, coupon rate, maturity, maturity type, seniority, and S&P rating, from Bloomberg. Bonds without information on the coupon rate or maturity date were excluded.[10] Additionally, the maturity type was restricted to "At Maturity" (where bonds are only repaid with interest after the full life cycle and cannot be redeemed by the issuer in between) to avoid the need for option-adjusted spreads (OASs) to account for embedded options (Ivashkovskaya and Mikhaylova, 2020; Nanayakkara and Colombage, 2019). Since only four sovereign green bonds had other options, they were removed from the analysis. The final sample comprises 36,797 unbalanced nested country–bond–quarter panels, with data ranging from January 1, 2017, to December 31, 2023. A visual representation of the data stratification is presented in Figure 1.5.




[10] Fiji and Isle of Man have been excluded from analysis due to lack of availability of credible bond as well as country-level data.

*Figure 1.5: Data stratification according to region, project and bond-labeling.*

I obtained the data for country-specific time-varying macroeconomic control variables from various sources, including the International Financial Statistics (IFS) by the IMF, the Organization for Economic Cooperation and Development (OECD), and the World Bank Open Data (WBOD). Specifically, I obtained real GDP, the consumer price index (CPI), the trade balance, the fiscal deficit, and public debt were extracted from the IFS, and the financial development (FD) index from the IMF. I obtained the real effective exchange rate (REER) from Bruegel[11], which provides the most comprehensive and updated database on exchange rates and includes information for all countries in the dataset. Together, these variables control for internal and external country risk determinants (G. Cheng, Ehlers, and Packer, 2022).

There is considerable observed variability and skewness in the sample groups, particularly between issuing currencies and credit ratings. Figure 1.6 presents an overview of currency composition across the AE and EMDE economies, grouped by green label[12]. Stronger currencies such as the Euro (EUR), U.S. dollar (USD), and Japanese yen (JPY) still dominate both markets, but bonds issued in local currencies are increasingly represented in EMDE countries, especially for nongreen bonds in the South Asian region. Several emerging economies, such as India, Nigeria, and Colombia, have issued sovereign bonds exclusively in local currencies. The literature has established that yields can vary significantly on the basis of the risk perceptions and volatility associated with international versus local currencies, particularly for green bonds (Nanayakkara & Colombage, 2019; Zerbib, 2019). For example, while the average yield at issuance ranges between 1% and 2% for EUR-, USD-, and JPY-denominated bonds, it ranges from 7% to 8% for Indian rupees (INRs) and Indonesian rupiahs and up to 13.5% for Nigerian naira (NGNs), all of which have at least one green-labeled bond issued.

[11] Retrieved from Darvas, Zsolt (2021) 'Timely measurement of real effective exchange rates', Working Paper 2021/15, Bruegel, 23 December 2021. Accessed using: https://www.bruegel.org/sites/default/files/private/wp_attachments/WP-2021-15-231221-1.pdf. Last access: 2 August 2024

[12] GSS bonds not labeled green are combined with conventional in Figure 1.5, as no significant difference is observed across those groups.

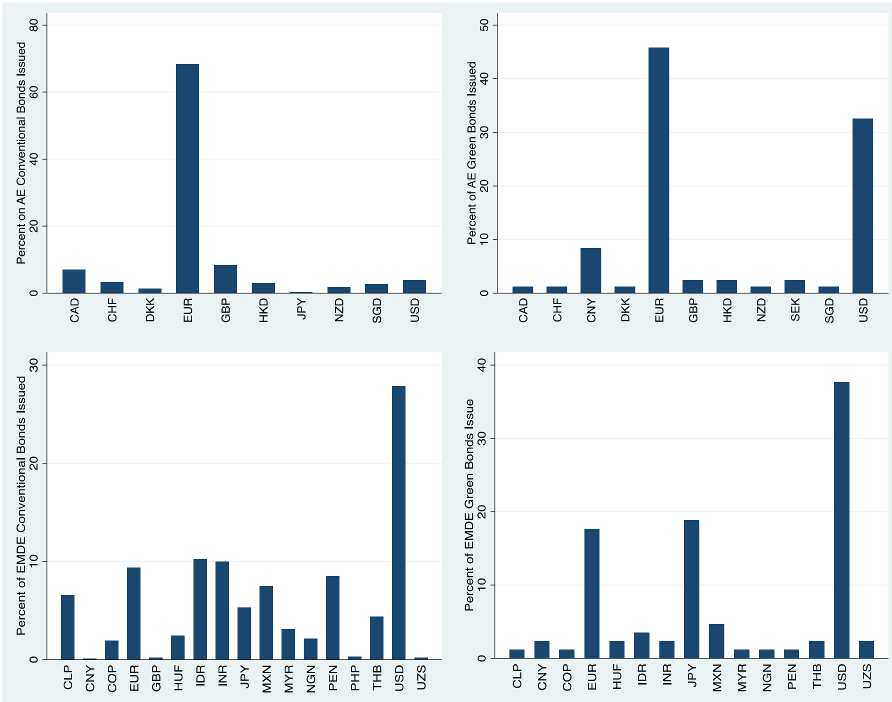



*Figure 1.6: Distribution of sovereign green and conventional bonds by currency, for advanced (AE) and emerging economies (EMDE).*

Figure 1.7 illustrates the Standard & Poor's (S&P) credit rating composition of bonds. Following the S&P credit system, bonds rated AAA-BBB are assigned investment grade, whereas those rated BB-B- and N/A or NR (not rated) are assigned speculative grade. Approximately 95% of bonds from AEs are rated as investment grade, whereas 50--55% for emerging economies (excluding the NR rated). However, the investment grade composition for the latter group increases significantly for both GSS and green-labeled bonds. While only 4.93% of CBs have a high A- rating, 23.53% and 17.95% of GSSs and green bonds, respectively, command the same rating, indicating the possibility of *greenium* stemming from higher credibility assigned to clean energy project-based debts in EMDEs. The observations of the mean coupon rate for each S&P rating category show an upward trend from the investment grade (NR to BBB-) to the speculative grade (BB+ to N/A). The data indicate that a higher credit rating is associated with longer bond maturities, and a larger amount issued generally allows for lower liquidity and coupon rates, which range from 1.45% for investment-grade bonds to 9.125% for speculative-grade bonds.

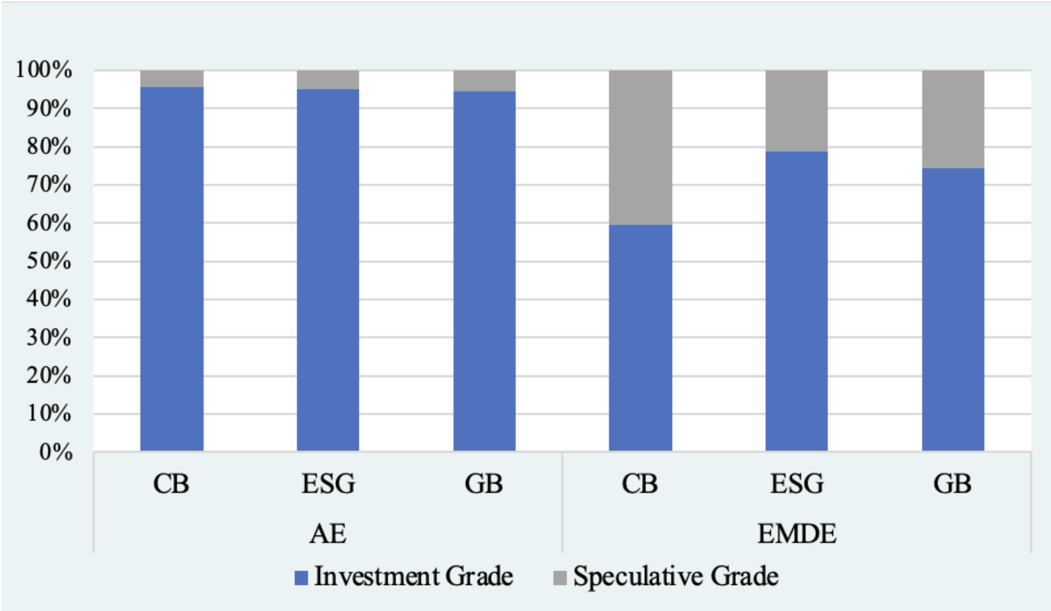



*Figure 1.7: Distribution of bonds conventional (CB), non-labeled ESG (Environmental, Social and Government) bonds and Green Bonds (GB) by credit rating, for advanced (AE) and emerging (EMDE) economies. Following Standard & Poor's credit rating standards, bonds rated between AAA and BBB- are assigned to the investment grade bond group, whereas bonds rated between BB+ to B- and N/A or NR (not rated) are assigned to the speculative grade bond group.*

Table 1.1 presents the statistics for the main bond identifications, including the coupon rate, maturity, and amount issued, highlighting structural differences across bond tranches and country groups. EMDE conventional bonds have the highest interest rates, which gradually decrease for GSS and green-labeled bonds. AE-issued bonds still have lower rates, indicating skewed risk perceptions toward financially developed economies, but rates increase slightly with the greenness of the bonds. In the case of both bond maturity and amount issued, higher values signify greater exposure to volatility and illiquidity and are generally associated with higher interest rates to compensate for expected future risks. Since AEs benefit from country-risk hedging, they can issue higher amounts and longer-maturity bonds at comparatively lower interest rates (Gopinath et al., n.d.).

*Table 1.1. Summary statistics*

| | All countries | | | Advanced economies | | | Emerging and developing economies | | |
|---|---|---|---|---|---|---|---|---|---|
| | Conventional bond | GSS Bonds (unlabeled) | Green bonds | Conventional bond | GSS Bonds (unlabeled) | Green bonds | Conventional bond | GSS Bonds (unlabeled) | Green bonds |
| *Coupon Rate (%)* | | | | | | | | | |
| Mean | 4.23 | 3.29 | 2.81 | 2.12 | 2.38 | 2.36 | 5.74 | 4.17 | 3.65 |
| SD | 3.21 | 2.73 | 2.21 | 1.80 | 1.72 | 1.60 | 3.14 | 3.22 | 2.87 |
| Min | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.73 | 0.73 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Max | 16.29 | 14.50 | 14.50 | 9.41 | 6.50 | 5.25 | 16.29 | 14.50 | 14.50 |
| *Maturity (years)* | | | | | | | | | |
| Mean | 16.18 | 12.29 | 11.36 | 16.84 | 11.39 | 11.72 | 15.71 | 13.17 | 10.68 |
| SD | 12.32 | 9.63 | 9.26 | 13.21 | 9.23 | 9.77 | 11.63 | 9.99 | 8.29 |
| Min | 0.50 | 0.25 | 0.25 | 0.50 | 0.25 | 0.25 | 0.50 | 1.75 | 2.00 |
| Max | 100.75 | 50.25 | 50.00 | 100.00 | 50.00 | 50.00 | 100.75 | 50.25 | 30.75 |
| *Amount Issued (USD millions)* | | | | | | | | | |
| Mean | 9340 | 2580 | 3290 | 17900 | 4160 | 4600 | 3330 | 1050 | 877 |
| SD | 12900 | 4960 | 5900 | 15800 | 6650 | 6980 | 4490 | 1050 | 647 |
| Min | 0 | 22.20 | 38.60 | 44.10 | 81.50 | 81.50 | 0 | 22.20 | 38.60 |
| Max | 87200 | 35400 | 35400 | 87200 | 35400 | 35400 | 26600 | 6780 | 2500 |

Note: ‘Green, social and sustainability bonds’ is abbreviated as ‘GSS’.

# 1.5. Methods

## 1.5.1. Correcting for Selection Bias

The data description indicates a statistical imbalance between the treatment and control groups for the country-level and bond-level analyses. Without a matching technique amount, the maturity, currency and credit rating of a bond might drive the assignment of the label, region and yield. As a result, selection bias hinders causal inference (Löffler et al., 2021). To resolve this concern, I applied a matching method to achieve comparability across three categories: AE-EMDE, green-labeled versus non-green-labeled and GSS versus non-GSS.

### 1.5.1.1. Propensity Score Matching

In previous studies that assess green bond market performance, various matching approaches have been utilized to compare pairs of securities that are similar across all attributes, except for one differing characteristic targeted for the analysis (Gianfrate and Peri 2019; Löffler, Petreski, and Stephan 2021; Zerbib 2019). The choice of technique originates from theories of statistical inference working on the axiom that the data are generated by simple random sampling, where each population unit has the same probability of selection (Abadie & Imbens, 2011). The key goal of matching is to prune observations from the data so that the remaining data have a better balance between the treated and control groups. Unfortunately, studies employing some form of approximate matching estimators (e.g., nearest neighbor matching, radius matching, kernel matching, and propensity score matching (PSM)) routinely violate this balancing goal to draw causal inference (S. Iacus et al., 2009), which guarantees a reduction in variance (precision) but not imbalance within groups (comparability).

A correctly specified PSM model can achieve both covariate balance and variance minimization. Table 1.2 presents the results of the logit regression used to estimate a PSM variation. The following control variables are employed: the coupon rate, the log of the amount issued, the maturity of the bond, the currency, the credit rating, the country of issue, and the quarter of the year under analysis. To avoid multicollinearity issues with the country variable, currency is divided into 2 groups: domestic and international. Credit ratings are also stratified into two groups: investment-grade bonds and speculative-grade bonds. The estimated coefficients for the quarter dummy variables indicate an increasing likelihood of green bond issuance over time relative to the base period of 2017Q1. The probability of issuing green bonds in international currencies and with investment-grade ratings is significantly greater. Furthermore, the results demonstrate that, compared with conventional bonds, green bonds tend to have significantly lower coupon rates and issuance amounts.

PSM, however, has two major drawbacks in the context of this study. It relies on estimating a propensity score through a regression model to restrict the data to a region of common empirical support. In cases with high-dimensional data or closely related variables such as currency, ratings or countries, collinearity issues that necessitate broader, less precise stratifications are faced. It also lacks the flexibility of defining acceptable thresholds or meaningful data bins for covariate balance, which might lead to a noncomparable control bond group, even with low imbalance and variance. For example, when comparing sovereign bonds, exact matching is required for variables such as country, as even small differences could introduce significant bias. In contrast, other variables, such as the coupon rate, could be allowed to vary within an acceptable range according to the financial literature, ensuring that comparability is maintained without over restricting the sample.

*Table 1.2. Logit estimation of green bonds (treatment=1). Estimated coefficients of selected variables.*

| | Green Bond=1 | SD |
|---|---|---|

| | | |
|---|---|---|
| Constant | 2.043 | (1.261) |
| Coupon | -0.310*** | (0.0315) |
| Log of Amount Issued | -0.331*** | (0.0279) |
| Maturity | -0.00451 | (0.00441) |
| Domestic currency [a] | -4.952*** | (0.293) |
| Investment grade [b] | 5.045*** | (0.432) |
| 2017Q2 [c] | -0.0272 | (1.456) |
| 2017Q3 | -0.0543 | (1.455) |
| 2017Q4 | -0.0808 | (1.454) |
| 2018Q1 | 1.001 | (1.193) |
| 2018Q2 | 1.281 | (1.155) |
| 2018Q3 | 1.237 | (1.155) |
| 2018Q4 | 1.472 | (1.131) |
| 2019Q1 | 1.990* | (1.088) |
| 2019Q2 | 2.276** | (1.071) |
| 2019Q3 | 2.251** | (1.071) |
| 2019Q4 | 2.227** | (1.071) |
| 2020Q1 | 2.319** | (1.066) |
| 2020Q2 | 2.338** | (1.060) |
| 2020Q3 | 2.395** | (1.057) |
| 2020Q4 | 2.495** | (1.054) |
| 2021Q1 | 2.549** | (1.051) |
| 2021Q2 | 2.600** | (1.048) |
| 2021Q3 | 2.668** | (1.046) |
| 2021Q4 | 2.747*** | (1.045) |
| 2022Q1 | 2.848*** | (1.043) |
| 2022Q2 | 2.892*** | (1.042) |
| 2022Q3 | 2.970*** | (1.041) |
| 2022Q4 | 3.036*** | (1.041) |
| 2023Q1 | 3.150*** | (1.039) |
| 2023Q2 | 3.280*** | (1.038) |
| 2023Q3 | 3.276*** | (1.038) |
| 2023Q4 | 3.285*** | (1.038) |
| Pseudo $R^2$ | 0.3604 | |
| LR Chi-squared | 2979.84*** | |
| N | 25,310 | |

Note: ∗∗∗Significant at $p < 0.01$, ∗∗Significant at $p < 0.05$, ∗Significant at $p < 0.1$. Country as a categorical variable is included but not reported. [a] Reference category is international currency. [b] Reference category is speculative grade bond. [c] Reference category is 2017 Q1.

### 1.5.1.2. Coarsened Exact Matching (CEM)

In this study, I use the CEM, a comparatively less explored matching technique devised by Iacus, King, and Porro (2012). The CEM automates the manual method of matching formulated by Zerbib (2019), with the distinction that it is able to choose any n-number of units from the control group in defined proximity to the treatment unit analyzed. The CEM is a type of matching method known as monotonic imbalance bounding (MIB), which allows bounding of the higher level of imbalance in some characteristics of the distribution through an *ex-ante* choice (coarsening, in the case of CEM). In simpler terms, the level of imbalance is chosen *ex ante* by the user based on specific and substantive information about the data, and the MIB algorithm ensures that the imbalance is not larger than the data stratum defined. Any observation that does not match the stratum is therefore eliminated. Being regression model-free, it also allows the flexibility of using high-dimensional data and makes it suitable for use with proportionately very large control groups (Bertoni et al. 2020; S. M. Iacus, King, and Porro 2012).

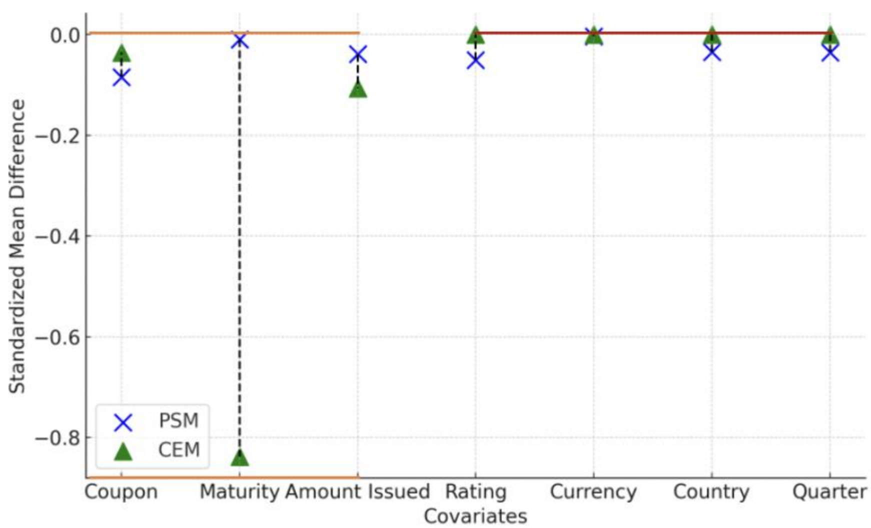



*Figure 1.8: Comparison of standardized mean differences between matched control variables through Coarsened Exact Matching (CEM) and Propensity Score Matching (PSM). The imbalance acceptance threshold for the coupon, maturity and amount issued is specified as 0--1 (orange line), and that for the rest of the variables.*

A comparison between standardized mean differences of covariates of matched data through PSM and CEM is presented in Figure 1.8. While PSM can achieve a greater balance for some variables, such as the amount issued, especially maturity, it maintains slight variability in the categorical variables of currency, country and quarter, which results in noncomparability. The CEM, on the other hand, achieves exact matching in categorical variables. Stratification can be performed to reduce imbalance further in continuous variables.

I follow the steps outlined by Blackwell et al. (2009) to perform CEM on the curated dataset[13]. First, I check the imbalance factor, given by the L1 global or multivariate imbalance distance between the treatment and control groups based on the variables to be matched. This can be interpreted through a similar reasoning strand used for R-squared estimates of any regression, i.e., the relative reduction in L1 distance matters more than absolute values. Larger values up to a maximum of 1 would indicate a larger imbalance between the groups, and perfect global balance would be indicated by $L1 = 0$. Next, stratified bins are temporarily defined to set the imbalance limit. Since CEM provides the option of both automated and manual setting of strata within the same algorithm, matching is designed according to established financial literature:

For the EMDE country group as a treatment, I performed exact matching on the currency, quarter, and green labels. Credit ratings are classified into investment groups and speculative groups to increase the number of matched units. The maturity dates are divided into 5 groups from very short (less than 1 year) to very long (over 20 years) periods. The coupon rate is allowed to be automatically stratified, which results in +/- 0.5 coarsening. For a green labeled bond as a treatment, exact matching is performed on the currency, rating, quarter and country ticker[14] of a bond and is divided as above for the maturity date. The coupon rate is allowed to be automatically stratified, which results in +/- 0.5 coarsening. For bonds with GSS use of proceeds as treatment, I follow a similar procedure as that of the green label.

No matched bond's issue date has a gap of more than 6 years. All bonds under consideration are "At Maturity" and "Senior Unsecured" (repaid as priority in case of default)[15]. After matching, the L1 distance is reduced to below 0.4 for all categories[16]. The matching results for the green bond treatment

[13] CEM is done using the Stata package cem designed by (Blackwell et al. 2010).
[14] Same country can have sovereign bonds being traded under separate tickers based on bond characteristics. For example, German DBR bonds have longer-term maturity and considered equivalent to 10-year US Treasury bonds. German OBL bonds have shorter-term maturities and higher yields. Both differ greatly in their market demand and supply.
[15] Should not be confused with 'unsecured' corporate bonds, which are not backed by collaterals. Sovereigns are mostly unsecured and issued under country's good faith.
[16] See Appendix for other matching results.

group are presented in Table 1.3. Note that the mean difference is zero to negligible for all covariates. For country group and use of proceeds stratifications, refer to the Appendix A.

*Table 1.3. Matching summary. Treatment: Green label.*

Number of strata: 18927

Number of matched strata: 458

| | 0 | 1 |
|---|---|---|
| All bonds | 35799 | 998 |
| Matched | 1452 | 523 |
| Unmatched | 34347 | 475 |

Multivariate L1 distance: 0.38869765

Univariate distance:

| | L1 | mean | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|
| Ticker | 0.00 | 0.00 | 0 | 0 | 0 | 0 | 0 |
| Currency | 0.00 | 0.00 | 0 | 0 | 0 | 0 | 0 |
| Quarter | 0.00 | 0.00 | 0 | 0 | 0 | 0 | 0 |
| Credit Rating | 0.00 | 0.00 | 0 | 0 | 0 | 0 | 0 |
| Coupon rate | 0.21 | 0.05 | 0 | 0.17 | 0.125 | -0.25 | -0.5 |
| Maturity (stratified) | 0.00 | 0.00 | 0 | 0 | 0 | 0 | 0 |

For each matched unit, CEM generates "importance" weights (weights assigned to normalize the variance of strata within the treatment and control groups), which can be used to estimate sample average treatment effects on the treated (SATT) via regular regression methods. All unmatched units are assigned a 0 (automatically eliminated if CEM weights are used). Each matched treatment and control member is assigned a value anywhere between >0 & ≤1 or ≥1 in accordance with equation 1.2:

$$iWeight = \frac{\frac{Number\ of\ Treated\ Matched\ within\ strata}{Number\ of\ Controls\ matched\ within\ strata}}{\frac{Total\ controls\ matched}{Total\ treatments\ matched}} \quad (1.2)$$

### 1.5.2. Empirical Model

The three hypotheses developed from the background and literature review (see Section 1.3) aim to test whether green labeling significantly mitigates risk for sovereign climate bonds, especially in the case of EMDEs, and whether it leads to a significant reduction in the cost of capital inequality between AEs and EMDEs. Based on these hypotheses, I employ a two-way fixed-effects model to examine both between-and within-group differences in the yield premium of green bonds compared with that of conventional sovereign bonds. Specifically, the CEM-weighted ordinary least squares (WLS) model is formulated according to equation 1.3:

$$Yield_{jit} = \beta_0 + \beta_1 Treatment_i + \beta_2 ttm_{jit} + \beta_3 bidask_{jit} + +\beta_4 Amt_{jit} + c_j + \mu_t + \epsilon_{jit} \qquad (1.3)$$

The dependent variable is the quarterly ask yield-to-maturity ($Yield_{jit}$) of bond *j* of country *i* at quarter *t*. The ask yield is chosen because it represents the lowest price asked by the seller, providing the most conservative and realistic yield estimate, commonly used in the fixed-income literature (Baker et al. 2022; Fatica, Panzica, and Rancan 2021; Löffler, Petreski, and Stephan 2021; Zerbib 2019).

The variable of interest is $Treatment_i$, a binary variable representing the groups under consideration. For Hypothesis *H1*, $Treatment_i$ is 1 for the EMDEs and 0 for the AEs. If $\beta_1 > 0$ and is significant, it suggests that bonds in emerging markets are costlier due to higher yields over time. The regression is first run on the entire dataset and then stratified by green-labeled and conventional bonds.

Hypothesis *H2* tests the existence of *greenium*. Here, the variable of interest is the binary green-bond classification ($Treatment_i$), where green-labeled bonds are assigned a value of 1 and the others are assigned a value of 0. If $\beta_1 < 0$ is significant, it indicates the presence of greenium due to lower yields over time. This regression is initially run across all countries and then run separately for EMDEs and AEs to account for regional differences.

Hypothesis *H3* examines the risk-mitigating effect of the green label in line with GBP. The sample is restricted to conventional bonds only. The variable of interest is the binary project classification ($Treatment_i$) where bonds earmarked for green and sustainability projects but not labeled green are given a value of 1, and other bonds for corporate or nonreported purposes are assigned 0. If $\beta_1 = 0$, it suggests that GSS-purpose bonds not labeled green are not differentiated from conventional bonds by investors.

In fixed-income securities theory, substantial differences in liquidity can significantly affect yield levels and must be controlled ( Dick-Nielsen, Gyntelberg, and Lund, n.d.; Jong and Driessen 2012; Zerbib 2019). This study controls for liquidity via three variables:

i. **Bid-ask spread ($\mathbf{bidask}_{jit}$):** The difference between the highest bid price and the lowest ask price, controlling for the liquidity premium in the secondary bond market. Typically, assets with narrow bid-ask spreads have high demand (Zerbib, 2019).

ii. **Tenor or term-to-maturity ($\mathbf{ttm}_{jit}$):** The time remaining before the bond matures, controlling for the maturity risk premium. It is inversely proportional to the bond yield, compensating for increasing risk over time (Buse, 1970).

iii. **Amount issued ($\mathbf{Amt}_{jit}$):** The amount issued by the bond, inversely proportional to yield and normalized via the natural logarithm of the variable.

All other bond characteristics are controlled through matching. Table 1.4 presents summary statistics for the dependent and time-varying control variables (refer to Table 1.1 for other variables), where $c_j$ denotes the time-invariant country fixed effects, $\mu_t$ accounts for the country-invariant time fixed effects and $\epsilon_{jit}$ is the idiosyncratic error term.

*Table 1.4. Summary statistics for time-varying variables*

| Variable | Observations | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Ask Yield (%) | 36,797 | 3.506 | 3.037 | -6.735 | 22.506 |
| Bid-Ask Spread | 36,785 | 0.087 | 0.354 | -0.444 | 20.968 |
| TTM (quarters) | 36,797 | 52.718 | 45.450 | 0 | 403 |

Note: 'Time-to-maturity' is abbreviated as 'TTM'.

To test for time-varying country-risk factors, I run the specification given in equation 1.4:

$$Yield_{jit} = \beta_0 + \beta_1 Treatment_i + \beta_2 ttm_{jit} + \beta_3 bidask_{jit} + \beta_4 Amt_{jit} + \beta_5 risk_{jit} + c_j + \mu_t + \epsilon_{jit} \quad (1.4)$$

$risk_{jit}$ is a vector of economic determinants of bond *j* of country *i* at time *t* commonly used in the literature. It includes GDP growth, inflation, the fiscal deficit as a share of GDP, the current account balance as a percentage of GDP, and the real effective exchange rate (REER). The fixed-income securities literature shows that the effect of macroeconomic factors on bond yields can be explained by economic growth, price dynamics, fiscal health, debt sustainability, and terms of trade volatility indicators (Afonso and Nunes 2015; Poghosyan 2014; Zhou 2021). Damodaran (2012) suggest using market risk measures such as the yield of a sovereign bond itself (or its spread over U.S. Treasury Bonds) to control for the country risk premium. However, this study aims to measure the relative gap between sovereign bond yields rather than the absolute risk associated with each country. Moreover, each period's global market risk is controlled by time fixed effects. A comprehensive description of the variables with their respective expected signs in the regression is given in the appendix (see Appendix A).

Multicollinearity in the model decreases the precision of the coefficient estimates, making it difficult to determine which variables are statistically significant. Accordingly, I test for multicollinearity among the independent variables in the model by calculating the variance inflation factor (VIF), which identifies the correlation and the strength of that correlation between variables. The VIF of the independent variables is kept under 10[17] for all specifications.

## 1.6. Results

### 1.6.1. Main Results

The empirical results for all specifications in Tables 1.6-1.8 indicate that bond yields are significantly affected by regionality, labeling, and the underlying clean-energy investment. However, a limitation of using CEM is that it leads to the exclusion of several bonds where a suitable counterfactual was not found. This raises the concern that the results could be driven solely by data points selected through matching. To address this, I conducted a two-way ANOVA test on the unmatched sample to assess the significance of yield differences across groups. The results, presented in Table 1.5, show that the interaction term for green-labeled bonds and emerging

[17] Multicollinearity is not a problem in estimating the model if VIF of the variables in the model are below 10 (Gujarati, 2021).

*Table 1.5. Two-way ANOVA Test.*

| Number of observations =36797 R-squared=0.3265<br>Root MSE = 2.49302 Adj R-squared =0.3265 | | | | | |
|---|---|---|---|---|---|
| | Partial SS | df | MS | F | Prob>F |
| Model | 110873.22 | 3 | 36957.74 | 5946.41 | 0.0000 |
| GB | 18.27 | 1 | 18.27 | 2.94 | 0.0864 |
| EMDE | 5467.71 | 1 | 5467.71 | 879.74 | 0.0000 |
| GB#EMDE | 1235.69 | 1 | 1235.69 | 198.82 | 0.0000 |
| R-square | 0.3265 | | | | |
| Adj R-squared | 0.3265 | | | | |
| Root MSE | 2.4930 | | | | |
| N | 36797 | | | | |

Note: 'Green Bonds' is abbreviated as 'GB', and 'Emerging and Developing Economies' is abbreviated as 'EMDE'.

***Hypothesis H1: Regional differences in the cost of green debt***

Table 1.6 displays the results for the regional difference in the cost of capital[18]. The results show that the cost of green capital is significantly greater for emerging economies than for the developed. Models (1)-(3) indicate that for investment-grade bonds, the ask yield is 57.4 basis points (bps) greater for EMDEs for all bonds, 58.9 bps greater for conventional bonds, and 57.2 bps greater for green bonds, all of which are significant at the 1% level. Green labeling reduces this difference by 1.7 bps. Models (4)-(6) demonstrate that for speculative-grade bonds, which include the majority of EMDE bonds issued, green labeling reduces the yield by 184.3 bps. The ask yield is higher by 481.5 bps for all EMDE bonds, 485.2 bps for conventional bonds, and 300.9 bps for green bonds, all of which are significant at the 1% level.

The liquidity control measures have consistently significant effects and strong explanatory power. Tighter bid-ask spreads, larger bond sizes, and longer maturities are associated with higher yields to compensate investors for the inherent risk of low liquidity. This effect is more pronounced for speculative-grade bonds, which is consistent with previous findings (Löffler, Petreski, and Stephan 2021; Zerbib 2019).

*Table 1.6. Average Treatment Effect of the Treated (EMDE=1) estimated on the ask yield of bonds grouped according to green-labeling and credit rating.*

| Variables | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 |
|---|---|---|---|---|---|---|
| EMDE [a] | 0.574*** | 0.589*** | 0.572*** | 4.815*** | 4.852*** | 3.009*** |
| | (0.0437) | (0.0440) | (0.195) | (0.0791) | (0.0808) | (0.167) |

[18] Macroeconomic risk factors are removed from this specification due to issues of multicollinearity. Inclusion of variables could reduce the magnitude of sovereign bond yield difference as it is itself explained by the macroeconomic factors. Lower GDP and real effective exchange rate, and higher fiscal deficit, inflation and current account deficit, translates into higher country risk for EMDEs. However, the relative difference between conventional and green bonds would remain significant.

| | | | | | | |
|---|---|---|---|---|---|---|
| Term To Maturity | 0.0136*** | 0.0135*** | 0.00891*** | 0.0292*** | 0.0297*** | 0.0196*** |
| | (0.000350) | (0.000350) | (0.00195) | (0.00110) | (0.00113) | (0.00203) |
| Bid-Ask Spread | -2.256*** | -2.224*** | 0.166 | -2.761*** | -2.712*** | -4.094*** |
| | (0.270) | (0.273) | (0.797) | (0.175) | (0.177) | (0.664) |
| Log (Amt Issued) | -0.0377** | -0.0321** | 0.0510 | -0.0125 | -0.00180 | 0.134*** |
| | (0.0158) | (0.0159) | (0.0783) | (0.0184) | (0.0189) | (0.0454) |
| Constant | 2.756*** | 2.645*** | -0.926 | -2.072*** | -2.364*** | -3.273*** |
| | (0.349) | (0.351) | (1.789) | (0.693) | (0.706) | (1.137) |
| Time FE | YES | YES | YES | YES | YES | YES |
| Observations | 3,908 | 3,823 | 85 | 5,198 | 5,010 | 188 |
| R-squared | 0.663 | 0.664 | 0.960 | 0.612 | 0.612 | 0.905 |

Note: ∗∗∗Significant at $p < 0.01$, ∗∗Significant at $p < 0.05$, ∗Significant at $p < 0.1$. Standard deviation in parenthesis. Ask yield is truncated at 2.5% and 97.5% to reduce the influence of outliers. Here, EMDE refers to Emerging and Developing Economies. [a] Reference category is advanced economies (AE). Model 1 estimates the association between weighted ask yield and a country's development group for all investment-grade bonds in the sample. Model 2 restricts the sample to investment-grade conventional bonds, and Model 3 tests for only investment-grade green bonds. Models 4-6 follow the same order but for speculative-grade bonds.

***Hypothesis H2: Estimating greenium across regions***

Table 1.7 presents the results for Hypothesis *H2*, which estimates *greenium* across regions. Model (1) shows a small *greenium* of -5.14 bps for all countries combined, which is not significant at the 10% level. Model (2) shows a small *positive* green bond premium of 5.81 bps for AEs, which is also not significant at the 10% level, and Model (3) shows a *greenium* of -17.3 bps for EMDEs, which is significant at the 1% level. However, these models do not control for country risk characteristics, which may introduce omitted variable bias. Models (4)-(6), which include country risk measures, yield significant results at the 1–5% level. Model (4) indicates a *positive* premium of 12.9 bps for green bonds for all countries, Model (5) shows a *positive* premium of 42.5 bps for AEs, and Model (6) reveals a *greenium* of -10.4 bps for EMDEs.

*Table 1.7. Average Treatment Effect of the Treated (Green Bond=1) estimated on the ask yield of bonds grouped according to development-level.*

| Variables | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 |
|---|---|---|---|---|---|---|
| Green Bond [a] | -0.0514 | 0.0581 | -0.178** | 0.129*** | 0.425*** | -0.104** |
| | (0.0494) | (0.0362) | (0.0833) | (0.0346) | (0.0413) | (0.0467) |
| Term To Maturity | 0.0110*** | 0.00243*** | 0.0219*** | 0.0104*** | 0.00316*** | 0.0156*** |
| | (0.000727) | (0.000587) | (0.00117) | (0.000482) | (0.000574) | (0.000674) |
| Bid-Ask Spread | -1.783*** | 0.208 | -9.690*** | -1.110*** | -0.989*** | -2.604*** |
| | (0.245) | (0.147) | (0.629) | (0.256) | (0.237) | (0.492) |
| Log (Amt Issued) | 0.832*** | 0.523*** | 0.868*** | 0.415*** | 0.559*** | 0.409*** |
| | (.02873) | (.03166) | (.04138) | (0.0295) | (0.0365) | (0.0389) |
| GDP % growth | - | - | - | -0.582 | -0.191 | -0.152 |
| | - | - | - | (0.370) | (0.503) | (0.534) |

| | | | | | | |
|---|---|---|---|---|---|---|
| CAD (%GDP) | - | - | - | 0.0603*** | 0.0371*** | 0.110*** |
| | - | - | - | (0.00874) | (0.00950) | (0.0153) |
| CPI | - | - | - | 0.00297 | 0.00353 | 0.0759*** |
| | - | - | - | (0.00401) | (0.00368) | (0.0150) |
| Constant | 0.950* | 1.624*** | 1.483** | -9.123*** | -11.85*** | -6.172*** |
| | (0.523) | (0.280) | (0.592) | (0.717) | (0.865) | (0.906) |
| Time FE | YES | YES | YES | YES | YES | YES |
| Country FE | YES | YES | YES | YES | YES | YES |
| Observations | 1,975 | 1,038 | 936 | 1,401 | 747 | 653 |
| R-squared | 0.846 | 0.897 | 0.852 | 0.940 | 0.930 | 0.958 |

Note: ∗∗∗Significant at $p < 0.01$, ∗∗Significant at $p < 0.05$, ∗Significant at $p < 0.1$. Standard deviation in parenthesis. Ask yield is truncated at 2.5% and 97.5% to reduce the influence of outliers. [a] Reference category is non-labeled conventional bond. Model 1 estimates the association between weighted ask yield and the green label for all countries in the sample without controlling for time-varying macroeconomic risk factors. Model 2 restricts the sample to AE economies, and Model 3 tests for EMDEs. Models 4-6 follow the same order but with risk factor controls.

Coefficients of liquidity measures are more pronounced in emerging markets, particularly the bid-ask spread, indicating greater volatility. The explanatory power of macroeconomic factors is supported by the increasing R-squared trend from Model (1) to Model (6). Lower GDP growth rates (and higher inflation) are associated with lower yields, reflecting compensation for country risk, although the effects are not significant. A higher current account deficit significantly increases yields, especially for EMDEs, by 11 bps. Robustness checks using CEM k2k matched weights confirm the *greenium* results (see Appendix A).

***Hypothesis H3: Differences in yields between non-labeled GSS bonds and conventional bonds***

Table 1.8 presents the results for Hypothesis *H3*, which examines yield differences between non-labeled GSS bonds and conventional bonds. This specification excludes green-labeled bonds and considers only sovereign GSS bonds and their conventional counterparts. Model (1) shows a *positive* premium of 29.7 bps for GSS bonds across all countries, which is significant at the 1% level. Model (2) shows a small negative premium of -2.91 bps for AE GSS bonds, which is not significant at the 10% level. Model (3) shows a *positive* premium of 27.3 bps for EMDE GSS bonds, which is significant at the 1% level, indicating that GSS bonds that are not labeled green are costlier for emerging markets than conventional bonds are. This finding deviates from the corporate bond literature, which finds slightly lower pricing for GSS-rated bonds (Grishunin et al., 2023; Immel et al., 2021).

*Table 1.8. Average Treatment Effect of the Treated (GSS=1) estimated on the ask yield of bonds.*

| Variables | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| GSS [a] | 0.297*** | -0.0291 | 0.273*** |
| | (0.0587) | (0.0665) | (0.0672) |
| Term To Maturity | 0.00781*** | 0.0172*** | 0.00758*** |
| | (0.000818) | (0.00343) | (0.000858) |
| Bid-Ask Spread | 2.076*** | -0.107 | 2.055*** |
| | (0.532) | (0.522) | (0.608) |
| Log (Amt Issued) | 0.676*** | -0.0754 | 0.672*** |
| | (0.0364) | (0.0735) | (0.0387) |
| GDP % growth | -0.993 | 0.395 | -1.606 |
| | (0.823) | (0.633) | (1.073) |
| Constant | -12.33*** | 0.731 | -11.91*** |
| | (0.823) | (1.549) | (0.896) |
| Time FE | YES | YES | YES |
| Country FE | YES | YES | YES |
| Observations | 538 | 98 | 439 |
| R-squared | 0.881 | 0.985 | 0.858 |

Note: ∗∗∗Significant at $p < 0.01$, ∗∗Significant at $p < 0.05$, ∗Significant at $p < 0.1$. Standard deviation in parenthesis. Ask yield is truncated at 2.5% and 97.5% to reduce the influence of outliers. Here, GSS stands for non-labeled Green, Social and Sustainability Bonds. [b] Reference category is non-labeled conventional bond. Model 1 estimates the association between weighted ask yield and the GSS mark for all countries in the sample. Model 2 restricts the sample to AE economies, and Model 3 tests for EMDEs.

### 1.6.2. Time Trends

The sample period from Q1 2017 to Q4 2023 can be divided into three phases: pre-COVID-19 (Q1 2017--Q4 2018), COVID-19 (Q2 2019--Q4 2021), and post-COVID-19 (Q1 2022--Q4 2023), coinciding with the Ukraine War era. Figure 1.9 illustrates the mean yields of sovereign green bonds and matched conventional bonds for AEs and EMDEs across these three phases. Over the period, the average yield for green bonds is slightly higher than that for conventional bonds in AEs, which is consistent with the results in Table 1.7. However, this gap decreases over time. For EMDEs, the average yield for conventional bonds is marginally greater than that for green bonds, with *greenium* peaking during the COVID-19 pandemic. The Kruskal–Wallis's equality-of-populations rank test, performed for green bonds and nongreen bonds separately, rejects the null hypothesis that the three phases have similar yields (see Appendix A) indicating significant time trends.

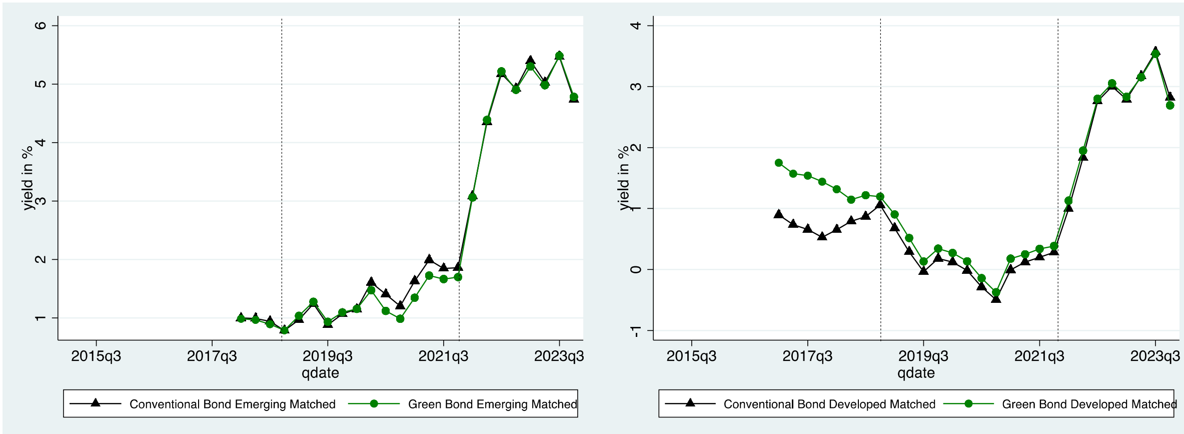



*Figure 1.9: Quarterly mean yield of sovereign green (green circles) and matched sovereign conventional (black triangles) bonds for emerging (left graph) and developed (right graph) economies. The vertical dotted lines mark different phases of the sample period. There is no visual evidence of greenium (green line lies above black line) for developed economies. For emerging economies, after 2018 Q4 (left vertical line) and before 2022 Q1 (right vertical line), a clear greenium exists.*

A two-way fixed effects model, using equation 1.5, is then applied to the matched dataset, with the periods as categorical variables instead of time fixed effects. The weighted regression results in Table 1.9 show a decreasing positive green bond premium for AEs over the three phases, although the decrease is not significant at the 10% level. For EMDEs, holding all else constant, the *greenium* is -27.2 bps greater (negative) in period 2 than in period 1, which is significant at the 10% level. The time differences for periods 1 and 3 are not significant. These results align with time trend studies of green bonds, demonstrating that green bonds are more resilient during volatile periods (e.g., COVID-19), with an average (negative) increase in *greenium* (Arat et al., 2023).

*Table 1.9: Average Treatment Effect of the Treated (Green Bond=1) estimated on the ask yield of bonds over three time periods.*

| Variables | Model (1) | Model (2) | Model (3) |
|---|---|---|---|
| Time to maturity | 0.0135*** | 0.00302*** | 0.0224*** |
| | (0.000691) | (0.000622) | (0.00105) |
| Bid-ask spread | 2.967*** | 0.976*** | 6.997*** |
| | (0.366) | (0.324) | (0.705) |
| Log (Amount Issued) | 0.830*** | 0.541*** | 0.962*** |
| | (0.0367) | (0.0400) | (0.0512) |

| | | | |
|---|---|---|---|
| Green Bond [a] | 0.362** | 0.456*** | 0.0819 |
| | (0.147) | (0.115) | (0.242) |
| 2019 Q2-2021 Q4 [b] | -1.285*** | -1.094*** | -1.476*** |
| | (0.0906) | (0.0723) | (0.150) |
| 2022 Q1-2023 Q4 | 0.796*** | 1.097*** | 0.282* |
| | (0.0885) | (0.0681) | (0.149) |
| GB [c] # 2019 Q2-2021 Q4 | -0.218 | -0.0270 | -0.354* |
| | (0.162) | (0.127) | (0.266) |
| GB [c] # 2022 Q1-2023 Q4 | -0.0147 | -0.0638 | 0.0252 |
| | (0.162) | (0.125) | (0.269) |
| GDP Growth (%) | -1.661*** | -1.054*** | -1.779*** |
| | (0.352) | (0.377) | (0.475) |
| Inflation | 0.0433*** | 0.0553*** | 0.0382*** |
| | (0.00859) | (0.00785) | (0.0127) |
| REER | -0.0174*** | -0.00266 | -0.00910 |
| | (0.00631) | (0.00840) | (0.00842) |
| Constant | -16.50*** | -10.95*** | -17.64*** |
| | (1.057) | (1.186) | (1.311) |
| Country FE | YES | YES | YES |
| Observations | 1,487 | 747 | 740 |
| R-squared | 0.890 | 0.915 | 0.895 |

Note: ∗∗∗Significant at $p < 0.01$, ∗∗Significant at $p < 0.05$, ∗Significant at $p < 0.1$. Standard deviation in parenthesis. Ask yield is truncated at 2.5% and 97.5% to reduce the influence of outliers. [a] Reference category is non-labeled conventional bond. [b] Reference category is the 2017 Q1- 2019 Q1 period. GB stands for Green Bonds. [c] Reference category is non-labeled conventional bond. REER is the real effective-exchange rate. Model 1 estimates the association between weighted ask yield and the green label for all countries in the sample. Model 2 restricts the sample to AE economies, and Model 3 tests for EMDEs.

### 1.6.3. Country Risk and Sovereign *Greenium*

The results from Table 6 and Table 7 suggest an intriguing positive relationship between the average green bond yield premia and conventional bond yield for all countries, implying a possible direct relationship between *greenium* and country risk. To test this, I generated a scatter plot, showing the average sovereign *greenium* for each country per quarter on the y-axis and the average sovereign yield as a proxy for the country's risk valuation on the x-axis. Figure 1.10 illustrates a positive correlation between these variables, indicating a direct relationship between a country's cost of debt and average *greenium*.

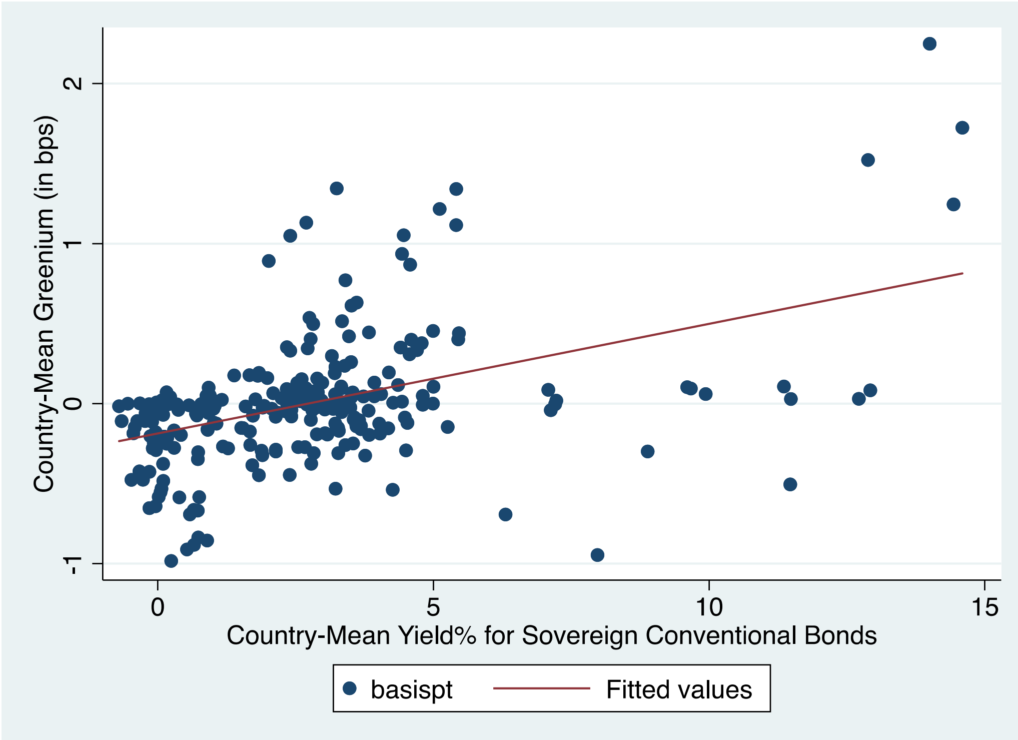



*Figure 1.10: Direct relationship between average greenium yield and average conventional yield.*

For empirical examination, I used a fixed-effects regression model with the average *greenium* of all matched bonds for each country per quarter as the dependent variable and the average sovereign conventional bond yield for each country per quarter as a proxy for the country's cost of debt (Damodaran, 2012). The results of the Fisher-type unit-root test show that the average *greenium* is stationary, and the Hausmann test predicts the suitability of the fixed effects regression model over random effects ($p<0.0005$) (see Appendix A). The Breusch–Pagan test indicates the presence of heteroscedasticity; therefore, robust errors are utilized, and the Wald test for joint significance indicates the use of time fixed effects (see Appendix A). The model is presented in equation 1.5:

$$Greenium_{it} = \beta_0 + \beta_1 Yield_{it} + \beta_2 bidask_{it} + \beta_3 lnamt_{it} + \beta_4 ttm_{it} + \delta_t + \epsilon_{it} \quad (1.5)$$

where $Greenium_{it}$ is the average *greenium* for country *i* for quarter *t*, $\text{Yield}_{it}$ is the average sovereign conventional yield for country *i* for quarter *t*, $bidask_{it}$ is the average bid-ask spread for country *i* for quarter *t*, $lnamt_{it}$ is the log of average amount issued for country *i* for quarter *t*, and $ttm_{it}$ is the average time-to-maturity for country $i$ for quarter $t$. $\delta_t$ represents the time-fixed dummy $\epsilon_{it}$, which are robust standard errors.

The results, shown in Table 1.10, confirm a positive and significant relationship between a country's cost of debt determined by macroeconomic risk factors and average *greenium.* Model (1) shows that for every one-unit increase in average sovereign conventional bond yield, the *greenium* increases by 5 bps, which is significant at the 1% level. Model (2) shows that for every 1 bps increase in average sovereign conventional bond yield, the *greenium* increases by 14.7 bps, which is significant at the 5% level. These results are consistent with those of (Tomczak, 2024), who used a similar model for sovereign green bonds but without a matching technique or triple control for liquidity.

*Table 1.10. Association between country-risk and greenium.*

| Variables | Model (1) | Model (2) |
|---|---|---|
| Conventional Bond Yield | 0.0587*** | 0.147** |
| | (0.0195) | (0.0662) |
| Bid-Ask Spread | -0.584 | 0.148 |
| | (0.439) | (0.263) |
| Log (Amount Issued) | -0.0595** | -0.577** |
| | (0.0265) | (0.258) |
| Time to maturity | -0.00329*** | -0.00652** |
| | (0.000955) | (0.00274) |
| Constant | 1.586*** | 13.90** |
| | (0.589) | (5.986) |
| Time FE | YES | YES |
| Observations | 260 | 260 |
| R-squared | 0.391 | 0.358 |
| Number of panel ID | | 23 |

Note: ***Significant at $p < 0.01$, **Significant at $p < 0.05$, *Significant at $p < 0.1$. Standard deviation in parenthesis. Ask yield is truncated at 2.5% and 97.5% to reduce the influence of outliers. Here, dependent variable is the country-mean *greenium* for each quarter. Conventional bond yield is averaged across each country.

## 1.7. Discussion and Implications

This research provides the first comprehensive global, bond-level study of the causal effects of sovereign green bond issuance on a country's cost of debt associated with green finance. Specifically, it estimates the regional variation in sovereign *greenium* between developmentally segregated economies to assess the viability of sovereign green bonds as risk-mitigating public instruments for climate finance, especially in the case of emerging economies. This study is particularly timely, given the urgent need for direct government participation in green finance (IMF) and the exponential share of sovereign-issued bonds in the green bond market. The findings demonstrate that the green labeling of sovereign GSS bonds has distinct advantages for emerging economies, which is in line with the results of (Xiao, n.d.).

### 1.7.1. Implications for Emerging and Developing Economies

The issuance of sovereign green bonds as benchmark climate securities presents distinct risk-mitigating advantages for emerging economies as a public green finance instrument. Sovereign green bonds can reduce the cost of climate debt in three ways:

First, sovereign green bonds in emerging economies are found to trade at yields approximately 10.4 bps lower than those of their conventional counterparts. This suggests a robust demand, indicative of investor confidence and the potential for future growth despite administrative and transaction costs associated with green labeling. Back-of-the-envelope calculations using IMF[19] cost estimates reveal net benefits for emerging economies even for minimal *greenium*. For a representative USD 750 million, 10-year, 6.125% coupon bond at a yield of 6.17%, the study finds an additional green labeling cost of 266 thousand USD. However, an average 4 bps lower yield after green labeling leads to 1.9 million USD more funds raised by the bond.

Second, the premium of 27.3 bps for unlabeled sustainable bonds over conventional bonds suggests a market preference for transparency provided by green labels. This, coupled with the significant spillover effects of sovereign green reporting on corporate bond information asymmetry reported by Xiao (n.d.) and Oman (n.d.), underscores the need for nationally standardized verification processes.

Third, the study highlights a substantial reduction in yield disparities for speculative-grade bonds. Owing to underdeveloped financial markets, emerging economies generally command low credit ratings (R. Cheng et al., 2023), leading to high country risk premiums. This disadvantage over developed economies

[19] Retrieved from IMF, "Sovereign ESG Bond Issuance, A Guidance Note for Sovereign Debt Managers". https://www.imf.org/en/Publications/WP/Issues/2023/03/11/Sovereign-ESG-Bond-Issuance-A-Guidance-Note-for-Sovereign-Debt-Managers-530638. Last access: 2 August 2024.

is offset by an average of 185 bps for sovereign, green-labeled bonds. Moreover, evidence suggests that demand for emerging economy sovereign green bonds increases during volatile times (e.g., the COVID-19 pandemic). The result is corroborated by similar studies on private bonds that find lower green yields during volatile markets (Arat et al., 2023). Both cross-sectional and time series resilience underscores the strong position of sovereign green bonds during periods of market uncertainty.

To solidify the risk-mitigating nature of green-labeled sovereign bonds, results demonstrate that higher average yields on conventional bonds correspond with greater yield differentials between conventional and green bonds. Specifically, for every 1 basis point increase in conventional bond yields, the yield gap between conventional and green bonds widens by 14.7 basis points. This finding indicates that in riskier countries and during volatile periods, sovereign green bonds attract relatively higher demand. These findings align with those of Tomczak (2024).

However, several concerns regarding sovereign green bonds have emerged. Liquidity analyses reveal that their demand is, on average, volatile, leading to potential price instability. Yields also exhibit greater sensitivity to issuance size and maturity. Furthermore, the lack of financial institutions in developing countries presents a more systematic challenge than do administrative costs or transparency issues (Ameli et al., 2021). Macroeconomic risks, such as high current account deficits and inflation, can exert a relatively strong influence on green bonds. Despite these challenges, the study emphasizes the role of sovereign green bond issuance as *benchmark green securities*, providing a clear signal of a national long-term climate strategy and hence suggesting potential mitigation of country risk associated with climate debt.

### 1.7.2. Implications for Developed Economies

In contrast with other findings on general *greenium* (Ivashkovskaya & Mikhaylova, 2020), this study shows that sovereign green bonds in developed economies, surprisingly, trade at a yield 42.5 bps higher than that of their conventional counterparts. This suggests a higher cost of debt for green-labeled instruments, which could be attributed to the “safe haven effect”.

Advanced economy green bonds sell in competition with their own conventional sovereign bonds, which are widely regarded as risk-free investments. Both sell at low liquidity and low demand volatility. Moreover, no significant price difference is observed between conventional and non-labeled sustainable bonds, indicating that a yield premium is solely explained by the green label. In fact, recent trends reported by Bloomberg News indicate a shift in investor preference toward GSS bonds over green-labeled bonds in the United States. Further analysis is needed to understand these pricing dynamics for developed countries’ sovereign green bonds.

## 1.8. Conclusion

In this study, I estimate the relative cost of green debt for developed and emerging economies using sovereign green bonds as an instrument. This study has significant policy implications for the green labeling of sovereign bonds. By employing a coarsened exact matching technique to create a control group of conventional bonds that are closest possible counterfactuals to each green bond, it provides a comparative analysis of the magnitude and volatility of *greenium* across developed and emerging economies. Notably, this research is the first to estimate yield differences associated with sustainable, non-labeled bonds and to explore the direct relationship between country risk and sovereign *greenium*. The findings clearly demonstrate the risk-mitigating effects of green certification for emerging markets—a benefit that does not extend to advanced economies.

However, the study has certain limitations. It does not delve into other determinants of sovereign *greenium*, such as ratings or currency, as these factors are controlled through matching. Additionally, it does not explore the impact of sovereign green issuance on other sources of public or private finance, corporate bonds, or the effect of bond proceeds on environmental goals. Assessing the exact cost of institutional development for green certification falls beyond the scope of this chapter, making it challenging to determine whether green labeling would be net profitable for each country. However, within a broader context, it is expected to support countries in their path toward a green transition.

As Stern and Stiglitz (2023) argue, even if green instruments are exposed to market fluctuations, *"green transition is coming at a time when, both because of persistent deficiencies of aggregate demand and advances in technology...the macroeconomic opportunity costs of strong climate actions may be especially low and the benefits particularly high."* These conditions suggest that, despite volatility, sovereign *greenium* is likely to remain significant for emerging economies. The sustainable bond market represents just one step in addressing the substantial challenge of green finance. Further research is essential to explore public and private green bond issuance and other aspects of public climate finance that can sustainably support the green transition.

# 2. Breaking News…or Was It? Understanding Stock Market Response to the Inflation Reduction Act

## 2.1. Introduction

The Inflation Reduction Act of 2022 (IRA) remains the largest climate policy action ever undertaken in U.S. history (Bauer et al., n.d.). Contingent on political stability, the IRA was designed to offer significant financial support for the renewable energy industry through tax credits and direct government spending (Bistline et al., 2023a). It also proposed incentives aimed at encouraging U.S. households and businesses to invest in the necessary equipment and capital to lower their carbon emissions. Measured in terms of total fiscal cost, the cumulative budgetary requirement of the climate bill was estimated to reach around $1.2 trillion over the next 10 years (Bistline et al., 2023b). Although, subsequent legislative changes under the Trump administration have impacted its implementation[20], the IRA still represents a major realization of climate transition risk and can therefore provide valuable insights into investor behavior to a significant climate policy action.

Given the relatively recent enactment of the IRA, few studies have thus far examined its impact on the U.S. financial markets (Bauer et al., n.d.; Fedorova & Iasakova, 2024; Pham et al., 2023). These studies uniformly report a positive and significant immediate effect on the performance of 'green' or environmentally friendly stocks. However, their analyses are concerned with short time horizons following legislative actions pertaining to the IRA's passage. Additionally, they do not distinguish between renewable energy stocks and the broader category of green stocks[21]. Evidence indicates that the

[20] Report by Thomson Reuters, February 27, 2022, "IRA's uncertain future: How the Trump administration's approach could impact corporate tax functions". Retrieved from https://www.thomsonreuters.com/en-us/posts/corporates/ira-uncertain-future/

[21] A note on the difference between *green* and strictly renewable energy firms is in order here. Environmentally friendly companies which also include those transitioning to low-carbon technologies, or what S&P Global terms as climate transition stocks (retrieved from S&P Dow Jones Indices. https://www.spglobal.com/spdji/en/indexfamily/sustainability/climate/#overview. Last access: November 10, 2024) are conventionally included in the broad category of green firms. This study is restricted to firms whose principal business activity concerns the production and dissipation of renewable energy (see Section 3.1.1). While there is a rapidly growing literature on the pricing of climate risks in green and brown (fossil fuel heavy) stocks (Ardia et al., 2023; Bauer et al., n.d.; Bolton et al., 2023; Carattini & Sen, 2019; Cassidy, 2023; Hsu et al., 2021; Kacperczyk et al., n.d.;

pricing of the former follows a markedly different trajectory and is driven by distinct factors compared to the latter (L. Li et al., 2024). This divergence has not yet been fully explored in the context of the IRA. In this study, I pose the following questions: What was the immediate investor reaction to the IRA climate act as reflected in renewable energy stock price movements in the U.S.? By extension, how did climate narratives during the high transition risk period of the Biden administration influence the financial market performance of the renewable energy sector? And finally, after accounting for other climate-related impulses, macroeconomic factors, and firm-specific characteristics, was there a significant prolonged impact of the act on renewable energy stock prices?

A broad range of behavioral and economic literature sheds light on the importance of narrative sentiment in driving financial systems, and that how and why "similar thinking among large groups of people" commands market sentiment in the form of shared group narratives evoking either excitement or anxiety (Shiller, 2015). For example, evidence suggests that irrational exuberance among investors before the global financial crisis dictated the magnitude of the market crash in 2007 (Shiller, 2015) . Similarly, there has been a recent proliferation of literature that studies the role of narratives and biases in financing climate mitigation through determination of asset prices of climate sensitive firms (Ardia et al., 2023; Engle et al., 2020; Faccini et al., 2023; Nyman et al., 2021; Santi, 2023).

Any possibility of climate action is accompanied by beliefs about anticipated or abrupt financial and operational shifts in businesses arising out of government intervention. This is termed as "transition risk" (Ardia et al., 2023). Political signaling that affirms (denies) climate beliefs like rejoining of (withdrawal from) the Paris Agreement by President Biden (Trump) in 2020 (2016) indicates a high (low) transition risk period. These periods often signal potential disruptions for pollution-heavy industries (Stroebel & Wurgler, 2021) but may foster positive or even volatile sentiments towards clean-energy sectors (Ramelli et al., 2021). For example, Antoniuk & Leirvik, (2024) found that the Paris Agreement raised public

Monasterolo & de Angelis, 2020; Pastor et al., 2021; Pham et al., 2023), literature on renewable energy stocks is limited (Cao et al., 2020; Fahmy, 2022; Guinea et al., 2024; Liu et al., 2021; Yildiz & Karan, 2020).

awareness of global warming and support towards climate change legislation benefiting the overall U.S. renewable energy sector. In case of IRA,  Bauer et al., (n.d.) performed an event study analysis to show that clean energy indices reacted positively to major news that improved the likelihood of the passage of IRA. This suggested that equity markets had expected clean energy companies to benefit by its policies. IRA however, is a unique case of both realized transition risk upon the passage of the policy action (Bauer et al., n.d.) and perceived transition risk concerning its future implementation. It could therefore be construed that the whole effect of the IRA passage on the renewable energy stock market took longer than a few days to play out.

Another reason to investigate this trajectory is to inform the *ex-ante* and *ex-post* reaction of renewable energy firms to an *anticipated* policy action. While price effects of unanticipated climate shocks can be fairly accurately isolated, effects of anticipated changes are confounded by pricing in of both current and the present value of future path of policy (Gürkaynak et al., 2004). This is because over time, investor sentiments are susceptible to belief updating driven by news coverage and social interaction (Ardia et al., 2023; Faccini et al., 2023; Fedorova & Iasakova, 2024; Santi, 2023; Yazici & Gültekin, 2023). Santi, (2023) shows that when investors have positive sentiments about climate change originating from high news coverage about natural disasters and carbon policies during times of high social interaction, it leads to shift towards green investment. But since part of the belief updating is irrational and more emotionally charged than fact- or knowledge-based , the spike in prices goes back to zero in the longer term. This phenomenon, based on adaptive market hypothesis (Lo, 2004) is illustrated in Figure 2.1 for the case of IRA.

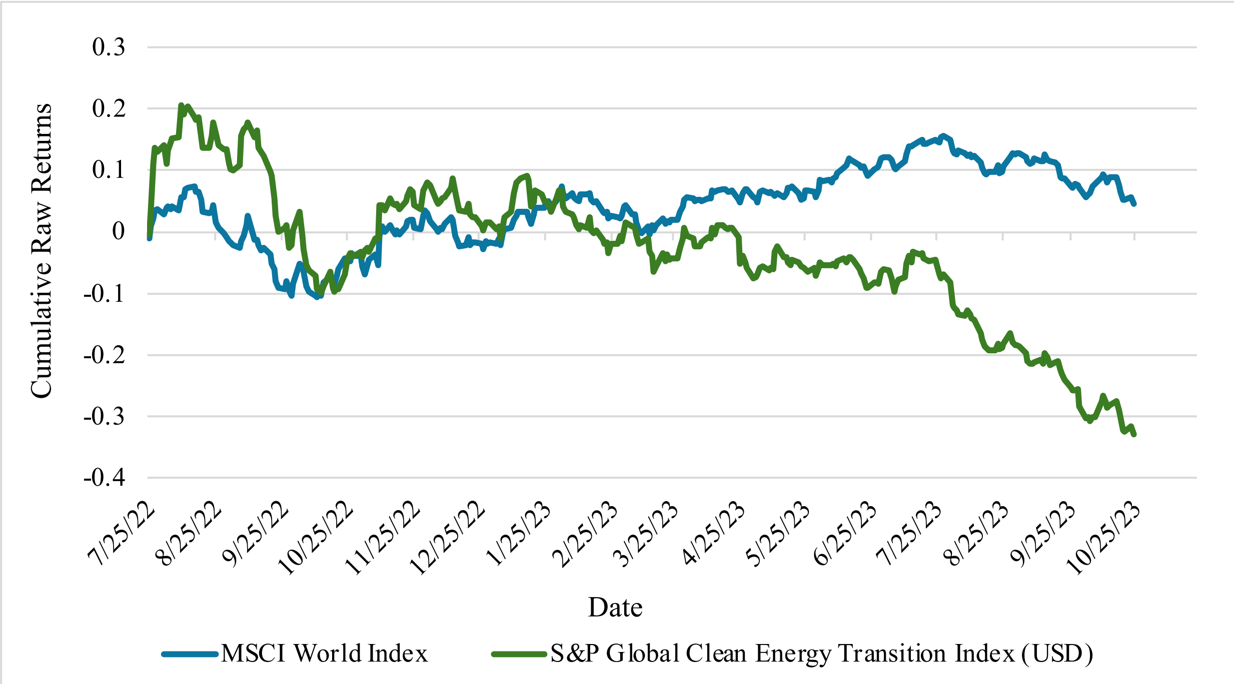



*Figure 2.1. Cumulative raw returns of S&P Global Clean Energy Transition Index (green), which constitutes 100 largest renewable energy firms in the world, and MSCI World Index (blue), a global stock market representative of large firms in developed markets. Returns are illustrated from July 27, 2022, when the Inflation Reduction Act (IRA) was announced in the Senate up till November 2023.*

Figure 2.1 shows the cumulative raw returns of the MSCI World Index and the S&P Global Clean Energy Transition Index. Constituents of the latter include 100 large-cap renewable energy firms in the world. The graph begins on July 27, 2022, when the Inflation Reduction Act (IRA) was announced in the Senate and goes up till November 2023. Evidence suggests that July 27 experienced the bulk of the market shock resulting from the IRA passage (see Section 2.4.1). The initial outperformance followed by a steady and sharp decline of the clean energy index signifies possible overcorrection and then price reversal by the market. However, is it not clear whether the observed divergence reflects policy-driven overvaluation or broader macroeconomic headwinds.

Accordingly, I use two timeframes to examine how the renewable energy financial market initially interprets and subsequently adjusts to an uncertain policy intervention like the IRA. I assess the immediate effect using the Fama-French 3-factor (FF3) asset pricing model, grounded in the Efficient Market Hypothesis (Fama & French, 2007). It posits a linear relationship between expected returns and systematic risk and allows for the identification of immediate, risk-adjusted pricing reactions under the assumption of rational investor behavior and rapid information assimilation (Fama, 1970). Subsequently, I analyze the extended period response through the lens of the adaptive market hypothesis to capture gradual market adjustments and behavioral responses to evolving policy signals (Lo, 2004).

While there is a well-established short-horizon asset pricing analysis methodology in financial literature, approaches to longer term horizons vary. One of the traditional easy-to-apply models is the Buy-and-Hold-Abnormal-Returns (BHAR). It computes cumulative abnormal returns over extended periods but suffers from cross-sectional and time-series interdependencies, leading to confounding results (Dionysiou, 2015). Studies have also used structural Vector Autoregressive Models (Engle et al., 2020), panel-data fixed effects model (Santi, 2023) as well as generalized method of moments to study long-run variations in stock prices. However, such methods do not consider ex-ante effects of policy.

Therefore, I employ the Difference-in-Differences (DiD) framework to isolate the extended term causal impact of IRA on renewable energy stock prices. DiD is an improvement on BHAR in that it circumvents its biases by introducing control variables and a counterfactual period prior to the event under analysis[22]. Since this is an individual-firm study, I can use various specifications of DiD to investigate firm-size heterogeneity. Additionally, I perform a dynamic DiD analysis to assess the intertemporal variations in renewable energy sector cumulative returns.

[22]Short-term market models like the Fama-French 3-factor model used in Section 2.4.1 are grounded in the Efficient Market Hypothesis (EMH), which posits that asset prices fully reflect all available information, thus suggesting that any observed abnormal returns are short-lived anomalies that should quickly vanish (Fama, 1998). With this assumption, they fulfil the causal inference tenets, namely covariation between stock and event, temporal precedence (event happens before stock disruption), no confounding variables (due to very small timeframe considerations) and counterfactual modeling (beta calculations capture normal stock returns prior to the event) (Stone, 1993). BHAR also depicts association between event under analysis and stock price compared to a reference group, but its design does not isolate causal impacts due to non-fulfilment of the 'no confounding variables and 'counterfactual' clause. The biases discussed by Barber & Lyon, (1997) that BHAR suffers from relate broadly to the choice of benchmark which can be partially rectified by matching portfolios of similar size and book-to-market ratios. The intertemporal bias, however, cannot be resolved without a counterfactual that considers a prior period with no event impact. The model suffers from issues of cross-sectional as well (Bolton & Kacperczyk, 2021) due to long time frames and omission of control variables. In this context, DiD incorporates the tenets of causal inference much like the short-term asset pricing method. A well-established method for policy evaluation (Pearl, 2010), it includes a pre-treatment counterfactual measure as well as controls for other confounding variables to isolate the impact of specific events or policies.

Literature shows that media narratives and communicated social norms play a significant role in forming investor beliefs (Botzen et al., 2021; Howlett & Rawat, n.d.). Therefore, apart from macroeconomic and firm-specific controls, I use news sentiment measures in my model to control for narrative biases. To build the controls, I implement textual and sentiment analysis of climate news coverage over the period of 2021-2023 using natural language processing (NLP) methods on full-text articles from major financial news sources. The methods are consistent with the burgeoning literature on application of machine learning to identify the relation between media attention and climate sentiments (Ardia et al., 2023; Engle et al., 2020; Faccini et al., 2023; Fedorova & Iasakova, 2024; Jiang et al., 2017; Noailly et al., 2021; Patronella, 2021; Santi, 2023).

After collecting news on climate change from ProQuest, I first employ the Latent Dirichlet Allocation (LDA) to identify underlying textual themes in climate news reporting. Next, I perform a sentiment analysis of the text using the transformer-based ClimateBERT model (see Section 2.3.3). Both measures provide daily and monthly time-series scores of average thematic weightage and sentiment score which are then used as controls in the DiD model. Further, I process the news scores to identify windows of high media coverage pertaining to the four identified themes of climate policy, extreme weather phenomena, geopolitics and energy transition. I use these to gain insight into the immediate effect of thematic events on renewable energy stocks during high transition risk periods.

In order to limit the analysis to a comprehensive set of U.S. based renewable energy firms, I combine the Bloomberg Industry Classification (BIC) and North American Industry Classification (NAICS) codes for identification of relevant firms. The final list consists of 263 renewable energy firms, with most of them being small- to mid- cap. A control group is then built from the subsample of S&P500, S&P 600 and S&P400 index constituents following the guidelines prescribed by Barber & Lyon (1997a), that suggests matching on size, book-to-market ratio and geography while excluding energy firms that might directly be impacted by the IRA (see Section 2.3.1). Daily and monthly data for stock and firm characteristics are obtained from Center for Research in Security Prices (CRSP) and Compustat via the Wharton Research Data Services (WRDS).

This study reveals sharp, short-horizon stock market responses of renewable energy firms to the passage of the Inflation Reduction Act (IRA) and to high-salience news events related to climate policy, physical risk, and geopolitical developments. Results from the FF3 model show that renewable stocks experienced the strongest abnormal returns (up to +13%) following the surprise July 27, 2022, IRA announcement, while earlier policy reversals and legislative uncertainty—such as the failure of the Build Back Better bill—led to sharp market declines. Notably, there was no significant market reaction to the final passage of the IRA on August 16, 2022, indicating that the policy had already been priced in. Extreme weather events generated consistently negative abnormal returns prior to the IRA, suggesting investors perceived renewable infrastructure as vulnerable to physical risks. In contrast, news surrounding the Ukraine war and geopolitical summits yielded modest positive returns, likely reflecting renewed attention to energy security and clean energy transition. These patterns underscore how investor sentiment, news narratives, and behavioral biases interact with policy signals, producing swift but varied short-term market responses.

Extended term study results indicated strong sustained market response to the IRA driven largely by medium and large sized renewable energy firms—cumulative abnormal returns rose by 12.5% within ±30 days and 13.4% within ±4 months of the announcement—followed by a gradual price dissipation over the subsequent year. Importantly, cumulative trading volumes surged significantly during this period, reflecting elevated price correction. Thematic news interactions revealed that geopolitical developments reinforced market optimism, whereas weather-related events consistently dampened returns. Other climate policy news had negligible effects, underscoring the unique signaling power of the IRA. These findings underscore that large-scale climate policies like the IRA can significantly influence clean energy financial markets and investor expectations. However, the eventual price correction suggests that implementation faced economic bottlenecks—such as high interest rates, inflation, and supply chain disruptions—that diluted initial investor optimism for future profitability. Policymakers should align climate action with broader macroeconomic conditions and ensure clear, timely communication to reinforce credibility and investor confidence, particularly when public discourse is fragmented or politically polarized.

This study contributes to literature in several ways. It is the first to analyze extended term causal effect of IRA on the renewable energy financial market. It is also one of the few studies to take the complete sample of U.S. -based renewable energy firms into consideration. This research adds to the financial event study methodology by proposing a model to combine the best practices of BHAR with the event study framework applied in economic literature. Using a dynamic framework, it adds to the understanding of market adaptation to a huge climate policy event. Lastly, textual and sentiment news analysis in a period of high transition risk provides insights into the impact of media attention on clean energy stocks. Overall, the study adds to the narrative on the impacts of decarbonization pathways on investor sentiments towards shift to clean energy.

The rest of the chapter is divided in following sections: Section 2.2 provides a review of literature, Section 2.3 describes the data and news analysis, Section 2.4 outlines the method and present the results for short-term asset pricing analysis, Section 2.5 describes the method for long-term event study, Section 2.6 discusses its results and implications, and Section 2.7 concludes.

## 2.2. Review of Literature

This study is related to and expands on three strands of the literature: renewable energy financial market response to climate policy; impact of physical on renewable energy stock price dynamics; and investor behavior towards climate risk communicated through media attention and narratives.

Within the first strand of literature, no study has yet examined the effect of IRA specifically on renewable energy stocks. Bauer et al., (n.d.) uses asset pricing and a fixed-effects model to examine the stock market effect of IRA on green and brown stocks. They find that although financial market response to the act was economically important, it did not lead to industry instability in the short run, suggesting that transition risks posed by climate policies even as ambitious as the IRA may be manageable. Pham et al. (2023) uses asset-pricing to investigate the effect of IRA among other climate policies and finds that reactions vary between the tightening and loosening of climate policy and across subgroups of the green stock markets.

In the extant literature on other significant climate policy events, Barnett (2023) identifies several climate policy events and shows that industries with a larger exposure to changes in oil prices exhibit a more negative stock market response to events that increase the likelihood of future climate policy action. Cassidy (2023) constructs a dataset of climate policy announcements and documents that brown stocks perform better than green stocks around events with a large amount of climate policy news. Monasterolo and De Angelis (2020) documents shifts in the risk characteristics of green and brown stock indices before and after the announcement of the 2015 Paris Agreement.

Few studies have examined the renewable energy sector in relation to other climate policies. An early study by Sadorsky, (2012) shows that for the renewable company sales growth has a negative impact on company risk while oil price increases have a positive impact on company risk. On the other hand, Cao et al. (2020) uses Generalized Method of Moments (GMM) to finds that oil price uncertainty has negative impact on renewable energy firms in China, especially on the more volatile small size firms. (Antoniuk & Leirvik, 2024) find that clean energy firms benefitted from the Paris Agreement, Climategate, and Fukushima since these events increased climate change awareness and favor toward policies related to reducing the impact of climate change.

With regard to dynamics between physical risk and renewable energy prices, Liu et al., (2021) investigates the largest clean energy stock performance in the U.S to most notorious, economically damaging hurricanes in the North Atlantic Ocean using the structural VAR model and finds the most positive and statistically significant impact for renewable energy. Fahmy (2022) uses portfolio choice model to examine investor’s adaptation to climate change. They find that investors who believe that climate hazards are rising over time tend to be skeptical of investments in clean energy and/or mitigation or adaptation projects. (Faccini et al., 2023) does not find any significant result in the pricing of natural disasters or physical climate risk. Survey results from (Krueger et al., 2020; Stroebel & Wurgler, 2021) show that different kinds of risks are priced differently, and that physical risk in general is underpriced by Environmental-Social-Governance (ESG) stocks. (Alehile et al., 2025) use the GARCH-MIDAS model to compare the resilience of renewable and non-renewable energy stocks to climate-related risks. Results suggest that investors may perceive renewable stocks as more resilient and stable considering climate-induced shocks.

There has been a recent proliferation of literature on news sentiment analysis. Specifically in case of renewable energy stocks, (Santi, 2023) document investors overreaction to clean stocks during climate change risk and reversal in longer horizons. They show that report on climate change and abnormal weather events, facilitate the investor learning process and correction of the mispricing. Guinea et al., (2024) shows that combination of news shocks captured in renewable energy stock prices significantly affect economic volatility. Noailly et al., (2021) finds that salience of environmental policy in newspapers is associated with a greater probability of cleantech startups receiving venture capital funding and reduced stock returns for high-emissions firms. Yildiz & Karan (2020) investigate the effect of country-level environmental performance and national culture on the stock price crash risk of the renewable energy sector, using 626 firms across 31 countries, and find them to strong but nonlinear predictors, which is not the case for fossil fuel firms. Yazici & Gültekin (2023) discusses the news framing effects of media on renewable energy firms, which in turn is driven by the current socio-economic situation, eco-political agenda and even international relations. Baker & Wurgler (2007) show that stocks which are hard to value are more affected by investor sentiments, which is the case with renewable energy firms.

In other contexts, seminal research by Engle et al.( 2020) and Ardia et al. (2023) shows that unexpected increases in a news-based index of climate change concerns benefit green stocks over brown stocks. Faccini et al. (2023) finds that transition risk is priced in the stock market, while physical risk is not. Ramiah et al. (2015) examines the interplay between environmental regulations, capital markets, and political leadership in Barack Obama's administration that advocates for the adoption of green initiatives. Based on industry level analyses, they find that polluters have negative abnormal returns, while climate-responsible firms see non-significant responses indicating that these regulations may not be effective enough. Ramelli et al. (2021) shows that Biden's 2020 election shifted climate policy sentiments dramatically upward. However, firms with climate-responsible strategies gained during Trump's tenure as well. (Misev & Balles, n.d.) examine green and brown ETF to show that media attention devoted to climate change concerns drives shifts in investor behavior towards green investments.

Outside of the U.S, (Teutrine et al., 2024) investigates the Stoxx Europe 600 constituents response to the sixth Intergovernmental Panel on Climate Change report published between 2018 and 2023, and find greater volatility for climate-sensitive stocks than emission-graded. Hengge et al. (2023) study carbon policy news related to the European Union Emission Trading System. They examine events with exogenous changes in the price of emission permits following Känzig (2023) and show that a surprise increase in the carbon price leads to negative abnormal returns of brown stocks compared with green stocks, measured using emission intensities.

Hence, prior research underscores that market responses to climate policy announcements vary significantly by firm characteristics and event context, highlighting both the opportunities and challenges faced by renewable energy firms. Additionally, physical climate risks have shown mixed influence on stock valuations, with broader investor uncertainty regarding long-term climate risks. Lastly, literature on media narratives emphasizes the significant role news sentiment and salience play in shaping investor sentiment and market outcomes for renewable energy investments, both in short- and longer-term horizon.

## 2.3. Data and Natural Language Processing

### 2.3.1. Stock Market and Firm-Level Data

#### 2.3.1.1. Renewable Energy Firms

Most market response studies take either one or a combination of stock market indices that are commonly used to represent the sectors under consideration (Monasterolo et al., 2022; Morina et al., 2021; Pham et al., 2023). Individual firm studies, however, can inform the extent to which the policy is affecting the expected financial performance of a comprehensive sector. It allows for a more granular investigation of the policy's variable impact on heterogenous firm characteristics, especially in the longer term (Faccini et al., 2023; Pastor et al., 2021; Pham et al., 2023). In this study, I construct a universe of renewable energy companies incorporated on the U.S. by following the definition provided by WilderHill Clean Energy Index (ECO), one of the major global trackers of clean energy sectors. It defines renewable energy companies as those that "contribute to advancement of clean energy, including those developing and selling energy technologies and energy management services[23]." This includes primary businesses that fall into the following broad categories: (i) Renewable Energy Harvesting (ii) Energy Storage (iii) Power Delivery and Conservation (iv) Energy Conversion (v) Greener Utilities and (vi) Cleaner Fuels.

I first obtain information on the 209 renewable energy firms listed under the Bloomberg Industry Classification (BICS) classification for "Renewable Energy" [24]. Next, I identify primary NAICS codes for Electric Power Generation from clean energy sources (221111 and 221114-7), and other relevant codes pertaining to renewable energy supplies, energy storage, and semiconductors using the Mergent database[25]. Out of these, I manually select firms by scrutinizing primary business details of listings under each code and choosing those that match the specifications provided by ECO. This delivers a final list of

[23] Retrieved from WilderHill Clean Energy Index ECO. https://wildershares.com/about.php. Last access: November 10, 2024

[24] No other widely used industry classifications, including the Global industry Classification (GICS), the North American Industry Classification (NAICS) or the Fama-French Industry portfolio have an explicitly stated renewable energy firm category. In fact, Bauer et al., (n.d.) find that in case of Fama-French Industry portfolio, the industry's level of greenness is a poor predictor of its stock market reactions.

[25] See Appendix for a list of NAICS codes used.

263 renewable energy firms, out of which 216 have stock price data and firm-level data. 67.32% of the firms are small to micro-cap, that is their market capitalization is less than $2 billion, 15.45% are medium-cap (market capitalization between $2 billion to $10 billion) and 17.23% are large-cap (market capitalization above $10 billion).

### 2.3.1.2. Benchmark Group and Other Controls

A benchmark portfolio is required for detecting abnormal stock returns of renewable energy firms. For the causal investigation of policy impact, this benchmark serves as a control group. Since S&P 600, 400 and 500 indices are U.S. stock market benchmarks for small-, medium- and large- cap firms, I construct a control group out of their combination by following a matching procedure similar to Barber & Lyon, (1997). In this method, the sample or treatment firms (here, renewable energy firms) are matched to control firms of similar sizes (market capitalization) and book-to-market (book value of equity divided by market value of equity) ratios, excluding firms exposed to specific events. Treatment and fossil-fuel firms are therefore excluded from the control portfolio, and the size-factor is controlled for in the empirical design (see Section 2.5.2). Firm-distribution by market-cap for both groups is presented in Table 2.1.

*Table 2.1. Firm-size distribution across renewable energy (treatment) and benchmark (control) group.*

| | **Control** | | **Renewables** | |
|---|---|---|---|---|
| **Market-Cap** | **Frequency** | **Percent** | **Frequency** | **Percent** |
| Small | 11,999 | 36.10% | 3,090 | 67.32% |
| Medium | 6,938 | 20.87% | 709 | 15.45% |
| Large | 14,305 | 43.03% | 791 | 17.23% |
| Total | 33,242 | 100% | 4,590 | 100% |

Finally, for the cross-section of all firms, I obtain data for daily and monthly stock prices, trading volumes, and monthly financial ratios from the Center for Research in Security Prices (CRSP) and Compustat via the Wharton Research Data Services (WRDS). Firm-level financial variables include firm size measured by market capitalization, profitability measured by return on asset, leverage measured by total debt divided by earnings before interest, taxes, depreciation, and amortization (EBITDA), company valuation measured by book-to-market ratio and cash effective tax rate (total income taxes paid divided by pretax income). Chicago Board Options Exchange (CBOE) Volatility index (VIX) to represent market expectations and monthly Gross Domestic Product (GDP), are downloaded from the Federal Reserve Bank of St. Louis website (FRED), monthly inflation rate is extracted from the Bureau of Labor Statistics (BLS) and the Dow Jones Commodity Index Crude Oil from S&P Global. The dataset ranges from January 1, 2021, to December 31, 2023. Summary statistics are presented in Table 2.2.

### 2.3.2. News Articles from ProQuest

Building on the methods used by numerous studies to quantify climate risk portrayed in news reports and media sentiments (Ardia et al., 2023; Engle et al., 2020; Faccini et al., 2023; Fedorova & Iasakova, 2024), I collect all news articles related to the subject of  climate change from major financial newspapers based in the U.S. between 2021-2023. Next, I implement the natural language processing (NLP) models for textual and sentiment analysis for two purposes: (i) to identify windows of high-impact news to test their effect on short-term renewable energy asset prices (ii) to construct a time-series score of daily thematic and sentiment weights to be used as proxies for climate risk perception variability in the causal panel-data analysis.

I first extract an initial collection of news articles using the ProQuest US New stream based on a single query "*climate change*" for full-text articles between January 1, 2021, and December 31, 2023, without any duplicates. This collection consists of 64,072 articles published across the digital and print versions of major financial news sources including *The New York Times, Boston Globe, USA Today, Washington Post, Wall Street Journal, The Barron's, Los Angeles Times, and Chicago Tribune*. Each source is a national key player in delivery of financial information, and this makes them likely to affect stock market prices by means of dissemination of news and communication of related narratives.

Next, I apply further filters to discard entries that are irrelevant summaries, article corrections, or simply company and stock market reports. The remaining sample, however, includes a diverse set of subjects such as healthcare, technology, politics, finance, agriculture among others. While they contain at least one appearance of the bigram "*climate change*", the topics are largely extraneous to climate risk, which is the focus of this study. There is also the concern of omission of articles related to subjects of renewable energy and transition risk which might not contain the query. I therefore expand the algorithm to the following series of bi- and trigrams with the connecting operator "OR": *Inflation Reduction Act, global warming, climate bill, climate change Biden, green jobs, renewable energy, solar energy, electric vehicles, clean energy, wind energy, fossil fuel, gas price, oil energy, coal energy, carbon tax.* This yields the final sample for analysis consisting of 6,726 articles.

Since the period under consideration is a high transition risk, the textual corpus extracted comprises a very eclectic set of climate-related news reflecting rapidly fluctuating sentiments. Entries describe climate change policies, views expressed in domestic and national political debates, scientific research, investment and deployment of renewable energy, corporate views and marketing initiatives, the aftermath of pandemic, energy repercussions of the Ukraine war, reports on extreme meteorological events, and a few regionally confined climate events. To group the heterogenous news into comprehensible subcategories and optimally extract news with high-media attention, I conduct textual and sentiment analysis using natural language processing methods described in the following sections.

### 2.3.3. Natural Language Processing: Concepts and Estimation

NLP is a burgeoning field of artificial intelligence focused on enabling machines to understand, interpret, and generate human language in a manner that is meaningful and contextually appropriate. To prepare the news articles, the standard procedure is to preprocess the articles using the Natural Language Tool Kit (Bird et al., 2009). As a first step, I combine all full-text articles into a single document which will form the text data or textual corpus for analysis. Punctuation marks, newlines and tabs are then removed, and all letters are converted to lower case. Next, I remove stop words (for example: the, is, are) and reduce words to their respective word stems to limit textual variability through the process of lemmatization. Finally, I tokenize the textual corpus (the corpus is trimmed such that the words or '*tokens*' that appear less than 5 times and in more than 90% of the documents are removed to filter tokens that are either very rare or common). I then execute textual and sentiment analysis over this prepared text corpus.

### 2.3.3.1. Textual analysis: Latent Dirichlet Allocation

The first method I use is the Latent Dirichlet Allocation (LDA) to extract underlying thematic structures in the extensive textual data that will help infer systemic risk factors. LDA is a statistical method used to detect hidden themes or *topics* within a large collection of documents by grouping words that frequently appear together (Blei et al., 2003). It is one of the most commonly used topic modeling methods employed in notable climate risk studies (Faccini et al., 2023; Zhao et al., 2015). LDA is essentially an unsupervised machine learning method, i.e., it is the method, rather than the user, which dissects textual heterogeneity in topics. It lets the user predefine the number of topics they want the whole text to be divided into, but not specific themes like in dictionary-based methods (Apel et al., 2023; Ardia et al., 2023; Bua et al., 2022; Engle et al., 2020). Once LDA delivers the topics in the form of a list of words weighted by probability of appearance, the user can interpret and label them based on defining characteristics of words[26].

Results from LDA deliver two metrics: a categorical variable of a single highest probability topic for each article, and a continuous variable of each topic's probability-weights in each article, with each topic's share indicating its relative intensity within the article. Summing up the topic shares in the second metric across all daily articles generates a measure of daily topic intensity. This delivers a time-series of news coverage by climate topic based on the articles' timestamps. An increase in a news topic can reflect either an increase in the number of articles published, and/or an increase in the media's attention to a particular

[26] Essentially, LDA is a Bayesian factor model for discrete data. In a model with K topics, each topic is a probability vector β^k over the V unique words in the textual corpus (k=1…K). Each article is modeled as a distribution over topics, with articles being independently but not identically distributed. Analogous to Principal Component Analysis, a topic being a probability distribution over the unique words, reduces the dimensionality of thematic patterns. For this study, the LDA model is implemented using the scikit-learn library. This implementation uses variational Bayes approximation for estimating the posterior distributions, similar to the approach originally introduced by Blei et al. (2003).

topic, for a given number of articles published. Both can therefore lead to short-term but significant investor sentiment and stock market disruptions.

Through trial and error, I choose the corpus to be divided into 5 topics as any larger division reveals idiosyncratic themes. A word cloud of 4 major topics resulting from the final LDA iteration is presented in Figure 2.2. *Topic 1* is about events related to U.S. climate policy developments and therefore highlights policy transition risk. *Topic 2* elucidates events pertaining to extreme weather events or physical risk. *Topic 3* collects news on climate geopolitics and international climate summits with underlying transition risk. *Topic 4* is about news reported from the lenses of energy transition from fossil fuels to renewable energy. While it may not largely contain news events different from other topics, the narrative's direct focus is on domestic transition risk. *Topic 5*, which mainly contains news about Rhode Island and Providence is discarded for its regional nature that does not affect majority of the treatment group firms.

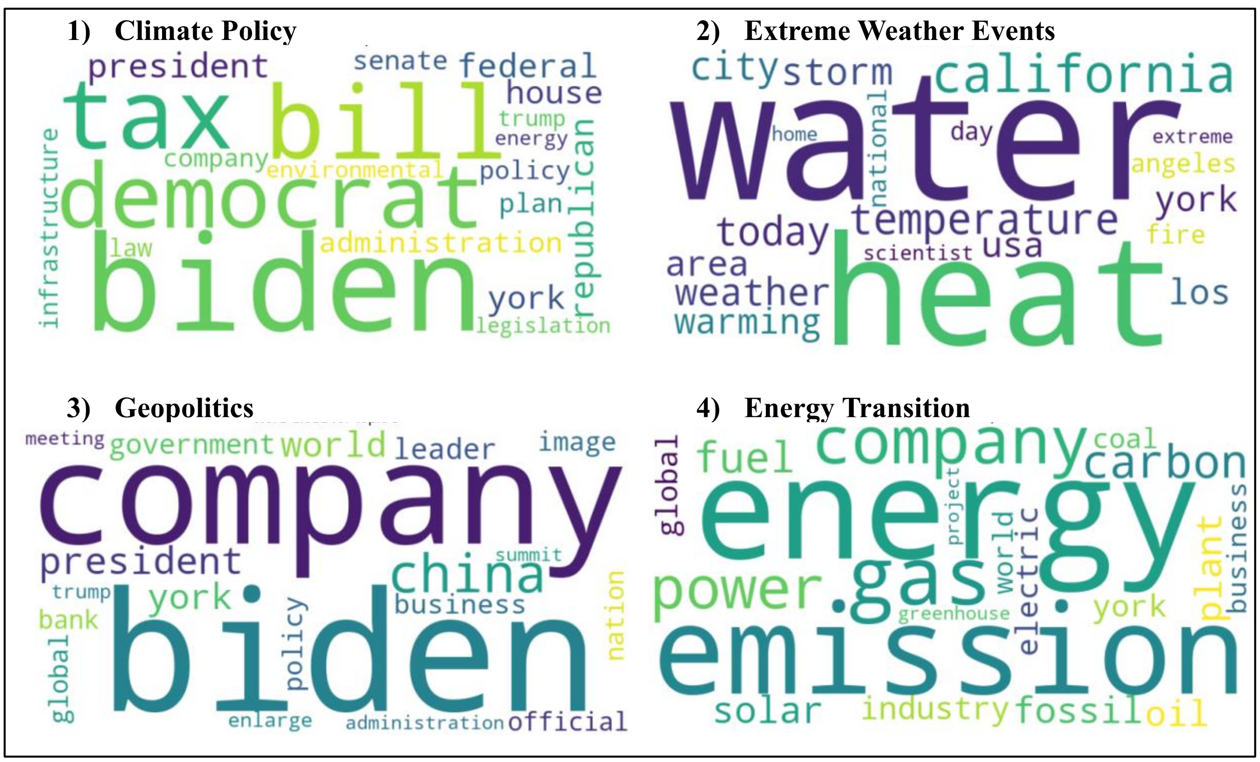



*Figure 2.2: Word clouds for 4 climate news textual factors. Word clouds are delivered by the Latent Dirichlet Allocation (LDA) method. Words in bigger fonts occur more frequently in the articles. The title for each word cloud characterizes its broad theme.*

Figure 2.3 illustrates the time-series evolution with marked news events of very high media-attention[27] for each topic separately. It is assumed that intensive news coverage depicts sources of concern (Engle et al., 2020; Faccini et al., 2023) or of high importance to the economy. For example, note that the trajectory of Figure 2.3(i) indicates concentrated news weights during 2021 and 2022, but they are significantly subdued in 2023. The trend is corroborated by Biden administrations' term activity which starts with the U.S. rejoining the Paris Agreement in January 2021[28], but ends with Biden's approval of a major Alaskan oil drilling project[29] and forgoing of climate summits[30] in 2023 within the study period. Holding radically different views about climate change from his predecessor, Joe Biden called for a bold set of climate measures concerning green investment and jobs immediately after he took office in 2021. This encompassed announcement of the Build Back Better (BBB) program in March 2021, the even more sweeping and ambitious $3.5 trillion Infrastructure Investment and Jobs Act (IIJA) through the Bipartisan Infrastructure Bill in April 2021, as well as the capstone IRA bill. Each program was passed after considerable debates and deliberations in both the House and the Senate. A turn in the likelihood of each legislation being passed was dictated by statements of key politicians, especially Senators Manchin and Schumer, and it reflected prominently in policy news weights as well as asset prices (see Section 2.4.1).

Figure 2.3(ii) illustrates news weight trend of catastrophic natural disasters, extreme weather events, as well as the Ukraine War[31] through the study period. As a depiction of physical risk, it followed a steady trajectory in contrast to policy news. While concerns of global warming got amplified with the seasonal regularity of extreme temperatures, hurricanes were most prominently featured in the news. Chief events

---

[27] The threshold for very high media-attention is taken as 3 standard deviations above the mean for each topic, illustrated by dotted lines in each graph in Figure 2.3. Event on the dates that have topic weightage higher than the threshold are described and tested in Section 2.4.1.

[28] Report by USA Today, January 20, 2021, "Joe Biden rejoins Paris Agreement, requires masks on federal property in swift Day 1 directives". Retrieved from ProQuest.

[29] While the government later in the year took steps to control and stop the drilling project, the reversal was not as frequently or intensely reported. Report by Boston Globe, March 16, 2023, "*The Willow Project: What to know about the massive Alaska oil-drilling venture Biden approved this week*". Retrieved from ProQuest.

[30] Report by New York Times, November 29, 2023, "*Biden's Absence at Climate Conference Highlights His Fossil Fuel Conundrum*". Retrieved from ProQuest.

[31] While the Ukraine War is not a natural disaster, it is nevertheless a "physical risk" and appears prominently in Topic 3 of the LDA analysis.

included Hurricane Ida, Ian and Idalia in August 2021, 2022, and 2023 respectively, winter storms in January, tornado outbreaks in February, and heat waves, droughts and floods during the summer months of each year. News about the Ukraine war expressed concerns about gas supplies and advised strategic shift towards renewable energy, unlike the narratives about natural phenomena which highlighted institutional and infrastructural vulnerability[32].

The time-series weights for news topic on geopolitics and international climate summits is presented in Figure 2.3(iii). There was surprisingly high coverage of the annual Conference of the Parties (COP) summits, with the daily frequency of articles ranging between 15 (for COP28) and 34 (for COP26) which were some of the highest news volumes for any event. Earth Day summits that involved clean energy negotiations with other countries were also featured in the theme. Narratives on COP26, COP27 and other global climate negotiations might have signaled economic concern stemming from possible increase in global tax on pollutants, climate contributions and reduction in emissions (Faccini et al., 2023). A tightening of carbon policy can lead to escalation in energy prices, reducing risk and increasing immediate investments in renewable energy companies (Morão, 2024; Sadorsky, 2012). Ambiguous geopolitical relations and climate stance can however communicate mixed signals and volatility. Note that the trend here mimics that of climate policy in that the summits in 2023 are not weighted above threshold. This can be explained by waning international climate policy stronghold of the U.S. democrats due to their unclear fossil fuel stance[33].

---

[32] For example, report by Boston Globe, September 20, 2022, "Energy officials warn that winter could bring blackouts here: Natural gas shortages driven by Ukraine war pose threat." Report by USA Today, September 18, 2021, "Rising seas, sinking land: Life on this Hurricane Ida-battered Louisiana barrier island may never be the same". Retrieved from ProQuest.

[33] For example, report by Los Angeles Times, April 13, 2021, "Biden Wants Leaders to Make Climate Commitments for Earth Day". Report by New York Times, November 27, 2023, "Could Biden's Clean Energy Push Be a Victim of Its Success?" Retrieved from ProQuest.

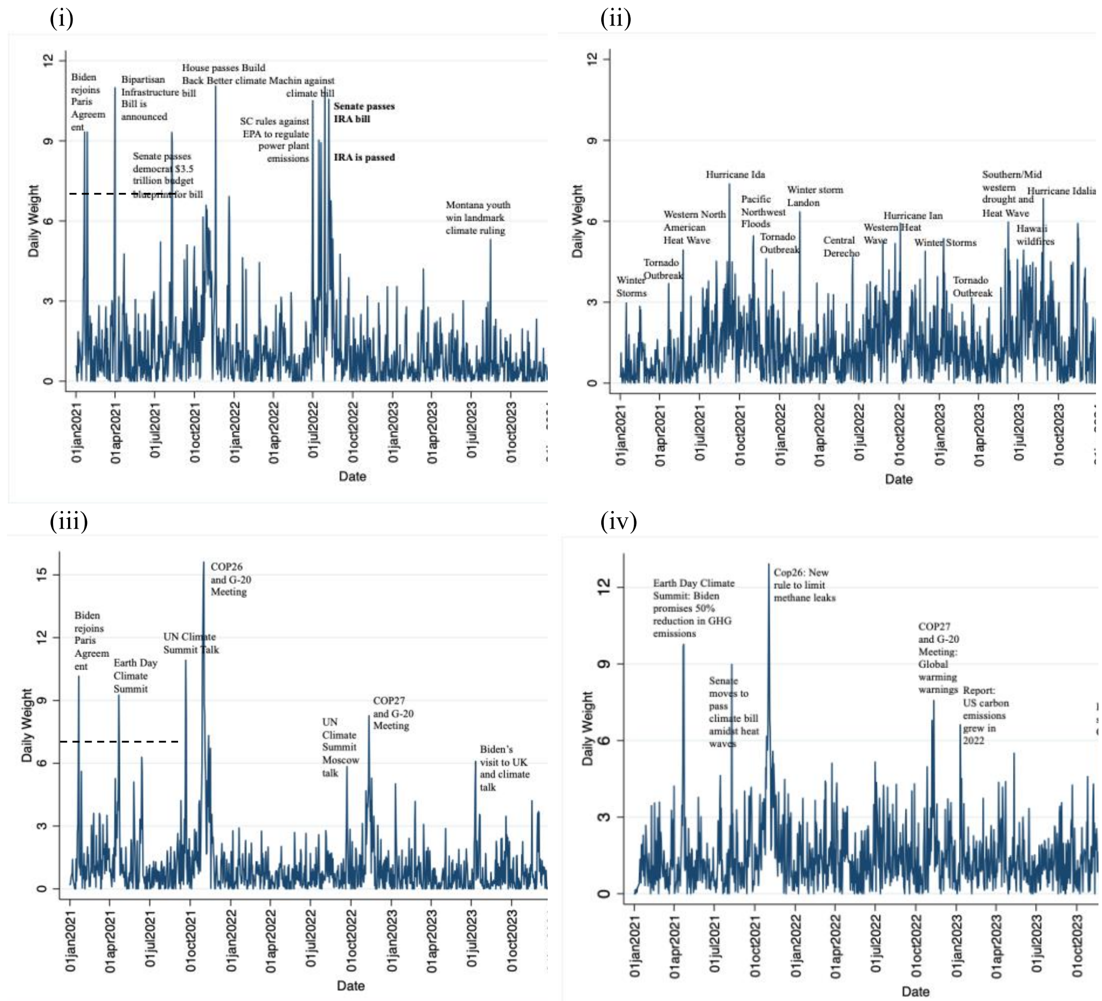



*Figure 2.3: Climate news textual factors over January 1, 2021- December 31, 2023, and their associated with news releases. The vertical axis measures the topic shares for each factor, i.e. the percentage of words in each article associated with a given factor. To obtain the daily topic share associated with a given factor, the topic shares of all articles published on that day are added up. Dotted lines show thresholds placed for values 3 standard deviations above mean.*

Figure 2.3(iv) demonstrates the news weights trend for the energy transition textual factor. The theme collected domestic news on solar and wind energy infrastructure projects, electricity grid and storage, gas price inflation, tax incentives for electric vehicles, solar projects in new-income households, and Environmental Protection Agency (EPA) proposed rules on Methane emissions. It also featured international statistics on fossil fuel usage, carbon emissions and cost of energy transition. However, news with the most rigorous coverage are events spilt over from other themes. The focal point of the content of such articles is the impact of those events on renewable energy or fossil fuels. For example, Biden's promise on the Earth Day climate summit to reduce greenhouse gas emissions by half during his term garnered substantial media attention. Solar and wind investment and tax provisions under the IRA bill received their separate share of spotlight. Media scrutiny of negative data insights on rising global emissions as well as oil and gas usage towards the second half of 2023 may have led to the dampening of democrat's climate efforts, among other factors. While asset price impact evaluation of the energy transition theme can add to a multi-dimensional understanding of energy market reactions, it is difficult to isolate any such news event for the purpose of analysis, at least through current event study methods.

#### 2.3.3.2. Sentiment Analysis: Pretrained ClimateBERT model

News stories are usually written from a biased perspective depending on publications and can drive the market in different directions based on the angle of reporting (Jiang et al., 2017). While LDA facilitates bifurcation of systemic risk, sentiment analysis of articles can provide insight into whether climate news reflects positive or concerning signals for the economy i.e. it indicates behavioral risk patterns. Many studies use different methods to generate sentiment-marked factors. Engle et al., (2020), Ardia et al., (2023) and Jiang et al., (2017) use "bag of words" based dictionary[34] methods to classify articles, whereas Faccini et al., (2023) marks the contents manually.

Similar to Fedorova & Iasakova, (2024), I use ClimateBERT (Bidirectional Encoder Representations from Transformers), a pre-trained transformer neural network designed to understand contextual relationship in climate text data designed by Webersinke et al., (2022)[35]. ClimateBERT classifies climate-related paragraphs into one of the three sentiment classes: a positive *opportunity*, a *neutral*, or a negative *risk*. A notable advantage of this model therefore is that it considers communicated narratives between words and sentences in climate-related text.

[34] In most dictionary methods, the tone of textual data is estimated by using a lexicon and calculating the frequency of word occurrence in the text. The meaning of separate words is considered, but the context and semantics of the text are ignored.
[35] Webersinke et al. (2022) uses the state-of-art DistilROBERTA model and 135,391 news articles on climate change topics such as climate politics, climate actions, floods and droughts to train the model, reducing the margin of error by 3.58% in comparison to similar Language models. This study uses package from the Hugging Face open-source library updated by the authors to run the model on the collected corpus of full-texts (Retrieved from the Hugging Face transformers library. https://huggingface.co/climatebert/distilroberta-base-climate-detector. Last access: November 10, 2024).

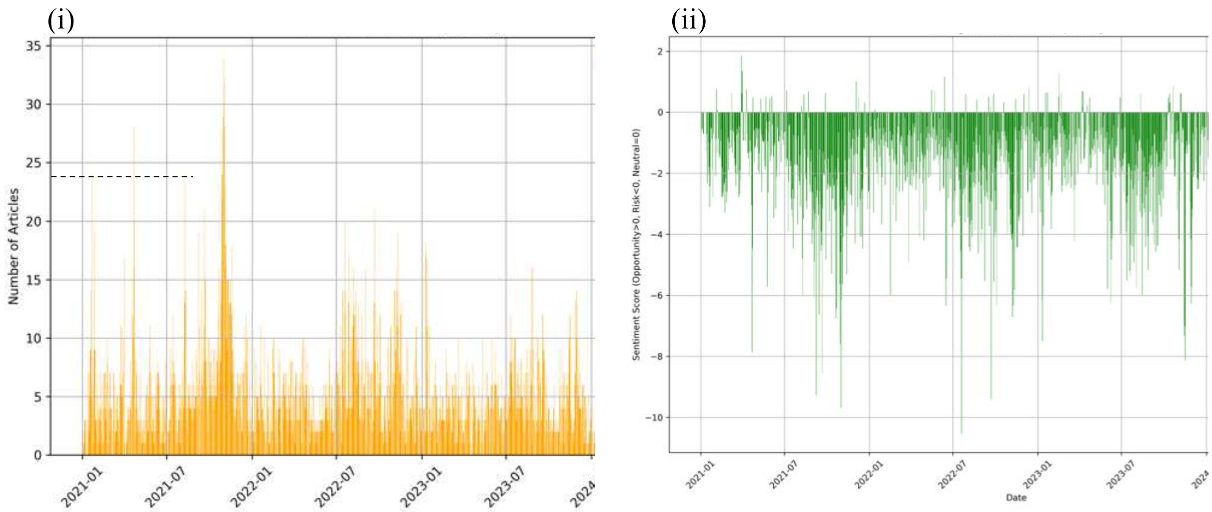



*Figure 2.4: Daily climate sentiment scores and article volumes over January 1, 2021- December 31, 2023. The vertical axis for sentiment analysis measures the sentiment score. Risky news is assigned a value below -1, neutral is assigned 0 while opportunity is assigned above 1 by the ClimateBert sentiment analysis model. To obtain the daily scores, all scores for each article published on that day are added up. Dotted lines show thresholds placed for values 3 standard deviations above mean.*

Like in the case of LDA, results generate a categorical series of sentiment-class-annotated news articles and a continuous series of sentiment scores for each article. I then sum up the scores across all daily articles forming a time-series of news sentiment scores and average them for monthly measures. The largest share is of articles communicating risky climate sentiments, with the class forming 47.8% of the corpus. Neutral articles that do not lean towards any bias also hold a substantial 47.4% share. The smallest share is of articles conveying opportunity sentiments, which form only 4.8% of the articles. Figure 2.4(ii) illustrates the daily sentiment weight trend over the 2021-2023 period. The event with the largest negative sentiment score of -11 was on July 20, 2022, days after Senator Manchin's withdrawal of support from the IRA bill. Amidst public reaction to deadly heat waves, senatorial obstacles to passing of the climate bill, and republican's criticism to Biden's plans to convert an out-of-operation coal mine in Massachusetts to a wind energy production facility, the President was urged by democrats to declare a climate emergency[36]. Other adverse sentiment days included narratives of and reactions to extreme

[36] Report by Wall Street Journal, July 20, 2022, "Biden Is Pressed to Declare Emergencies After Climate, Abortion Setbacks; Some Democrats and activists want president to use executive powers to unlock more authority and funding; declarations would face criticism and legal challenges." Retrieved from ProQuest.

weather events and climate summit talks. While in most cases of textual analysis high frequency news days were earmarked to specific events, sentiment analysis outliers highlighted oppositional stories of overlapping events, such as Moscow summit talk amidst rising smog and asthma cases among black and Hispanic children in September 2022.

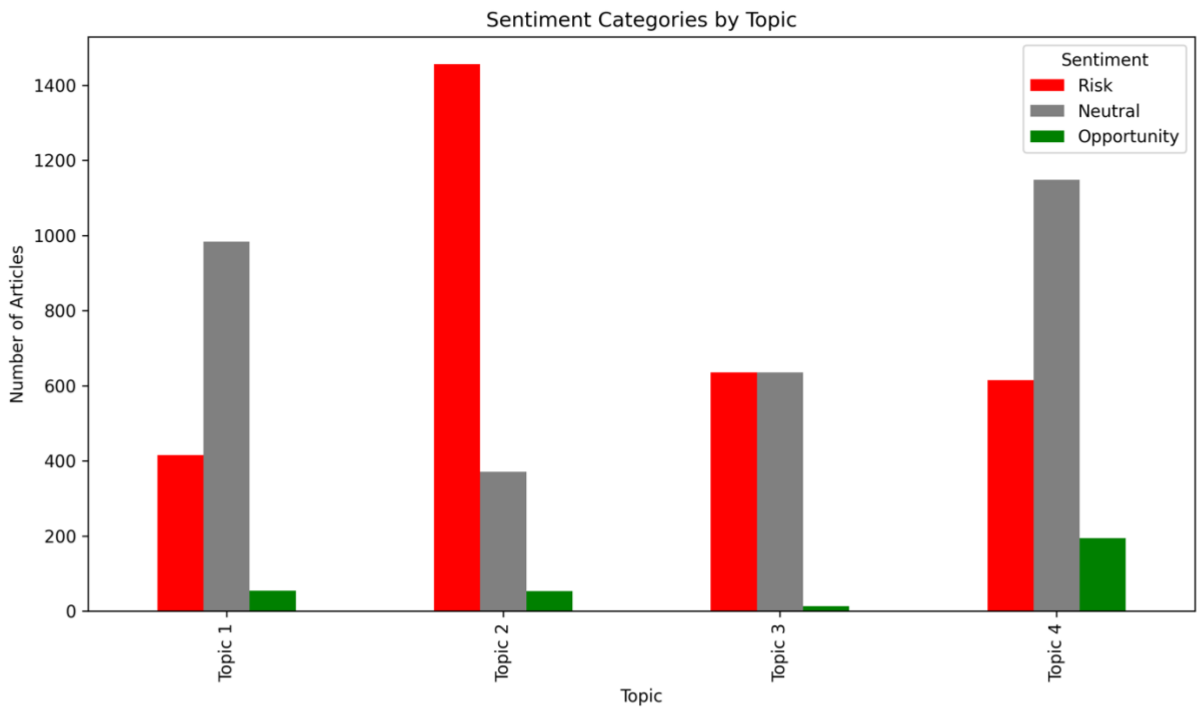



*Figure 2.5: Relationship between news topic, volume and sentiment. The vertical axis shows the number of articles per day. The four topics bifurcate news about U.S. climate policy (topic 1), extreme weather events (topic 2), global climate politics and international summits (topic 3) and energy transition (topic 4). Each bar for each topic shows division of sentiments across categories.*

A visualization of the number of articles per day is also presented in Figure 4(i). Although not necessarily indicative of a specific theme or sentiment, the sheer volume of news articles published within a single day can exert a considerable influence on market sentiment (Hsu et al., 2021). The day with the highest volume of news coverage (34 articles) is November 1, 2021, featuring Biden's visit to COP26 Glasgow summit. Other high frequency media days include the IRA climate bill passage on July 27, 2022 (16 articles), the BBB passage on April 1, 2022 (18 articles) and the Earth Day Summit on April 22, 2022 (20 articles).

Figure 1.5 is a perceptive depiction of correlations between textual and sentiment analysis for all articles. Associated sentiments serve as a possible measure of degree of riskiness for each theme. For example, note that the markers show a significant overlap of risky sentiments with textual topic on extreme weather events reinforcing their broadly concerning narrative of increased physical risk. Most news coverage for *Topic 1* (U.S. climate policy) have a neutral tone suggesting that the related article corpus might be elucidating on both positives and negatives of policy initiatives. *Topic 4* (energy transition) has the largest share of optimistic as well as neutral articles, mostly pertaining to solar and wind energy infrastructure development, deployment and planning. A concise summary of monthly time-series news sentiment measures in presented in Table 2.2.

*Table 2.2: Monthly summary statistics for renewable energy (treatment) and benchmark (control) group.*

| **Stock Variables** | | | | | | |
|---|---|---|---|---|---|---|
| **Variable** | **Group** | **Observations** | **Mean** | **SD** | **Min** | **Max** |
| Stock Price | Control | 33,242 | 115.883 | 257.3539 | 0.0001 | 7000.45 |
| | Renewables | 4,590 | 25.5916 | 50.64082 | 0.0001 | 498.56 |
| Cumulative Returns | Control | 33,242 | 0.10548 | 0.447214 | -0.999 | 5.633272 |
| | Renewables | 4,590 | -0.2081 | 1.367305 | -1.000 | 37.08164 |
| Trading Volume | Control | 33,214 | 49200000 | 135000000 | 6 | 2900000000 |
| | Renewables | 4,539 | 35900000 | 135000000 | 100 | 4140000000 |
| **Firm Characteristics** | | | | | | |
| Book to Market | Control | 27,287 | 0.5182 | 0.4961 | 0.0002 | 8.7762 |
| | Renewables | 1,978 | 0.6362 | 0.8679 | 0.0002 | 10.8001 |
| Return on Asset | Control | 28,552 | 0.1215 | 0.1082 | -0.7021 | 1.9887 |
| | Renewables | 2,012 | -0.0932 | 0.6540 | -12.5548 | 0.3163 |
| Effective Tax Rate | Control | 24,234 | 0.1970 | 0.5722 | -6.6417 | 9.0000 |
| | Renewables | 970 | 0.1537 | 0.6681 | -0.6481 | 6.1367 |
| Total Debt to EBITDA | Control | 28,493 | 3.5060 | 103.2776 | -2288.1670 | 9237.2420 |
| | Renewables | 2,061 | 4.0570 | 61.3998 | -529.0426 | 1183.5870 |

| **Macroeconomic Variables** | | | | | |
|---|---|---|---|---|---|
| **Variable** | **Observations** | **Mean** | **SD** | **Min** | **Max** |
| CBOE Volatility Index (VIX) | 37,832 | 20.60 | 4.5200 | 12.72 | 30.01 |
| Crude Oil Index | 37,832 | 41.65245 | 7.8841 | 28.16 | 67.5 |
| Gross Domestic Product | 37,832 | 0.0320 | 0.0308 | -0.0434 | 0.1262 |
| Inflation Rate | 37,832 | 0.4537 | 0.4054 | -0.30 | 1.40 |
| **News Sentiment Measures** | | | | | |
| **Variable** | **Observations** | **Mean** | **SD** | **Min** | **Max** |
| Climate Policy Factor | 37,832 | 1.169148 | .7528101 | .3016624 | 3.378952 |
| Extreme Weather Events Factor | 37,832 | 1.398581 | .5319905 | .5300457 | 2.495405 |
| Geopolitics Factor | 37,832 | 1.087603 | .7548139 | .3628842 | 3.789615 |
| Energy Transition Factor | 37,832 | 1.522645 | .5785140 | .8219599 | 3.871828 |
| Article Sentiment | 37,832 | -1.710179 | 0.693577 | -3.417571 | -0.698384 |

| | | | | | |
|---|---|---|---|---|---|
| Article Volume | 37,832 | 5.336885 | 1.962505 | 2.866667 | 12.36667 |

## 2.4. Short Horizon Event Study: Immediate Stock Market Responses

This section illustrates the immediate market reaction of renewable energy stocks to (i) the passage of IRA and (ii) highly publicized news shocks pre- and post- IRA. To establish a threshold for each news measure, an average for all time-series factors built in Section 2.3.3 is computed and only those dates are chosen for analysis which display higher (or lower) values than 3 standard deviations above (or below) the mean. Specifically, all dates with a news volume of 20 stories per day, with a sentiment score less than -6.61 or more than 1.25, and with a weightage of more than 6.89 for *topic 1*, 5.25 for *topic 2*, 6.66 for *topic 3* and 5.95 for *topic 4* are chosen. These thresholds are marked by a dashed black horizontal line in respective time-series figures.[37]

To conduct this study, I employ an asset-pricing model from the well-established financial literature on event studies to calculate abnormal returns for each event. Abnormal returns are derived from the difference between the observed raw returns and the expected returns predicted by a multifactor framework, following the Fama and French, (1993) methodology. Specifically, I estimate the Fama-French three-factor model (FF3) by regressing daily, equal-weighted raw returns of renewable energy stocks on expected returns of the market portfolio, the size factor (Small-Minus-Big or SMB) and the value factor (High-Minus-Low or HML) obtained from the Kenneth R. French Data Library[38][39]. By incorporating the size and value factors, the model provides an unbiased measure of abnormal returns, allowing for an improved understanding of the risk-adjusted performance in response to news events. I

[37] In most news analysis studies, variations of structural vector autoregressive models are used to identify news shocks or innovations (Engle et al., 2020; Hsu et al., 2021; Liu et al., 2021; Morão, 2024). While SVARs are robust models to identify few precise and unanticipated shocks over extended periods, this study seeks to capture a broader range of influential events by identifying multiple windows of heightened media coverage across 2021-2023 to gain insight into various news themes. Rather than focusing solely on shocks, the threshold approach targets periods of elevated significance in public discourse, as reflected in media attention.

[38] Data on market risk-free rate, size factor (Small-Minus-Big or SMB) and value factor (High-Minus-Low or HML) from October 1, 2020, to December 31, 2023, is obtained from the Kenneth R. French Data Library. See Fama/French 3 factor, Kenneth R. French Data Library. https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. Last access: November 10, 2024.

[39] See Appendix A1 for detailed asset pricing method.

use the '*estudy*' package in STATA to perform the event study analysis on cumulative stocks of all renewable energy firms. For each event, I report the 1-day, 3-day and 5-day cumulative average abnormal returns (CAARs). Returns are accumulated over each window for multiple days and averaged over multiple stocks.

### 2.4.1. FF3 Results

The CAARs for all renewable energy firms around climate policy, extreme weather and geopolitical news events as identified through extensive media coverage during January 2021 to December 2023 are shown in Figure 1.6[40][41]. Note that the dates analyzed do not constitute an exhaustive list of *all* events affecting renewable energy stocks. This section primarily addresses the short-term, immediate responses to very high transition and physical risk periods. Particularly, I examine the swift and pronounced market reactions to abrupt legislative changes preceding the IRA's enactment, assuming that the market, under the Efficient Market Hypothesis, quickly assimilates such impacts. The observed market disturbances offer insights into investor risk perceptions and the magnitude of events, potentially highlighting deviations influenced by behavioral biases and herding behaviors. (Botzen et al., 2021; Bua et al., 2022; Pham et al., 2023; Ramiah et al., 2015). The insight can help policymakers respond rapidly and efficiently to discourse shifts (Stede & Patz, 2021).

I start by looking at the impact of climate policy (*Topic 1*) events. Results for the passage of IRA are consistent with (Bauer et al., n.d.; Pham et al., 2023). The first legislative step towards the policy initiative was arguably the house passing the highly debated Build Back Better (BBB) program. The program was in many ways a more ambitious economic and social policy bill with similar aims as the

[40] High intensity energy transition news as well as extreme sentiment events overlap with other topics, and they are discussed in the results but not illustrated separately. However, it must be noted that as time-series measures, they still represent different dimensions of climate risk.
[41] For more detailed results, see Appendix **Error! Reference source not found.**. Table B2: Results from FF3 model for different news textual factors.

IRA[42] and was ultimately stalled by the Senate. Figure 1.6 shows that returns from the portfolio of renewable energy firms significantly outperformed the expected market return by 4-6% over a period of 5 days on November 19, 2021, when the BBB was passed by the House. A month later the returns dropped below market expectations by as much as -8% when Senator Manchin, the key holdout in an evenly divided senate announced his decision to vote against the bill.

This led to months of negotiations to redesign the bill to a more economically workable Inflation Reduction Bill. However, returns plunged to abnormally low (-3%) when press reported Senator Schumer's and Manchin's dissention to the IRA. The market showed rapid recovery by day 5, signaling anticipated pessimistic investor expectation. This also explains their sizeable jump on July 27, when the IRA was announced by Schumer and Manchin as a new climate legislation. Renewable energy stocks outperformed the expected market returns by 13% over 5 days, highest among all events examined in this study. The increasing trend in abnormal returns over days 1, 3 and 5 indicates a considerably unanticipated shock. In fact, subsequent legislative changes including passage of the act by the Senate and the House on August 7 and 12 respectively, and even the final signing of the bill into an act by Biden on August 16 did not experience significantly abnormal renewable energy market returns[43]. Bauer et al., (n.d.), who examines the clean energy indices like the Wilderhill and S&P Global clean energy index finds similar results.

Prior policy announcement questioned the ability of the democrats to convert their claims into actionable policies with significant Senate backlash. Announcement of the BBB as well as passage of IIJA by the Senate had a progressively negative impact on the market returns driven probably by sentiments and narratives. While the total sentiment score for April 1, 2021, was 1 (optimistic) resulting in slightly higher

[42] Report by Joint Economic Committee Democrats, "11 Ways the Build Back Better Act Would Reduce Inflationary Pressure and Bring Down Costs for Families." Retrieved from https://www.jec.senate.gov/public/_cache/files/f9a6f7a3-9a50-4530-bc43-c7215abc8d27/bbb-and-inflation-fact-sheet.pdf

[43] Dampened renewable energy stock returns can also be explained by heterogeneity and subjectivity in media coverage to fully anticipated news. Most news reports on August 7, 12 and 16 bear a neutral stance. Some examples of headlines on August 16 include report by News York Times, "*Biden Signs Climate, Health Bill into Law as Other Economic Goals Remain*" and report by Los Angeles Times, "*Climate bill is big deal, but drama persists; Inflation Reduction Act has $370 billion for clean energy, but scientists say much more must be done*". Retrieved from ProQuest.

returns on day 1, subsequently featured debates in the Senate dampened the market. On the other hand, sentiment score for August 10, 2021, was -6 as news articles continued to elucidate on the challenges facing the Democrats after passing a $3.5 trillion bill[44]. Other studies reveal a large increase in green stock returns on Biden's election and rejoining of Paris Agreement (Pham et al., 2023). However, I do not test for news before April 1, 2021, in this study to allow a beta calculation period of at least 120 days before all events.

Analyses of *Topic 2* events reveal interesting patterns and forms another significant contribution of this study. Overall, market performance shows that the depressing effect of physical risk arising out of natural disasters and extreme weather phenomena was not neutralized by renewable energy stocks. News on winter storms, Hurricane Ida and tornado outbreaks in 2021 lead to underperformance of renewable energy stock returns by -6 to -10%. Other highly publicized natural disturbances also produced negative abnormal returns. But note that their magnitude was somewhat reduced after the year 2021. Only the Ukraine war resulted in significantly positive abnormal returns.

These results fit well with the tenets of climate policy uncertainty, limited attention hypothesis and behavioral myopia among investors (Botzen et al., 2021; Horváth et al., 2025; Song & Dong, 2024). The limited number of studies on the relationship between natural disasters and energy stocks reveal heterogenous and complex dynamics (Misev & Balles, n.d.)[45]. Climate shocks, especially hurricanes, are invariably related to incurred costs of infrastructural disruption and energy availability (Mukherjee et al., 2018). Although growing in quality, renewable energy infrastructure is still more vulnerable than that of fossil fuels. In such a case, restricted cognitive abilities prohibit investors from processing an overload of information. Their attention is limited to media portrayal of the event, leading to myopia or heavy discounting of future risk reduction benefits and over-weighting of upfront costs (Botzen et al., 2021) (see

[44] Report by Wall Street Journal, August 10, 2021, "Senate Moves to Pass Democrats' $3.5 Trillion Budget Blueprint; Democrats will face difficult choices, as they work to transform the budget framework into detailed antipoverty and climate legislation." Retrieved from ProQuest.

[45] There is considerable evidence to suggest that fossil-fuel stocks are more vulnerable to climate shocks that renewable energy stocks (Alehile et al., 2025; Liu et al., 2021; Misev & Balles, n.d.). But here, the comparison is between renewable energy stock movements and a neutral benchmark.

Section 2.3.3). With reduced climate policy uncertainty however, rebuilding funds after disasters and prospects of clean energy availability increased (Song & Dong, 2024), leading to neutralizing of renewable energy stock prices to climate shocks.

Conversely, articles on the Ukraine war highlighted the sudden supply chain disruption of gas[46]. The portrayal of the war bears similarity with the Covid-19 pandemic as an external, non-climate-related disruption which exposed the vulnerability of dependence on oil (Albuquerque et al., 2020; Garel & Romec, 2020).

Stock price responses to geopolitical summits generally exhibited positive trends following President Biden's commitments to lead international clean energy transitions. Exceptions were observed at the 2021 Earth Day Summit and the September 2022 U.N. climate talks, which recorded lower abnormal returns. These were attributed to market uncertainties stemming from the announcement of the Build Back Better (BBB) plan and the resignation of World Bank President David Malpass due to his climate-related stances, respectively. Results are consistent with the study by (Antoniuk & Leirvik, 2024) that show that clean energy indices benefited from Paris Agreement, Climategate, and Fukushima events.

[46] Report by The Washington Post, February 26, 2022, "How the Ukraine invasion scrambles American energy politics." Retrieved from ProQuest.

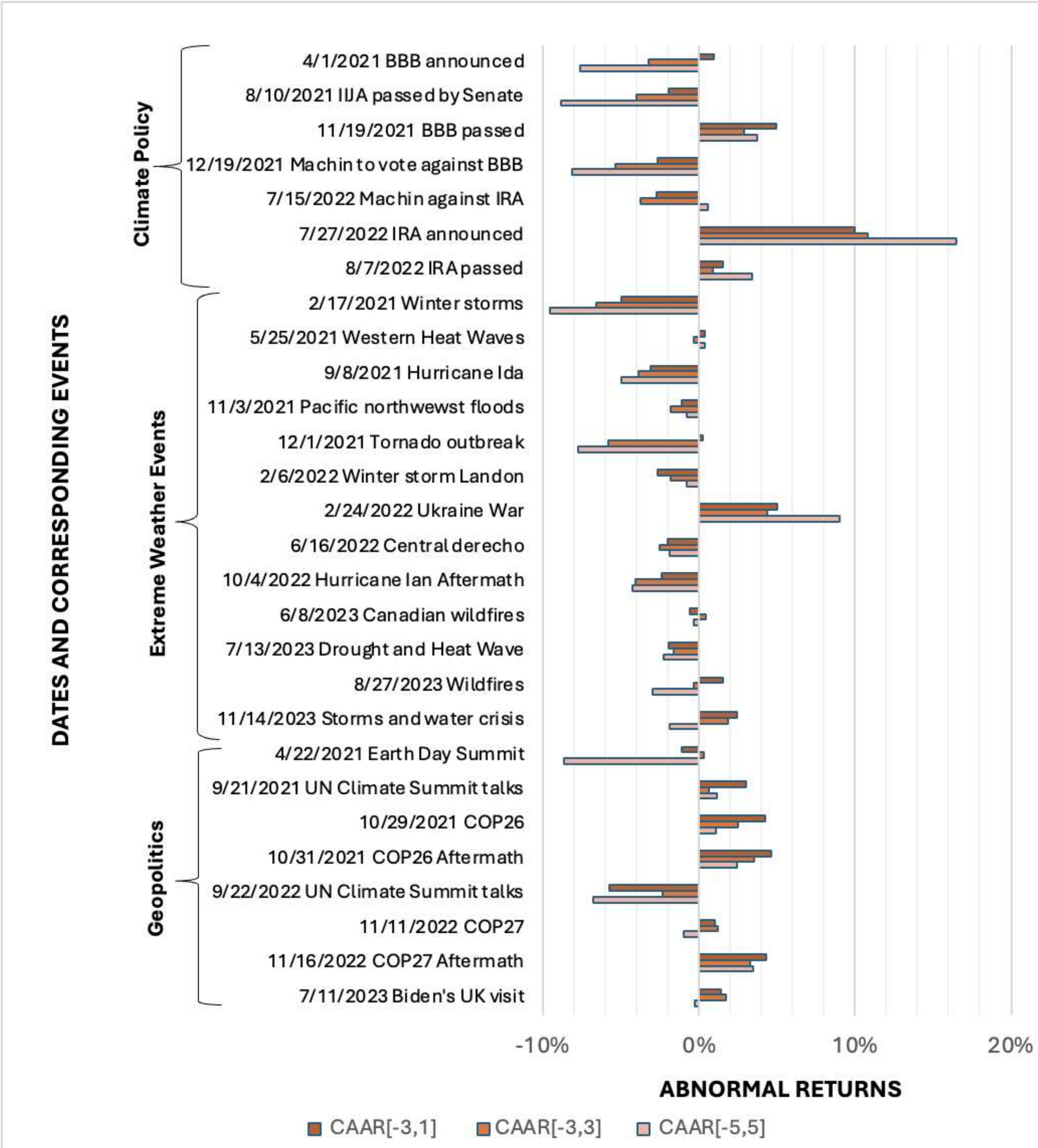



*Figure 2.6: Cumulative Average Abnormal Returns (CAARs) for renewable energy firms over multiple windows calculated using the Fama-French 3 factor model. Results are presented for various high attention news events segregated by thematic textual analysis using the Latent Dirichlet Allocation (LDA).*

## 2.5. Extended Horizon Event Study: The design

In this section, I extend the stock market impact evaluation of the IRA over a relatively longer period up to the point where the abnormal returns are discernable. For this, I employ the DiD framework for extended term asset price analysis[47]. I assign daily stock-returns for renewable energy firms to the treatment group and use the control group for benchmark formed by daily stock-returns of S&P 500, 400 and 600 constituents as described in Section 2.3.1.2. I weigh the daily cumulative returns by market capitalization to facilitate comparison across heterogenous firm sizes.

An explanation of event-date choice is in order here. I select July 27, 2022, (rather than the official date of August 16, 2022, when IRA was passed into law) to mark the passage of IRA as event under analysis, This is for three key reasons: (i) based on insight from the study's short-term asset pricing test, the immediate market impact of the IRA was observed on July 27; by August 16 the effect had been largely anticipated and priced in (see Section 2.4.1); (ii) Bauer et al. (n.d.) corroborates this by showing that it was July 27, marking the announcement of IRA by Manchin and Schumer, that saw the highest gains in clean energy stock indices; and (iii) the parallel trends analysis depicted in Figure 2.7 demonstrates a similar noticeable trend shift beginning on July 27 rather than August 16. For these reasons, July 27, 2022[48], is assumed to represent the event date for the passage of IRA for extended term stock price analysis. The subsections below outline the econometric method followed for each model.

### 2.5.1. Difference-in-Differences (DiD) Model

The primary goal of the DiD model is to identify the average causal impact of IRA on daily/monthly cumulative returns and daily/monthly volume of traded shares of renewable energy firms. The primary identifying assumption is that in the absence of IRA, the treated (renewable energy) firms would have experienced the same trends in outcomes as the control group firms after controlling for confounding factors. This "parallel trends" assumption is illustrated in Figure 2.7. For a baseline model, a $2 \times 2$ (two groups, two periods) panel fixed effects DiD approach is employed, with errors clustered on state. A daily frequency regression specification is as follows:

[47] To facilitate comparison of results, I also run Buy and Hold Abnormal Returns (BHAR) model for similar specifications. See Appendix **Error! Reference source not found.** for model and results.
[48] Placebo test with other dates do not reveal significant trends. See Table .

$$Y_{it} = \alpha + \beta_1 Post_t + \beta_2 Treat_i + \delta(Post_t \times Treat_i) + \beta_3 X_{it} + \epsilon_{it} \qquad (2.1)$$

Where $Y_{it}$ are the daily value-weighted cumulative returns of each stock $i$ on closing day $t$, $\text{Post}_t$ is the post-IRA period indicator or post-July 27, 2022, and $Treat_i$ is the treatment group indicator (here, renewable energy firm sample). $X_{it}$ is the vector of control variables—daily volume of shares traded to capture liquidity, daily weightage for each of the four news topics and daily news sentiment score to control for media influence and public sentiment dynamics, and the CBOE VIX index to account for expected market volatility. Firm characteristics are only available in monthly frequency and are therefore included in a modified low frequency specification. Specifications are also run with log of volume traded as the dependent variable and for different firm-size groups.

$(\text{Post}_t \times \text{Treat}_i)$ is the primary variable of interest and equals one if an observation is in the intervention (renewable energy) group and from the post-treatment (IRA) period. $\delta$ measures the average treatment effect of the intervention. If $\delta$>0 and significant, it suggests extended term average positive abnormal returns for renewable energy firms after the passing of the IRA, in comparison that of the control group. It reflects lower risk perception of clean energy stock prices, probability of future profits and expected growth leading to higher actual returns today. If $\delta$=0, it indicates the dissipation of the effect of IRA on renewable energy firm prices, and therefore a complete market absorption of any benefits arising from the climate bill. This is also a semi-positive effect as it suggests no market disruption even after such an ambitious policy (Bauer et al., n.d.). A negative and significant $\delta$, will however suggest extended term negative abnormal returns for renewable energy firms after the passing of the IRA, in comparison to the control group, indicating increased transition risk perceptions and reduced growth in future. Finally, $\epsilon_{it}$ is error term clustered around state of incorporation of the firm. The results for all specifications are presented in Section 2.6.2.

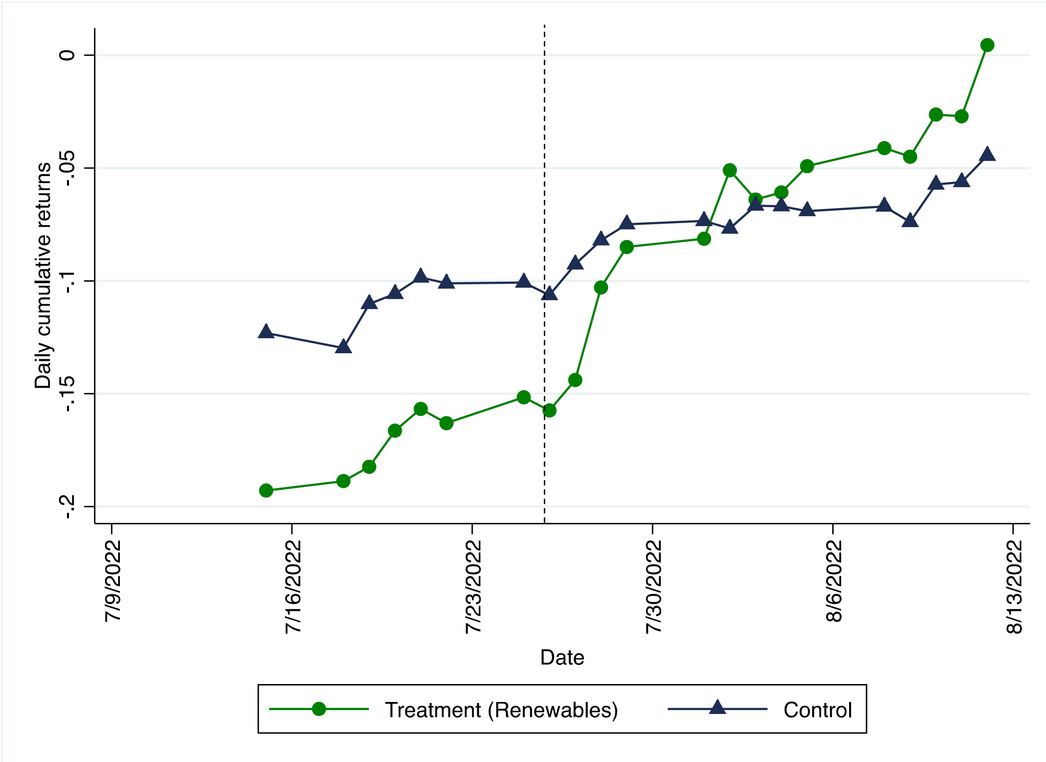



*Figure 2.7: Parallel trends between treatment and control group. Diversion occurs on July 27, 2022, represented by the vertical dotted line.*

### 2.5.2. Dynamic DiD Model

Based on insights about high volatility of energy stock market returns in general (Işık et al., 2024), I utilize a dynamic DiD approach within an event-study framework to estimate the effects of the IRA intervention on monthly cumulative returns and volume traded of renewable energy stocks over the period. I slice the timeframes in monthly intervals, from 5 months before the event, that is January 2022 to 12 months after the event, that is July 2023 to measure intertemporal trends. The dynamic DiD has two chief advantages; first, the estimation of pre-treatment intervention effects makes it possible to statistically inspect the parallel trend assumption; second, the model is able to deal with treatment effect heterogeneity and captures the dynamic effects of the IRA over time. I use the STATA package *'eventstudyinteract'* developed by Sun and Abraham (2021)[49] to run the model. The equation is as follows:

$$Y_{it} = \alpha + \beta_1\, Time_t + \beta_2\, Treat_i + \sum_{k=-3}^{13} \delta_k (Time_{t+k} \times Treat_i) + \beta_3 X_{it} + \epsilon_{it} \quad (2.2)$$

Where $Y_{it}$, $Treat_i$, $X_{it}$ and $\epsilon_{it}$ are the same as above, including firm characteristics. The variable $Time_t$ indicates the relative month of an observation from 3 months before to 13 months after the implementation of IRA. The parameter of interest, $\delta_k$ captures the temporal effects of the intervention by comparing the difference in cumulative returns between intervention and control groups to such a difference in the reference period (June 2022-a month prior to the event occurrence month). Results are provided in the next section.

## 2.6. Results and Discussion

### 2.6.1. DiD and Dynamic effects

Table 2.3 and Table 2.4 summarize the findings from the DiD estimation examining cumulative abnormal returns (CARs) of renewable energy firms associated with the enactment of the IRA.

Table 2.3 reports the shorter-term daily CARs. The DiD estimator indicates that renewable energy firms exhibited statistically significant positive abnormal returns of 12.5% within ±30 days ($p<0.01$) and 13.4% within ±120 days ($p<0.05$) around the policy event. Disaggregating by firm size, the results demonstrate significant positive CARs for medium-cap (6.87%, $p<0.01$) and large-cap firms (10.9%, $p<0.1$), whereas small-cap firms exhibit statistically insignificant effects.

Table 2.4 extends this analysis to monthly CARs of renewable energy firms to facilitate incorporation of firm-level financial controls and macroeconomic indicators other than the VIX index. The DiD estimator highlights robust abnormal returns of 14.8% within ±6 months ($p<0.05$), although the longer-term (±12-

---

[49] *'reghdfe'*, which is a commonly used two-way fixed effects regressions that includes leads and lags of the treatment, might lead to coefficient contamination of related events.

month) effect becomes statistically indistinguishable from zero. Further size-specific analysis reveals statistically significant positive CARs among medium-cap (6.53%, $p<0.05$) and large-cap firms (18.7%, $p<0.05$). Additionally, incorporating climate-specific news factors indicates that geopolitical news significantly enhances CARs, whereas weather-related news exerts a negative impact. The effect of climate policy news (other than the passage of IRA) is not statistically significant[50].

*Table 2.3: Extended term event study results of daily average cumulative returns from DiD analysis.*

| | **All firms** | **All firms** | **Small cap** | **Medium cap** | **Large cap** |
|---|---|---|---|---|---|
| | CAR (-30, +30) | CAR (-120, +120) | CAR (-120, +120) | CAR (-120, +120) | CAR (-120, +120) |
| | (1) | (2) | (3) | (4) | (5) |
| Post × Treated (DiD Estimator) | 0.125*** | 0.134** | 0.0576 | 0.0687*** | 0.109* |
| | (0.0350) | (0.0506) | (0.0356) | (0.0211) | (0.0603) |
| Post (after IRA) | 0.0105** | -0.0623*** | -0.0283*** | -0.0116 | -0.0626*** |
| | (0.00513) | (0.00844) | (0.00677) | (0.00895) | (0.00833) |
| Treated (Renewable Firms) | -0.0827** | -0.0684** | -0.0271 | -0.0358*** | - |
| | (0.0325) | (0.0300) | (0.0244) | (0.0130) | - |
| News sentiment controls | Yes | Yes | Yes | Yes | Yes |
| Macroeconomic controls | Yes | Yes | Yes | Yes | Yes |
| Stock FE | Yes | Yes | Yes | Yes | Yes |
| Time FE | No | No | No | No | No |
| Observations | 46,560 | 193,514 | 96,039 | 32,455 | 65,020 |
| R-squared | 0.373 | 0.491 | 0.066 | 0.123 | 0.519 |

Note: ∗∗∗Significant at $p < 0.01$, ∗∗Significant at $p < 0.05$, ∗Significant at $p < 0.1$. Standard errors are clustered around state. Cumulative returns are weighted by market cap. All values are winsorized at the 1st and 99th percentiles to mitigate the influence of extreme outliers. CAR (-X, +X) indicates cumulative abnormal returns from X days before to X days after July 27, 2022.

Table 2.5 presents the Difference-in-Differences (DiD) analysis examining cumulative abnormal trading volumes (CATVs) of renewable energy firms surrounding the announcement of the Inflation Reduction Act (IRA). The findings indicate significant increases in trading activities of renewable energy firms within shorter-term windows, with CATVs rising by 30.7% (±3 months, $p<0.05$) and 26.1% (±6 months, $p<0.05$). For small-cap firms, the CATVs increase by 11.9% over the ±12-month window, although this result lacks statistical significance. Further decomposition reveals that climate-related news significantly influences trading activity. Geopolitical factors positively drive abnormal volumes at the 6-month (16.0%,

[50] Correlation test (see Appendix **Error! Reference source not found.Error! Reference source not found.**) reveals high factor correlation between sentiment measure and extreme weather phenomena news theme, as well as geopolitics and energy transition theme. Therefore, only topics 1,2 and 3 factors are included in the regression specification presented in Table 2.3, Table 2.4 and Table 2.5The results are robust if the topic factors are exchanged with the sentiment score factor. See Appendix Table  for robustness checks.

p<0.01) and 12-month (8.07%, p<0.01) horizons. In contrast, weather and climate policy-related factors negatively affect abnormal trading volumes consistently across these windows.

*Table 2.4: Extended term event study results of monthly average cumulative returns from DiD analysis.*

| | **All firms** CAR (-6, +6) | **All firms** CAR (-12, +12) | **Small cap** CAR (-6, +6) | **Medium cap** CAR (-6, +6) | **Large cap** CAR (-6, +6) |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Post × Treated (DiD Estimator) | 0.148** | 0.112 | 0.0390 | 0.0653** | 0.187** |
| | (0.0734) | (0.0686) | (0.0627) | (0.0304) | (0.0852) |
| Post (after IRA) | -0.0163 | -0.0725* | 0.00441 | -0.0199 | -0.0968* |
| | (0.0188) | (0.0176) | (0.0123) | (0.0156) | (0.0245) |
| Treated (Renewable Firms) | -0.0866** | -0.0878** | -0.0502 | -0.0290 | - |
| | (0.0390) | (0.0345) | (0.0757) | (0.0402) | - |
| Climate policy factor x Treated | -0.00279 | -0.00402 | 0.0214 | 0.0147 | 0.0174 |
| | (0.00813) | (0.0100) | (0.0268) | (0.00888) | (0.00826) |
| Weather factor x Treated | -0.0807*** | -0.0612*** | -0.0244 | -0.0948* | -0.0348*** |
| | (0.0231) | (0.0195) | (0.0712) | (0.0507) | (0.00815) |
| Geopolitics factor x Treated | 0.0651*** | 0.0296* | -0.0210 | 0.0661** | 0.0344** |
| | (0.0205) | (0.0166) | (0.0374) | (0.0278) | (0.0127) |
| Firm controls | Yes | Yes | Yes | Yes | Yes |
| Macroeconomic controls | Yes | Yes | Yes | Yes | Yes |
| Stock FE | Yes | Yes | Yes | Yes | Yes |
| Time FE | No | No | No | No | No |
| Observations | 8,666 | 16,792 | 2,827 | 1,854 | 7,564 |
| R-squared | 0.696 | 0.619 | 0.157 | 0.171 | 0.637 |

Note: ***Significant at $p < 0.01$, **Significant at $p < 0.05$, *Significant at $p < 0.1$. Cumulative returns are weighted by market cap. All values are winsorized at the 1st and 99th percentiles to mitigate the influence of extreme outliers. CAR (-X, +X) indicates cumulative abnormal returns from X months before to X months after July 2022.

All regression models incorporate comprehensive macroeconomic controls, and sentiment-based news variables, with standard errors clustered by state, while monthly frequency models also include firm-specific characteristics. The CARs reported are market-cap-weighted and have been winsorized at the 1st and 99th percentiles to address potential biases arising from extreme observations.

While the immediate impact model results (see Section 2.4.1) are explained largely by investor sentiments driven by news portrayal of policy legislations within days of the event, the extended impact measured through the DiD entails behavioral updating over time (Bauer et al., n.d.; Santi, 2023). Santi, (2023) uses the adaptive market hypothesis (Lo, 2004) to explain observed time variation in market efficiency. Behavioral finance models predict that during policy changes subjective valuation of a firms' performance due to informational asymmetry along with the limits to arbitrage can lead to prolonged mispricing of asset (Shleifer & Vishny, 1997). A sudden upsurge in CAR followed by its gradual nullification implies that part of the investor reaction to climate sentiment was irrational. It could indicate that overtime renewable energy firm's response to phased policy implementation aided in rationalizing beliefs about future firm profits. Bauer et al., (n.d.) suggests three channels though which IRA implementation could affect green stocks: *cost channel*, through which supply-side subsidies reduce the green firm's marginal costs; *demand channel* or demand-side subsidies which increase demand for clean energy; and the *cost of capital channel*, wherein transition uncertainty for emission-heavy firms raises the expected returns for green firms.

*Table 2.5: Extended term event study results of average cumulative share volume traded from DiD analysis.*

| | **All firms** CATV (-3, +3) | **All firms** CATV (-6, +6) | **All firms** CATV (-12, +12) |
|---|---|---|---|
| | (1) | (2) | (3) |
| Post × Treated (DiD Estimator) | 0.307** | 0.261** | 0.119 |
| | (0.141) | (0.127) | (0.112) |
| Post (after IRA) | -0.105*** | 0.103 | -0.00592 |
| | (0.0162) | (0.0820) | (0.0415) |
| Treated (Renewable Firms) | -0.138 | -0.153* | -0.165*** |
| | (0.0832) | (0.0882) | (0.0611) |
| Climate policy factor x Treated | 0.00284 | -0.0382** | -0.0450*** |
| | (0.00562) | (0.0178) | (0.0141) |
| Weather factor x Treated | -0.0247*** | -0.178*** | -0.104** |
| | (0.00736) | (0.0630) | (0.0397) |
| Geopolitics factor x Treated | 0.0146 | 0.160*** | 0.0807*** |
| | (0.0137) | (0.0468) | (0.0229) |
| Firm controls | No | Yes | Yes |
| Macroeconomic controls | Yes | Yes | Yes |
| Stock FE | Yes | Yes | Yes |
| Time FE | No | No | No |
| Observations | 193,514 | 8,666 | 16,792 |
| R-squared | 0.443 | 0.630 | 0.566 |

Note: ∗∗∗Significant at $p < 0.01$, ∗∗Significant at $p < 0.05$, ∗Significant at $p < 0.1$. Cumulative volumes are weighted by market cap. All values are winsorized at the 1st and 99th percentiles to mitigate the influence of extreme outliers. CAR (-X, +X) indicates cumulative abnormal trading volumes from X months before to X months after July 2022.

The apparent effectiveness of these channels became clearer over months after the passage of IRA. A 2024 MorningStar report[51] suggest that U.S. solar and wind energy sector recorded their highest growth in

[51] Valerio Baselli, MorningStar, Aoril 18, 2024, "*Clean Energy is the Future. So Why Have Investors Struggled*?" Retrieved from https://www.morningstar.co.uk/uk/news/248370/clean-energy-is-the-future-so-why-have-investors-struggled.aspx

2022 at the end of November and beginning of December, largely attributed to regulatory certainty and investment tax-credits. But clean energy projects were weighed down by interest rate hikes, high inflation supply chain bottlenecks, and increased development costs resulting in lower investor profits. An explanation of gradual reversion in equity prices could indicate that the high cost of capital and excess supply to meet current demand diminished expected profitability channels and investor beliefs.

The adaptive behavior timeline can be further visualized through results from the dynamic DiD model, illustrated in Figure 2.8. The graph shows the temporal progression of cumulative abnormal returns (CARs) before and after the enactment of the Inflation Reduction Act (IRA). In this plot, the marked vertical line at time zero represents the policy event (July 2022), with cumulative abnormal returns measured from three months prior to thirteen months after the event.

Initially, there was a notable and statistically significant surge in CARs immediately following the policy announcement. This rapid increase in returns is consistent with investor optimism and a swift, yet partial, market reaction to new information—reflecting short-term mis-pricing opportunities. The progressive decline in abnormal returns in the following months suggests the market initially overestimated future firm performance, subsequently adjusting valuations downward toward equilibrium as the true economic impacts of the transition policy became clearer. The phenomenon is explained through the lens of market inefficiencies arising from bounded rationality and cognitive biases resulting in investor myopia. Such transient irrational exuberance could create arbitrage opportunities that persist until market participants gradually process the available information.

This hypothesis is corroborated further by the elevated levels of CATV for a prolonged period, suggesting persistent investor disagreement and ongoing arbitrage activity (Chordia et al., 2001). As investors adapted to new information, high trading activity from IRA policy implementation led to price reversal and final assimilation into the market by August 2023.

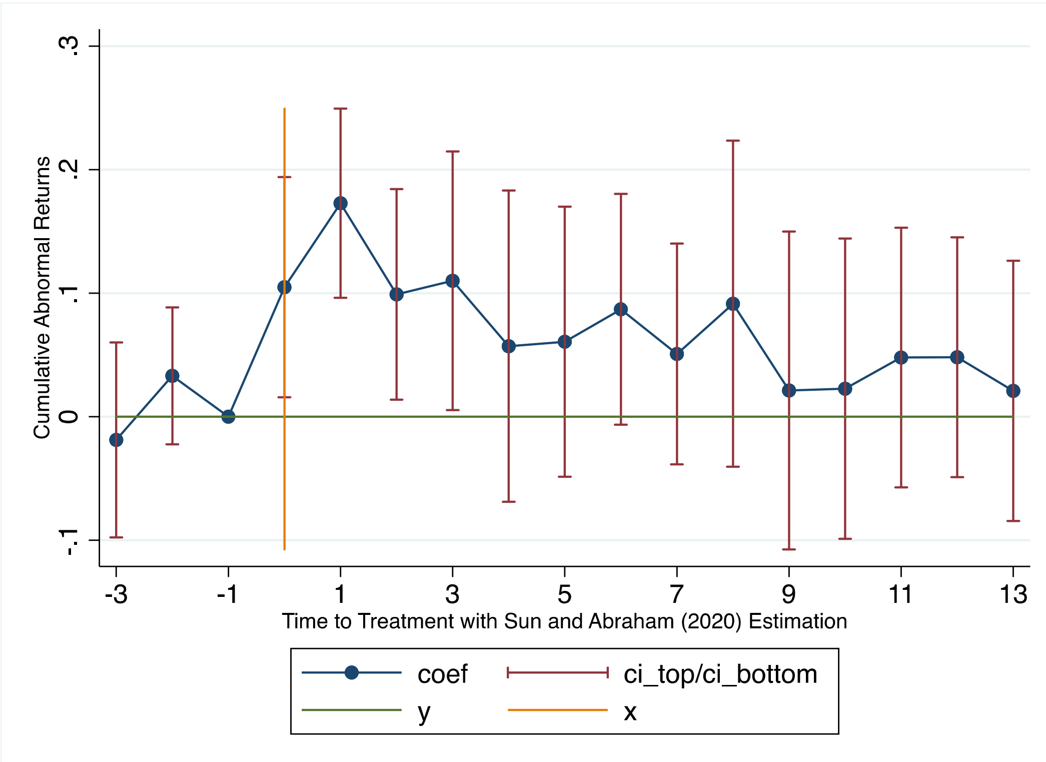



*Figure 2.8: Dynamic Impact of the Inflation Reduction Act on average monthly cumulative returns of renewable energy stocks relative to the control group.*

Additionally, the market volatility is found to be concentrated on mid- and large-cap renewable firms. This differential responsiveness based on market capitalization can be attributed to a combination of operational scale effects, policy compliance resources, and institutional investor base of large- and mid-cap firms which helps them navigate supply-chain bottlenecks more efficiently (Seetharam, 2017). Bauer et al., (n.d.) finds that industrial sectors- particularly electrical equipment manufacturers, utilities, and construction firms- exhibiting stronger positive equity response to IRA policy announcements were disproportionately represented by larger firms. However, the size-effect of climate policy impact on stock prices remains underexplored.

Positive CARs for geopolitical news interactions with renewable energy firms indicate that investors interpreted international summits and climate negotiations as beneficial to future profitability, possibly due to Biden's pro-climate stance (Ramelli et al., 2021). Higher CATV however indicates rapid price correction, suggesting the effects were short-lived. Conversely, a stable downward correction in prices (negative CATV) in case of weather-related news denote investor caution regarding physical climate risks, reflecting heightened operational and profitability uncertainty during high-interest rate periods. The insignificant influence of climate policy news interactions might signal that the investors already anticipated such policy developments, resulting in muted incremental market reactions.

These findings provide critical insights for policymakers aiming to maximize the effectiveness and market acceptance of climate policies such as the IRA. Most importantly, they prove that such a large-scale transition policy effort did have a sustained positive impact on the renewable energy market. Additionally, the investigation underscores the practicability of aligning climate policy implementation, with broader economic conditions to enhance investor confidence and ensure optimal market outcomes. The observed prolonged market adjustment, persistent abnormal trading volumes, and investor sensitivity to external shocks like geopolitical and weather-related events suggest policymakers should carefully consider timing and macroeconomic context—including inflationary pressures, interest rate trends, and supply chain stability—when introducing major policy interventions. Clear, transparent, and consistent policy communication is also essential to minimize informational asymmetries, reduce prolonged price disturbances, and mitigate unnecessary volatility driven by arbitrage activity. Additionally, given the varied responses among firms based on market capitalization, tailored policy measures may be necessary to ensure broad-based effectiveness across the renewable energy sector.

## 2.7. Conclusion

In this study, I investigate how renewable energy financial markets responded to the IRA, a landmark climate policy aimed at accelerating the clean energy transition. Specifically, I examine the immediate- and extended-term effects of the IRA and related climate news on the stock prices and trading volumes of individual firms. While previous literature has explored the general impact of climate policy on financial markets, few have isolated the causal effect of the IRA on clean energy equities, nor accounted for the role of news sentiment and external shocks in shaping investor behavior.

To address this gap, I employ a two-pronged empirical strategy. A short-horizon event study, based on the Fama-French three-factor model, is used to capture immediate market reactions to high-salience policy and climate-related news events. For longer-term effects, I use a DiD framework, to estimate CARs and CATVs around the IRA's announcement and passage. The analysis integrates firm-level financial controls, macroeconomic indicators, and sentiment-based news measures to isolate the policy's effect from broader market dynamics. News measures are built using NLP techniques, specifically LDA for topic modeling and ClimateBERT for sentiment analysis, to dissect the role of media attention and investor sentiment in shaping market responses.

The findings reveal a strong and statistically significant positive response of renewable energy stocks to the IRA's announcement, with CARs reaching up to 17% over a 5-day window and remaining elevated for several months. However, this initial optimism gradually faded, suggesting that the market reassessed its expectations as implementation challenges—such as inflation, interest rate hikes, and supply chain disruptions—became more apparent. The initial investor euphoria followed by a phased price reversal is explained by the adaptive market hypothesis. Thematic news interactions further reveal that geopolitical developments amplified market responses, while weather-related news negatively affected returns and trading volumes.

These results underscore several important policy implications. First, the IRA had a meaningful and lasting effect on clean energy markets, reinforcing the influence of large-scale climate legislation on investor sentiment and capital allocation. However, the subsequent price correction highlights the need for policymakers to anticipate and mitigate implementation bottlenecks that may undermine long-term market confidence. Aligning climate policy with favorable macroeconomic conditions and ensuring transparent, credible communication are essential to sustaining investor engagement. Overall, this study contributes to the growing evidence base on how financial markets respond not only to the content of climate policy but also to its timing, communication, and real-world feasibility.

Future research could expand on these findings by examining the IRA's effects on fossil fuel and oil-price movements and performing comparative analysis over extended time-horizons. Studies can build on these findings through a more granular firm-level analysis to uncover heterogeneity in policy responsiveness based on factors such as technology type, geographic exposure, or ownership structure. It must be noted that while the results of the study can be explained by implementation bottlenecks, the direct impact of infrastructural vulnerability is not tested, which can significantly add to the understanding of climate policy design. Finally, comparative studies across different policy regimes—such as the EU Green Deal or Asia's renewable finance frameworks—could offer valuable insights into the global financial dynamics of the low-carbon transition.

# 3. Actions Speak Louder Than Words: Determinants of Energy Transition in PPP Projects

## 3.1. Introduction

An International Energy Agency (IEA) 2021 report on climate financing in Emerging and Developing Economies (EMDEs) states that while EMDEs represent two-thirds of the global population, they receive only one-fifth of clean energy investment and hold just one-tenth of global financial assets[52]. Since 2016, energy investments in these regions have declined by 20%, reflecting persistent barriers to clean energy finance (IEA, 2021). Over 70% of clean energy investments are publicly financed, particularly in the renewable power sector. While clean technologies like the solar PV cells often require high upfront costs, they offer long-term savings through lower operating expenditures. Blended finance mitigates the initial barrier by combining concessional public resources with private capital, reducing initial financial risks and improving the investment attractiveness of these technologies. Consequently, it can be an efficient route to mobilizing private capital through private participation in infrastructure (PPI), especially in high-risk or early-stage markets.

Sovacool, (2013) argues that pro-poor Public-Private Partnerships (PPP) are one of the best mechanisms to supplement and overcome government budgetary constraints for widening access to energy services. Renewable energy PPIs (REPPI) in particular can introduce private sector capital, technological innovation as well as managerial efficiency into public service provisions (Cedrick & Long, 2017). Evidence also suggests that this private sector mobilizing mechanism also offers a transition pathway to mitigate the environmental impact typically associated with foreign direct investment (Caetano et al., 2023). There is a bourgeoning literature that studies the determinants of REPPI in developing economies (Abba et al., 2022; Azhgaliyeva et al., 2023; Baldwin et al., 2017; Fleta-Asín & Muñoz, 2021a; Kim,

[52] Report by IEA, 2021, "Financing Clean Energy Transition in Emerging and Developing Economies." Accessed using: https://www.iea.org/reports/financing-clean-energy-transitions-in-emerging-and-developing-economies.

2020; Meckling et al., 2022; Othman et al., 2024; Polzin et al., 2019; Ragosa & Warren, 2019; Vagliasindi, 2012). Studies suggest the importance of targeted local and international support (Fleta-Asín & Muñoz, 2021a), holistic enabling clean energy policy mechanisms (Abba et al., 2022), institutional capacity and regulatory certainty (Azhgaliyeva et al., 2023) as pertinent to increasing PPI in renewable infrastructure.

However, almost no research focuses on factors driving energy transition in PPI projects, that is, the systemic compositional shift in PPP investments from fossil fuel to renewable energy technology. Only one study by Vagliasindi, (2012) shows that government schemes and institutional quality affect the entry of PPI in the renewable market, but do not drive the overall switching to renewable energy. In this study, therefore, I address the question of determinants of this *compositional shift* in PPI projects in EMDEs.

There is strong evidence that suggests persistent energy transition in PPP investments. Figure 3.1 illustrates a clear upward trend in the share of renewable energy project volumes and monetary investments within the EMDE PPP portfolio since the early 2000s, with particularly sharp growth after 2010. Vagliasindi, (2012) explains this jump through external factors such as the establishing of the Kyoto Protocol amidst rising oil prices and energy security concerns. However, despite volatility in absolute renewable investment, there has been a consistent rise in both share indicators of infrastructure financing towards clean energy. This motivates the need to understand the policy and institutional drivers of this transition in PPI.

Private sector involvement generally needs guarantees to face policy and the financing uncertainties in EMDEs (Alloisio & Carraro, 2015b). The effectiveness of climate policies in directing PPPs towards renewable energy is dependent on their ability to facilitate smoother investment environments for the private investor. Consequently, current literature emphasizes on risk-management policies and their role in reducing transaction costs in EMDEs (Aziz & Jahan, 2023; Cedrick & Long, 2017; Fleta-Asín & Muñoz, 2021b; H. Wang et al., 2018). This includes project-based infrastructural support, demand creation as well as domestic and international public finance guarantees. More recent literature also explores the synergistic relationships between internal enabling environments of host countries instead of a particular factor in facilitating blended finance (Abba et al., 2022; Ameli et al., 2021; Kerr & Hu, 2025a). Consequently, the effectiveness of policy is shown to vary substantially across income groups and regions (Baldwin et al., 2017). Ciplet et al., (2022) argues that "*climate finance in many ways reproduces relationships of dependency*," that is it favors higher income countries which are less vulnerable to climate change, infrastructural bottlenecks as well as financial volatility.

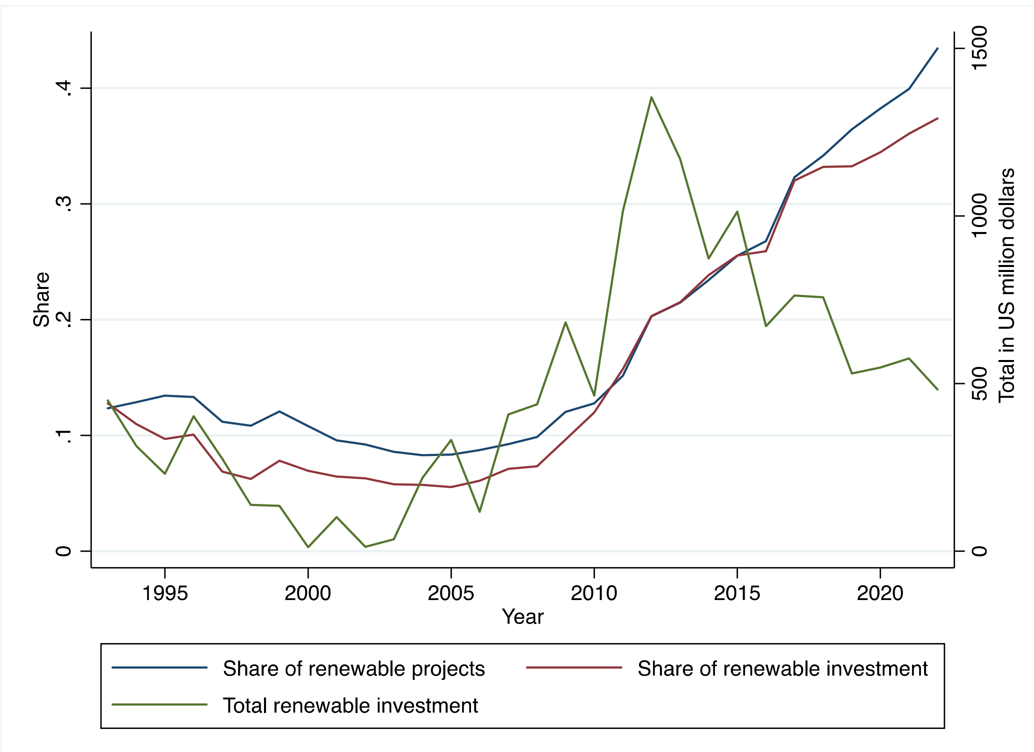



*Figure 3.1. Trends in renewable energy project volumes and monetary investments in Public-Private Partnerships (PPP) in emerging and developing economies between 1994–2022. The blue and red lines (corresponding to the left-axis) indicate the annual share of renewable projects and renewable investment, respectively, as a proportion of total energy PPP activity. The green line (corresponding to the right axis) shows the total volume of renewable investment in millions of U.S. dollars. Sourced from World Bank PPI dataset and author's calculations.*

Following from extant literature, renewable energy engagement through PPPs may not be driven by a single instrument but by the interplay of many factors including energy access expansion, R&D support, market mechanisms, trade relationships and enabling regulatory environments. Hence, in this study, I adopt a mixed-method approach to examine the determinants of renewable energy transitions in PPPs across emerging and developing economies (EMDEs). I integrate quantitative econometric models with text-based analysis of project documentation and policy sources. I draw on a panel dataset of PPI projects undertaken in 72 low- and middle-income countries from 1996 to 2023, constructed by merging the World Bank's PPI database with institutional indicators from the Worldwide Governance Indicators (WGI), macroeconomic variables, and project-level characteristics. I use a keyword-based policy extraction technique to systematically classify local support given to specific renewable energy projects. To perform the empirical analysis, I first apply a probit model to identify distinguishing characteristics of renewable PPPs at the project level. Subsequently, I estimate the Tobit models and the dynamic difference Generalized Method of Moments (GMM) specifications for country-level data to assess how public finance, cumulative policy actions, income group interactions, and regional heterogeneity influence the intertemporal share of renewable PPPs in both volume and investment value.

The findings underscore that realized, quantifiable and directed public action- like local and multilateral development bank support given to projects, higher public investment in RE and electricity production through renewable sources- has more consistent associations with compositional change in PPI investments than planned policies and contributions. Moreover, market and trade policies are more responsive in upper-middle income economies.  While government institutions matter in initial investment decisions, they do not drive the transition of PPI to renewable energy. These results support the view that energy transition in infrastructure through PPPs needs quantifiable, directed, and regionally tailored policy frameworks to be effective, especially in low-income economies.

This research makes several contributions to the literature on private sector mobilization for infrastructure decarbonization. It is the first study to examine energy transition within the context of PPI projects. By combining static Tobit models with a dynamic GMM framework, the study offers new insights into how policy complementarities, and public finance shape long-term transition trajectories. It further contributes to the data by extracting and quantifying renewable energy-related policy instruments from project-level documentation. The findings offer both diagnostic and prescriptive value for policymakers seeking to design integrated and adaptive policy regimes that crowd in private investment for clean energy infrastructure.

The rest of the chapter is divided as follows: Section 3.2 presents a review of extant literature, Section 3.3 luminates the data and the local support extraction process, Section 3.4 describes the project level analysis model and the corresponding results, Section 3.5 elucidates on the country-level analysis, results and policy insights and Section 3.6 concludes.

## 3.2. Review of Literature

### 3.2.1. Risk-Management in PPI

Risk-management policies, specifically feed-in tariffs (FiTs) and their role in reducing transaction costs for private investors have been a prevalent topic in the extant literature on PPI (Aziz & Jahan, 2023; Cedrick & Long, 2017; Fleta-Asín & Muñoz, 2021a; H. Wang et al., 2018). Lower costs of participation, determined by risk sharing and profit guarantees leads to higher private participation with the public sector (Fleta-Asín & Muñoz, 2021). Aziz & Jahan, (2023) show that renewable energy regulations, FiTs, tendering and public investments have a positive role in attracting renewable investment. Azhgaliyeva et al., (2023) uses panel fixed-effects on 13 countries to illustrate the high impact of smoother investment environments, enhanced FiT mechanisms and government R&D in facilitating private investment from asset finance in developing countries. Kim, (2020) focuses on the variability in PPP policy strength based on technology diffusion stages and finds that government regulatory schemes are more potent that FiT mechanisms. However, multilateral support, prior knowledge, and economy-wide market stability in the host country are all major factors for private finance mobilization. Romano et al., (2017) corroborates these findings, citing green policies as essential in the initial phase of renewable transition.

Alloisio & Carraro, (2015) emphasize on the public-private cooperation for mutual risk sharing in PPP projects. Othman & Khallaf, (2022) use questionnaire survey design to collects opinions of 60 PPP experts and identify political and regulatory barriers as the main global risk factors in renewable energy

PPI investment. An interesting result from a panel-data study by Vagliasindi, (2012) is that the likelihood of switching to renewable PPI is driven more by long-run factors like oil prices and the introduction of Kyoto Protocol rather than the short-run policies. The study also finds that FiT schemes have no impact on reducing the amount of fossil fuel generation through PPP projects.

### 3.2.2. Regional Variations in Policy Effectiveness

Several renewable energy PPP case studies on specific regions concentrate on more granular policy approaches. For example, study of PPP in thermal and electric power production through biomass in Greece and Italy (Manos et al., 2014) suggest tailored incentives for local needs and stakeholders. Arbulú et al., (2017) illustrate the efficacy of waste-to-energy in small tourism-dependent islands in Spain. Insights from South Africa's Renewable Energy Independent Power Producer Procurement Program show that private finance in renewable energy can be mobilized through well-designed procurement process, reasonable profitability guarantee and risk mitigation by the government (Eberhard et al., 2014). Baldwin et al., (2017) finds that RE generation is driven by feed-in-tariffs and renewable portfolio standards in high-income countries, feed-in tariffs alone in middle-income countries, and by subsidies in low-income countries. Alloisio & Carraro, (2015) concentrates on the MENA region and shows that the private sector needs guarantee to deal with policy and financing risks associated with the time gap between the project's planning phase and its actual implementation.

### 3.2.3. A Holistic Approach

More recent literature on mobilizing private finance for clean energy transition in emerging and developing economies (EMDEs) stresses on the importance of enabling environments of host countries, rather than a particular factor. (Abba et al., 2022; Ameli et al., 2021; Azhgaliyeva et al., 2023; Kerr & Hu, 2025b). The systematic literature review of renewable energy (RE) risks and methods used for risk assessment by Abba et al., (2022) with focus on the Sub-Saharan African countries recognizes that RE risks are complex, dynamic and require multidisciplinary perspectives for effective mitigation. Kerr &

Hu, (2025) shows that closing the green finance gap in EMDEs requires leveraging private finance which must involve cohesive packages of public, private, and market support to establish socioeconomic and political frameworks conducive to effective policy execution.

Othman & Khallaf, (2022) reviews PPP projects across 6 regions to report that a combination of government support, strategic planning and policy framework, as well as minimized operating costs drive private investment in EMDEs. Fleta-Asín & Muñoz, (2021) use Tobit estimation technique to demonstrate the importance of better institutional and economic environments, combined with support of multilateral development banks (MDBs) in attracting private renewable investment. Ragosa & Warren, (2019) uses linear and logistic fixed effects model to test the determinants of foreign private capital flows into renewable projects and finds that international public finance is a strong factor, as well as regulatory support and feed-in-tariffs. L. Wang et al., (2024) studies PPP projects across 36 Belt and Road Initiative countries and cites the role of synergetic institutions rather than a single factor resulting high participation of private investors.

### 3.2.4. Energy Transition

Comparative studies of circumstantial and contractual characteristics of renewable and conventional energy PPPs or those analyzing degree of energy transition in PPPs remain scarce. Casady et al., (2024) shows that low-carbon and clean infrastructure are associated with more creative risk-sharing tools and larger stakeholders. Vagliasindi, (2012) also looks at fossil-to-clean energy switching factors, but being an early study, only considers China, Brazil, Peru and Mexico. Čaušević, (2022) discusses risk mitigation for renewable energy investments in developing countries, emphasizing the need for more research on how PPP structures influence the pace and quality of energy transition, especially in Sub-Saharan Africa.

## 3.3. Data

### 3.3.1. Private Participation in Infrastructure

In order to test for the determinants of energy transition in PPPs, I collect the sample of PPP projects from The World Bank Private Participation in Infrastructure Database (WBPPI), which records "*projects that are owned or managed by private companies in low- and middle-income countries*" with at least 20% stake[53]. To define the sample, I select all projects from the electricity sub-sector, each pertaining to either conventional or renewable technologies[54]. The final sample contains 2075 renewable and 3211 conventional PPPs deployed in 106 countries during the period between 1996-2023. Figure 3.2 plots the relative percentages of projects across technologies. While diesel and natural gas dominate in electricity production, solar photovoltaic and onshore wind production also account for considerable shares, higher than hydroelectricity.

[53] Retrieved from the World Bank Private Participation in Infrastructure Database. https://ppi.worldbank.org/en/ppi.
[54] Projects from other sub-sectors in the database, like Information & Communication Technologies and Transport do not use renewable energy and are therefore not included in the study, in line with previous literature (Fleta-Asín & Muñoz, 2021a).

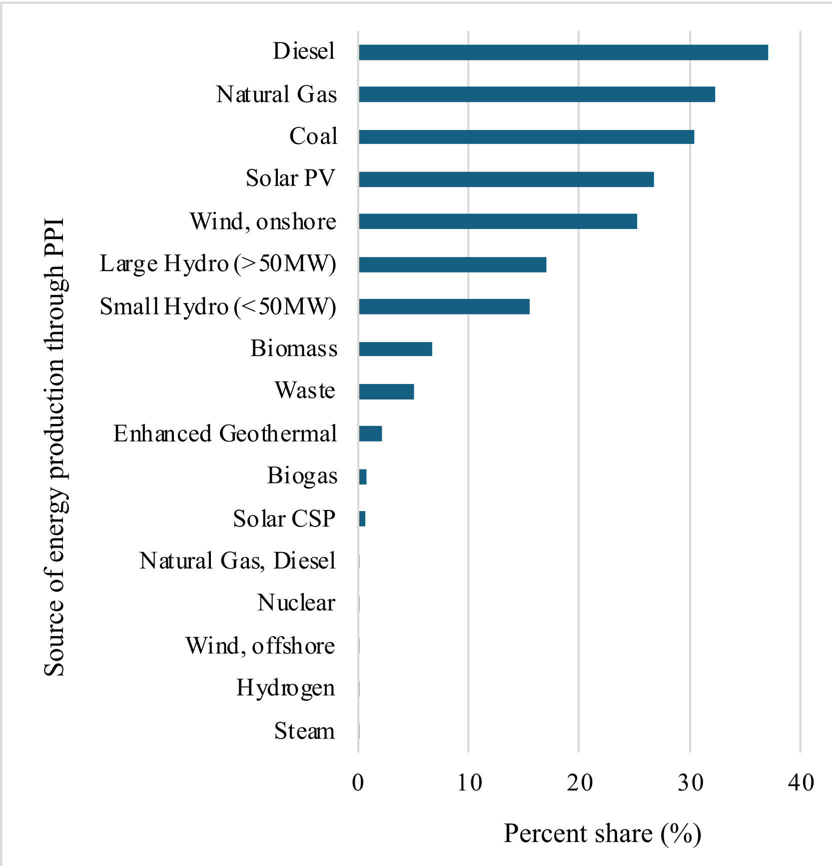



*Figure 3.2: Distribution of private participation in infrastructure (PPI) energy projects across the sources of production.*

WBPPI also provides details of other characteristics for each project, including total private investment commitments (in USD million), period of project in years, percentage of private participation, direct and indirect local government support, bilateral and multilateral support, type of project (greenfield, brownfield, management and lease and divestiture), power capacity produced (in kwh), competitive bidding criteria, the status of project (active, completed, distressed or canceled), as well as the region of PPP and its corresponding income group. Additionally, the database keeps a record of project descriptions which provides comprehensive information about the corporation involved, risk-mitigating tools used, circumstances surrounding updated statuses of projects if applicable, and other granular details. Table 3.1 presents summary statistics of all continuous and categorical project-level variables. The statistics illustrated show that renewable projects are on average smaller in capacity, planned for shorter periods and with lesser investment commitments, but with higher percentage` of private risk-sharing.

*Table 3.1. Summary statistics for project-level data*

| Continuous variables | Obs. | Mean | SD | Min. | Max. |
|---|---|---|---|---|---|
| **Power Generation Capacity (in kilowatt hours)** | | | | | |
| Conventional: | 2,531 | 1562.563 | 9063.172 | 1 | 350000 |
| Renewable: | 2,037 | 686.6504 | 19472.52 | 0.25 | 850000 |
| **Private participation (in %)** | | | | | |
| Conventional: | 3,027 | 84.7371 | 22.69977 | 1 | 100 |
| Renewable: | 2,065 | 97.54973 | 12.79128 | 8.5 | 400 |
| **Period of project (in years)** | | | | | |
| Conventional: | 1,698 | 30.09482 | 15.7215 | 1 | 95 |
| Renewable: | 1,025 | 24.27317 | 8.13362 | 3 | 70 |
| **Private investment amount (in USD million)** | | | | | |
| Conventional: | 2,662 | 259.3261 | 549.4361 | 0.0521 | 8637 |
| Renewable: | 1,982 | 121.2021 | 167.6661 | 1.03 | 2270 |
| **Categorical Variables** | **Conventional** | **Renewable** | | | |
| **Status of project** | | | | | |
| Active | 2848 (88.7%) | 2062 (99.37%) | | | |
| Cancelled | 111 (3.46%) | 6 (0.29%) | | | |
| Concluded | 49 (1.53%) | 7 (0.34%) | | | |
| Distressed | 203 (6.32%) | | | | |
| **Type of project** | | | | | |
| Brownfield | 821 (25.57%) | 36 (1.73%) | | | |
| Divestiture | 881 (27.44%) | 21 (1.01%) | | | |
| Greenfield project | 1460 45.47%) | 2015 (97.11%) | | | |
| Management and lease contract | 48 (1.49%) | 1 (0.05%) | | | |
| **Income Group** | | | | | |
| Low income | 66 (2.06%) | 57 (2.75%) | | | |
| Lower middle income | 828 (25.79%) | 633 (31%) | | | |
| Upper middle income | 2317 (72.16%) | 1385 (66.75%) | | | |
| **Region** | | | | | |
| AFR | 153 (4.76%) | 196 (9.45%) | | | |
| EAP | 616 (19.18%) | 613 (29.54%) | | | |
| ECA | 495 (15.42%) | 250 (12.05%) | | | |
| LAC | 1494 (46.53%) | 612 (29.49%) | | | |
| MENA | 50 (1.56%) | 83 (4%) | | | |
| SAR | 403 (12.55%) | 321 (15.47%) | | | |
| **Bilateral Support** | 83 (2.58%) | 236 (11.37%) | | | |
| **Multilateral Support** | 702 (21.86%) | 412 (19.86%) | | | |

Note: AFR stands for Sub-Saharan Africa, EAP for East Asia and Pacific, ECA for Europe and Central Asia, LAC for Latin America and the Caribbean, MENA for Middle East and North Africa, and SAR for South Asia Region.

### 3.3.2. Extraction of Local Support Tools

Indicator for the type of local support, however, does not contain any information for 87.47% of the projects. WBPPI classifies various support instruments into sub-categories: Direct government support entails government liabilities that cover project costs, either through cash payments or in-kind contributions. It is further categorized into capital subsidies, which fund physical assets during construction; revenue subsidies, which assist with operational revenue recovery (e.g., availability payments); and in-kind contribution, such as land provision. Indirect government support, by contrast, includes contingent liabilities and policy-based incentives that facilitate investment. These include payment guarantees and purchase agreements, debt guarantees, revenue guarantees (ensuring minimum revenue thresholds), exchange rate guarantees, construction cost guarantees, interest rate guarantees, and tariff rate guarantees. Additionally, tax deductions or government credits are considered support if tied specifically to a project or project type (e.g., renewable energy), though broad-based incentives are excluded.

Many such instruments, while not explicitly stated as sovereign support, appear in contracts of private partnerships with government entities in project descriptions. For example, the Gunung Salak Geothermal Power Plant, a 165 MW facility in West Java, Indonesia was developed as a PPP between PT Dayabumi Salak Pratama (Unocal affiliate) and PT Nusamba Geothermal. It was not provided any direct local support. However, the description notes that "*the project involved expansion of an existing plant operated by the national utility, PLN, under a 30-year power purchase agreement signed in 1995*." Alternatively, PLN promised to purchase electricity produced by the Gunung Salak Geothermal Power Plant on pre-agreed price terms for the next 30 years, hence guaranteeing revenue. The Ergon Peru rural electrification project, another major Peruvian solar PV PPP with planned 173,000 kwh capacity, benefited from a publicly tendered investment contract awarded by the Supervisory Agency for Investment in Energy and Mining. It was supported by a blended finance package from the Peruvian development bank COFIDE and SMBC.

While such projects lack an explicit government guarantee, the involvement of state-owned banks and national utilities suggests strong institutional backing that enhances creditworthiness without constituting a direct sovereign liability. They also, therefore, act as risk-mitigating instruments (Kerr & Hu, 2025b). To identify such public support tools, I employed a systematic keyword-matching approach based on the WBPPI classification. I first scanned the project descriptions for the presence of predefined keywords grouped under three overarching categories: (i) direct support, (ii) indirect support, as well as (iii) clean energy-specific financial instruments. For the first two categories, I utilized the keyword groups mirroring those defined by WBPPI, with an addition of political tools criteria which collects instruments like political risk insurance. The more specific clean energy tools comprised of: (i) *Green finance instruments* (e.g., "green bond", "climate finance"), (ii) *Climate funds* (e.g., "Green Climate Fund", "Climate Investment Fund"), (iii) *Clean energy subsidies* (e.g., "feed-in tariff", "renewable auction"), and (iv) *Market mechanisms* (e.g., "carbon credit", "renewable energy certificate", "clean development mechanism"). I then computed *Tool Count* which aggregates the number of distinct support instruments associated with each project, drawing both from support tool tags in the original database and those identified through keyword extraction. After the extraction, percentage of projects without any form of support dropped to 65.34% (71.35% for conventional and 56.05% for renewable projects). Figure 3.3 presents a heatmap for category-wise tool count distribution across RE technologies, and Figure 3.4 shows their corresponding clean-energy tool count concentrations (see Appendix C for conventional tool count distribution).

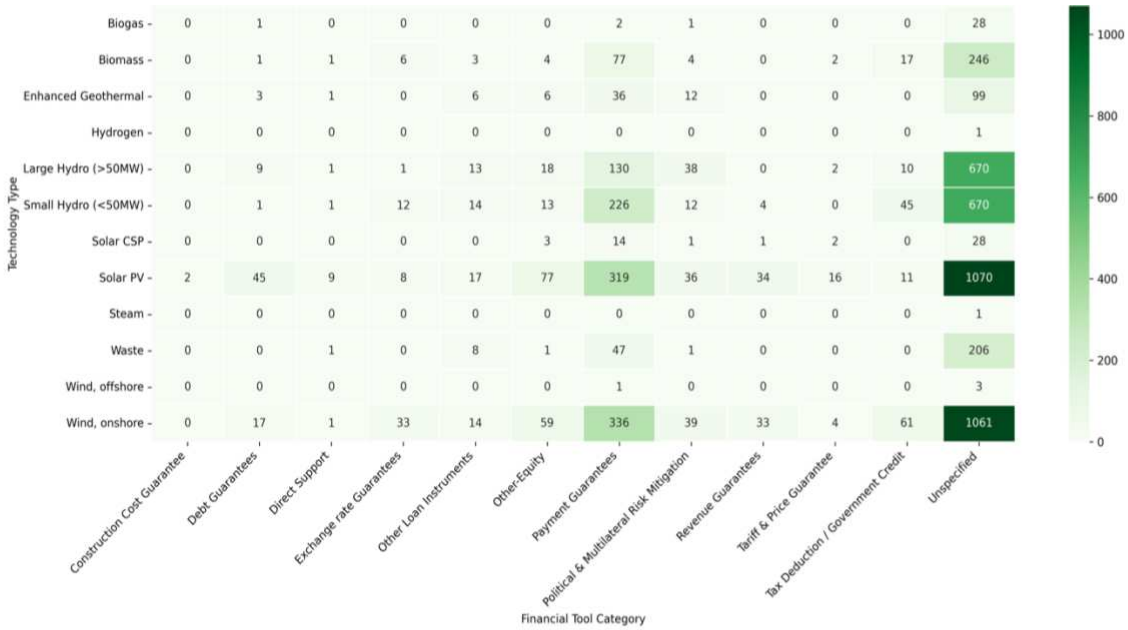



*Figure 3.3: Heat map of renewable energy project-specific local support tool count categorized according to instrument (x-axis) and technology (y-axis). Tool count is calculated from the World Bank private participation in infrastructure database by summing up the local support data and tools extracted from the project description using a keyword extraction process.*

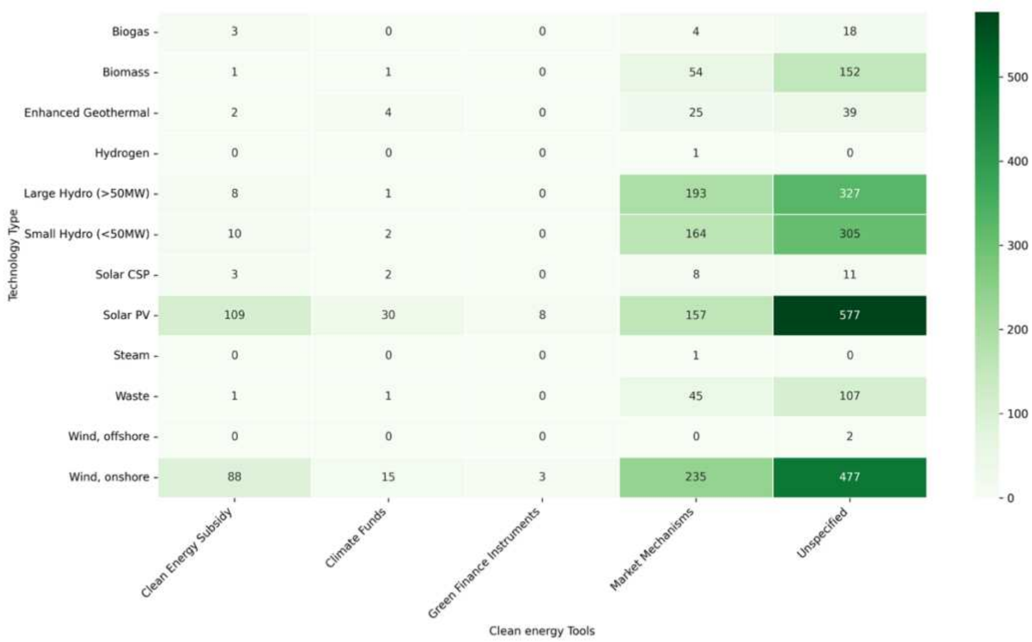



*Figure 3.4: Heat map of renewable energy project-specific clean energy tool count categorized according to instrument (x-axis) and technology (y-axis). Clean energy tool count is extracted from the World Bank private participation in infrastructure database from the project description using a keyword extraction process.*

Solar PV and onshore wind projects are most frequently supported, with 1,070 and 1,061 occurrences respectively, followed by small hydro and large hydro projects. Among financial tools, payment guarantees appear prominently across multiple technologies, followed by tax deductions and debt guarantees. Biogas and biomass technologies remain largely unsupported, reflecting different risk profiles across technology types. Solar PV and onshore wind projects are also associated with substantial clean market mechanisms, subsidy tools as well as climate funds (in many cases, green bonds), which can possibly be explained by high upfront costs and a more mature technology diffusion stage (Fleta-Asín & Muñoz, 2021a; Kim, 2020).

### 3.3.3. Country-Level Patterns

To examine the dynamics of energy transition within public-private partnerships (PPPs), I construct share variables by dividing the total volumes and investments in renewable energy PPPs by those in all energy-related PPPs at the country-year level. This generates a panel dataset that captures the relative prevalence of renewable energy investments over time and across countries. Figure 3.5 plots the number of projects pertaining to countries with at least 10 active renewable PPPs while rest are combined under 'Others' category. 22 countries do not have any active renewable energy PPP as of 2023[55]. While many of these are island countries, Ghana is a surprising entry. According to (Kerr & Hu, 2025b), Ghana aims to meet 55% of its conditional emissions cuts via Article 6 under the Paris Agreement, supported by a USD 4.9 billion investment plan, a 2023 carbon market framework, and MOUs with partner countries—positioning it well for future large-scale cooperation. However, it has not exploited the PPP pathway for emission reduction yet.

[55] Countries with only conventional energy PPP: Bolivia, Cameroon, Comoros, Cuba, Dominica, Fiji, The Gambia, Ghana, Grenada, Guinea-Bissau, Guyana, Haiti, Iraq, Kyrgyz Republic, Lebanon, Moldova, Papua New Guinea, Timor-Leste, Uruguay, Venezuela (RB), West Bank and Gaza, and Yemen (Rep.).

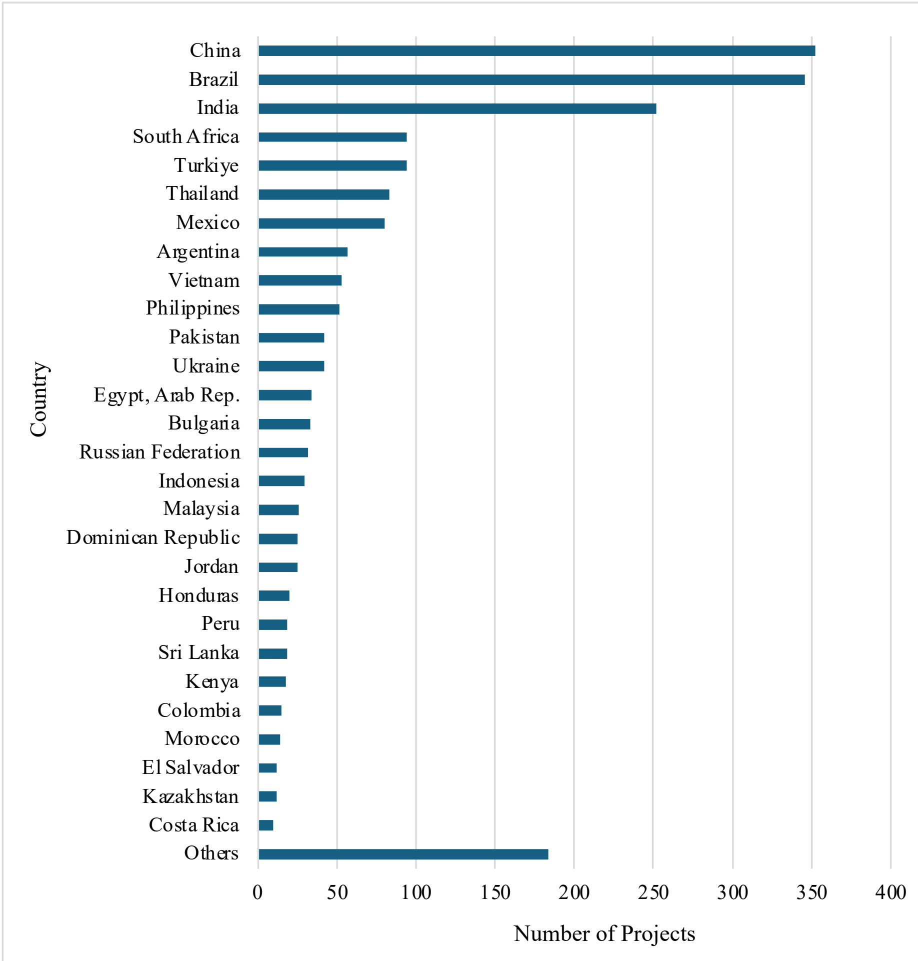



*Figure 3.5: Distribution of private participation in infrastructure (PPI) renewable energy projects across countries.*

As per (Kerr & Hu, 2025b), participation in Clean Development Mechanisms (CDMs) has been historically concentrated in a few countries- China, Brazil and India. Similar pattern is reflected in renewable PPP participation, wherein the three countries together account for 58.89% of all RE projects. However, within-country transition of PPP concentration from conventional to renewable technologies in many countries has also been remarkable. Figure 3.6 shows trends of shares of RE PPP volume and investments across top 10 countries. In many cases, including Mexico, Pakistan, South Africa, Turkey and Ukraine, there is a discontinuous jump between the period 2009-2012. Studies cite growing energy security concerns; rising oil and gas prices; as well as establishment of the Kyoto Protocol in early 2005 as reasons for this momentous shift (Vagliasindi, 2012). Another point to note is the divergence of volume and investment in the case of India, Turkey, Thailand and others, possibly due to higher risks associated with larger investments. Such trends however necessitate a relative (over absolute) study of energy sources for nuanced policy perspectives.

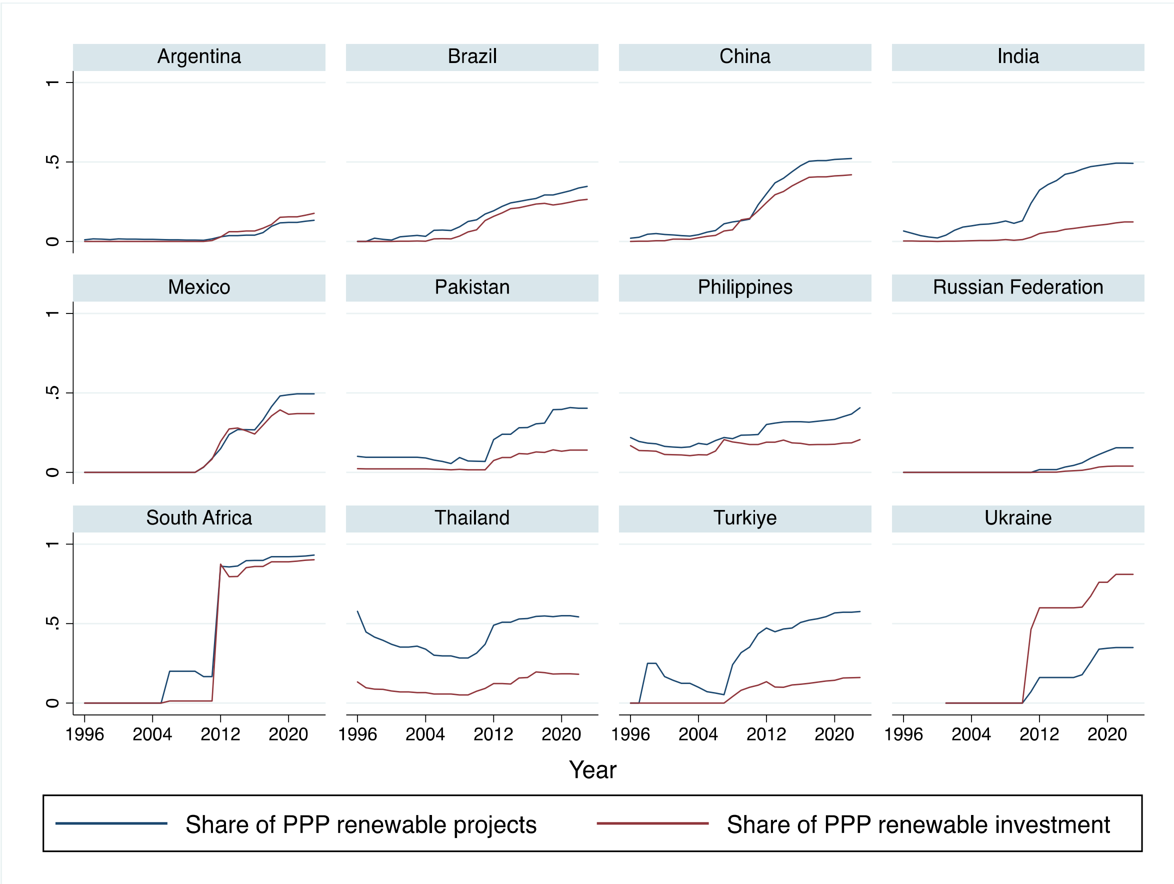



*Figure 3.6: Trends in renewable energy project volumes and monetary investments in Public-Private Partnerships (PPP) in top 10 emerging and developing economies between 1994–2022. The blue and red lines indicate the annual share of renewable projects and renewable investment, respectively, as a proportion of total energy PPP activity.*

### 3.3.4. Climate Policy

I construct policy instruments using the IEA/IRENA Renewable Energy Policies and Measures Database[56,57]. I divide the policies into six categories based on instrument type: regulatory instruments, market-based instruments, public finance and R&D, planning and framework, free-trade agreements and energy access. *Regulatory instruments* represent obligations schemes that have legally binding targets like utilities and generators required to meet the quantity goals on purchase, ban or limitations on fossil fuel generation, antidumping measures on solar PV cells, steel coils and other industrial waste related to energy production, and greenhouse gas emissions allowance. While obligation schemes have been found to have positive impact on RE PPP adoption (Fleta-Asín & Muñoz, 2021a), other policies have not been adequately tested in literature.

*Market-based instruments* include FiT, carbon pricing schemes, and tax relief. FiTs offer revenue certainty by ensuring that producers receive a fixed payment to cover production costs. Prior research has explored the risks associated with FiTs (Carley et al., 2017). Structurally, FiTs are designed to deliver a predictable income stream over time; however, this future revenue is contingent on the continued existence of the policy. As a result, in developing countries, investors often prefer immediate financial support over deferred returns. Tax incentives offer time-bound reductions in tax obligations to encourage investment. Carbon tax is a powerful instrument that can increase relative competitiveness of RE technologies in host countries (J. E. T. Bistline et al., 2023). It has only been enacted by five countries in the sample: Argentina, Colombia, Mexico, Chile, Ukraine and South Africa.

*Public finance* refers to government spending in various transition measures, such as carbon capture and storage, investment in clean technologies, infrastructure, transport and power. It also includes grants to

---

[56] The database is the most comprehensive cross-country compilation of renewable energy policy measures available from internationally recognized agencies. It has been widely used by studies for developing country analysis (Baldwin et al., 2017; Carley et al., 2017; Fleta-Asín & Muñoz, 2021a). Data retrieved from the IEA's renewables policies and measures website (https://www.iea.org/policies/about) in April 2025.

[57] Note that policy indicators designed in this section differ from project-based local support in Section 3.3.2. The former are over-arching country-wide measures which can be assumed to have lagged effects on PPP adoption (Fleta-Asín & Muñoz, 2021a), while the latter can differ across projects and serves to assess risk-mitigation by the government.

provide financial support to project developers by lowering upfront costs of RE projects in various scales. Public finance has also not received proper attention in literature (Polzin et al., 2019). *R&D* entails training programs for innovation and green jobs, incentives for innovations, and knowledge management. Not many countries have adopted these measures. Nationally Determined Contributions (NDCs) and strategic plans for RE capacity targets to achieve fall under *Planning and framework instruments.* While not obligatory, such schemes demonstrate government's willingness for RE transition.

Clean energy provisions under *Free Trade Agreements (FTAs)* relate exclusively to cross-border PPPs. While studies find that international cooperation can accelerate energy transition (Raghutla & Kolati, 2023), degree of quantifiability of FTA provisions matter (Dent, 2021). However, the relationship between PPP and FTAs has been understudied. Another underexplored policy area is the spillover effects of increasing *access to energy* on PPP. While the literature finds positive impact of PPP on renewable energy consumption (Yin & Qamruzzaman, 2024a), policies tagged as promoting socioeconomic inclusion may attract PPP through indirect provisions. For example, the Peruvian government created the Social Inclusion Energy Fund (FISE) in 2012 to bring clean energy to the most vulnerable segments of the population. The programs financed by this fund consisted of granting subsidies on LPG prices and electricity tariffs to low-income households, promoting car conversions to LPG or natural gas, and installing solar PVs in isolated homes that are not physically connected to the grid. This led to 177 609 solar panels being installed by 2019. Peru also had solar PV PPPs during the period. Empirical tests of this association may reveal interesting insights.

All policy indicators are coded as binary: they take the value 1 if a policy is in force, and 0 if it has ended or not introduced. They are then aggregated for each country for each year. The country-level summary statistics for each policy instrument is given in Table 3.2.

*Table 3.2: Summary statistics for country-level data*

| | Obs. | Mean | SD | Min. | Max. |
|---|---|---|---|---|---|
| **Project variables** | | | | | |
| Share of renewable PPP investments | 1,705 | 0.1838 | 0.2973 | 0 | 1 |
| Share of renewable PPP projects | 1,705 | 0.2161 | 0.2774 | 0 | 1 |
| Cumulative local support | 1,705 | 1.7916 | 3.5680 | 0 | 25.5957 |
| Cumulative international support | 1,705 | 0.9419 | 1.7586 | 0 | 10.8833 |
| **Macroeconomic Indicators** | | | | | |
| GDP | 1,692 | 4.0339 | 4.5355 | -28.7586 | 34.5000 |
| Inflow of FDI (% GDP) | 1,689 | 4.0085 | 6.3164 | -37.1727 | 103.3374 |
| Inflation (CPI) | 1,692 | 9.8406 | 31.7097 | -27.0487 | 921.5357 |
| Public investment in renewables | 1,693 | 219.8092 | 673.2811 | 0.0000 | 6821.4700 |
| Infrastructure Score | 568 | 53.1778 | 20.5326 | 10.0000 | 100.0000 |
| Renewable Electricity Production (in million kwh) | 1,355 | 6820 | 50800 | 0 | 1110000 |
| Fossil fuel consumption (%total) | 1,490 | 63.3837 | 27.4996 | 0 | 100 |
| **Climate Policy Action** | | | | | |
| Regulatory policy score | 1,693 | 1.9421 | 4.2367 | 0.0000 | 41.0000 |
| Market mechanism score | 1,693 | 0.4282 | 1.1190 | 0.0000 | 12.0000 |
| Planning and framework score | 1,693 | 0.4595 | 1.2064 | 0.0000 | 10.0000 |
| Investment policy score | 1,693 | 1.0248 | 3.4314 | 0.0000 | 47.0000 |
| Trade policy score | 1,693 | 4.6078 | 5.9488 | 0.0000 | 42.0000 |
| Access to energy policy score | 1,693 | 4.2717 | 10.8179 | 0.0000 | 147.0000 |
| **World Governance Indicators** | | | | | |
| Voice & Accountability | 1,693 | -0.3383 | 0.7112 | -2.2333 | 1.2221 |
| Control of corruption | 1,685 | -0.5085 | 0.5243 | -1.6728 | 1.3309 |
| Government Effectiveness | 1,685 | -0.3675 | 0.5226 | -1.9870 | 1.2377 |
| Political Stability | 1,690 | -0.4446 | 0.7604 | -2.8100 | 1.2752 |
| Rule of Law | 1,693 | -0.4822 | 0.5306 | -1.9225 | 0.9122 |
| Regulatory quality | 1,685 | -0.3243 | 0.5791 | -2.3486 | 1.2602 |

### 3.3.5. Governance Indicators and Other Variables

Apart from policy architectural tools, a possibly important yet understudied driver of RE PPP is direct public expenditure in renewable energy (Kim, 2020). Distinct from domestic planned investment and R&D schemes as described in Section 3.3.4, RE public investment as measured by the International Renewable Energy Agency (IRENA) includes all domestic, international and MDB contributions to the host country's renewable infrastructure through various instruments including debt, equity, and grants. It therefore represents all realized public financial flows towards renewable projects and can spur transition through targeted funding and early-stage risk-management. I include country-wise public investment (in USD million) for each year to test this association.

Developing countries pose higher political, management and administrative risks for investors (Ameli et al., 2021). To account for institutional factors, I therefore use the World Bank's Worldwide Governance Indicators database (WGI). WGI has been used widely in literature examining the governance impact on PPP (Fleta-Asín & Muñoz, 2021a; Percoco, 2014; Spohr et al., 2024) due to its comprehensive, multi-dimensional framework. It covers six measures: voice and accountability (VA), political stability and absence of violence (PS), government effectiveness (GE), regulatory quality (RQ), rule of law (RL), and control of corruption (CC). Kaufmann et al., (2010) defines governance indicators as follows: control of corruption measures the misuse of public power for private gain; government effectiveness captures the quality and independence of public services and policymaking; political stability reflects the risk of government destabilization through violence; regulatory quality assesses the ability to design policies supporting private sector growth; rule of law measures confidence in legal institutions and protection of rights; and voice and accountability capture citizen participation and freedoms of expression, association, and media. However, to avoid collinearity, combinations of uncorrelated indicators are used together in the empirical model (see Appendix C for the correlation matrix).

Additionally, I use renewable electricity production (in kilowatt hours) as a proxy for adoption and scaling of renewable energy technology. While not a perfect measure, it serves to account for degree of technology diffusion in the host country (Kim, 2020). I also use percentage of energy consumption from fossil fuel sources to measure the change in structural composition of energy demand. Infrastructure score is used to account for infrastructural quality in the host country, including grid connectivity and renewable energy integration. Finally, I use GDP (% growth), inflation (% CPI) and inflow of FDI (% of GDP) to control for economy size, macroeconomic stability and degree of openness of the economy. All abovementioned variables are extracted from the World Development Indicators (WDI) by World Bank. Summary statistics for all variables are given in Table 3.2.

## 3.4. Project-Level Analysis

### 3.4.1. Probit Model

To test for hypothesis H1 (Section 3.2), I examine the project-level characteristics distinguishing renewable PPPs from conventional ones. Given the binary nature of the dependent variable, probit regression is an appropriate methodology to estimate the probability of a PPP being renewable (or conventional) based on relevant characteristics. This initial step will help identify significant predictors and provide preliminary evidence, guiding variable selection and structuring subsequent aggregated country level analysis.

In line with previous literature (Kim, 2020), projects are restricted to non-hydro renewable energy (NHRE) due to the prevalent skepticism regarding large hydropower's classification as a sustainable source (Chala et al., 2019). The probit model is specified as:

$$Pr(ren_i = 1/X_i) = \Phi\big(\alpha + \beta_1 Income_i + \beta_2 Type_i + \beta_3 Status_i + \beta_4 Int\_Support_i + \beta_5 Tool\_Count_i + \beta_6 Inv_i + \beta_7 Period_i + \beta_8 Region_i + \beta_9 Private_i + \beta_{10} Capacity_i\big) \tag{3.1}$$

where Φ is the cumulative distribution function of the standard normal distribution. $ren_i$ is the binary dependent variable that takes the value 1 if the project is renewable and 0 if conventional. The independent categorical variables include host-country's category according to income-level ($Income_i$), project type ($Type_i$), project status ($Status_i$), degree of international support ($Int\_Support_i$), and region of PPP deployment ($Region_i$). The continuous explanatory variables are number of policy tools ($Tool\_Count_i$), project investment size ($Inv_i$), project period ($Period_i$), private sector participation share ($Private_i$), and project capacity ($Capacity_i$). To construct the degree of international support, I assign 0 to projects with no support, 1 to projects with either bilateral or multilateral support, and 2 to projects with both supports. All other variable descriptions follow from section 3.3.

### 3.4.2. Probit Results

Results from the probit model confirms the hypothesis H1: *Renewable energy PPPs are significantly different in circumstantial and contractual characteristics from conventional energy PPPs*. The marginal effects for project characteristics with statistically significant explanatory power are illustrated in Figure 3.7 (see Appendix C for detailed results). In line with (Kerr & Hu, 2025b), results indicate PPP concentration in comparatively well-equipped countries. Figure 3.7(i) shows that projects in lower-middle (p-value=0.012) and upper-middle-income (p-value=0.000) countries are significantly more likely to be renewable compared to low-income countries. Regional differences are also statistically significant, with lower renewable PPP probabilities observed in Latin America and the Caribbean (LAC) and South Asia Region (SAR) (Figure 3.7(v)). This is interesting, as although Brazil and India are countries with highest number of renewable projects, fossil fuels have historically dominated most of these regions' PPP portfolio. After controlling for project and country characteristics, the relative likelihood of a PPP being renewable remains lower in LAC and SAR regions due to the continued prevalence of conventional energy projects.

Project type, status, capacity, amount of investment, private participation, tool count and international support, together account for the project's degree of risk-loading. Categories within project type range from management and lease contract (in which the private contractor only assumes the risk of managing a public asset) to full divestiture (wherein the private investor bears ownership of building, operating and running the project). Greenfield projects that are usually build-operate-transfer projects also hand over substantial risk to private firms and they significantly predict renewable investment (p-value = 0.000) (Figure 3.7(ii)). Fleta-Asín & Muñoz, (2020) uses this project type as a proxy for degree of risk-transfer to the private investor. They show that higher risk-transfer relates to higher probability of PPP success. This association seems to explain RE deployment as well. Figure 3.7(vi) shows that greater private sector involvement is associated with higher probabilities of a PPP being renewable, and Figure 3.7(iii) illustrates that cancelled and concluded projects negatively predict renewable status.

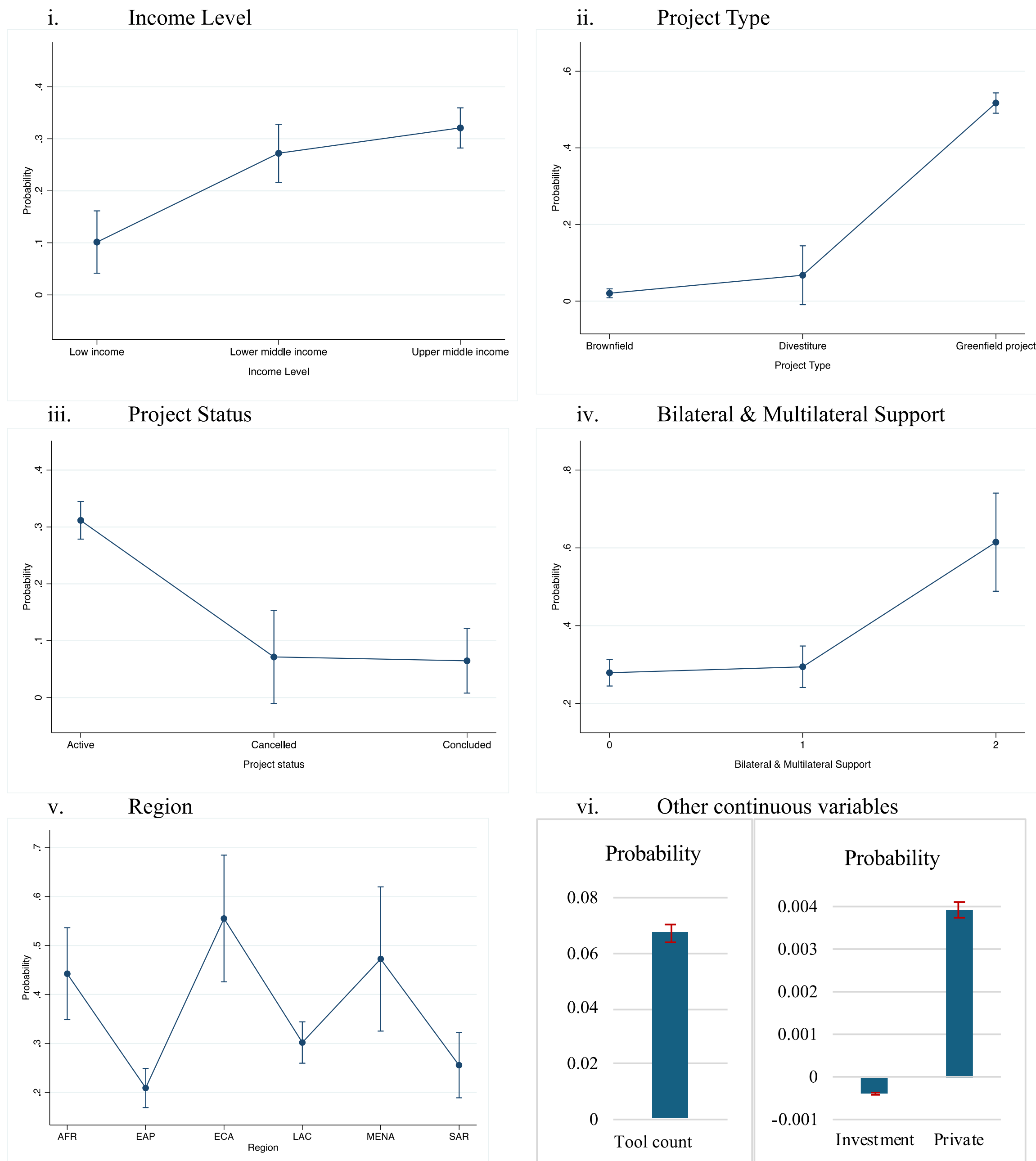



*Figure 3.7: Marginal effects from the probit model estimating the probability of a PPP project being renewable. The plots display average marginal effects with 95% confidence intervals for (i) income level, (ii) project type, (iii) project status, (iv) bilateral/multilateral support, (v) regional groupings, (vi) Other continuous variables including local support tool count, total private investment, and private participation.*

However, other factors suggest that the additional ownership borne by private firms is also backed by more risk-management tools in case of RE projects. In line with literature, more international support and numbers of policy tools significantly increases renewable PPP likelihood (p = 0.000) (Fleta-Asín & Muñoz, 2021a). These results highlight the importance of supportive policy environments in facilitating renewable PPPs. Subsequent country-level analysis incorporates the relative share of project type, status and tool count to systematically assess the policy, macroeconomic and institutional drivers of renewable energy transitions in PPP markets. Model specifications also distinguish across regions and income-levels.

## 3.5. Country-Level Analysis

### 3.5.1. Method

I use two methods to test for hypotheses H2-H4 (Section 3.2). H2: '*Share of renewable energy in PPPs is influenced by a multidimensional set of systemic factors rather than being predominantly driven by a singular policy instrument*' and H3: '*Impact of factors driving share of renewable energy vary across regions and income groups*' address structural but static questions. Accordingly, I use the panel-data Tobit model censored at lower limit 0 and upper limit 1, to examine the drivers of share of renewable energy projects and investment in PPP. Given that data for explanatory variables is not available for many developing countries, the final panel contains observations for 72 countries across 23 years (1996-2023).

The Tobit model has been commonly used in the PPP literature (Fleta-Asín & Muñoz, 2021a; H. Wang et al., 2018; L. Wang et al., 2024), but it is not without its limitations (Kim, 2020). In this research, since the data distribution is such that a large proportion of values of the dependent variables are clustered at 0 and 1 (see Appendix C) which reflects actual private investor choices rather than data deficiencies, the Tobit model is the most appropriate modeling choice (Amore & Murtinu, 2021). Given the high degree of correlation among several policy and institutional indicators (see Appendix C), I employ four distinct model specifications, each incorporating different combinations of variables, to examine systematic associations. Model specification 1 (Equation 3.2) assesses the role of energy access and policy support instruments. Model specification 2 (Equation 3.3) isolate the impact of regulatory and institutional frameworks. Model specification 3 (Equation 3.4) analyzes investment-related drivers. And Model specification 4 (Equation 3.5), examine the influence of market-oriented policy factors. The model specifications are respectively:

$$Ren\_share_{it} = \beta_0 + \beta_1 Macro_{it} + \beta_2 GE_{it} + \beta_3 Plan_{it} + \beta_4 (Access_{it} \times Inc_i) + \beta_5 Tools_{it} + \beta_6 Int\_sup_{it} + \gamma_t + \mu_i + \epsilon_{it} \tag{3.2}$$

$$Ren\_share_{it} = \beta_0 + \beta_1 Macro_{it} + \beta_2 GE_{it} + \beta_3 VA_{it} + \beta_4 RL_{it} + \beta_5 \left(Reg_{it} \times Inc_i\right) + \beta_6 Tools_{it} + \beta_7 Int\_sup_{it} + \gamma_t + \mu_i + \epsilon_{it} \tag{3.3}$$

$$Ren\_share_{it} = \beta_0 + \beta_1 Macro_{it} + \beta_2 GE_{it} + \beta_5 (Inv_{it} \times Inc_i) + \beta_6 Tools_{it} + \beta_7 Int\_sup_{it} + \gamma_t + \mu_i + \epsilon_{it} \tag{3.4}$$

$$Ren\_share_{it} = \beta_0 + \beta_1 Macro_{it} + \beta_2 GE_{it} + \beta_3 \left(Market_{it} \times Region_i\right) + \beta_4 Trade_{it} + \beta_6 Tools_{it} + \beta_7 Int\_sup_{it} + \gamma_t + \mu_i + \epsilon_{it} \tag{3.5}$$

where $Ren\_share_{it}$ represents the share of monetary amount of private investment commitment in RE projects in developing county $i$ in the year $t$, *Macro* is the vector of macroeconomic variables, *GE* is institutional indicator for government effectiveness. It is used as a proxy for governance quality control in all models except Model 2 that tests for institutional framework (L. Wang et al., 2024). *Int_sup* is the aggregated multilateral and bilateral support and *Tools* is the aggregated domestic support provided for each project in a country in a year and they act as proxy for degree of targeted risk-mitigation. $\gamma_t$ indicates country fixed-effects and $\mu_i$ time fixed-effects. $\epsilon_{it}$ represents robust standard errors. I incorporate the abovementioned variables in all models, while the rest I employ as per model specifications.

A combination of energy access policy factor, *Access*, and planning and framework policy factor, *Plan* is used in Model 1. *VA* is the governance indicator for voice and accountability and *RL* for rule of law. These are incorporated in Model 2 with *GE*[58] and the regulatory policy indicator, *Reg*. *Inv* is the public finance and R&D policy factor used in Model 3. And Model 4 comprises of *Market* representing market mechanism policy factor and *Trade* representing FTA policy factor. I interact the policy factors with categorical variables for income, *Inc*, and for region, *Region,* to test for spatial heterogeneity in policy adoption. I also run all models with share of number of renewable projects, *Ren_count* as the dependent variable.

Hypothesis H4: '*Energy transition in PPP is a trend dependent phenomenon influenced by endogenous policies and institutions'* states a dynamic phenomenon. Consequently, to account for the growth trajectory of renewable energy participation over time, I employ a Generalized Method of Moments (GMM) estimation strategy. The GMM framework is particularly suited to modeling dynamic processes, as it allows for the inclusion of lagged dependent variables as regressors while addressing potential endogeneity issues. For instance, if more climate policy actions lead to higher RE PPP concentration, higher concentration can also prompt supporting policy actions, leading to simultaneity problem in the Tobit model (Pindyck, 1998). I employ a two-step Arellano-Bond dynamic panel GMM estimator (Arellano & Bond, 1991; Arellano & Bover, 1995), which is widely used for instrumental variable (IV) estimation. GMM offers efficiency gains over conventional 2SLS, particularly under heteroskedasticity, by exploiting orthogonality or first-difference conditions between instruments and error terms. The problem of autocorrelation caused by lagged dependent variable is also resolved by instrumenting it with past levels.

Likewise, I use lagged values of dependent and independent variables in level form as instruments in a first difference equation. This method controls for weak forms of endogeneity since it assumes these

[58] Since the correlation factor for GE, VA and RL is less than 0.5, they can be used together in the model. However, other WGI indicators are highly correlated with either GE, VA or RL, and are excluded from the model.

variables are weakly exogenous, which is theoretically relevant for this study. While the systems GMM (Blundell & Bond, 1998) is suited for strong cases of endogeneity, it requires the additional assumption that the differences used as instruments are uncorrelated with the error term (mean stationarity). I augment difference GMM with Ahn-Schmidt nonlinear moment conditions (Ahn & Schmidt, 1995) which not only overcomes the weak instrument problem of Arellano & Bond, (1991) but is also robust to deviations from mean stationarity. I also run the model with the Arellano & Bond, (1991) estimator, and find that the results are robust (see Appendix C).

To address the prevalence of zeros, I exclude countries with no renewable PPP projects before 2015, which reduces the panel by 17 countries. The 4 model specifications follow from the Tobit model, with the addition of lagged first-difference variables. A general form is presented below:

$$Ren\_share_{it} - Ren\_share_{it-1} = \beta_1(Macro_{it} - Macro_{it-1}) + \beta_2(WGI_{it} - WGI_{it-1}) + \beta_3(Project_{it} - Project_{it-1}) + \beta_4(Policy_{it} - Policy_{it-1}) + \epsilon_{it} \tag{3.6}$$

where the subscript $t-1$ represents l lag for the corresponding variable, *WGI* are the vector of selected WGI indicators, *Project* represent project-level controls and *Policy* is the vector for selected policy factors as per model specifications given above.

### 3.5.2. Results and Discussion

Table 3.3-3.6 present the results from the Tobit (marginal effects) and GMM regression models for the dependent variables: share of renewable PPP investment (*ren_share*) and share of renewable PPP volumes (*ren_count*). Results are divided according to model specifications: Table 3.3 primarily shows the association with energy access and framework policies, Table 3.4 that with regulatory policies, Table 3.5 that with public finance and R&D policies and Table 3.6 with market mechanisms and trade policies.

***Direct public investment***

The strong positive association between public investment in renewables and the share of renewable PPP is observed across all specifications (Table 3.3-Table 3.6) in both static (Tobit) and dynamic (GMM) models. The data reveals statistically significant positive coefficients for public investment across both Tobit (0.0142 for renewable share, 0.0123 for renewable count) and GMM (0.0151 for renewable share, 0.0131 for renewable count) specifications. Consequently, not only is public contribution to climate finance associated with higher shares of RE PPP, but also increasing public RE investment enables energy transition. This highlights the catalytic role of public capital in mobilizing private participation for energy infrastructure (Meckling et al., 2022). Literature shows that public investment provides crucial early-stage risk mitigation by absorbing initial costs and uncertainties that typically deter private investors in emerging markets (Ameli et al., 2020); it signals government commitment to renewable energy policy stability; and it creates demonstration effects that validate technology viability and market potential (Azhgaliyeva et al., 2023).

This enabling relationship of public finance is corroborated by the statistically significant positive coefficients for the investment and R&D policy factor (*Inv*) in Table 3.5. The static association (from the Tobit model) is strongest for low-income countries, in which case 1-unit increase in public finance policy factor is related to 0.17 units larger share of RE PPP investments and 0.21 units larger share of RE PPP project numbers. However, the dynamic relation (from the GMM model) is statistically significant only in case of upper-middle income countries, indicating long foundational phases for emerging markets before climate investment policy can be effectively operationalized (Kim, 2020). This result is supported by study by Ragosa & Warren, (2019) that show that while policies drive the early decision to invest, international public finance is what might ultimately push investors to provide more RE capital. The stronger explanatory power of direct investment over finance policy demonstrates the effectiveness of immediate over planned action. While the magnitude of the effect of investment *policies* is higher, it is not always significant, that is, corresponding policy outcomes are context-dependent, and the efficacy of such interventions may not be uniformly realized. This is not the case with direct public finance, which consistently results in statistically significant, albeit small, private RE investment.

*Table 3.3: Results from Tobit and Generalized Method of Moments (GMM) model specification 1*

| | **Tobit Ren_share** | **Tobit Ren_count** | **GMM Ren_share** | **GMM Ren_count** |
|---|---|---|---|---|
| Energy Access | -0.0013 | 0.0000 | 0.00131*** | 0.00136*** |
| | (0.0008) | (0.0007) | (0.000331) | (0.000269) |
| Plan | 0.0295* | 0.0176 | 0.00198 | 0.00361 |
| | (0.0129) | (0.0116) | (0.00225) | (0.00228) |
| Int_sup x Low income | 0.1276*** | 0.0817*** | 0.0216** | 0.0258** |
| | (0.0209) | (0.0185) | (0.0128) | (0.0151) |
| Int_sup x Lower middle income | 0.0206** | 0.0164** | 0.0134* | 0.00901* |
| | (0.0059) | (0.0054) | (0.00715) | (0.00518) |
| Int_sup x Upper middle income | 0.0303** | 0.0496*** | 0.00236* | 0.000251* |
| | (0.0088) | (0.0079) | (0.00694) | (0.00763) |
| Tools | 0.0150*** | 0.0093** | -0.00269 | 0.000903 |
| | (0.0031) | (0.0028) | (0.00308) | (0.00277) |
| Public investment* | 0.0149*** | 0.0128*** | 0.00385** | 0.00312** |
| | (0.0037) | (0.0033) | (0.00151) | (0.00131) |
| Fossil fuel energy cons. (%) * | 0.1330 | 0.2803** | 0.0135* | 0.0919* |
| | (0.0869) | (0.0766) | (0.0471) | (0.0348) |
| RE electricity prod. (kwh) * | 0.0263*** | 0.0245*** | | |
| | (0.0052) | (0.0046) | | |
| Constant | | | 0.0589** | 0.0652*** |
| | | | (0.0250) | (0.0173) |
| Regulation controls | YES | YES | YES | YES |
| Macroeconomic controls | YES | YES | YES | YES |
| Lagged DV | NO | NO | YES | YES |
| Observations | 777 | 777 | 792 | 792 |
| Number of countries | 61 | 61 | 46 | 46 |

Note: ∗∗∗Significant at $p < 0.01$, ∗∗Significant at $p < 0.05$, ∗Significant at $p < 0.1$. *All variables have been logged and centered. Results are presented for Tobit and GMM models for share of renewable PPP investments (*ren_share*) and share of renewable PPP volumes (*ren_count*) respectively. Only marginal effects from the Tobit model are shown here. All variables for GMM specification are lagged by 1 degree. *L.Depvar* is the corresponding lagged dependent variable for the GMM model. *Int_sup* is the international support indicator. *Access* is the energy access policy indicator, and *Plan* is the planning and framework policy indicator.

***Local and International Support***

Project-specific MDB support (*Int_sup*) and domestic government tools (*Tools*) also exhibit consistently strong and statistically significant positive associations with the share and count of renewable energy PPPs. 1-unit higher MDB support is associated with 0.013 higher shares on average (Tables 3.3-3.6) and this link dynamically increases over time, reflecting the compounding nature of targeted support. Also, while being statistically significant across all income levels, the magnitude of coefficients is strongest for low-income countries and for RE PPP shares of monetary investments (Table 3.3). The pattern is corroborated by the extant literature. (Fleta-Asín & Muñoz, 2021a) show that both international and local financial support, as well as the deployment of risk-mitigation instruments (such as guarantees, subsidies, and blended finance), are crucial for attracting private investment in RE infrastructure. In developing countries where market and policy risks are higher, supportive mechanisms and multilateral backing act as universal drivers for renewable PPP adoption.

Furthermore, note that the magnitude of the coefficients for local and international support and even public finance and investment policy is larger for share of renewable PPP investments than project volumes (Tables 3.3-3.6). This somewhat explains the puzzling decoupling of the two variables experienced by countries like India, Turkey and Ukraine (Figure 3.6). Climate policies and infrastructure support drive private participation in renewable projects. However, such projects (in most cases, solar PV) tend to be smaller in size. Kim, (2020) explains this through easier division of technology in the cases of solar PV and onshore wind; but it may also be the case that the projects lack technical and financial government support more necessary for scaling up investments.

***Energy Access***

Energy access (*Access*) policies are not significantly associated with static PPP share (in the Tobit model) but become strongly positive and highly significant ($p<0.01$) in the dynamic GMM model (Table 3.1). The magnitude of coefficients is however small. Table 3.1 results show that a unit increase in policies targeted at inclusive growth is associated with a rise in both investment and volume shares by about 0.0013 units. Consequently, the impact of energy access policies on renewable PPP deployment is realized over time, likely due to cumulative effects and lagged responses in private sector participation. In contrast, planning and framework policies do not show significance in both models. These findings indicate that actionable, inclusive energy policies-rather than non-binding plans like the NDCs-are stronger determinants of energy transition in PPPs (Ragosa & Warren, 2019; Yin & Qamruzzaman, 2024b).

*Table 3.4: Results from Tobit and Generalized Method of Moments (GMM) model specification 2*

| | **Tobit Ren_share** | **Tobit Ren_count** | **GMM Ren_share** | **GMM Ren_count** |
|---|---|---|---|---|
| Reg x Low income | 0.0084 | 0.0093 | 0.00409 | 0.0151 |
| | (0.0404) | (0.0368) | (0.00276) | (0.0110) |
| Reg x Lower middle income | -0.0085 | -0.0083 | 0.00428 | 0.00582* |
| | (0.0060) | (0.0054) | (0.00330) | (0.00302) |
| Reg x Upper middle income | 0.0084** | 0.0088** | 0.00293*** | 0.00271*** |
| | (0.0030) | (0.0028) | (0.000834) | (0.000805) |
| Int_sup | 0.0383*** | 0.0375*** | 0.0129*** | 0.0113*** |
| | (0.0066) | (0.0058) | (0.00450) | (0.00426) |
| Tools | 0.0109** | 0.0085* | 0.00205 | 0.00376** |
| | (0.0037) | (0.0034) | (0.00178) | (0.00181) |
| Public investment* | 0.0117* | 0.0101* | 0.00360** | 0.00281** |
| | (0.0048) | (0.0042) | (0.00165) | (0.00135) |
| Fossil fuel energy cons. (%) * | 0.2827* | 0.5829** | 0.0125* | 0.0847* |
| | (0.1306) | (0.1174) | (0.0444) | (0.0332) |
| RE electricity prod. (kwh)* | 0.0233*** | 0.0243*** | | |
| | (0.0056) | (0.0050) | | |
| GE* | -0.0357 | -0.0453* | -0.00803 | -0.00782 |
| | (0.0217) | (0.0189) | (0.0199) | (0.0111) |
| VA* | 0.0102 | 0.0102 | | |
| | (0.0220) | (0.0201) | | |
| PV* | 0.0002 | 0.0017 | | |
| | (0.0120) | (0.0108) | | |
| Constant | | | 0.0458** | 0.0559*** |
| | | | (0.0219) | (0.0170) |
| Macroeconomic controls | YES | YES | YES | YES |
| Lagged DV | NO | NO | YES | YES |
| Observations | 519 | 519 | 792 | 792 |
| Number of countries | 51 | 51 | 46 | 46 |

Note: ∗∗∗Significant at $p < 0.01$, ∗∗Significant at $p < 0.05$, ∗Significant at $p < 0.1$. *All variables have been logged and centered. Results are presented for Tobit and GMM models for share of renewable PPP investments (*ren_share*) and share of renewable PPP volumes (*ren_count*) respectively. Only marginal effects from the Tobit model are shown here. All variables for GMM specification are lagged by 1 degree. *L.Depvar* is the corresponding lagged dependent variable for the GMM model. *Int_sup* is the international support indicator. *Reg* is the regulation policy indicator.

A related finding is the robust and positive association of renewable electricity production with both dependent variables across all model specifications. The coefficients are also relatively higher in magnitude, predicting 0.0263 higher monetary investment shares and 0.0245 higher project volume shares for 1-unit increase in electricity production (Tables 3.3-3.6). Electricity production in literature serves as a proxy for greater technological diffusion and more developed energy infrastructure (Kim, 2020). The results are in with line with (Mitra & Al Farhad, 2023) who argue that advancing electricity sectors facilitate renewable integration by providing the necessary grid infrastructure, technical expertise, and institutional capacity required for large-scale deployment. A higher magnitude of this association compared to the energy access policy indicator highlights the efficacy of realized infrastructural investments over planned.

*Table 3.5: Results from Tobit and Generalized Method of Moments (GMM) model specification 3*

| | **Tobit Ren_share** | **Tobit Ren_count** | **GMM Ren_share** | **GMM Ren_count** |
|---|---|---|---|---|
| Inv x Low income | 0.1783* | 0.2134** | 0.0466 | 0.0300 |
| | (0.0773) | (0.0730) | (0.0369) | (0.0207) |
| Inv x Lower middle income | 0.0091* | 0.0019 | 0.00201 | 0.00560 |
| | (0.0045) | (0.0041) | (0.00263) | (0.00431) |
| Inv x Upper middle income | 0.0083* | 0.0085** | 0.00141** | 0.000769* |
| | (0.0034) | (0.0031) | (0.000592) | (0.000454) |
| Trade | 0.0060* | 0.0055** | 0.00199 | 0.00406*** |
| | (0.0024) | (0.0018) | (0.00122) | (0.00153) |
| Int_sup | 0.0256*** | 0.0248*** | 0.0116*** | 0.00877*** |
| | (0.0059) | (0.0053) | (0.00433) | (0.00438) |
| Tools | 0.0142*** | 0.0110*** | 0.00127 | 0.00175 |
| | (0.0033) | (0.0030) | (0.00190) | (0.00187) |
| Public investment* | 0.0169*** | 0.0155*** | 0.00358** | 0.00257** |
| | (0.0037) | (0.0034) | (0.00152) | (0.00127) |
| Fossil fuel energy cons. (%) * | 0.2389** | 0.2822** | 0.0121* | 0.0934* |
| | (0.0837) | (0.0744) | (0.0456) | (0.0367) |
| RE electricity prod. (kwh) * | 0.0217*** | 0.0271*** | | |
| | (0.0051) | (0.0045) | | |
| Constant | | | 0.0428* | 0.0490*** |
| | | | (0.0221) | (0.0181) |
| Regulation controls | YES | YES | YES | YES |
| Macroeconomic controls | YES | YES | YES | YES |
| Lagged DV | NO | NO | YES | YES |
| Observations | 777 | 777 | 792 | 792 |
| Number of countries | 61 | 61 | 46 | 46 |

Note: ∗∗∗Significant at $p < 0.01$, ∗∗Significant at $p < 0.05$, ∗Significant at $p < 0.1$. *All variables have been logged and centered. Results are presented for Tobit and GMM models for share of renewable PPP investments (*ren_share*) and share of renewable PPP volumes (*ren_count*) respectively. Only marginal effects from the Tobit model are shown here. All variables for GMM specification are lagged by 1 degree. *L.Depvar* is the corresponding lagged dependent variable for the GMM model. *Int_sup* is the international support indicator. *Inv* is the investment policy indicator.

***Governance and Regulation***

Results reveal nuanced effects of governance quality and regulatory policies (*Reg*) on renewable energy PPP development. Unlike investment policies, regulatory policies demonstrate a clear income-gradient effect (Table 3.4). In both Tobit and GMM models, the variables show statistically significant explanatory power (p>0.01) only in the case of upper-middle income countries. This suggests that regulatory frameworks require a certain threshold of institutional capacity to effectively mobilize private renewable investment. Governance indicators (Table 3.4) are also not statistically significant in any specification.

Although existing literature emphasizes the role of governance quality in facilitating private capital mobility (L. Wang et al., 2024), the results presented here suggest that governance alone does not account for the reallocation of private investment from fossil fuels to renewable energy.

*Table 3.6: Results from Tobit and Generalized Method of Moments (GMM) model specification 4*

| | **Tobit Ren_share** | **Tobit Ren_count** | **GMM Ren_share** | **GMM Ren_count** |
|---|---|---|---|---|
| Market x AFR | 0.1328*** | 0.1103*** | 0.0388*** | 0.0355*** |
| | (0.0233) | (0.0206) | (0.0125) | (0.0122) |
| Market x EAP | -0.0019 | 0.0022 | 0.00731*** | 0.00713*** |
| | (0.0094) | (0.0084) | (0.00255) | (0.00212) |
| Market x ECA | 0.1486*** | 0.0411 | -0.00378 | -0.000710 |
| | (0.0275) | (0.0287) | (0.00966) | (0.00634) |
| Market x LAC | 0.0405* | 0.0349* | -0.0184 | -0.0184 |
| | (0.0186) | (0.0167) | (0.0165) | (0.0129) |
| Market x MENA | 0.1532*** | 0.2646*** | -0.0496 | -0.00759 |
| | (0.0346) | (0.0306) | (0.246) | (0.145) |
| Market x SAR | -0.0294 | 0.0236 | -0.00285 | 0.0290 |
| | (0.0173) | (0.0155) | (0.0154) | (0.0283) |
| Trade | 0.0047* | 0.0028 | 0.00172* | 0.00366*** |
| | (0.0024) | (0.0018) | (0.000990) | (0.00139) |
| Int_sup | 0.0239*** | 0.0234*** | 0.0131*** | 0.00907** |
| | (0.0056) | (0.0049) | (0.00439) | (0.00384) |
| Tools | 0.0116** | 0.0102** | 0.00263 | 0.00263 |
| | (0.0034) | (0.0030) | (0.00225) | (0.00194) |
| Public investment * | 0.0106** | 0.0091** | 0.00375** | 0.00282** |
| | (0.0036) | (0.0032) | (0.00162) | (0.00130) |
| Fossil fuel energy cons. (%) * | 0.3030** | 0.2963** | 0.120** | 0.0960** |
| | (0.0811) | (0.0700) | (0.0427) | (0.0347) |
| RE electricity prod. (kwh) * | 0.0211*** | 0.0281*** | | |
| | (0.0048) | (0.0042) | | |
| Constant | | | 0.0463** | 0.0549*** |
| | | | (0.0213) | (0.0175) |
| Regulation controls | YES | YES | YES | YES |
| Macroeconomic controls | YES | YES | YES | YES |
| Lagged DV | NO | NO | YES | YES |
| Observations | 777 | 777 | 792 | 792 |
| Number of countries | 61 | 61 | 46 | 46 |

Note: ∗∗∗Significant at $p < 0.01$, ∗∗Significant at $p < 0.05$, ∗Significant at $p < 0.1$. *All variables have been logged and centered. Results are presented for Tobit and GMM models for share of renewable PPP investments (*ren_share*) and share of renewable PPP volumes (*ren_count*) respectively. Only marginal effects from the Tobit model are shown here. All variables for GMM specification are lagged by 1 degree. *L.Depvar* is the corresponding lagged dependent variable for the GMM model. *Int_sup* is the international support indicator. *Market* is the market mechanism policy indicator and *Trade* is the trade policy indicator.

***Regional variation in market mechanisms***

Market-based mechanisms are analyzed through regional rather than income interactions based on literature (Alloisio & Carraro, 2015b). Results (Table 3.6) demonstrate heterogeneous effects, reflecting that market instruments like feed-in tariffs and carbon pricing depend heavily on localized market structures and complementary institutional frameworks. The AFR (African) region shows the most statistically significant association across all models. However, the MENA (Middle East and North African) region exhibits the strongest explanatory power: 1-unit more of market instruments is related to 0.15 units higher investment shares and 0.21 units higher project volumes (Table 3.6). The LAC (Latin American and Caribbean) region also shows somewhat significant and positive relation ($p>0.01$). Market policies in ECA (European and Central Asia) are associated with more investment shares but not volumes. Only the dynamic associations in the case of EAP (East Asia and Pacific region) are statistically significant ($p<0.001$). The results collectively suggest that policy effectiveness is contextual, requiring careful calibration to country-specific institutional environments (D. Li et al., 2020). Meanwhile, trade policies appear to be statistically significant ($p<0.001$) for renewable PPP volumes in the dynamic GMM model (Table 3.6). It follows that clean energy provisions in FTAs function strongly in temporally pushing up renewable PPP volumes, but not so much in the case of investments.

Another interesting outcome of the study is the consistently positive association between share of fossil fuel consumption and energy transition across all specifications. In literature, this relation is explained through complementary technological and strategic mechanisms. Othman & Khallaf, (2022) suggests that countries with higher fossil fuel dependency tend to develop more robust renewable PPP frameworks as part of a diversification strategy to address future energy security concerns. The technological complementarity hypothesis proposed by Verdolini et al., (2016). They demonstrate that fast-reacting fossil fuel generation systems provide critical backup capacity. Another possible explanation is that in most emerging markets, growth is still fossil fuel led even with heavy investment in clean pathways. (Aziz & Jahan, 2023) argues that high energy dependence has a positive impact on PPI, and that energy poverty does not always attract funds.

### 3.5.3. Policy Insights

Three overarching insights can be drawn from this study. First, the findings suggest that quantifiable policy actions like targeted support and realized public investments are stronger mobilizers of private participation than the less tangible policies. This is not to say that policies are discardable; policies, especially those designed for catalyzing affordability of energy and human capital development are essential to form country priorities and PPP framework (Kerr & Hu, 2025b). However, such mitigation efforts must be supported by active public finance to make them impactful, credible, and equitable.

Secondly, the findings confirm the multidimensionality of a supportive environment (Kerr & Hu, 2025b; L. Wang et al., 2024) to drive private participation in renewable infrastructure. Most importantly, international and local support targeted at specific projects for risk-mitigation as well as active public investment in renewable electricity generation to build foundational infrastructure support facilitates investment reallocation. But energy access policies, carbon pricing and feed-in-tariffs that stimulate renewable electricity demand, and clean energy R&D that induces knowledge dissemination and skill creation also play a role in targeted energy transition. Moreover, obligation schemes and anti-dumping measures, while also encouraging inflow of renewable capital through FTAs' can be useful tools to attract cross-border investments.

However, the third overarching insight draws from the path dependency theory of energy transition in PPP investment (Ciplet et al., 2022). Results confirm that not only is private sector involvement regionally heterogenous, but it is also reliant on predetermined income and infrastructure capacities. Upper middle-income countries account for about 66% of all renewable PPP projects, even when their own within-country renewable shares are less than that of low-income (Table 3.1). The need for radical clean energy policy frameworks is highlighted by their stronger associations in low-income countries. However, for such policies to be practicably operationalized requires initial groundwork through public finance (Kim, 2020). This itself is constrained by limited resources of such countries, which also augments their risk profile. The argument is supported by the theory of climate investment trap given by (Ameli et al., 2021) that higher capital costs are reinforced in underdeveloped markets. Through their spatial study, Ciplet et al., (2022) argue that climate finance to some extent reproduces relations of dependency. They show that funding flows somewhat neglect economically peripheral, climate vulnerable countries, while favoring strong administrative capacity. However, positive associations between energy access policies and private participation in renewable infrastructure provide possible readjustment channels.

## 3.6. Conclusion

In this study, I examine the drivers of transition to renewable energy within the framework of PPPs in EMDEs. Motivated by the increasing share of renewable projects in PPP investments and the persistent gaps in energy access and clean infrastructure financing in emerging economies, I ask how the compositional shift in PPPs respond to distinct policy, institutional, and macroeconomic factors.

To address this question, I employ a mixed-method strategy that combines project-level analysis with country-level econometric modeling. I combine data from the comprehensive World Bank PPI dataset, CPI climate policy database, the WGI governance indicators and other macroeconomic variables. I first use text-based keyword extraction of policy content from project documentation to populate the data on local government support provided in the PPI dataset. I then run a probit regression using over 2,000 project-level observations to identify structural characteristics that differentiate renewable PPPs from non-renewable ones. In the second stage, I estimate Tobit and difference GMM model specifications using a panel of 72 countries from 1996 to 2023. I construct cumulative measures of access, regulatory, investment, trade and market-based policy instruments, and interact them with country income levels and regions. These models allow me to assess both contemporaneous drivers and intertemporal dynamics of renewable PPP participation in terms of project volumes and monetary investments.

My findings indicate that there is no singular factor explaining the growth of renewable PPPs. Rather, the transition is enabled by a combination of access policies, international financial support, public investment, and project-based policy tools—each with varying importance across income groups and regions. Dynamic panel models show that prior levels of renewable participation strongly predict current engagement, reinforcing the path-dependent nature of clean infrastructure development. Notably, international support has the strongest and most consistent effect in low- and lower-middle-income countries, while regulatory and market-based instruments are more effective in middle-income and institutionally stronger contexts. Public investment and the availability of risk-sharing tools play a central role in both initiating and sustaining renewable energy PPPs.

These results offer several important policy insights. First, countries seeking to scale renewable energy PPPs must adopt a coordinated, long-term strategy that bundles regulatory clarity, public capital, and private de-risking instruments. Second, international support—particularly in blended or concessional form—remains essential for crowding in private actors in markets where risks are high and energy access gaps persist. Third, regional and institutional heterogeneity must inform policy design, as the same policy instrument may yield very different outcomes depending on the enabling environment. By shifting the analytical lens from absolute investment volumes to the evolving composition of PPP portfolios, this study contributes a novel perspective to the literature on infrastructure finance and energy transition. It is the first study, to my knowledge, that analyzes renewable energy participation in PPPs through a dynamic share-based framework, integrating project characteristics with country-level policy contexts. In doing so, I provide not only empirical insights but also a diagnostic tool for policymakers aiming to build greener, more inclusive energy systems through public-private collaboration.

# References


Abadie, A., & Imbens, G. W. (2011). Bias-Corrected Matching Estimators for Average Treatment Effects. Journal of Business & Economic Statistics, 29(1), 1–11. https://doi.org/10.1198/jbes.2009.07333

Abba, Z. Y. I., Balta-Ozkan, N., & Hart, P. (2022). A holistic risk management framework for renewable energy investments. Renewable and Sustainable Energy Reviews, 160, 112305. https://doi.org/10.1016/j.rser.2022.112305

Adom, P. K. (2024). The socioeconomic impact of climate change in developing countries over the next decades: A literature survey. Heliyon, 10(15), e35134. https://doi.org/10.1016/j.heliyon.2024.e35134

Afonso, A., & Nunes, A. S. (2015). Economic forecasts and sovereign yields. Economic Modelling, 44, 319–326. https://doi.org/10.1016/j.econmod.2014.03.012

Agliardi, E., & Agliardi, R. (2021). Corporate Green Bonds: Understanding the Greenium in a Two-Factor Structural Model. Environmental and Resource Economics, 80(2), 257–278. https://doi.org/10.1007/s10640-021-00585-7

Ahn, S. C., & Schmidt, P. (1995). Efficient estimation of models for dynamic panel data. Journal of Econometrics, 68(1), 5–27. https://doi.org/10.1016/0304-4076(94)01641-C

Albuquerque, R., Koskinen, Y., Yang, S., & Zhang, C. (2020). Resiliency of Environmental and Social Stocks: An Analysis of the Exogenous COVID-19 Market Crash. The Review of Corporate Finance Studies, 9(3), 593–621. https://doi.org/10.1093/rcfs/cfaa011

Alehile, K. S., Mohammed, S. S., Musa, N., & Ali, M. (2025). Comparative Analysis of Climate Change Financing Potential of Renewable and Non-Renewable Energy Stocks: A Predictive Approach. Energy RESEARCH LETTERS, 6(Early View). https://doi.org/10.46557/001c.125865

Alloisio, I., & Carraro, C. (2015a). Public-Private Partnerships for Energy Infrastructure: A Focus on the MENA Region. In S. Caselli, G. Corbetta, & V. Vecchi (Eds.), Public Private Partnerships for Infrastructure and Business Development: Principles, Practices, and Perspectives (pp. 149–168). Palgrave Macmillan US. https://doi.org/10.1057/9781137541482_9

Alloisio, I., & Carraro, C. (2015b). Public-Private Partnerships for Energy Infrastructure: A Focus on the MENA Region (S. Caselli, G. Corbetta, & V. Vecchi, Eds.; pp. 149–168). Palgrave Macmillan US. https://doi.org/10.1057/9781137541482_9

Ameli, N., Dessens, O., Winning, M., Cronin, J., Chenet, H., Drummond, P., Calzadilla, A., Anandarajah, G., & Grubb, M. (2021). Higher cost of finance exacerbates a climate investment trap in developing economies. Nature Communications, 12(1), 4046. https://doi.org/10.1038/s41467-021-24305-3
Ameli, N., Dessens, O., Winning, M., Cronin, J., Chenet, H., Drummond, P., Calzadilla, A., Anandarajah, G., & Grubb, M. (2021). Higher cost of finance exacerbates a climate investment trap in developing economies. Nature Communications, 12(1), 4046. https://doi.org/10.1038/s41467-021-24305-3
Ameli, N., Drummond, P., Bisaro, A., Grubb, M., & Chenet, H. (2020). Climate finance and disclosure for institutional investors: Why transparency is not enough. Climatic Change, 160(4), 565–589. https://doi.org/10.1007/s10584-019-02542-2

Amore, M. D., & Murtinu, S. (2021). Tobit models in strategy research: Critical issues and applications. Global Strategy Journal, 11(3), 331–355. https://doi.org/10.1002/gsj.1363

Ando, S., Fu, C., Roch, F., & Wiriadinata, U. (2023). How Large is the Sovereign Greenium? IMF Working Papers, 2023(080). https://doi.org/10.5089/9798400235160.001.A001

Antoniuk, Y., & Leirvik, T. (2024). Climate change events and stock market returns. Journal of Sustainable Finance & Investment. https://www.tandfonline.com/doi/abs/10.1080/20430795.2021.1929804

Apel, M., Betzer, A., & Scherer, B. (2023). Real-time transition risk. Finance Research Letters, 53, 103600. https://doi.org/10.1016/j.frl.2022.103600

Arat, E., Hachenberg, B., Kiesel, F., & Schiereck, D. (2023). Greenium, credit rating, and the COVID-19 pandemic. Journal of Asset Management, 24(7), 547–557. https://doi.org/10.1057/s41260-023-00320-5

Arbulú, I., Lozano, J., & Rey-Maquieira, J. (2017). The challenges of tourism to waste-to-energy public-private partnerships. Renewable and Sustainable Energy Reviews, 72(C), 916–921.

Ardia, D., Bluteau, K., Boudt, K., & Inghelbrecht, K. (2023). Climate Change Concerns and the Performance of Green vs. Brown Stocks. Management Science, 69(12), 7607–7632. https://doi.org/10.1287/mnsc.2022.4636

Arellano, M., & Bond, S. (1991). Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. The Review of Economic Studies, 58(2), 277–297. https://doi.org/10.2307/2297968

Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. Journal of Econometrics, 68(1), 29–51. https://doi.org/10.1016/0304-4076(94)01642-D

Azhgaliyeva, D., Beirne, J., & Mishra, R. (2023). What matters for private investment in renewable energy? Climate Policy, 23(1), 71–87. https://doi.org/10.1080/14693062.2022.2069664

Aziz, S., & Jahan, S. M. (2023). Determinants of international development investments in renewable energy in developing countries. Energy for Sustainable Development, 74, 215–230. https://doi.org/10.1016/j.esd.2023.04.008

Bachelet, M. J., Becchetti, L., & Manfredonia, S. (2019). The Green Bonds Premium Puzzle: The Role of Issuer Characteristics and Third-Party Verification. Sustainability, 11(4), Article 4. https://doi.org/10.3390/su11041098

Baker, M., & Wurgler, J. (2007). Investor Sentiment in the Stock Market. Journal of Economic Perspectives, 21(2), 129–152. https://doi.org/10.1257/jep.21.2.129

Baker, M., Bergstresser, D., Serafeim, G., & Wurgler, J. (2022). The Pricing and Ownership of US Green Bonds. Annual Review of Financial Economics, 14(1), 415–437. https://doi.org/10.1146/annurev-financial-111620-014802

Baldwin, E., Carley, Sanya, Brass ,Jennifer N., & and MacLean, L. M. (2017). Global Renewable Electricity Policy: A Comparative Policy Analysis of Countries by Income Status. Journal of Comparative Policy Analysis: Research and Practice, 19(3), 277–298. https://doi.org/10.1080/13876988.2016.1166866

Bang, H.-K., Ellinger, A. E., Hadjimarcou, J., & Traichal, P. A. (2000). Consumer concern, knowledge, belief, and attitude toward renewable energy: An application of the reasoned action theory. Psychology & Marketing, 17(6), 449–468. https://doi.org/10.1002/(SICI)1520-6793(200006)17:6<449:AID-MAR2>3.0.CO;2-8

Banga, J. (2019). The green bond market: A potential source of climate finance for developing countries. Journal of Sustainable Finance & Investment, 9(1), 17–32. https://doi.org/10.1080/20430795.2018.1498617

Barber, B. M., & Lyon, J. D. (1997). Detecting long-run abnormal stock returns: The empirical power and specification of test statistics. Journal of Financial Economics, 43(3), 341–372. https://doi.org/10.1016/S0304-405X(96)00890-2

Bauer, M. D., Offner, E. A., & Rudebusch, G. D. (n.d.). The Effect of U.S. Climate Policy on Financial Markets: MONETARY POLICY.

Bertoni, D., Curzi, D., Aletti, G., & Olper, A. (2020). Estimating the effects of agri-environmental measures using difference-in-difference coarsened exact matching. Food Policy, 90, 101790. https://doi.org/10.1016/j.foodpol.2019.101790

Bevilaqua, J., Hale, G. B., & Tallman, E. (2020). Corporate yields and sovereign yields. Journal of International Economics, 124, 103304. https://doi.org/10.1016/j.jinteco.2020.103304

Bilir, L. K., Chor, D., & Manova, K. (2019). Host-country financial development and multinational activity. European Economic Review, 115(C), 192–220.

Bird, S., Klein, E., & Loper, E. (2009). Natural Language Processing with Python: Analyzing Text with the Natural Language Toolkit. O'Reilly Media, Inc.

Bistline, J. E. T., Brown, M., Domeshek, M., Marcy, C., Roy, N., Blanford, G., Burtraw, D., Farbes, J., Fawcett, A., Hamilton, A., Jenkins, J., Jones, R., King, B., Kolus, H., Larsen, J., Levin, A., Mahajan, M., Mayfield, E., McFarland, J., … Zhao, A. (2023). Power sector impacts of the Inflation Reduction Act of 2022. Environmental Research Letters, 19(1), 014013. https://doi.org/10.1088/1748-9326/ad0d3b

Bistline, J. E. T., Brown, M., Domeshek, M., Marcy, C., Roy, N., Blanford, G., Burtraw, D., Farbes, J., Fawcett, A., Hamilton, A., Jenkins, J., Jones, R., King, B., Kolus, H., Larsen, J., Levin, A., Mahajan, M., Mayfield, E., McFarland, J., … Zhao, A. (2023). Power sector impacts of the Inflation Reduction Act of 2022. Environmental Research Letters, 19(1), 014013. https://doi.org/10.1088/1748-9326/ad0d3b

Bistline, J., Blanford, G., Brown, M., Burtraw, D., Domeshek, M., Farbes, J., Fawcett, A., Hamilton, A., Jenkins, J., Jones, R., King, B., Kolus, H., Larsen, J., Levin, A., Mahajan, M., Marcy, C., Mayfield, E., McFarland, J., McJeon, H., … Zhao, A. (2023). Emissions and energy impacts of the Inflation Reduction Act. Science, 380(6652), 1324–1327. https://doi.org/10.1126/science.adg3781

Blackwell, M., Iacus, S., King, G., & Porro, G. (2009). Cem: Coarsened Exact Matching in Stata. The Stata Journal, 9(4), 524–546. https://doi.org/10.1177/1536867X0900900402

Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent dirichlet allocation. J. Mach. Learn. Res., 3(null), 993–1022.

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. Journal of Econometrics, 87(1), 115–143. https://doi.org/10.1016/S0304-4076(98)00009-8

Bolton, P., Buchheit, L., Gulati, M., Panizza, U., di Mauro, B. W., & Zettelmeyer, J. (2023). On Debt and climate. Oxford Open Economics, 2, odad005. https://doi.org/10.1093/ooec/odad005

Botzen, W., Duijndam, S., & van Beukering, P. (2021). Lessons for climate policy from behavioral biases towards COVID-19 and climate change risks. World Development, 137, 105214. https://doi.org/10.1016/j.worlddev.2020.105214

Bua, G., Kapp, D., Ramella, F., & Rognone, L. (2022). Transition Versus Physical Climate Risk Pricing in European Financial Markets: A Text-Based Approach (SSRN Scholarly Paper No. 4154034). Social Science Research Network. https://doi.org/10.2139/ssrn.4154034

Buse, A. (1970). Hicks, Lutz, Meiselman and the Expectations Theory1. The Review of Economic Studies, 37(3), 395–406. https://doi.org/10.2307/2296728

Caetano, R. V., Marques, A. C., Afonso, T. L., & Vieira, I. (2023). Could Private Investment in Energy Infrastructure soften the environmental impacts of Foreign Direct Investment? An assessment of developing countries. Economic Analysis and Policy, 80, 961–977. https://doi.org/10.1016/j.eap.2023.09.030

Cao, H., Guo, L., & Zhang, L. (2020). Does oil price uncertainty affect renewable energy firms' investment? Evidence from listed firms in China. Finance Research Letters, 33, 101205. https://doi.org/10.1016/j.frl.2019.06.003

Caramichael, J., & Rapp, A. C. (2024). The Green Corporate Bond Issuance Premium. Journal of Banking & Finance, 107126. https://doi.org/10.1016/j.jbankfin.2024.107126

Carattini, S., & Sen, S. (2019). Carbon Taxes and Stranded Assets: Evidence from Washington State (SSRN Scholarly Paper No. 3434841). https://doi.org/10.2139/ssrn.3434841

Carley, S., Baldwin, E., MacLean, L. M., & Brass, J. N. (2017). Global Expansion of Renewable Energy Generation: An Analysis of Policy Instruments. Environmental and Resource Economics, 68(2), 397–440. https://doi.org/10.1007/s10640-016-0025-3

Casady, C. B., Cepparulo, A., & Giuriato, L. (2024). Public-private partnerships for low-carbon, climate-resilient infrastructure: Insights from the literature. Journal of Cleaner Production, 470, 143338. https://doi.org/10.1016/j.jclepro.2024.143338

Cassidy, W. M. (2023). Elections Have Consequences: The Impact of Political Agency on Climate Policy and Asset Prices [Ph.D., The University of Chicago]. https://www.proquest.com/docview/2825333691/abstract/35C828EFEF07417APQ/1

Čaušević, A. (2022). Private-public partnerships in the Association of Southeast Asian Nations and CAREC and their scope for renewable energy projects. https://doi.org/10.4324/9781003228790

Cedrick, B. Z. E., & Long, Pr. W. (2017). Investment Motivation in Renewable Energy: A PPP Approach. Energy Procedia, 115, 229–238. https://doi.org/10.1016/j.egypro.2017.05.021

Chala, G. T., Ma'Arof ,M. I. N., & and Sharma, R. (2019). Trends in an increased dependence towards hydropower energy utilization—A short review. Cogent Engineering, 6(1), 1631541. https://doi.org/10.1080/23311916.2019.1631541

Cheng, G., Ehlers, T., & Packer, F. (2022). Sovereigns and sustainable bonds: Challenges and new options.

Cheng, R., Gupta, B., & Rajan, R. S. (2023). Do green financial policies offset the climate transition risk penalty imposed on long-term sovereign bond yields? Research in International Business and Finance, 65, 101976. https://doi.org/10.1016/j.ribaf.2023.101976

Chiesa, M., & Barua, S. (2019). The surge of impact borrowing: The magnitude and determinants of green bond supply and its heterogeneity across markets. Journal of Sustainable Finance & Investment, 9(2), 138–161. https://doi.org/10.1080/20430795.2018.1550993

Chordia, T., Roll, R., & Subrahmanyam, A. (2001). Market Liquidity and Trading Activity. The Journal of Finance, 56(2), 501–530. https://doi.org/10.1111/0022-1082.00335

Ciplet, D., Falzon, D., Uri, I., Robinson, S., Weikmans, R., & Roberts, J. T. (2022). The unequal geographies of climate finance: Climate injustice and dependency in the world system. Political Geography, 99, 102769. https://doi.org/10.1016/j.polgeo.2022.102769

Complementarity of sovereign and corporate debt issuance: Mind the gap | Review of Finance | Oxford Academic. (n.d.). Retrieved July 19, 2024, from https://academic.oup.com/rof/article/28/4/1187/7619293

Damodaran, A. (2012). Investment valuation: Tools and techniques for determining the value of any asset (Vol. 666). John Wiley & Sons. https://books.google.com/books?hl=en&lr=&id=E8-30Pga-nkC&oi=fnd&pg=PA1&dq=info:zC2MBhrN3EQJ:scholar.google.com&ots=9CT8nmtv8R&sig=ZnInHOUt9JR0zqY3JdAaAhhmQLw

Dent, C. M. (2021). Trade, Climate and Energy: A New Study on Climate Action through Free Trade Agreements. Energies, 14(14), Article 14. https://doi.org/10.3390/en14144363

Dick-Nielsen, J., Gyntelberg, J., & Lund, J. (n.d.). From Funding Liquidity to Market Liquidity: Evidence from Danish Bond Markets.

Dionysiou, D. (2015). Choosing Among Alternative Long-Run Event-Study Techniques. Journal of Economic Surveys, 29(1), 158–198. https://doi.org/10.1111/j.1467-6419.2012.00742.x

Dittmar, R. F., & Yuan, K. (2008). Do Sovereign Bonds Benefit Corporate Bonds in Emerging Markets? The Review of Financial Studies, 21(5), 1983–2014. https://doi.org/10.1093/rfs/hhn015

Dong, H., Zhang, L., & Zheng, H. (2024). Green bonds: Fueling green innovation or just a fad? Energy Economics, 135, 107660. https://doi.org/10.1016/j.eneco.2024.107660

Dorfleitner, G., Utz, S., & Zhang, R. (2022). The pricing of green bonds: External reviews and the shades of green. Review of Managerial Science, 16(3), 797–834. https://doi.org/10.1007/s11846-021-00458-9

Doronzo, R., Siracusa, V., & Antonelli, S. (2021). Green Bonds: The Sovereign Issuers' Perspective (SSRN Scholarly Paper 3854966). https://doi.org/10.2139/ssrn.3854966

Eberhard, A., Kolker, J., & Leigland, J. (2014, May 1). South Africa's Renewable Energy IPP Procurement Program: Success Factors and Lessons. https://www.semanticscholar.org/paper/South-Africa's-Renewable-Energy-IPP-Procurement-%3A-Eberhard-Kolker/eed422c6e190e7058cc1df3042ae98ee20ad17e0

Egli, F., Steffen, B., & Schmidt, T. S. (2019). Bias in energy system models with uniform cost of capital assumption. Nature Communications, 10(1), 4588. https://doi.org/10.1038/s41467-019-12468-z

Engle, R. F., Giglio, S., Kelly, B., Lee, H., & Stroebel, J. (2020). Hedging Climate Change News. The Review of Financial Studies, 33(3), 1184–1216. https://doi.org/10.1093/rfs/hhz072

Faccini, R., Matin, R., & Skiadopoulos, G. S. (2023). Dissecting Climate Risks: Are they Reflected in Stock Prices? (SSRN Scholarly Paper No. 3795964). Social Science Research Network. https://doi.org/10.2139/ssrn.3795964

Fahmy, H. (2022). Investors' Adaptation to Climate Change: A Temporal Portfolio Choice Model with Diminishing Climate Duration Hazard. In T. Walker, S. Wendt, S. Goubran, & T. Schwartz (Eds.), Business and Policy Solutions to Climate Change: From Mitigation to Adaptation (pp. 239–262). Springer International Publishing. https://doi.org/10.1007/978-3-030-86803-1_11

Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. The Journal of Finance, 25(2), 383–417. https://doi.org/10.2307/2325486

Fama, E. F. (1998). Market efficiency, long-term returns, and behavioral finance1. Journal of Financial Economics, 49(3), 283–306. https://doi.org/10.1016/S0304-405X(98)00026-9

Fama, E. F., & French, K. R. (2007). Disagreement, tastes, and asset prices. Journal of Financial Economics, 83(3), 667–689. https://doi.org/10.1016/j.jfineco.2006.01.003

Fama, E. F., & French, K. R. (2007). Disagreement, tastes, and asset prices. Journal of Financial Economics, 83(3), 667–689. https://doi.org/10.1016/j.jfineco.2006.01.003

Fatica, S., Panzica, R., & Rancan, M. (2021). The pricing of green bonds: Are financial institutions special? Journal of Financial Stability, 54, 100873. https://doi.org/10.1016/j.jfs.2021.100873

Fedorova, E., & Iasakova, P. (2024). The impact of climate change news on the US stock market. The Journal of Risk Finance, 25(2), 293–320. https://doi.org/10.1108/JRF-06-2023-0133

Flammer, C. (2021). Corporate green bonds. Journal of Financial Economics, 142(2), 499–516. https://doi.org/10.1016/j.jfineco.2021.01.010

Fleta-Asín, J., & Muñoz, F. (2020). How does risk transference to private partner impact on public-private partnerships' success? Empirical evidence from developing economies. Socio-Economic Planning Sciences, 72, 100869. https://doi.org/10.1016/j.seps.2020.100869

Fleta-Asín, J., & Muñoz, F. (2021). Renewable energy public–private partnerships in developing countries: Determinants of private investment. Sustainable Development, 29(4), 653–670. https://doi.org/10.1002/sd.2165

Garel, A., & Romec, A. (2020). Investor Rewards to Environmental Responsibility: Evidence from the COVID-19 Crisis (SSRN Scholarly Paper No. 3620109). Social Science Research Network. https://doi.org/10.2139/ssrn.3620109

Gautam, K., Purkayastha, D., & Widge, V. (n.d.). RECOMMENDED CITATION.

Gianfrate, G., & Peri, M. (2019). The green advantage: Exploring the convenience of issuing green bonds. Journal of Cleaner Production, 219, 127–135. https://doi.org/10.1016/j.jclepro.2019.02.022

Gopinath, G., Meyer, J., Berlin, D., Reinhart, C., & Trebesch, C. (n.d.). Sovereign vs. Corporate Debt and Default: More Similar Than You Think.

Grishunin, S., Bukreeva, A., Suloeva, S., & Burova, E. (2023). Analysis of Yields and Their Determinants in the European Corporate Green Bond Market. Risks, 11(1), Article 1. https://doi.org/10.3390/risks11010014

Guinea, L., Puch, L. A., & Ruiz, J. (2024). Energy news shocks and their propagation to renewable and fossil fuels use. Energy Economics, 130, 107289. https://doi.org/10.1016/j.eneco.2023.107289

Gujarati, D. N. (2021). Essentials of Econometrics. SAGE Publications.

Gürkaynak, R. S., Sack, B. P., & Swanson, E. T. (2004). Do actions speak louder than words? The response of asset prices to monetary policy actions and statements. Finance and Economics Discussion Series, Article 2004–66. https://ideas.repec.org//p/fip/fedgfe/2004-66.html

Hachenberg, B., & Schiereck, D. (2018). Are green bonds priced differently from conventional bonds? Journal of Asset Management, 19(6), 371–383. https://doi.org/10.1057/s41260-018-0088-5

Heinkel, R., Kraus, A., & Zechner, J. (2001). The Effect of Green Investment on Corporate Behavior. The Journal of Financial and Quantitative Analysis, 36(4), 431–449. https://doi.org/10.2307/2676219

Horváth, R., Kalistová, A., Lyócsa, Š., Miškufová, M., & Moravcová, M. (2025). Do hurricanes cause storm on the stock market? The case of US energy companies. International Review of Financial Analysis, 97, 103816. https://doi.org/10.1016/j.irfa.2024.103816

Howlett, M., & Rawat, S. (n.d.). Behavioral Science and Climate Policy. In Oxford Research Encyclopedia of Climate Science. Retrieved March 28, 2025, from https://oxfordre.com/climatescience/display/10.1093/acrefore/9780190228620.001.0001/acrefore-9780190228620-e-624

Hsu, Y.-J., Lu, Y.-C., & Yang, J. J. (2021). News sentiment and stock market volatility. Review of Quantitative Finance and Accounting, 57(3), 1093–1122. https://doi.org/10.1007/s11156-021-00971-8

Hu, X., Zhu, B., Lin, R., Li, X., Zeng, L., & Zhou, S. (2024). How does greenness translate into greenium? Evidence from China's green bonds. Energy Economics, 133, 107511. https://doi.org/10.1016/j.eneco.2024.107511

Hyun, S., Park, D., & Tian, S. (2021). Pricing of Green Labeling: A Comparison of Labeled and Unlabeled Green Bonds. Finance Research Letters, 41, 101816. https://doi.org/10.1016/j.frl.2020.101816

Hyun, S., Park, D., & Tian, S. (2023). The price of frequent issuance: The value of information in the green bond market. Economic Change and Restructuring, 56(5), 3041–3063. https://doi.org/10.1007/s10644-022-09417-0

Iacus, S. M., King, G., & Porro, G. (2012). Causal Inference Without Balance Checking: Coarsened Exact Matching. Political Analysis, 20(1), 1--24.

Iacus, S., King, G., & Porro, G. (2009). CEM: Software for Coarsened Exact Matching. Journal of Statistical Software, 30.

Idzorek, T. M., Kaplan, P. D., & Ibbotson, R. G. (2023). The CAPM, APT, and PAPM (SSRN Scholarly Paper 4566414). https://doi.org/10.2139/ssrn.4566414

Immel, M., Hachenberg, B., Kiesel, F., & Schiereck, D. (2021). Green bonds: Shades of green and brown. Journal of Asset Management, 22(2), 96–109. https://doi.org/10.1057/s41260-020-00192-z

Işık, C., Kuziboev, B., Ongan, S., Saidmamatov, O., Mirkhoshimova, M., & Rajabov, A. (2024). The volatility of global energy uncertainty: Renewable alternatives. Energy, 297, 131250. https://doi.org/10.1016/j.energy.2024.131250

Ivashkovskaya, I., & Mikhaylova, A. (2020). Do Investors Pay Yield Premiums on Green Bonds? (SSRN Scholarly Paper 3752102). https://papers.ssrn.com/abstract=3752102

Jain, K., Gangopadhyay, M., & Mukhopadhyay, K. (2022). Prospects and challenges of green bonds in renewable energy sector: Case of selected Asian economies. Journal of Sustainable Finance & Investment, 0(0), 1–24. https://doi.org/10.1080/20430795.2022.2034596

Jiang, Y., Song, X., Harrison, J., Quegan, S., & Maynard, D. (2017). Comparing Attitudes to Climate Change in the Media using sentiment analysis based on Latent Dirichlet Allocation. In O. Popescu & C. Strapparava (Eds.), Proceedings of the 2017 EMNLP Workshop: Natural Language Processing meets Journalism (pp. 25–30). Association for Computational Linguistics. https://doi.org/10.18653/v1/W17-4205

Jong, F. de, & Driessen, J. (2012). Liquidity Risk Premia in Corporate Bond Markets. The Quarterly Journal of Finance. https://doi.org/10.1142/S2010139212500061

Kacperczyk, M., Peng, L., & Xie, J. (n.d.). ESG Investing and Stock Return Comovements.

Kanamura, T. (2020). Are green bonds environmentally friendly and good performing assets? Energy Economics, 88, 104767. https://doi.org/10.1016/j.eneco.2020.104767

Kapraun, J., Latino, C., Scheins, C., & Schlag, C. (2021). (In)-Credibly Green: Which Bonds Trade at a Green Bond Premium? (SSRN Scholarly Paper 3347337). https://doi.org/10.2139/ssrn.3347337

Karpf, A., & Mandel, A. (2018). The changing value of the ‘green’ label on the US municipal bond market. Nature Climate Change, 8(2), 161–165. https://doi.org/10.1038/s41558-017-0062-0

Kaufmann, D., Kraay, A., & Mastruzzi, M. (2010). The Worldwide Governance Indicators: Methodology and Analytical Issues (SSRN Scholarly Paper No. 1682130). Social Science Research Network. https://papers.ssrn.com/abstract=1682130

Kerr, S., & Hu, X. (2025). Filling the climate finance gap: Holistic approaches to mobilise private finance in developing economies. Npj Climate Action, 4(1), 1–10. https://doi.org/10.1038/s44168-025-00220-x

Kim, J. E. (2020). Regulation trumps economics? Examining renewable energy policy, diffusion and investment in 80 developing countries. Energy Research & Social Science, 70, 101613. https://doi.org/10.1016/j.erss.2020.101613

Krueger, P., Sautner, Z., & Starks, L. T. (2020). The Importance of Climate Risks for Institutional Investors. The Review of Financial Studies, 33(3), 1067–1111. https://doi.org/10.1093/rfs/hhz137

Leitao, J., Ferreira, J., & Santibanez-Gonzalez, E. (2021). Green bonds, sustainable development and environmental policy in the European Union carbon market. Business Strategy and the Environment, 30(4), 2077–2090. https://doi.org/10.1002/bse.2733

Li, D., Heimeriks ,Gaston, & and Alkemade, F. (2020). The emergence of renewable energy technologies at country level: Relatedness, international knowledge spillovers and domestic energy markets. Industry and Innovation, 27(9), 991–1013. https://doi.org/10.1080/13662716.2020.1713734

Li, L., Zheng, X., & Wang, S. (2024). Renewable Energy Stocks' Performance and Climate Risk: An Empirical Analysis. Journal of Risk and Financial Management, 17(3), 121. https://doi.org/10.3390/jrfm17030121

Liaw, K. T. (2020). Survey of Green Bond Pricing and Investment Performance. Journal of Risk and Financial Management, 13(9), Article 9. https://doi.org/10.3390/jrfm13090193

Liu, H., Ferreira, S., & Karali, B. (2021). Hurricanes as news? Assessing the impact of hurricanes on the stock market returns of energy companies. International Journal of Disaster Risk Reduction, 66, 102572. https://doi.org/10.1016/j.ijdrr.2021.102572

Lo, A. W. (2004). The Adaptive Markets Hypothesis: Market Efficiency from an Evolutionary Perspective (SSRN Scholarly Paper No. 602222). Social Science Research Network. https://papers.ssrn.com/abstract=602222

Löffler, K. U., Petreski, A., & Stephan, A. (2021). Drivers of green bond issuance and new evidence on the "greenium." Eurasian Economic Review, 11(1), 1–24. https://doi.org/10.1007/s40822-020-00165-y

MacAskill, S., Roca, E., Liu, B., Stewart, R. A., & Sahin, O. (2021). Is there a green premium in the green bond market? Systematic literature review revealing premium determinants. Journal of Cleaner Production, 280, 124491. https://doi.org/10.1016/j.jclepro.2020.124491

Magale, E. G. (2021). Developing a green bond market in Kenya: Perspectives from practitioners and lessons from developing markets. Journal of Sustainable Finance & Investment, 0(0), 1–18. https://doi.org/10.1080/20430795.2021.1953930

Mankata, L. M., Owusu-Manu, D.-G., Hosseini, M. R., & Edwards, D. J. (2022). Analysis of success-dependent factors for green bond financing of infrastructure projects in Ghana. Journal of Sustainable Finance & Investment, 12(3), 832–848. https://doi.org/10.1080/20430795.2020.1803640

Manos, B., Bartocci, P., Partalidou, M., Fantozzi, F., & Arampatzis, S. (2014). Review of public–private partnerships in agro-energy districts in Southern Europe: The cases of Greece and Italy. Renewable and Sustainable Energy Reviews, 39, 667–678. https://doi.org/10.1016/j.rser.2014.07.031

Meckling, J., Aldy, J. E., Kotchen, M. J., Carley, S., Esty, D. C., Raymond, P. A., Tonkonogy, B., Harper, C., Sawyer, G., & Sweatman, J. (2022). Busting the myths around public investment in clean energy. Nature Energy, 7(7), 563–565. https://doi.org/10.1038/s41560-022-01081-y

Misev, M. A., & Balles, P. (n.d.). Natural Disasters, Investor Attention, and Non-Fundamental Green Asset Demand.

Mitra, N., & Al Farhad, M. M. (2023). Sustainable Urban Infrastructure: Achieving Green Economic Growth through Public-Private Partnerships (pp. 85–95).

Monasterolo, I., & de Angelis, L. (2020). Blind to carbon risk? An analysis of stock market reaction to the Paris Agreement. Ecological Economics, 170, 106571. https://doi.org/10.1016/j.ecolecon.2019.106571

Monasterolo, I., Mandel, A., Battiston, S., Mazzocchetti, A., Oppermann, K., Coony, J., Stretton, S., Stewart, F., & Dunz, N. (2022). The Role of Green Financial Sector Initiatives in the Low-Carbon Transition: A Theory of Change. The World Bank. https://doi.org/10.1596/1813-9450-10181

Morão, H. (2024). The impact of carbon policy news on the national energy industry. Energy Economics, 134, 107596. https://doi.org/10.1016/j.eneco.2024.107596

Morina, F., Ergün, U., & Hysa, E. (2021). Understanding Drivers of Renewable Energy Firm's Performance. Environmental Research, Engineering and Management, 77(3), Article 3. https://doi.org/10.5755/j01.erem.77.3.29230

Mukherjee, S., Nateghi, R., & Hastak, M. (2018). A multi-hazard approach to assess severe weather-induced major power outage risks in the U.S. Reliability Engineering and System Safety, 175(C), 283–305.

Nanayakkara, M., & Colombage, S. (2019). Do investors in Green Bond market pay a premium? Global evidence. Applied Economics, 51(40), 4425–4437. https://doi.org/10.1080/00036846.2019.1591611

Noailly, J., Nowzohour, L. M., & Van Den Heuvel, M. (Eds.). (2021). Heard the news ? Environmental policy and clean investments. Graduate Institute of International and Development Studies, Centre for International Environmental Studies.

Nyman, R., Kapadia, S., & Tuckett, D. (2021). News and narratives in financial systems: Exploiting big data for systemic risk assessment. Journal of Economic Dynamics and Control, 127, 104119. https://doi.org/10.1016/j.jedc.2021.104119

Obaid, K., & Pukthuanthong, K. (2022). A picture is worth a thousand words: Measuring investor sentiment by combining machine learning and photos from news. Journal of Financial Economics, 144(1), 273–297. https://doi.org/10.1016/j.jfineco.2021.06.002

Oehmke, M., & Opp, M. M. (2024). A Theory of Socially Responsible Investment (SSRN Scholarly Paper 3467644). https://doi.org/10.2139/ssrn.3467644

Oman, A. P., Elena Loukoianova,Alan Xiaochen Feng,William. (n.d.). Mobilizing Private Climate Financing in Emerging Market and Developing Economies. IMF. Retrieved March 18, 2024, from https://www.imf.org/en/Publications/staff-climate-notes/Issues/2022/07/26/Mobilizing-Private-Climate-Financing-in-Emerging-Market-and-Developing-Economies-520585

Othman, K., & Khallaf, R. (2022a). A REVIEW OF PUBLIC-PRIVATE PARTNERSHIPS FOR RENEWABLE ENERGY PROJECTS IN DEVELOPING COUNTRIES. Proceedings of International Structural Engineering and Construction, 9(1). https://doi.org/10.14455/ISEC.2022.9(1).ENR-01

Othman, K., & Khallaf, R. (2022b). Identification of the Barriers and Key Success Factors for Renewable Energy Public-Private Partnership Projects: A Continental Analysis. Buildings, 12(10), Article 10. https://doi.org/10.3390/buildings12101511

Othman, K., Khallaf, R., Othman, K., & Khallaf, R. (2024). Analyzing the factors that affect the renewable energy PPP market: A comparative analysis between developing and developed countries. AIMS Energy, 12(2), Article energy-12-02-024. https://doi.org/10.3934/energy.2024024

Pastor, L., Stambaugh, R., & Taylor, L. A. (2021). Sustainable investing in equilibrium. Journal of Financial Economics, 142(2), 550–571.

Pastor, L., Stambaugh, R., & Taylor, L. A. (2021). Sustainable investing in equilibrium. Journal of Financial Economics, 142(2), 550–571.

Patronella, A. M. (2021). Covering Climate Change: A Sentiment Analysis of Major Newspaper Articles from 2010 - 2020. Inquiries Journal, 13(09). http://www.inquiriesjournal.com/articles/1910/covering-climate-change-a-sentiment-analysis-of-major-newspaper-articles-from-2010--2020

Pedersen, L. H., Fitzgibbons, S., & Pomorski, L. (2021). Responsible investing: The ESG-efficient frontier. Journal of Financial Economics, 142(2), 572–597. https://doi.org/10.1016/j.jfineco.2020.11.001

Percoco, M. (2014). Quality of institutions and private participation in transport infrastructure investment: Evidence from developing countries. Transportation Research Part A: Policy and Practice, 70(C), 50–58.

Petralia, S., Balland, P.-A., & Morrison, A. (2017). Climbing the ladder of technological development. Research Policy, 46(5), 956–969. https://doi.org/10.1016/j.respol.2017.03.012

Pham, L., Hao, W., Truong, H., & Trinh, H. H. (2023). The impact of climate policy on U.S. environmentally friendly firms: A firm-level examination of stock return, volatility, volume, and connectedness. Energy Economics, 119, 106564. https://doi.org/10.1016/j.eneco.2023.106564

Pindyck, R. S. (with Internet Archive). (1998). Econometric models and economic forecasts. Boston, Mass.: Irwin/McGraw-Hill. http://archive.org/details/econometricmodel0000pind_f3j9

Poghosyan, T. (2014). Long-run and short-run determinants of sovereign bond yields in advanced economies. Economic Systems, 38(1), 100–114. https://doi.org/10.1016/j.ecosys.2013.07.008

Polzin, F., Egli, F., Steffen, B., & Schmidt, T. S. (2019). How do policies mobilize private finance for renewable energy?—A systematic review with an investor perspective. Applied Energy, 236, 1249–1268. https://doi.org/10.1016/j.apenergy.2018.11.098

Presbitero, A. F., Ghura, D., Adedeji, O. S., & Njie, L. (2016). Sovereign bonds in developing countries: Drivers of issuance and spreads. Review of Development Finance, 6(1), 1–15. https://doi.org/10.1016/j.rdf.2016.05.002

Raghutla, C., & Kolati, Y. (2023). Public-private partnerships investment in energy as new determinant of renewable energy: The role of political cooperation in China and India. Energy Reports, 10, 3092–3101. https://doi.org/10.1016/j.egyr.2023.09.139

Ragosa, G., & Warren, P. (2019). Unpacking the determinants of cross-border private investment in renewable energy in developing countries. Journal of Cleaner Production, 235, 854–865. https://doi.org/10.1016/j.jclepro.2019.06.166

Ragosa, G., & Warren, P. (2019). Unpacking the determinants of cross-border private investment in renewable energy in developing countries. Journal of Cleaner Production, 235, 854–865. https://doi.org/10.1016/j.jclepro.2019.06.166

Ramelli, S., Wagner, A. F., Zeckhauser, R. J., & Ziegler, A. (2021). Investor Rewards to Climate Responsibility: Stock-Price Responses to the Opposite Shocks of the 2016 and 2020 U.S. Elections. The Review of Corporate Finance Studies, 10(4), 748–787. https://doi.org/10.1093/rcfs/cfab010

Ramiah, V., Pichelli, J., & Moosa, I. (2015). Environmental regulation, the Obama effect and the stock market: Some empirical results. Applied Economics. https://www.tandfonline.com/doi/abs/10.1080/00036846.2014.980572

Romano, A. A., Scandurra, G., Carfora, A., & Fodor, M. (2017). Renewable investments: The impact of green policies in developing and developed countries. Renewable and Sustainable Energy Reviews, 68, 738–747. https://doi.org/10.1016/j.rser.2016.10.024

Sadorsky, P. (2012). Modeling renewable energy company risk. Energy Policy, 40, 39–48. https://doi.org/10.1016/j.enpol.2010.06.064

Santi, C. (2023). Investor climate sentiment and financial markets. International Review of Financial Analysis, 86, 102490. https://doi.org/10.1016/j.irfa.2023.102490

Seetharam, I. (2017). Environmental Disasters and Stock Market Performance ∗. https://www.semanticscholar.org/paper/Environmental-Disasters-and-Stock-Market-%E2%88%97-Seetharam/e65ddfe4b9a2c63785583f8244ed130d6343a1c6

Shiller, R. J. (2015). Irrational Exuberance. Economics Books. https://ideas.repec.org//b/pup/pbooks/10421.html

Shleifer, A., & Vishny, R. W. (1997). The Limits of Arbitrage. The Journal of Finance, 52(1), 35–55. https://doi.org/10.1111/j.1540-6261.1997.tb03807.x

Song, Y., & Dong, J. (2024). Impact of climate policy uncertainty on corporate green investment: Examining the moderating role of financing constraints. Frontiers in Marine Science, 11. https://doi.org/10.3389/fmars.2024.1456079

Sovacool, B. K. (2013). Expanding renewable energy access with pro-poor public private partnerships in the developing world. Energy Strategy Reviews, 1(3), 181–192. https://doi.org/10.1016/j.esr.2012.11.003

Spohr, J., Wikström, K., Ronikonmäki, N.-M., Lepech, M., & In, S. Y. (2024). Are private investors overcompensated in infrastructure projects? Transport Policy, 152, 1–8. https://doi.org/10.1016/j.tranpol.2024.04.009

Steckel, J., & Jakob, M. (2018). The role of financing cost and de-risking strategies for clean energy investment. International Economics, 155(C), 19–28.

Stede, M., & Patz, R. (2021). The Climate Change Debate and Natural Language Processing. In A. Field, S. Prabhumoye, M. Sap, Z. Jin, J. Zhao, & C. Brockett (Eds.), Proceedings of the 1st Workshop on NLP for Positive Impact (pp. 8–18). Association for Computational Linguistics. https://doi.org/10.18653/v1/2021.nlp4posimpact-1.2

Stern, N., & Stiglitz, J. E. (2023). Climate change and growth. Industrial and Corporate Change, 32(2), 277–303. https://doi.org/10.1093/icc/dtad008

Stroebel, J., & Wurgler, J. (2021). What Do You Think About Climate Finance? (No. w29136). National Bureau of Economic Research. https://doi.org/10.3386/w29136

Sun, L., & Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. Journal of Econometrics, 225(2), 175–199. https://doi.org/10.1016/j.jeconom.2020.09.006

Tang, Y., Wang, B., Pan, N., & Li, Z. (2023). The impact of environmental information disclosure on the cost of green bond: Evidence from China. Energy Economics, 126, 107008. https://doi.org/10.1016/j.eneco.2023.107008

Teutrine, C., Schuster, M., Bornhöft, S. C., Lueg, R., & Bouzzine, Y. D. (2024). Stock price reactions to climate science information from the Intergovernmental Panel on Climate Change: A mitigation function of corporate and sector emissions responsibility? Business Strategy and the Environment, 33(6), 5346–5365. https://doi.org/10.1002/bse.3761

Tomczak, K. (2024). Sovereign Green Bond Market: Drivers of Yields and Liquidity. International Journal of Financial Studies, 12(2), Article 2. https://doi.org/10.3390/ijfs12020048

Torricelli, C., & Pellati, E. (2022). Social Bonds and the â€œSocial Premiumâ€. Centro Studi Di Banca e Finanza (CEFIN) (Center for Studies in Banking and Finance), Article 0085. https://ideas.repec.org//p/mod/wcefin/0085.html

Vagliasindi, M. (2012). The Role of Policy Driven Incentives to Attract PPPs in Renewable-Based Energy in Developing Countries: A Cross-Country Analysis. World Bank, Washington, DC. https://doi.org/10.1596/1813-9450-6120

Verdolini, E., Vona, F., & Popp, D. (2016). Bridging the Gap: Do Fast Reacting Fossil Technologies Facilitate Renewable Energy Diffusion? (Working Paper No. 22454). National Bureau of Economic Research. https://doi.org/10.3386/w22454

Wang, H., Xiong, Wei, Wu ,Guangdong, & and Zhu, D. (2018). Public–private partnership in Public Administration discipline: A literature review. Public Management Review, 20(2), 293–316. https://doi.org/10.1080/14719037.2017.1313445

Wang, L., Sun, Y., & Tiong, R. L. K. (2024). Institutional quality configuration for encouraging private capital participation in PPP projects: Evidence from 36 belt and road countries. International Journal of Managing Projects in Business, 17(6/7), 898–922. https://doi.org/10.1108/IJMPB-06-2024-0144

Webersinke, N., Kraus, M., Bingler, J. A., & Leippold, M. (2022). ClimateBert: A Pretrained Language Model for Climate-Related Text (No. arXiv:2110.12010). arXiv. http://arxiv.org/abs/2110.12010

Xiao, G. C., Torsten Ehlers,Frank Packer,Yanzhe. (n.d.). Sovereign Green Bonds: A Catalyst for Sustainable Debt Market Development? IMF. Retrieved July 11, 2024, from https://www.imf.org/en/Publications/WP/Issues/2024/06/14/Sovereign-Green-Bonds-A-Catalyst-for-Sustainable-Debt-Market-Development-550527

Yazici, M., & Gültekin, D. G. (2023). Framing Effects on Renewable Energy News. In H. Dincer & S. Yüksel (Eds.), Economic Development and the Environmental Ecosystem: The Role of Energy Policy in Economic Growth (pp. 35–46). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-26596-9_4

Yildiz, Y., & Karan, M. B. (2020). Environmental policies, national culture, and stock price crash risk: Evidence from renewable energy firms. Business Strategy and the Environment, 29(6), 2374–2391. https://doi.org/10.1002/bse.2508

Yin, C., & Qamruzzaman, M. (2024a). Empowering renewable energy consumption through public-private investment, urbanization, and globalization: Evidence from CS-ARDL and NARDL. Heliyon, 10(4), e26455. https://doi.org/10.1016/j.heliyon.2024.e26455

Yin, C., & Qamruzzaman, M. (2024b). Empowering renewable energy consumption through public-private investment, urbanization, and globalization: Evidence from CS-ARDL and NARDL. Heliyon, 10(4), e26455. https://doi.org/10.1016/j.heliyon.2024.e26455

Zerbib, O. D. (2019). The effect of pro-environmental preferences on bond prices: Evidence from green bonds. Journal of Banking & Finance, 98, 39–60. https://doi.org/10.1016/j.jbankfin.2018.10.012

Zettelmeyer, M. d C., Erik Klok,Vimal V. Thakoor,Jeromin. (n.d.). Debt-for-Climate Swaps: Analysis, Design, and Implementation. IMF. Retrieved March 18, 2024, from https://www.imf.org/en/Publications/WP/Issues/2022/08/11/Debt-for-Climate-Swaps-Analysis-Design-and-Implementation-522184

Zhao, W., Chen, J. J., Perkins, R., Liu, Z., Ge, W., Ding, Y., & Zou, W. (2015). A heuristic approach to determine an appropriate number of topics in topic modeling. BMC Bioinformatics, 16(13), S8. https://doi.org/10.1186/1471-2105-16-S13-S8

Zhou, S. (2021). Macroeconomic determinants of long-term sovereign bond yields in South Africa. Cogent Economics & Finance, 9(1), 1929678. https://doi.org/10.1080/23322039.2021.1929678

# Appendices

## A: Chapter 1

### Sources of Public and Private Climate Financing

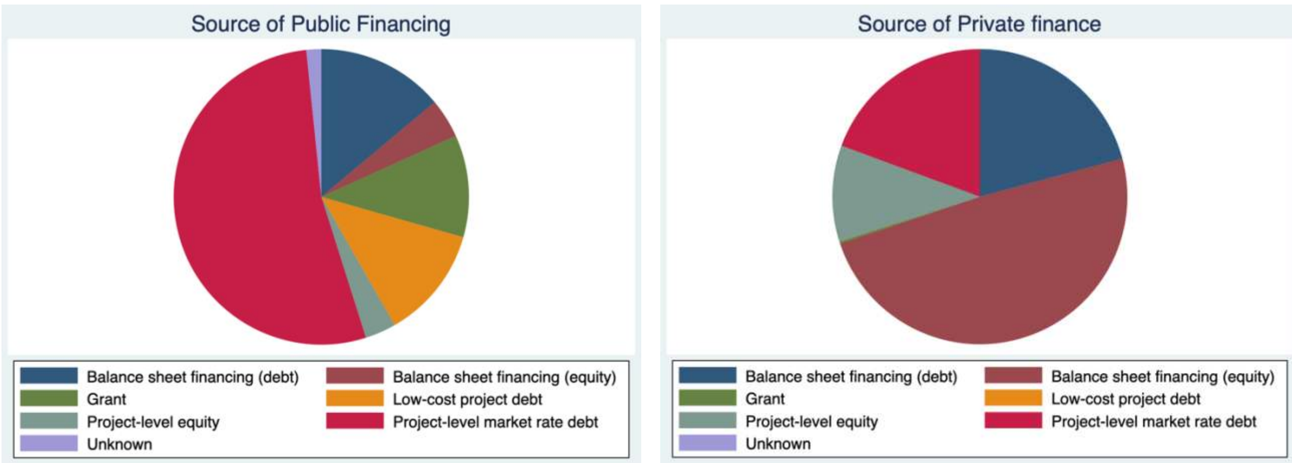



*Figure A1: Global private and public investments as of 2022. Only Grants and Low-cost project debts are not exposed to market-risk. Proportions are uniform across developed and developing regions, except for a much higher share of public over private debt in developing regions. Sourced from Global Landscape of Climate Finance 2022, Climate Policy Initiative (CPI) and authors' calculations.*

### Chile's GSS and Green Twin Bond Pair

*Table A1: Chile's green-labeled vs non-, green-labeled sovereign bond pairs:*

| Quarter | Yield | Bond ID | Amount Issued | Coupon | Maturity | Rating | Green Bond |
|---|---|---|---|---|---|---|---|
| **2021q2** | 3.223 | BO8615516 | 1.50E+09 | 3.5 | 2053q2 | A- | 0 |
| **2021q3** | 3.455 | BO8615516 | 1.50E+09 | 3.5 | 2053q2 | A- | 0 |
| **2021q4** | 3.288 | BO8615516 | 1.50E+09 | 3.5 | 2053q2 | A- | 0 |
| **2022q1** | 4.054 | BO8615516 | 1.50E+09 | 3.5 | 2053q2 | A- | 0 |
| **2022q2** | 5.014 | BO8615516 | 1.50E+09 | 3.5 | 2053q2 | A- | 0 |
| **2022q3** | 5.858 | BO8615516 | 1.50E+09 | 3.5 | 2053q2 | A- | 0 |
| **2022q4** | 5.395 | BO8615516 | 1.50E+09 | 3.5 | 2053q2 | A- | 0 |
| **2023q1** | 5.11 | BO8615516 | 1.50E+09 | 3.5 | 2053q2 | A- | 0 |
| **2023q2** | 5.143 | BO8615516 | 1.50E+09 | 3.5 | 2053q2 | A- | 0 |
| **2023q3** | 5.909 | BO8615516 | 1.50E+09 | 3.5 | 2053q2 | A- | 0 |
| **2023q4** | 5.067 | BO8615516 | 1.50E+09 | 3.5 | 2053q2 | A- | 0 |

| Quarter | Yield | Bond ID | Amount Issued | Coupon | Maturity | Rating | Green Bond |
|---|---|---|---|---|---|---|---|
| **2021q2** | 3.204 | AZ1913575 | 2.32E+09 | 3.5 | 2050q1 | A- | 1 |
| **2021q3** | 3.461 | AZ1913575 | 2.32E+09 | 3.5 | 2050q1 | A- | 1 |
| **2021q4** | 3.243 | AZ1913575 | 2.32E+09 | 3.5 | 2050q1 | A- | 1 |
| **2022q1** | 3.967 | AZ1913575 | 2.32E+09 | 3.5 | 2050q1 | A- | 1 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **2022q2** | 4.982 | AZ1913575 | 2.32E+09 | 3.5 | 2050q1 | A- | 1 |
| **2022q3** | 5.813 | AZ1913575 | 2.32E+09 | 3.5 | 2050q1 | A- | 1 |
| **2022q4** | 5.391 | AZ1913575 | 2.32E+09 | 3.5 | 2050q1 | A- | 1 |
| **2023q1** | 5.186 | AZ1913575 | 2.32E+09 | 3.5 | 2050q1 | A- | 1 |
| **2023q2** | 5.199 | AZ1913575 | 2.32E+09 | 3.5 | 2050q1 | A- | 1 |
| **2023q3** | 5.993 | AZ1913575 | 2.32E+09 | 3.5 | 2050q1 | A- | 1 |
| **2023q4** | 5.124 | AZ1913575 | 2.32E+09 | 3.5 | 2050q1 | A- | 1 |

### Bond Labeling by Use of Proceeds

*Table A2: Detailed distribution of Use of Proceeds*

| **Conventional Bonds** | **Frequency** | **Green, Social and Sustainability Bonds** | **Frequency** |
|---|---|---|---|
| #N/A Field Not Applicable | 1,343 | Capital Expenditures Sustainability | 1 |
| Acquisition Financing | 1 | General Corporate Purposes Green Bond/Loan | 2 |
| Bond Exchange General Corporate | 2 | General Corporate Purposes Refinance Green | 4 |
| Capital Expenditures | 1 | General Corporate Purposes Refinance | 1 |
| Collateral for Swap | 1 | General Corporate Purposes Sustainability | 1 |
| General Corporate Purposes | 247 | General Corporate Purposes Sustainability | 2 |
| General Corporate Purposes Investment | 4 | Green Bond/Loan | 99 |
| General Corporate Purposes Investment | 1 | Pandemic Sustainability Bond/Loan | 2 |
| General Corporate Purposes Pandemic | 4 | Project Finance Green Bond/Loan | 2 |
| General Corporate Purposes Project | 2 | Project Finance Refinance Sustainability | 1 |
| General Corporate Purposes Refinance | 75 | Refinance Green Bond/Loan | 5 |
| General Corporate Purposes Refinance | 1 | Refinance Pandemic Sustainability | 2 |
| Investment | 7 | Sustainability Bond/Loan | 44 |
| Pandemic | 8 | Sustainability Linked | 2 |
| Project Finance | 1 | | |
| Project Finance Refinance | 2 | | |
| Refinance | 54 | | |
| Refinance Pandemic | 4 | | |
| Social Bond/Loan | 13 | | |
| Total | 1,771 | Total | 168 |

**CEM Matching Summary**

*Table A3: Matching Summary, Treatment- EMDE*

Multivariate L1 Distance: 0.98263944

Univariate Distance:

| | L1 | mean | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|
| Currency | 0.83773 | 7.2736 | 2 | 4 | 8 | 16 | 1 |
| Rating | 0.7478 | -3.4692 | 0 | -4 | -3 | -1 | 0 |
| Coupon | 0.4802 | 2.9951 | 0 | 2.475 | 3.275 | 3.275 | 6.885 |
| Maturity (stratified) | 0.06186 | 5.90E-05 | 0 | 0 | 0 | 0 | 0 |

Number of strata: 9282

Number of matched strata: 914

| | 0 | 1 |
|---|---|---|
| All | 16199 | 20598 |
| Matched | 8710 | 4982 |

Multivariate L1 distance: .53235902

Univariate Imbalance

| | L1 | mean | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|
| Currency | 2.90E-15 | -2.70E-13 | 0 | 0 | 0 | 0 | 0 |
| Rating (stratified) | 1.30E-15 | -1.30E-12 | 0 | 0 | 0 | 0 | 0 |
| Coupon | 1.70E-15 | -5.90E-17 | 0 | 0 | 0 | 0 | 0 |
| Maturity (stratified) | 0.34553 | 0.09575 | 0 | -0.05 | -0.125 | 0.25 | 0.5 |
| Green Bond | 5.10E-15 | 2.00E-14 | 0 | 0 | 0 | 0 | 0 |

*Table A4: Matching Summary, Treatment- GSS:*

Multivariate L1 Distance: 0.99692038

Univariate Distance:

| | L1 | mean | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|
| Currency | 0.43059 | 4.5966 | 2 | 0 | 14 | 5 | 1 |
| Rating | 0.54132 | -2.8146 | 0 | -4 | -6 | -3 | 0 |
| Coupon | 0.41414 | -0.88338 | 0 | -0.55 | -1.25 | -1.8 | -2.29 |
| Maturity (stratified) | 0.4552 | 11.937 | 3 | 16 | 14 | 16 | -198 |

Number of strata: 18636

Number of matched strata: 168

| | 0 | 1 |
|---|---|---|
| All | 35396 | 403 |
| Matched | 410 | 206 |

Multivariate L1 distance: 0.44838188

Univariate Imbalance

| | L1 | mean | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|
| Ticker | 2.90E-16 | -3.60E-15 | 0 | 0 | 0 | 0 | 0 |
| Currency | 5.80E-16 | -3.90E-14 | 0 | 0 | 0 | 0 | 0 |
| Quarter | 6.80E-17 | 1.40E-13 | 0 | 0 | 0 | 0 | 0 |
| Rating | 1.00E-16 | 2.30E-14 | 0 | 0 | 0 | 0 | 0 |
| Coupon | 0.17783 | -0.1246 | 0 | 0.16 | -0.5 | 0.14 | -0.375 |
| Maturity (stratified) | 3.50E-16 | -3.60E-15 | 0 | 0 | 0 | 0 | 0 |

**Summary Statistics**

*Table A5: Summary of variables used in the regression*

| Variables | Exp. Sign | Description | Source |
|---|---|---|---|
| ***Dependent Variable*** | | | |
| Ask-Yield | NA | Quarterly rate of return on the respective bond | Bloomberg |
| ***Bond Characteristics*** | | | |
| Coupon Rate (in %) | + | Interest rate paid by the bond at the time of issue. | Bloomberg |
| Issue Date | NA | Date at which the bond was issued by the country. | Bloomberg |
| Tenor (in quarter) | + | Length of time remaining until the bond matures (in | Authors' |
| Bid-Ask Spread | + | A proxy of a liquidity measure. A lower spread or | Authors' |
| Bond Rating | - | Standard letter-based credit scores given to the bond | Bloomberg |
| Country of Issue | Fixed Effects | Country which issued the bond. | Bloomberg |
| Currency of Issue | (Categorical) | Currency in which the bond was issued. Domestic | Bloomberg |
| Amount Issued (in | + | Total amount raised by the issue of bond. Higher | Bloomberg |
| Use of Proceeds | - | The purpose/project for which the amount issued is | Bloomberg |
| Green Labeled | 1/0 "-" | A dummy variable equals 1 if the bond is labeled | Bloomberg |
| EMDE Category | 1/0 "+" | A dummy variable equals 1 if country of issue is | IMF |
| ***Country Risk Measures*** | | | |
| GDP Growth (in %) | - | Quarterly GDP growth of the country of respective | IFS IMF |
| Consumer Price Index | + | Quarterly CPI. The higher the inflation, the higher | IFS IMF |
| REER | +/- | Quarterly real effective exchange rate (REER). | Bruegel, 2023 |
| Fiscal Deficit (%GDP) | + | Quarterly measure, can lead to higher yield due to | IFS IMF |
| Current Account | - | Quarterly measure, can lead to lower yield if country | IFS IMF |

**Kruskal–Wallis's Test**

*Table A6: Kruskal–Wallis's equality-of-populations rank test for time trends*

**Green Bond=0:**

| Period | Observations | Rank Sum |
|---|---|---|
| 1 | 11,196 | 2.02E+08 |
| 2 | 14,852 | 2.13E+08 |
| 3 | 9,751 | 2.27E+08 |

Chi-squared= 4393.053 with 2 d.f.

Probability=0.0001

Chi-Squared with ties= 4393.053 with 2 d.f.

Probability=0.0001

**Green Bond=1:**

| Period | Observations | Rank Sum |
|---|---|---|
| 1 | 82 | 38845.5 |
| 2 | 357 | 91467 |
| 3 | 559 | 368188.5 |

Chi-squared= 425.416 with 2 d.f.

Probability=0.0001

Chi-Squared with ties= 425.416 with 2 d.f.

Probability=0.0001

**Robustness Check: CEM k2k Matching**

*Table A7: Ask yield (with CEM k2k weights)*

| VARIABLES | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| Green Bond=1 | 0.149*** | 0.475*** | -0.0967* |
| | (0.0433) | (0.0519) | (0.0580) |
| Term To Maturity | 0.0103*** | 0.00299*** | 0.0152*** |
| | (0.000675) | (0.000818) | (0.000915) |
| Bid-Ask Spread | 1.015*** | 0.843*** | 2.442*** |
| | (0.322) | (0.296) | (0.606) |
| Log(Amt Issued) | 0.422*** | 0.593*** | 0.415*** |
| | (0.0395) | (0.0494) | (0.0517) |
| GDP growth % | -0.513 | -0.111 | -0.0228 |
| | (0.521) | (0.701) | (0.752) |
| Inflation | 0.0476*** | 0.0239* | 0.0983*** |
| | (0.0123) | (0.0132) | (0.0216) |
| CAD | 0.00438 | 0.00331 | 0.0832*** |
| | (0.00565) | (0.00513) | (0.0210) |
| Constant | -9.154*** | -12.52*** | -6.214*** |
| | (0.964) | (1.182) | (1.217) |
| Country FE | YES | YES | YES |
| Time FE | YES | YES | YES |
| Observations | 736 | 390 | 346 |
| R-squared | 0.939 | 0.930 | 0.958 |

Note: Model 1 estimates the association between k2k-weighted YTM and GB for all countries in the sample. Model 2 restricts the sample to AE economies, and Model 3 tests for EMDEs. The yield is truncated at 2.5% and 97.5% to reduce the influence of outliers. The standard deviations in parentheses. ***, **, and * represent coefficients significantly different from 0 at the 1%, 5%, and 10% significance levels, respectively.

## Unit Root Test

*Table A8: Fisher Type Unit Root Test for Panel Data Fixed-Effects Model:*

Based on augmented Dickey–Fuller tests

**Null Hypothesis ($H_0$):** All panels contain unit roots
**Alternative Hypothesis ($H_1$):** At least one panel is stationary

- **Number of panels:** 23
- **Average number of periods:** 11.30
- **AR parameter:** Panel-specific
- **Asymptotics:** $T \rightarrow \infty$
- **Panel means:** Included
- **Time trend:** Not included
- **Drift term:** Not included
- **ADF regressions:** 3 lags

| Statistic | Value | p-value |
|---|---|---|
| Inverse chi-squared (36) | 207.3658 | 0.0000 |
| Inverse normal | -6.7447 | 0.0000 |
| Inverse logit t (59) | -15.3542 | 0.0000 |
| Modified inv. chi-squared | 20.1956 | 0.0000 |

## Hausmann Test

*Table A9: Hausmann Test.*

| Variable | Fixed Effects (b) | Random Effects (B) | Difference (b - B) | Std. Error |
|---|---|---|---|---|
| Yield | 0.147466 | 0.0571034 | 0.0903626 | 0.0383026 |
| Bid_ask | 0.145547 | -0.0278045 | 0.1753969 | 0.0758703 |
| Log (Amt.) | -1.5769547 | -1.0508978 | -0.5260569 | 0.1871781 |
| Maturity | -0.0065177 | -0.0051103 | -0.0014073 | 0.0010713 |

| Test Statistic | Value |
|---|---|
| Chi-squared (20 d.f.) | 110.16 |
| p-value | 0.0000 |
| Conclusion | Reject $H_0$: Differences in coefficients are systematic. Fixed effects model is preferred. |

## B. Chapter 2

*Table B1: NAICS codes for compilation of renewable energy companies*

| NAICS Code | Title |
|---|---|
| 221122 | Electric Power Distribution |
| 221114 | Solar Electric Power Generation |
| 221115 | Wind Electric Power Generation |
| 221116 | Geothermal Electric Power Generation |
| 221117 | Biomass Electric Power Generation |
| 221118 | Other Electric Power Generation |
| 221111 | Hydroelectric Power Generation |
| 333414 | Heating Equipment (except Warm Air Furnaces) Manufacturing |
| 333611 | Turbine and Turbine Generator Set Units Manufacturing |
| 335312 | Motor and Generator Manufacturing |
| 325193 | Ethyl Alcohol Manufacturing |

### Fama-French 3-factor model

Stock return for each stock for each day is defined as:

$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}}$$

Where $R_t$ is stock return for day *t*, $P_t$ and $P_{t-1}$ are closing prices of stock for day *t* and *(t-1)*. Expected daily return for each stock is then calculated from the following equation:

$$R_{\{it\}} = \alpha_i + \beta_{\{im\}} R_{\{mt\}} + \beta_{\{is\}} SMB_t + \beta_{\{iv\}} HML_t + \epsilon_{\{it\}}$$

Where $R_{it}$ is the expected return for stock *i* on day *t*. $R_{mt}$ is the risk-free market rate on day *t*, $SMB_t$ represents the size factor on day *t*, capturing the return differential between small-cap and large-cap stocks, $HML_t$ represents the value factor on day *t*, capturing the return differential between value stocks (high book-to-market ratio) and growth stocks (low book-to-market ratio), $\alpha_i$ is the intercept term for stock *i,* and $\beta_i$ is the sensitivity (beta coefficient) of stock *i* to respective factors, estimated by running an ordinary least squares regression. $\epsilon_{it}$ is the error term for stock *i* at time *t*. The abnormal return ($AR_{it}$) for stock *i* at day *t* is the difference between the actual and expected return:

$$AR_{it} = R_{it} - \left(\alpha_i + \beta_{\{im\}} R_{\{mt\}} + \beta_{\{is\}} SMB_t + \beta_{\{iv\}} HML_t\right)$$

This is then accumulated over the respective event window *(-t, t)* to get the CAR for security *i*:

$$\mathrm{CAR_i}(-t, t) = \sum_{j=-t}^{t} \mathrm{AR_{ij}}$$

The Cumulative Average Abnormal Returns (CAAR) is calculated for all securities taken together.

$$\mathrm{CAAR}(-t, t) = \frac{1}{N}\sum_{i=1}^{N} \mathrm{CAR_i}(-t, t)$$

Where N denotes the number of securities of renewable energy firms in the dataset. CAARs are reported for three event windows for each news shock, very short term (-3, 1), short term (-3, 3) and medium term (-5, 5). Note that the term here signifies the time-length with respect to multifactor model methodology, which is built for very short-run analysis and might not give reliable results for windows beyond the 30-day period. In the last step, this study uses the Pattel (1976) test, to test if the CAAR are statistically significant, given by:

$$Z = \frac{\sum_{t=-t_1}^{t_2} \mathrm{SAR_{it}}}{\sqrt{t_1 + t_2 + 1}}$$

Where $SAR_{it}$ is the standardized abnormal return for stock *i* at time *t.* The results are presented in the next subsection.

*Table B2: Results from FF3 model for different news textual factors.*

| Date | Event | CAAR [-3,1] | CAAR [-3,3] | CAAR [-5,5] |
|---|---|---|---|---|
| **Extreme Weather Phenomena** | | | | |
| 4/1/21 | BBB announced | 0.93% | -3.21% | -7.6238%*** |
| 8/10/21 | IIJA passed by Senate | -1.98% | -4.00% | -8.8337%** |
| 11/19/21 | BBB passed by house | 4.95% | 2.8684%* | 3.75% |
| 12/19/21 | Manchin to vote against BBB | -2.66% | -5.3753%** | -8.1370%*** |
| 7/15/22 | Manchin against IRA | -2.7319%* | -3.7303%** | 0.55% |
| 7/27/22 | IRA announced | 9.9755%*** | 10.7919%*** | 16.4730%*** |
| 8/7/22 | IRA passed | 1.50% | 0.91% | 3.4029%*** |
| **Climate Policy** | | | | |
| 2/17/21 | Winter storms | -4.9504%*** | -6.5860%*** | -9.5310%*** |
| 5/25/21 | Western Heat Waves | 0.39% | -0.35% | 0.3935%* |

| | | | | |
|---|---|---|---|---|
| 9/8/21 | Hurricane Ida | -3.12% | -3.90% | -4.97% |
| 11/2/21 | Pacific northwest floods | 1.97% | 0.15% | -1.12% |
| 2/6/22 | Winter storm Landon | -2.6332%** | -1.83% | -0.78% |
| 6/16/22 | Central derecho | -2.0384%** | -2.5327%* | -1.88% |
| 10/4/22 | Hurricane Ian Aftermath | -3.4319%*** | -5.1061%*** | -8.3010%*** |
| 6/8/23 | Canadian wildfires | -0.57% | 0.44% | -0.32% |
| 7/13/23 | Drought and Heat Wave | -1.94% | -1.60% | -2.26% |
| 8/27/23 | Wildfires | 1.54% | -0.37% | -3.0059%* |
| 11/14/23 | Storms and water crisis | 2.42% | 1.87% | -1.8548%*** |
| **Geopolitics** | | | | |
| 4/22/21 | Earth Day Summit | -1.09% | 0.32% | -9.6556%** |
| 9/21/21 | UN Climate Summit talks | 3.01% | 0.60% | 1.1277%* |
| 10/31/21 | COP26 | 4.6285%*** | 3.54% | 2.43% |
| 9/22/22 | UN Climate Summit talks | -5.7357%*** | -2.3094%*** | -6.7876%*** |
| 11/16/22 | COP27 | 4.27% | 3.27% | 3.4837%* |
| 7/11/23 | Biden's UK visit | 1.41% | 1.69% | -0.2461%* |

Note: ***Significant at $p < 0.01$, **Significant at $p < 0.05$, *Significant at $p < 0.1$. All values are winsorized at the 1st and 99th percentiles to mitigate the influence of extreme outliers. CAAR (-X, +X) indicates cumulative abnormal returns from X days before to X days after the event.

### Pairwise correlation between climate risk factors and other variables

*Table B3: Pairwise correlation between climate risk factors and other variables*

| | Topic1 | Topic2 | Topic3 | Topic4 | Sentiment | article Num | VIX | crudeoil | Inflation | GDP |
|---|---|---|---|---|---|---|---|---|---|---|
| Topic1 | 1 | | | | | | | | | |
| Topic2 | 0.1381 | 1 | | | | | | | | |
| Topic3 | 0.4739 | 0.1144 | 1 | | | | | | | |
| Topic4 | 0.5748 | 0.1313 | 0.7247 | 1 | | | | | | |
| Sentiment | -0.5176 | -0.8139 | -0.4849 | -0.4481 | 1 | | | | | |
| article Num | 0.7855 | 0.424 | 0.8211 | 0.8447 | -0.7564 | 1 | | | | |
| VIX | 0.117 | -0.312 | -0.1073 | -0.1563 | 0.1194 | -0.1197 | 1 | | | |
| crudeoil | 0.1731 | -0.2557 | -0.1064 | 0.0803 | 0.0929 | -0.0143 | 0.7885 | 1 | | |
| Inflation | -0.0439 | -0.4433 | 0.0266 | -0.1825 | 0.2825 | -0.1873 | 0.3964 | 0.2371 | 1 | |
| GDP | 0.3865 | 0.2314 | 0.5608 | 0.3182 | -0.403 | 0.5219 | -0.296 | -0.3305 | -0.0614 | 1 |

Notes: Entries report the pairwise Pearson correlations between the daily textual and sentiment climate change risk factors, the crude oil index, CBOE VIX (volatility index), Inflation and GDP, over January 1, 2021, – December 31, 2023.

### Buy and Hold Abnormal Returns (BHAR) Model

BHAR is a common approach to measuring longer-term abnormal returns in asset pricing studies. BHAR is designed to capture the cumulative performance of a stock relative to a benchmark (a market index or matched sample) over a specified period, providing insights into whether an asset outperforms or underperforms the benchmark consistently over time. For a given stock $i$, the BHAR over period $t$ is typically calculated as:

$$BHAR_{iT} = \prod_{t=1}^{T} (1 + R_{it}) - \prod_{t=1}^{T} (1 + R_{mt})$$

where $R_{it}$ is the raw return of stock *i* on day *t* and $R_{mt}$ is the return of the benchmark stock *m* on day *t*. The expressions $\prod_{t=1}^{T} (1 + R_{it})$ and $\prod_{t=1}^{T} (1 + R_{mt})$ represent the daily cumulative (buy-and-hold) return of each stock for treatment and benchmark group respectively over the period T. The difference generates the abnormal return per stock.

In the next step, I compute the average buy-and-hold abnormal return for treatment and benchmark group over the period T. I then use a t-test to determine the cumulative direction and statistical significance of BHAR. A significantly positive (negative) BHAR indicates that the stocks outperformed (underperformed) the benchmark over the period.

Results from the BHAR model are shown in **Error! Reference source not found.**. The mean BHAR indicates a substantial outperformance of the renewable energy sector weighted returns by 2.05% relative to that of the benchmark with a high level of statistical significance ($p < 0.001$) after the passage of IRA. There is an increasing trend in the magnitude of cumulative abnormal returns up till 4 months from the event, with a slight decline in BHAR at 6 months mark. The result is however statistically significant at only 10%. A year after the passage of IRA, the renewable energy firms were underperforming by 1.19% relative to the benchmark, but not statistically significant. The negative BHAR had increased in magnitude to 7.47% by 18 months with a statistical significance of 10%.

In all cases, the estimated BHAR conveys the mean difference between value weighted cumulative returns of renewable energy stock and control group after the passage of IRA. It does not convey that the difference was *associated* with the passage of IRA. The results are consistent in direction and duration with those from the DiD analysis but are markedly lower in magnitude. For example, the 4-month CAR from the DiD model is about 7 basis points larger than that from BHAR. Their interpretation is also different. The abnormal returns from the DiD analysis measure the isolated effect of the IRA policy on renewable energy firms, not just the post IRA market returns which is the case with BHAR. In the latter case, the results could still have been impacted by other concurrent events internal or external to the firms such as natural disasters, macroeconomic variability, policy changes or geopolitics.

*Table B4: Long-term asset pricing results from BHAR analysis.*

| | **Mean** | **Std. Err.** | **Std. Dev.** | **95% CI** | | **Pr(T><t)** |
|---|---|---|---|---|---|---|
| 1 month | 0.0405 | 0.0225 | 0.0504 | 0.0221 | 0.0632 | 0.0000 |
| 2 months | 0.0677 | 0.0077 | 0.0396 | 0.0517 | 0.0837 | 0.0000 |
| 4 months | 0.0650 | 0.0092 | 0.0882 | 0.0466 | 0.0834 | 0.0000 |
| 6 months | 0.0486 | 0.0196 | 0.0519 | 0.0005 | 0.0967 | 0.0481 |
| 12 months | -0.0119 | 0.0204 | 0.0763 | -0.0560 | 0.0321 | 0.5692 |
| 18 months | -0.0747 | 0.0295 | 0.1287 | -0.1368 | -0.0126 | 0.0210 |

Note: Cumulative returns are weighted by market cap. All values are winsorized at the 1st and 99th percentiles to mitigate the influence of extreme outliers.

## Robustness Checks

*Table B5: Robustness checks for extended term DiD event study of renewable energy firm's average cumulative returns.*

| | **All firms** CAR (-6, +6) | **All firms** CAR (-6, +6) | **All firms** CAR (-6, +6) |
|---|---|---|---|
| | (1) | (2) | (3) |
| Post × Treated (DiD Estimator) | 0.158** | - | - |
| | (0.0720) | - | - |
| Post (after IRA) | -0.0711*** | - | - |
| | (0.0130) | - | - |
| Treated (Renewable Firms) | -0.0532 | - | - |
| | (0.0389) | - | - |
| Placebo x Treated | - | -0.0291 | -0.000956 |
| | - | (0.0233) | (0.0438) |
| Post (after placebo date) | - | 0.220*** | 0.0449 |
| | - | (0.0345) | (0.0430) |
| Treated (Renewable Firms) | - | 0.0597** | -0.229*** |
| | - | (0.0291) | (0.0463) |
| Climate policy factor x Treated | - | -0.0128 | 0.0524*** |
| | - | (0.0259) | (0.0174) |
| Weather factor x Treated | - | -0.00897 | -0.0108 |
| | - | (0.0266) | (0.0215) |
| Geopolitics factor x Treated | - | 0.0367* | 0.0793*** |
| | - | (0.0185) | (0.0192) |
| Sentiment Score x Treated | 0.000718 | - | - |
| | (0.00969) | - | - |
| Firm controls | No | Yes | Yes |
| Macroeconomic controls | Yes | Yes | Yes |
| Stock FE | Yes | Yes | Yes |
| Time FE | No | No | No |
| Observations | 8,666 | 6,777 | 7,100 |
| R-squared | 0.656 | 0.186 | 0.247 |

Note: ∗∗∗Significant at $p < 0.01$, ∗∗Significant at $p < 0.05$, ∗Significant at $p < 0.1$. Cumulative returns are weighted by market cap. All values are winsorized at the 1st and 99th percentiles to mitigate the influence of extreme outliers. CAR (-X, +X) indicates cumulative abnormal trading volumes from X months before to X months after July 2022 in (1), random month December 2021 in (2) and random month December 2022 in (3).

## Dynamic DiD Results

*Table B6: Cumulative Abnormal Returns from the Dynamic DiD analysis.*

| | **Coef.** | **Std. Err.** | **t** | **P>t** | **[95% Conf.** | **Interval]** |
|---|---|---|---|---|---|---|
| March, 2022 | 0.0674225 | 0.0381247 | 1.77 | 0.183 | -0.0092746 | 0.1441196 |
| April, 2022 | -0.0291325 | 0.0420073 | -0.69 | 0.491 | -0.1136403 | 0.0553753 |
| May, 2022 | 0.0225675 | 0.0286094 | 0.79 | 0.434 | -0.0349871 | 0.0801221 |
| **July, 2022** | **0.0943417** | **0.0479076** | **1.97** | **0.055** | **-0.002036** | **0.1907194** |
| August, 2022 | 0.1615314 | 0.0438743 | 3.68 | 0.001 | 0.0732676 | 0.2497952 |
| September, 2022 | 0.0882306 | 0.0476275 | 1.85 | 0.07 | -0.0075836 | 0.1840448 |
| October, 2022 | 0.0992901 | 0.0586409 | 1.69 | 0.097 | -0.0186803 | 0.2172604 |
| November, 2022 | 0.046401 | 0.0692023 | 0.67 | 0.506 | -0.0928161 | 0.1856181 |
| December, 2022 | 0.0491485 | 0.0620326 | 0.79 | 0.432 | -0.075645 | 0.173942 |
| January, 2023 | 0.0764756 | 0.0553764 | 1.38 | 0.174 | -0.0349274 | 0.1878785 |
| February, 2023 | 0.0364935 | 0.0578968 | 0.63 | 0.532 | -0.0799799 | 0.1529669 |
| March, 2023 | 0.0772441 | 0.0797513 | 0.97 | 0.338 | -0.0831948 | 0.2376829 |
| April, 2023 | 0.0072669 | 0.0790186 | 0.09 | 0.927 | -0.1516981 | 0.1662319 |
| May, 2023 | 0.0077208 | 0.0754218 | 0.1 | 0.919 | -0.1440083 | 0.1594500 |
| June, 2023 | 0.0328677 | 0.0667600 | 0.49 | 0.625 | -0.1014362 | 0.1671715 |
| July, 2023 | 0.0333685 | 0.0605265 | 0.55 | 0.584 | -0.0883951 | 0.1551321 |
| August, 2023 | 0.0062841 | 0.0669903 | 0.09 | 0.926 | -0.1284831 | 0.1410513 |
| September, 2023 | -0.0914584 | 0.0593723 | -1.54 | 0.13 | -0.2109001 | 0.0279834 |
| October, 2023 | -0.0693017 | 0.0808958 | -0.86 | 0.396 | -0.2320431 | 0.0934397 |
| November, 2023 | -0.019137 | 0.1082508 | -0.18 | 0.86 | -0.2369096 | 0.1986356 |

Note: Cumulative returns are weighted by market cap. All values are winsorized at the 1st and 99th percentiles to mitigate the influence of extreme outliers. Reference period which is June 2022 has been omitted by design.

# C. Chapter 3

## Distribution of PPP projects

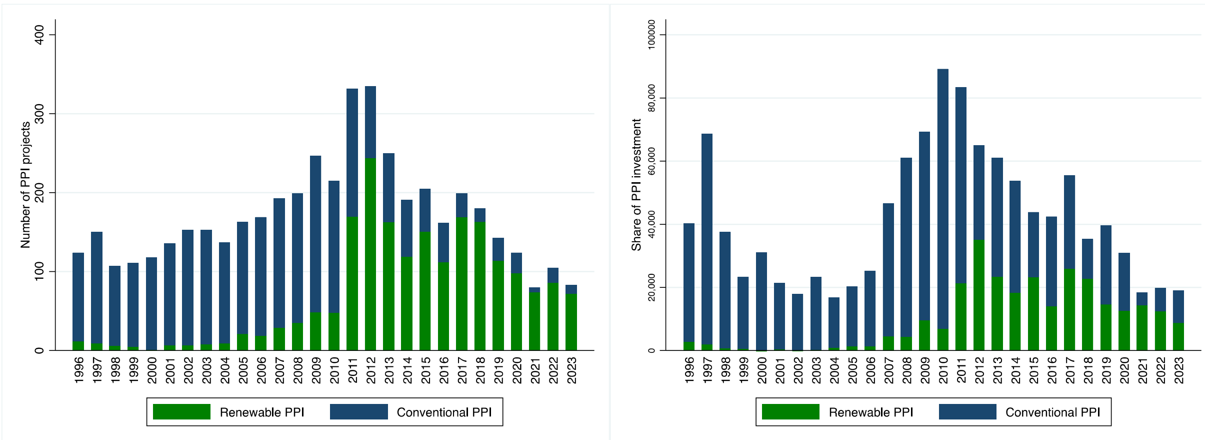



*Figure C1: Distribution of PPP investments (left) and number of projects (right) across renewable (green) and conventional (blue) energy infrastructure.*

## Histogram: Share of renewable projects

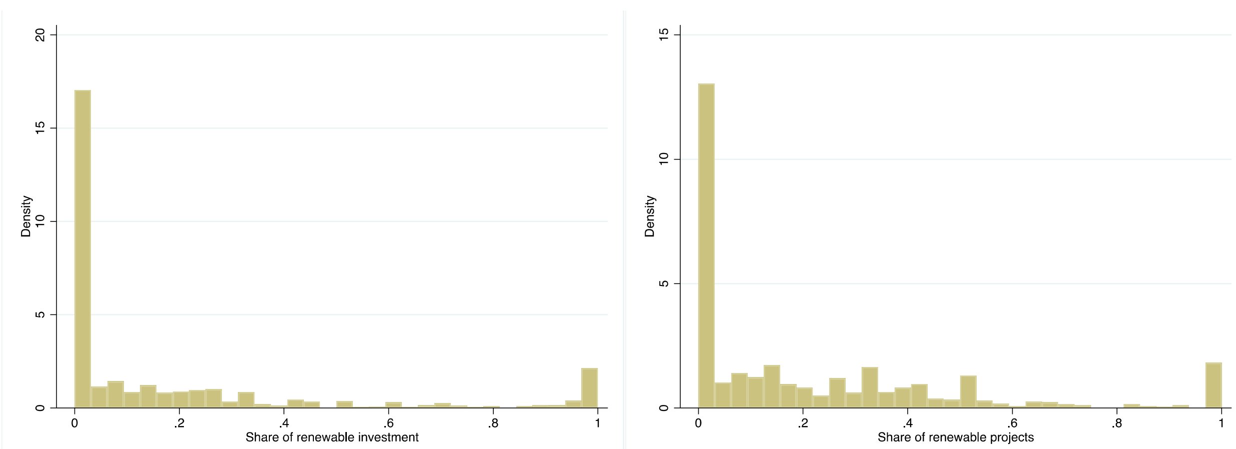



*Figure C2: Histogram showing the skewed distribution of share of renewable energy PPP investments and project volume, clustered at 0.*

## Marginal Effects: Project-level Probit Analysis

*Table C1: Marginal effects from Probit model.*

| | Marginal Effects | Std. Err. | P-value | 95% Conf. Interval | |
|---|---|---|---|---|---|
| **Income Level** | | | | | |
| Low income | 0.1015 | 0.0305 | 0.0010 | 0.0417 | 0.1613 |
| Lower middle income | 0.2722 | 0.0284 | 0.0000 | 0.2165 | 0.3278 |
| Upper middle income | 0.3210 | 0.0197 | 0.0000 | 0.2825 | 0.3596 |
| **Region** | | | | | |
| AFR | 0.4425 | 0.0479 | 0.0000 | 0.3486 | 0.5365 |
| EAP | 0.2091 | 0.0204 | 0.0000 | 0.1691 | 0.2490 |
| ECA | 0.5554 | 0.0660 | 0.0000 | 0.4259 | 0.6848 |
| LAC | 0.3019 | 0.0216 | 0.0000 | 0.2596 | 0.3443 |
| MENA | 0.4727 | 0.0751 | 0.0000 | 0.3254 | 0.6199 |
| SAR | 0.2556 | 0.0339 | 0.0000 | 0.1891 | 0.3222 |
| **Bilateral & Multilateral Support** | | | | | |
| No support | 0.2791 | 0.0173 | 0.0000 | 0.2452 | 0.3131 |
| Either/Or | 0.2945 | 0.0273 | 0.0000 | 0.2410 | 0.3480 |
| Both | 0.6148 | 0.0644 | 0.0000 | 0.4886 | 0.7411 |
| **Project Status** | | | | | |
| Active | 0.3116 | 0.0168 | 0.0000 | 0.2787 | 0.3444 |
| Cancelled | 0.0713 | 0.0418 | 0.0880 | -0.0105 | 0.1532 |
| Concluded | 0.0647 | 0.0290 | 0.0260 | 0.0078 | 0.1215 |
| **Project Type** | | | | | |
| Brownfield | 0.0205 | 0.0060 | 0.0010 | 0.0087 | 0.0323 |
| Divestiture | 0.0676 | 0.0392 | 0.0840 | -0.0091 | 0.1444 |
| Greenfield | 0.5169 | 0.0135 | 0.0000 | 0.4904 | 0.5434 |
| **Other continuous variables** | | | | | |
| Tool count | 0.0675 | 0.0087 | 0.0000 | 0.0505 | 0.0846 |
| Investment (US $m) | -0.0004 | 0.0000 | 0.0000 | -0.0005 | -0.0003 |
| Private participation | .0039199 | .000579 | 6.77 | 0.000 | .002785 |

Note: AFR stands for Sub-Saharan Africa, EAP for East Asia and Pacific, ECA for Europe and Central Asia, LAC for Latin America and the Caribbean, MENA for Middle East and North Africa, and SAR for South Asia Region.

## Local support tool count for conventional PPP projects

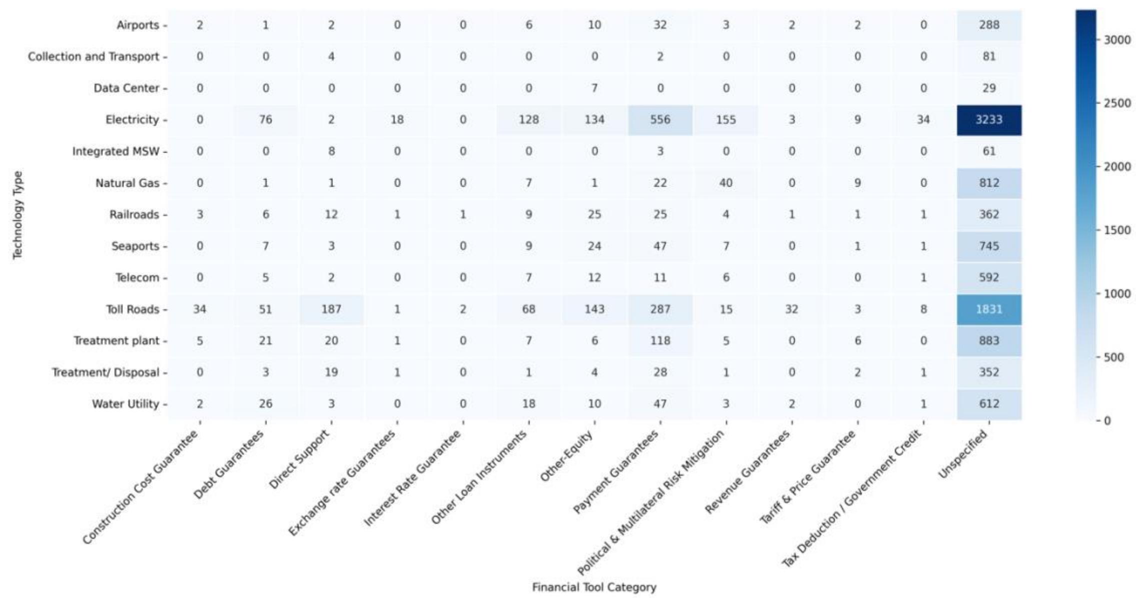



*Figure C3: Heat map of conventional energy project-specific local support tool count categorized according to instrument (x-axis) and technology (y-axis). Tool count is calculated from the World Bank private participation in infrastructure database by summing up the local support data and tools extracted from the project description using a keyword extraction process.*

## Correlation Matrix for policy and institutional variables:

| | Reg | Market | Plan | Inv | Trade | Access | VA | CC | GE | PV | RL | RQ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Reg** | 1.00 | | | | | | | | | | | |
| **Market** | 0.69 | 1.00 | | | | | | | | | | |
| **Plan** | 0.64 | 0.56 | 1.00 | | | | | | | | | |
| **Inv** | 0.62 | 0.64 | 0.59 | 1.00 | | | | | | | | |
| **Trade** | 0.38 | 0.30 | 0.29 | 0.24 | 1.00 | | | | | | | |
| **Access** | 0.67 | 0.63 | 0.49 | 0.67 | 0.30 | 1.00 | | | | | | |
| **VA** | 0.10 | 0.10 | 0.03 | 0.18 | 0.09 | -0.05 | 1.00 | | | | | |
| **CC** | 0.05 | 0.03 | 0.04 | 0.10 | 0.16 | 0.09 | 0.53 | 1.00 | | | | |
| **GE** | 0.19 | 0.18 | 0.14 | 0.19 | 0.30 | 0.25 | 0.49 | 0.77 | 1.00 | | | |
| **PV** | -0.03 | -0.07 | -0.01 | -0.05 | -0.01 | -0.04 | 0.33 | 0.44 | 0.35 | 1.00 | | |
| **RL** | 0.09 | 0.07 | 0.10 | 0.12 | 0.20 | 0.13 | 0.56 | 0.81 | 0.81 | 0.43 | 1.00 | |
| **RQ** | 0.12 | 0.08 | 0.11 | 0.10 | 0.30 | 0.07 | 0.66 | 0.70 | 0.79 | 0.37 | 0.76 | 1.00 |

## Results: Tobit Model

*Table C2: Result from Tobit model specifications for share of renewable investments.*

| | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| Access | 0.000977 | | | |
| | (0.000718) | | | |
| Plan | 0.0290** | | | |
| | (0.0117) | | | |
| Reg x Low income | | 0.00881 | | |
| | | (0.0368) | | |
| Reg x Lower middle income | | -0.00773 | | |
| | | (0.00546) | | |
| Reg x Upper middle income | | 0.00788*** | | |
| | | (0.00275) | | |
| Inv x Low income | | | 0.163** | |
| | | | (0.0705) | |
| Inv x Lower middle income | | | 0.00822** | |
| | | | (0.00414) | |
| Inv x Upper middle income | | | 0.00810*** | |
| | | | (0.00308) | |
| Market x AFR | | | | 0.116*** |
| | | | | (0.0213) |
| Market x EAP | | | | -0.000350 |
| | | | | (0.00861) |
| Market x ECA | | | | 0.140*** |
| | | | | (0.0251) |
| Market x LAC | | | | 0.0412** |
| | | | | (0.0171) |
| Market x MENA | | | | 0.147*** |
| | | | | (0.0316) |
| Market x SAR | | | | 0.0267* |
| | | | | (0.0158) |
| Trade | | | 0.00554** | 0.00445** |
| | | | (0.00217) | (0.00216) |
| Int_sup | | 0.0358*** | 0.0243*** | 0.0229*** |
| | | (0.00602) | (0.00535) | (0.00509) |
| Int_sup x Low income | 0.118*** | | | |
| | (0.0191) | | | |
| Int_sup x Lower middle income | 0.0176*** | | | |
| | (0.00549) | | | |
| Int_sup x Upper middle income | 0.0293*** | | | |
| | (0.00784) | | | |
| Tools | 0.0134*** | 0.00950*** | 0.0130*** | 0.0108*** |
| | (0.00281) | (0.00341) | (0.00306) | (0.00314) |
| Public investment * | 0.0140*** | 0.0109** | 0.0157*** | 0.00991*** |
| | (0.00340) | (0.00437) | (0.00342) | (0.00331) |
| Fossil fuel energy cons. (%) * | 0.0887 | 0.278** | 0.227** | 0.287** |
| | (0.0804) | (0.119) | (0.0765) | (0.0741) |
| RE electricity prod. (kwh) * | 0.0246*** | 0.0219*** | 0.0208*** | 0.0202*** |
| | (0.00475) | (0.00507) | (0.00462) | (0.00443) |
| GE* | -0.0314** | -0.0312 | -0.0301* | -0.0239 |
| | (0.0157) | (0.0198) | (0.0155) | (0.0148) |
| VA* | | 0.0111 | | |
| | | (0.0200) | | |
| PV* | | 0.000483 | | |
| | | (0.0110) | | |

| | | | | |
|---|---|---|---|---|
| GDP* | -0.0270 | -0.0297* | -0.0308* | -0.0255 |
| | (0.0112) | (0.0124) | (0.0112) | (0.0107) |
| CPI* | 0.0149 | 0.0157 | 0.0110 | 0.00374 |
| | (0.0107) | (0.0141) | (0.0107) | (0.0102) |
| FDI* | 0.0205 | 0.00686 | 0.0147 | 0.00270 |
| | (0.0145) | (0.0163) | (0.0143) | (0.0139) |
| Constant | -0.863 | -0.778 | -0.884 | -0.789 |
| | (23.03) | (29.37) | (30.15) | (25.51) |
| Year FE | YES | YES | YES | YES |
| Country FE | YES | YES | YES | YES |
| Log-likelihood | 271.8262 | 194.6813 | 265.7130 | 296.8272 |
| LR-$\chi$2 | 883.21*** | 620.72*** | 870.98*** | 933.21*** |
| Observations | 777 | 519 | 777 | 777 |
| Number of countries | 61 | 51 | 61 | 61 |

Note: ∗∗∗Significant at $p < 0.01$, ∗∗Significant at $p < 0.05$, ∗Significant at $p < 0.1$. *All variables have been logged and centered. Results are presented for Tobit model specifications for share of renewable PPP investments. Model 1 tests for energy access and planning policy, Model 2 for regulatory policy and governance institutions, model 3 for investment policy and model 4 for market and trade policy. All models test for support and public finance variables. *Int_sup* is the international support indicator.

*Table C3: Result from Tobit model specifications for share of renewable project volumes.*

| | **1** | **2** | **3** | **4** |
|---|---|---|---|---|
| Access | 0.0001 | | | |
| | (0.000711) | | | |
| Plan | 0.0176 | | | |
| | (0.0116) | | | |
| Reg x Low income | | 0.00931 | | |
| | | (0.0368) | | |
| Reg x Lower middle income | | -0.00829 | | |
| | | (0.00543) | | |
| Reg x Upper middle income | | 0.00879*** | | |
| | | (0.00276) | | |
| Inv x Low income | | | 0.213*** | |
| | | | (0.0730) | |
| Inv x Lower middle income | | | 0.00190* | |
| | | | (0.00415) | |
| Inv x Upper middle income | | | 0.00848*** | |
| | | | (0.00309) | |
| Market x AFR | | | | 0.110*** |
| | | | | (0.0206) |
| Market x EAP | | | | 0.00218 |
| | | | | (0.00838) |
| Market x ECA | | | | 0.0411 |
| | | | | (0.0287) |
| Market x LAC | | | | 0.0349** |
| | | | | (0.0167) |
| Market x MENA | | | | 0.265*** |
| | | | | (0.0306) |
| Market x SAR | | | | 0.0236 |
| | | | | (0.0155) |
| Trade | | | 0.00549*** | -0.00277 |
| | | | (0.00181) | (0.00175) |
| Int_sup | | 0.0375*** | 0.0248*** | 0.0234*** |
| | | (0.00584) | (0.00528) | (0.00493) |
| Int_sup x Low income | 0.0817*** | | | |
| | (0.0185) | | | |

| | | | | |
|---|---|---|---|---|
| Int_sup x Lower middle income | 0.0164*** | | | |
| | (0.00538) | | | |
| Int_sup x Upper middle income | 0.0496*** | | | |
| | (0.00788) | | | |
| Tools | 0.00930*** | 0.00850** | 0.0110*** | 0.0102*** |
| | (0.00278) | (0.00338) | (0.00303) | (0.00303) |
| Public investment * | 0.0128*** | 0.0101** | 0.0155*** | 0.00907*** |
| | (0.00330) | (0.00419) | (0.00335) | (0.00317) |
| Fossil fuel energy cons. (%) * | 0.280*** | 0.583*** | 0.282*** | 0.296*** |
| | (0.0766) | (0.117) | (0.0744) | (0.0700) |
| RE electricity prod. (kwh) * | 0.0245*** | 0.0243*** | 0.0271*** | 0.0281*** |
| | (0.00457) | (0.00496) | (0.00453) | (0.00422) |
| GE* | -0.0471* | -0.0453 | -0.0554* | -0.0491* |
| | (0.0146) | (0.0189) | (0.0146) | (0.0137) |
| VA* | | 0.0102 | | |
| | | (0.0201) | | |
| PV* | | 0.00169 | | |
| | | (0.0108) | | |
| GDP* | -0.0114 | -0.0137 | -0.0180 | -0.0184* |
| | (0.0111) | (0.0124) | (0.0112) | (0.0104) |
| CPI* | 0.0156 | 0.0147 | 0.00682 | -0.000585 |
| | (0.0104) | (0.0136) | (0.0104) | (0.00973) |
| FDI* | -0.00964 | -0.0319** | -0.0188 | -0.0314** |
| | (0.0142) | (0.0159) | (0.0141) | (0.0133) |
| Constant | -0.867 | -0.831 | -0.897 | -0.799 |
| | (24.00) | (35.30) | (23.24) | (27.40) |
| Year FE | YES | YES | YES | YES |
| Country FE | YES | YES | YES | YES |
| Log-likelihood | 309.8246 | 224.9273 | 304.0783 | 343.5910 |
| LR-$\chi$2 | 1038.47*** | 728.12*** | 1026.98*** | 1106.00*** |
| Observations | 777 | 519 | 777 | 777 |
| Number of countries | 61 | 51 | 61 | 61 |

Note: ***Significant at $p < 0.01$, **Significant at $p < 0.05$, *Significant at $p < 0.1$. *All variables have been logged and centered. Results are presented for Tobit model specifications for share of renewable PPP project volumes. Model 1 tests for energy access and planning policy, Model 2 for regulatory policy and governance institutions, model 3 for investment policy and model 4 for market and trade policy. All models test for support and public finance variables. *Int_sup* is the international support indicator.

### Robustness Check: Arellano & Bond GMM Model

*Table C4: Robustness check. Results using Arellano & Bond Difference GMM model for share of renewable energy investments*

| | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| L.ren_share | 0.734*** | 0.766*** | 0.765*** | 0.747*** |
| | (0.0562) | (0.0534) | (0.0533) | (0.0546) |
| L.GDP* | -0.00175 | -0.00130 | -0.00112 | -0.00122 |
| | (0.00485) | (0.00491) | (0.00491) | (0.00487) |
| L.CPI* | 0.00197 | 0.000886 | 0.00158 | 0.00164 |
| | (0.00452) | (0.00450) | (0.00452) | (0.00448) |
| L.FDI* | 0.00657 | 0.00633 | 0.00636 | 0.00681 |
| | (0.00807) | (0.00818) | (0.00816) | (0.00812) |
| L.Fossil fuel energy cons. (%) * | 0.150** | 0.144** | 0.144** | 0.149** |
| | (0.0446) | (0.0451) | (0.0451) | (0.0449) |
| L.Public investment * | 0.00375*** | 0.00349*** | 0.00356*** | 0.00350*** |
| | (0.00160) | (0.00162) | (0.00162) | (0.00161) |
| L.GE* | -0.00760 | -0.00674 | -0.00432 | -0.00575 |

| | | | | |
|---|---|---|---|---|
| | (0.0102) | (0.0103) | (0.0102) | (0.0102) |
| L.Access | 0.000893** | | | |
| | (0.000360) | | | |
| L.Plan | 0.000277 | | | |
| | (0.00398) | | | |
| L.Int_sup | 0.00931** | 0.0120*** | 0.0110** | 0.0104** |
| | (0.00478) | (0.00462) | (0.00468) | (0.00465) |
| L.Tools | 0.00230 | 0.00239 | 0.00120 | 0.00134 |
| | (0.00210) | (0.00212) | (0.00231) | (0.00228) |
| L.Reg | | 0.00299** | | |
| | | (0.00138) | | |
| L.Inv | | | 0.00240** | |
| | | | (0.0070) | |
| L.Trade | | | 0.00200 | 0.00170 |
| | | | (0.0139) | (0.00141) |
| L.Market | | | | 0.00755* |
| | | | | (0.00446) |
| Sargan test | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| AR (1) | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| AR (2) | 0.5109 | 0.4794 | 0.5137 | 0.5047 |
| Observations | 678 | 678 | 678 | 678 |
| Number of countries | 45 | 45 | 45 | 45 |

Note: ***Significant at $p < 0.01$, **Significant at $p < 0.05$, *Significant at $p < 0.1$. *All variables have been logged and centered. Results are presented for difference GMM specifications for share of renewable PPP investments *(ren_share)*. Model 1 tests for energy access and planning policy, Model 2 for regulatory policy and governance institutions, model 3 for investment policy and model 4 for market and trade policy. All models test for support and public finance variables.

*Table C5: Robustness check. Results using Arellano & Bond Difference GMM model for share of renewable energy investments*

| | **1** | **2** | **3** | **4** |
|---|---|---|---|---|
| L.ren_share | 0.666*** | 0.668*** | 0.658*** | 0.660*** |
| | (0.0368) | (0.0368) | (0.0369) | (0.0367) |
| L.GDP* | -0.00698* | -0.00693* | -0.00513 | -0.00524 |
| | (0.00401) | (0.00402) | (0.00402) | (0.00402) |
| L.CPI* | 0.00330 | 0.00237 | 0.00199 | 0.00211 |
| | (0.00378) | (0.00374) | (0.00371) | (0.00371) |
| L.FDI* | 0.00779 | 0.00843 | 0.00865 | 0.00864 |
| | (0.00665) | (0.00667) | (0.00662) | (0.00663) |
| L.Fossil fuel energy cons. (%) * | 0.0577** | 0.0625* | 0.0649** | 0.0642** |
| | (0.0392) | (0.0392) | (0.0390) | (0.0390) |
| L.Public investment * | 0.00295** | 0.00296** | 0.00265** | 0.00265** |
| | (0.00135) | (0.00136) | (0.00135) | (0.00135) |
| L.GE* | -0.00855 | -0.00603 | -0.00384 | -0.00405 |
| | (0.00829) | (0.00822) | (0.00816) | (0.00821) |
| L.Access | 0.00139*** | | | |
| | (0.000534) | | | |
| L.Plan | 0.00269 | | | |
| | (0.00335) | | | |
| L.Int_sup | 0.00184*** | 0.00315*** | 0.000369** | 0.000467*** |
| | (0.00039) | (0.00038) | (0.00038) | (0.00038) |

| | | | | |
|---|---|---|---|---|
| L.Tools | 0.00373* | 0.00512*** | 0.000913* | 0.00100* |
| | (0.00209) | (0.00198) | (0.00228) | (0.00229) |
| L.Reg | | 0.00197** | | |
| | | (0.00045) | | |
| L.Inv | | | 0.00136*** | |
| | | | (0.00075) | |
| L.Trade | | | 0.00415* | 0.00416* |
| | | | (0.00109) | (0.00109) |
| L.Market | | | | 0.00220** |
| | | | | (0.00192) |
| Sargan test | 0.6757 | 0.6602 | 0.8032 | 0.8041 |
| AR (1) | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| AR (2) | 0.1992 | 0.1754 | 0.2088 | 0.1992 |
| Observations | 678 | 678 | 678 | 678 |
| Number of countries | 45 | 45 | 45 | 45 |

Note: ∗∗∗Significant at $p < 0.01$, ∗∗Significant at $p < 0.05$, ∗Significant at $p < 0.1$. *All variables have been logged and centered. Results are presented for difference GMM specifications for share of renewable PPP project volu *(ren_count)*. Model 1 tests for energy access and planning policy, Model 2 for regulatory policy and governance institutions, model 3 for investment policy and model 4 for market and trade policy. All models test for support and public finance variables.