ADBI Working Paper Series

RENEWABLE ENERGY INVESTMENTS AND FEED-IN TARIFFS: FIRM-LEVEL EVIDENCE FROM SOUTHEAST ASIA

Dina Azhgaliyeva, Hai Le,
Resi Ong Olivares, and
Shu Tian

No. 1400
July 2023

Asian Development Bank Institute

Dina Azhgaliyeva is a Senior Research Fellow and Hai Le is a Research Associate, both at the Asian Development Bank Institute, Tokyo, Japan. Resi Ong Olivares is a Financial Market Analyst and Shu Tian is a Senior Economist, both at the Economic Research and Regional Cooperation Department of the Asian Development Bank, Mandaluyong, Philippines.

The Working Paper series is a continuation of the formerly named Discussion Paper series; the numbering of the papers continued without interruption or change. ADBI's working papers reflect initial ideas on a topic and are posted online for discussion. Some working papers may develop into other forms of publication.

The Asian Development Bank refers to “China” as the People's Republic of China and to “Laos” as the Lao People's Democratic Republic.

Suggested citation:

Azhgaliyeva, D., H. Le, R. O. Olivares, and S. Tian. 2023. Renewable Energy Investments and Feed-in Tariffs: Firm-Level Evidence from Southeast Asia. ADBI Working Paper 1400. Tokyo: Asian Development Bank Institute. Available: https://doi.org/10.56506/VRNO2480

Please contact the authors for information about this paper.

Email: dazhgaliyeva@adbi.org, hvle@adbi.org, rolivares.consultant@adb.org,
stian@adb.org

Asian Development Bank Institute
Kasumigaseki Building, 8th Floor
3-2-5 Kasumigaseki, Chiyoda-ku
Tokyo 100-6008, Japan

Tel: +81-3-3593-5500
Fax: +81-3-3593-5571
URL: www.adbi.org
E-mail: info@adbi.org

Abstract

This study examines the impact of feed-in tariffs (FITs) on promoting investments in renewable energy (RE) in Southeast Asia. Using a unique annual firm-level dataset from six Southeast Asian economies from 2012 to 2021, we find robust evidence that FITs in Southeast Asian economies substantially boost firms' investments in RE. Moreover, the impact of FITs on RE investments varies across RE technologies. We find significant and positive impacts of a solar FIT on promoting investments in RE, but such impacts are insignificant for FITs on other RE technologies including wind and biomass, geothermal, and hydro technologies. Further, the impact of FITs on RE investment is more pronounced among younger and smaller firms than in older and larger firms. Our empirical evidence has implications for policymakers in tailoring the design of new FITs to promote private sector investments in RE.

Keywords: renewable energy, feed-in tariff, green investment, Southeast Asia, firm level

JEL Classification: Q20, Q28, Q53, Q58, Q42, G32, G38

Contents

1. INTRODUCTION

Despite its considerable renewable energy (RE) potential, the production and consumption of fossil fuels still constitutes a major proportion of Southeast Asia's primary energy use. The heavy reliance on fossil fuels has exposed the region to environmental destruction and climate change risks. To mitigate carbon dioxide emissions in line with the climate goals established by the 2015 Paris Agreement, and to achieve the net-zero emission targets pledged by individual countries, Southeast Asian economies have made efforts to increase their RE supply. The Association of Southeast Asian Nations (ASEAN) Centre for Energy (ACE 2022) indicates that RE accounted for 18.8% of ASEAN's primary energy supply in 2020. By 2025, RE is expected to account for 35% of the region's installed capacity and 23% of its generating capacity for primary energy.

To facilitate this energy transition in the region, a significant increase in investments in RE is required. According to the estimate of IRENA and ACE (2022), the region will need to make an annual investment of $210 billion through 2050 to attain the 1.5°C warming scenario for Southeast Asia in line with the World Energy Transitions Outlook target of net-zero emissions globally by 2050. The region, however, has limited public resources and fiscal space, which has been exacerbated by significant COVID-19-related expenses. Therefore, the participation of the private sector in all economic sectors will play a crucial role in accelerating the deployment of RE. A solid regulatory environment is required to incentivize private investment.

Feed-in tariffs are among the most effective policies in stimulating the development of RE globally (ACE 2018). Most of the literature agrees that FITs have been effective in encouraging investments in RE (see, among others, Polzin et al. 2019; Azhgaliyeva, Beirne, and Mishra 2022). In six countries in Asia and the Pacific, Roslan et al. (2022) showed that increased returns on investment derived from solar FIT implementation raised the photovoltaic (PV) capacity of small-scale participants, especially in the residential sector. However, commercial-scale PV capacity may decline as returns on investment increase. This matches the conclusion of Sreenath et al. (2022) that FITs are the most important policy tool for boosting PV development as observed in Indonesia, Malaysia, the Philippines, and Thailand. Industry experts in Viet Nam also identify favorable FIT pricing as the main driver of the country's rapid solar expansion (Do et al. 2021).

Careful design is required to guarantee the appropriate degree of incentive, without placing an undue strain on energy off-takers or on government financial support. The effect of FITs on RE investment could be influenced by several factors, such as tariff duration (García-Álvarez, Cabeza-García, and Soares 2017); tariff rate (Criscuolo and Menon 2015; Rodríguez et al. 2015; Nicolini and Tavoni 2017); and future curtailment or intermittency charge policies. Polzin et al. (2019) also found that tariff premiums (on top of the market price), caps on rates (price limit to be paid by rate payers), and grid connection also affect diffusion and risk for RE projects. The success of FIT policies can be further strengthened in succeeding years. Tantisattayakul and Kanchanapiya (2017) recommend adjusting FIT rates to help support smaller participants within the framework. The same recommendation was made by Koerner et al. (2022), Do et al. (2020), and Barroco and Herrera (2019) to boost investments in Malaysia, the Philippines, and Viet Nam. Furthermore, the process and implementation should be reviewed regularly for simplicity and clarity (ACE 2018).[1] For example, current geothermal FIT laws in Indonesia need to consider the dominance of coal-fired power plants and the escalation treatment of applied tariffs to incentivize investors in the geothermal industry (Setiawan et al. 2022).

FITs have been introduced in five Southeast Asia economies: Indonesia, Malaysia, the Philippines, Thailand, and Viet Nam.[2] These economies have experienced remarkable growth in RE installation. Their current FIT rates are shown in Table 1. FIT rates can vary not only across countries and RE technologies, but also across power capacity (project scale), location, and year (Azhgaliyeva and Mishra 2022). Thailand has the highest average FIT rates among its regional peers, while Viet Nam has the lowest. Across RE technologies, solar power has higher average FIT rates than other technologies.

Table 1: Feed-in Tariff Rates in Southeast Asia ($0.01 per Kilowatt Hour)

	Biomass	**Hydropower**	**Solar**	**Wind**
Indonesia	6.28–14.28	6.28–14.38	8.00–30.00	
Malaysia	6.91–7.93	6.14–6.65	11.34–32	
Philippines	12.75	11.34	16.71	15.25
Thailand	13.50–17.00		18.02–21.81	19.29
Viet Nam	5.80	5.00	9.35	7.80

Source: Asian Centre for Energy (2018).

The literature finds that the positive effects of FITs on RE investments in Southeast Asia work through increased installed capacity. Figure 1 shows that the electricity generation capacity from renewable sources increased rapidly after 2009 when FIT policies started to take effect in Southeast Asia. In Thailand, in particular, the installed capacity for solar PVs has grown rapidly since the introduction of FITs. Tantisattayakul and Kanchanapiya (2017) report that Thailand reached 1,902 megawatts of installed solar PVs because of the FIT. The same effect was also observed in Malaysia, which saw an increased number of certified solar services and manufacturing firms after implementing a FIT (Koerner et al. 2022). In 2019, Viet Nam saw a huge boost of 4,500 megawatts in solar PV installation (Do et al. 2020). The Philippines also reported increased installation and generation from wind and solar PVs following FIT implementation (Barroco and Herrera 2019).

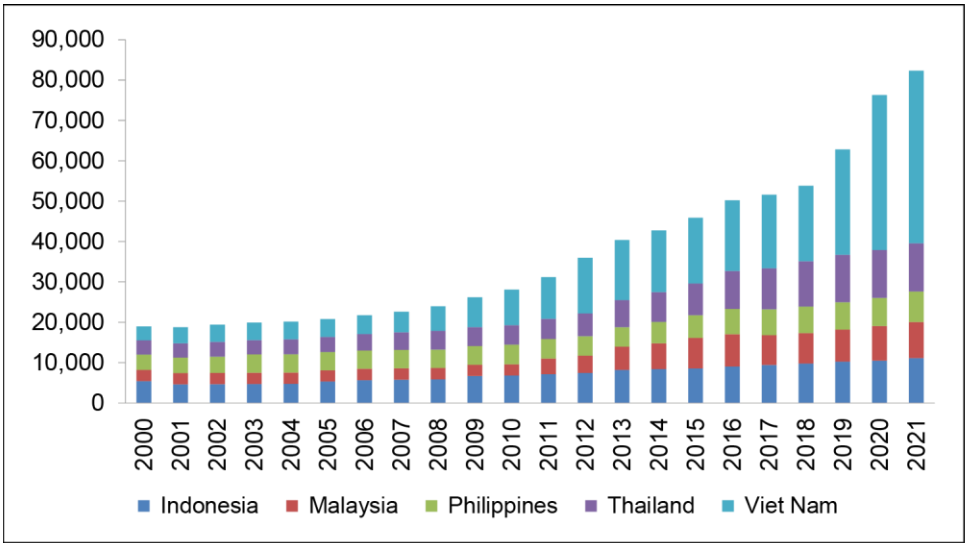
Figure 2 shows annual RE investments in Southeast Asia. Despite the COVID-19 outbreak, annual RE investment in Southeast Asia nearly tripled in 2020, although it retreated in 2021 due to the delayed impact of the pandemic. Investments in solar and wind energies remain the dominant technology compared to other RE technologies. Since 2018, Viet Nam has been the major investor in RE in Southeast Asia.

---

[1] Malaysia, the Philippines, Thailand, and Viet Nam based the design of their respective FITs on the levelized cost of energy plus some premiums that yield a return on investment for various technologies. Indonesia, however, set its FIT using a different incentive program, where the ceiling price is determined by the cost of electricity generated domestically and nationally.

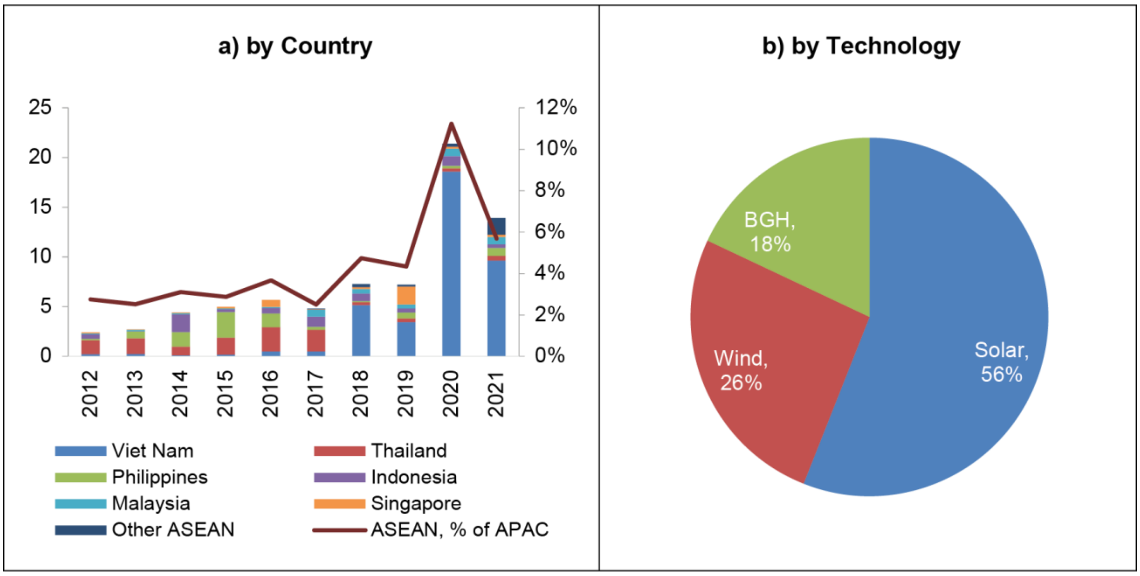
[2] As of 2022.

Figure 1: Electricity Capacity from Renewable Sources (megawatts)



Source: CEIC.

Figure 2: Annual Investments in Renewable Energy in Southeast Asia ($ billion)



ASEAN = Association of Southeast Asian Nations; APAC = Asia and the Pacific; BGH = biomass, geothermal, and hydro technologies.

Source: Authors' calculations using data from Bloomberg NEF.

While the literature has shown the effectiveness of FITs, most evidence is from a country-level perspective (see, for example, Romano et al. 2017; Carley et al. 2017; Eyraud, Clements, and Wane 2013) and a province-level perspective (see Zhao, Zhou, and Wen 2021). To the best of our knowledge, there is no empirical study on the effects of FITs on RE at the firm level. Enterprises are the key entities being influenced by policies to promote RE, and using country-level and province-level data ignores heterogeneity among firms. Therefore, this study fills the gap in the literature by investigating the impact of FITs on firms' investments in RE.

Using a unique firm-level dataset of 109 firms from six[3] Southeast Asian countries that invested in RE projects in the region from 2012 to 2021, we obtained the following key results on the impact of FITs on firms' investments in RE. First, firm investments in RE projects (as a share of firms' total assets) significantly increased with the introduction of an RE FIT. Further evidence shows that a segment that enjoys a higher FIT rate will make more RE investments. In terms of RE technologies, FIT programs for different RE technologies show different degrees of effectiveness in boosting RE investment. The implementation of a FIT for solar energy significantly promotes firms' RE investment. However, wind FITs and biomass, geothermal, and hydro technologies (BGH) FITs have no statistically significant impacts on firm investments in RE. This may be because solar has higher average FIT rates than other RE technologies. In terms of company attributes, smaller and younger firms are more responsive to RE FITs than bigger and older firms. This is possibly due to the fact that FIT rates tend to be higher for small-scale installations, and FITs also encourage the establishment of new RE facilities. These findings are robust to different model specifications and different measures of FIT variables.

The remainder of the paper is organized as follows. Section 2 describes the research data. Section 3 explains the research methodology. Section 4 discusses the empirical results. Section 5 presents robustness checks. Section 6 provides conclusions and policy recommendations.

2. SAMPLE CONSTRUCTION

To examine the impact of FITs in encouraging RE investment we use a panel dataset of 109 unique publicly listed firms that invested in RE projects between January 2012 and December 2021 (906 observations) in six Southeast Asian economies with and without FITs implemented—Indonesia, Malaysia, the Philippines, Singapore, Thailand, and Viet Nam. Firm-level RE investment data were retrieved from Bloomberg New Energy Finance (Bloomberg NEF). Firm-level characteristics of publicly listed companies were collected from S&P Capital IQ Pro. The global levelized cost of electricity for each RE technology was obtained from IRENA (2021) and country-level electricity prices from EnerData. For country-level FIT information, we follow Azhgaliyeva and Mishra (2022). We only focus on firms from these six Southeast Asian economies because data for publicly listed firms from the remaining Southeast Asian economies—Brunei Darussalam, Cambodia, the Lao People's Democratic Republic, and Myanmar—are limited during the sample period. The six countries included in this study accounted for 88% of RE investments in the ASEAN region in 2021.

Empirically, following Chang et al. (2019), we measure firm-level RE investment by dividing a firm's total annual RE investments by its total assets in the same year. RE across different technologies—such as solar, wind, and BGH—can be obtained similarly by dividing respective RE technology investments by the company's total assets. We measure FIT as a dummy variable that is equal to 1 if a FIT has been implemented in the economy or 0 otherwise. To compare the impact of FITs across different RE technologies, we define technology-specific FITs—solar, wind, and BGH—in a similar way. Table 2 shows the years when FITs for different RE technologies were introduced in five Southeast Asian economies (Singapore does not have a FIT during the sample period). As an alternative, we also used average FIT rates paid per kilowatt hour (kWh) instead of the dummy variables. These rates

---

[3] These six countries accounted for 88% of RE investments in the ASEAN region in 2021.

allow us to see how varying tariff rates affect investors' appetite for investing in renewable energy technologies.

Table 2: Year of Feed-in Tariffs for Renewable Energy in Southeast Asia

					Wind	
Country	**Biomass**	**Geothermal**	**Hydro**	**Solar**	**Onshore**	**Offshore**
Indonesia	2012	2012	2012	2016		
Malaysia	2011	2011	2011	2011		
Philippines	2010		2010	2010	2010	2010
Thailand	2014		2014	2013	2014	2014
Viet Nam	2014			2020		

Source: Authors' compilation based on Azhgaliyeva and Mishra (2022).

In examining the impacts of FITs on firms' RE investments, we also control for key firm characteristics, including firm size (*size*), which is measured as the natural log of a firm's market capitalization; systematic risk (*beta*), which is the market beta estimated from a market model for a particular year; financial leverage (*lev*), which is the ratio of total liabilities to total assets; firm experience (*age*), which is the natural log of the number of years since the firm's incorporation—following Kim et al. (2019); Lee (2010); and Bai, Lin, and Liu (2021); and firm profitability (*ROA*), which is the ratio of a firm's returns to its total assets. We also control for the relative cost of renewable electricity over conventional electricity using the renewable electricity cost difference (*RECD*), which is the difference between the levelized cost of electricity and the prevailing electricity price in each economy.

Table 3: Variable Descriptions

Variable	Abbreviation	Unit	Description	Source
Renewable energy investment (dependent variable)	RE	Ratio	Renewable energy investment by a firm annually divided by the firm's total assets	Bloomberg NEF and S&P Capital IQ Pro
Feed-in tariff	FIT	Binary	Equals 1 if FIT is implemented in a country where investment took place and 0 otherwise	Azhgaliyeva and Mishra (2022)
Feed-in tariff	FIT rates	$0.01 per kWh	Average FIT rates paid per kWh	Azhgaliyeva and Mishra (2022)
Carbon emissions	CAR	kg per $ (2015 prices) of GDP	Emissions of carbon dioxide from consumption of fossil fuels and manufacturing of cement	World Bank Open Data
Firm size	Size	ln($ million)	Natural log of market capitalization	S&P Capital IQ Pro
Risk relative to market	Beta	Ratio	The company's risk relative to the market	S&P Capital IQ Pro
Financial risk	Lev	Ratio	The total liability divided by total assets	S&P Capital IQ Pro
Experience	Age	ln(years)	Natural log of the years since firm's incorporation	S&P Capital IQ Pro
Firm profitability	ROA	percentage	Firm's returns divided by its total assets and multiplied by 100%	S&P Capital IQ Pro
Renewable electricity cost difference	RECD	$/kWh	The difference between levelized cost of electricity and prevailing electricity price per country	EnerData

GDP = gross domestic product, kWh = kilowatt hour.

Source: Authors' compilation.

To address possible endogenous issues, we use country-level carbon emissions as an instrumental variable for both FIT and FIT rates. The carbon emission intensity of a country is likely to be correlated with the implementation of FITs. Countries with high carbon emissions may be more likely to implement FITs to reduce their emissions and promote renewable energy investment. The country-level carbon emission intensity is unlikely to be directly related to firm investments in renewable energy. Data on the carbon emission intensity of a country are collected from the World Bank.

A panel dataset was constructed for the selected publicly listed firms headquartered in Southeast Asia that invested in RE from 2012 to 2021. A description of each variable is listed in Table 3, and related summary statistics are reported in Table 4.

Table 4: Summary Statistics for Key Variables

Variable	Observation	Mean	Std. Dev.	Min	Max
RE	906	0.02	0.08	0.00	1.04
FIT	906	0.18	0.38	0	1
FIT Rates	906	0.71	3.33	0.00	22.92
RECD	906	0.06	0.04	–0.15	0.10
CAR	906	0.08	0.24	0.00	1.07
size	906	5.49	2.06	1.09	10.24
beta	906	0.88	0.52	–1.16	2.57
lev	906	0.49	0.23	–0.90	1.93
age	906	3.38	0.64	1.10	5.23
ROA	906	3.14	4.70	–22.57	25.99

CAR = carbon emissions, FIT = feed-in tariff, RE = renewable energy, RECD = renewable energy cost difference, ROA = return on assets.

Source: Authors' own calculations.

3. RESEARCH METHODOLOGY

3.1 The Baseline Model: Impact by RE Technology

In the baseline model, we measure the impact of FIT on investments across RE technologies. We use FIT as a policy variable and control for the renewable electricity cost difference and firm characteristics mentioned in Section 2.3. Specifically, we estimate the following fixed-effects model:

$$RE_{ijt} = \alpha_0 + \alpha_1 FIT_{jt} + \boldsymbol{\beta}'\boldsymbol{X} + \mu_i + \nu_t + \varepsilon_{ijt}, \tag{1}$$

where RE_{it} is RE investment scaled by firm *i*'s total assets in year *t* and country *j*, and FIT_{jt} is equal to 1 if the FIT for the technology has already been introduced in year *t* and country *j* and 0 otherwise. α_0 and α_1 denote the constant and policy parameter, respectively. $\boldsymbol{X}$ indicates a set of control variables including RE cost difference ($RECD_{jt}$), firm size ($size_{ijt-1}$), systematic risk exposure ($beta_{ijt-1}$), financial leverage (lev_{ijt-1}), experience (age_{ijt-1}), and profitability (roa_{ijt-1}). $\boldsymbol{\beta}'$ is a vector of corresponding parameters. μ_i and ν_t are firm- and year-fixed effects, which are included to capture time-invariant firm attributes and information for a certain year, respectively, while ε_{ijt} denotes the error term. Lang, Ofek, and Stulz (1996) employed a pooling regression to estimate the investment equation, with the presumption of zero unobserved individual effects. However, this is a strong assumption given the significant degree of firm-specific heterogeneity. Thus, we follow Aivazian, Ge, and Qiu (2005) and employ fixed-effects models to overcome such concerns.

3.2 Instrumental Variable

There might be omitted variables that correlate with both RE investment and the FIT dummy variables. Accordingly, the above-mentioned fixed-effects models can suffer an endogeneity problem. To address any potential endogeneity problems, we instrumented FIT variables using country-level carbon emissions intensity as we suspect our FIT variables are endogenous.

The justification for the use of this instrument is as follows. First, at the macro level, a country's carbon emissions are highly likely to be correlated with the implementation of FITs. This is because after all developing Asian economies submitted nationally determined contributions (NDCs) under the Paris Agreement, larger emitters now have more motivation to introduce climate policies to reduce their emissions and achieve their climate pledges. Second, country-level carbon emission intensity is unlikely to be directly related to firm investments in renewable energy. This is because RE investment at the firm level will usually follow companies' normal investment decisions. Such business investment decisions normally lack compulsory compliance with climate considerations. If companies usually consider emissions, their RE investment will happen in the market naturally, thus no policy intervention is needed. The prevalence of climate policy intervention is evidence that companies in general still do not internalize climate costs in their investment decisions. Thus, policies are introduced precisely to correct such market failures, guide companies' investment decisions, and help internalize the externality of emissions. Third, companies respond to policies like FITs when making their own investment decisions. Overall, country-level emissions serve as a good instrumental variable (IV) to address possible endogenous issues in this context.

Empirically, we take a two-stage least-squares estimation approach in estimating the exogenous effects of FIT policies on investments in renewable energy technology projects in Southeast Asia. We checked the validity of our IV using a test of endogeneity and the Stock and Yogo (2005) test for weak instruments. The first stage isolates the proportion of FIT_{jt} that is uncorrelated with the error term by regressing FIT_{jt} on the country-level carbon emissions intensity, renewable energy cost difference, and other firm characteristic variables:

$$FIT_{jt} = \gamma_0 + \gamma_1 CAR_{jt} + \boldsymbol{\delta}'\boldsymbol{X} + \mu_i + \nu_t + e_{ijt}, \tag{2a}$$

where CAR_{jt} denotes the country-level carbon emissions intensity of country *j* in year *t*. γ_0, γ_1, and $\boldsymbol{\delta}$ are unknown parameters, and e_{ijt} is the error term. From this first-stage estimation, we obtain the predicted value of our FIT policy variable $\widehat{FIT}_{jt}$, which captures the exogenous part of FIT_{jt}. The second stage regresses firms' investments in RE on the predicted value of the FIT policy variable $\widehat{FIT}_{jt}$, the RE cost difference, and other firm characteristic variables:

$$RE_{ijt} = \alpha_0 + \alpha_1 \widehat{FIT}_{jt} + \boldsymbol{\beta}'\boldsymbol{X} + \mu_i + \nu_t + \varepsilon_{ijt}. \tag{2b}$$

We make use of our panel data structure and employ the lagged values of FIT as an additional instrument to check the sensitivity of our results.

3.3 Interaction Models: Impact by Firm Characteristics

To further understand how FIT impacts on firms' RE investment may vary across firm characteristics, we interact the introduction of a FIT with key firm characteristics such as firm size, financial leverage, operation experiences, and profitability. Empirically, we modify Equations 2a and 2b by including interaction terms in the following Equations 3a and 3b:

$$FIT'_{jt} = \gamma_0 + \gamma_1 CAR_{jt} + \boldsymbol{\delta}'\boldsymbol{X} + \mu_i + \nu_t + \mathrm{e}_{ijt}, \text{ and} \tag{3a}$$

$$RE_{ijt} = \alpha_0 + \alpha_2 \widehat{FIT'}_{jt} * chs + \alpha_5 \widehat{FIT'}_{jt} + \boldsymbol{\beta}'\boldsymbol{X} + \mu_i + \nu_t + \varepsilon_{ijt}, \tag{3b}$$

where FIT'_{jt} is the binary variable for the implementation of either the overall FIT policy or a FIT for solar.[4] The term CAR_{jt} denotes the country-level carbon emissions intensity of country *j* in year *t*. γ_0, γ_1, and $\boldsymbol{\delta}$ are unknown parameters, and e_{ijt} is the error term. We follow the two-stage least-squares regression described in the previous section to derive the predicted $\widehat{FIT'}_{jt}$ to be interacted with $chs,$ which denotes the set of binary variables with firm characteristics: small firms, low leverage firms, young firms, and low return-on-asset firms. Specifically, *small* is a binary variable that equals 1 if the firm's market capitalization is less than the median value of the annual average market capitalization of all firms that are headquartered in a home country, or 0 otherwise. We construct the binary variables *low leverage*, *young*, and *low ROA* in a similar way by replacing market capitalization with leverage, firm age, and return-on-assets, respectively.

3.4 Feed-in-Tariff Rates

The use of dummy variables for FIT policies might lead to biased and/or misleading results since the dummy variables can capture different events that occurred at the same time. Therefore, we use the average tariff rates for each technology in each country to address this concern when measuring the FIT policy effect.[5] The results from models with tariff rates also serve as a robustness check. The FIT rates paid per kWh are computed as weighted averages of the rates imposed by different countries for different technologies where a firm has placed an investment. This measure better captures the quantitative effects of FIT policies with varying rates. Empirically, we modify all the above-mentioned equations by replacing FIT_{jt} with $FIT\ Rate_{jt}$.

---

[4] We also estimate the models with FIT for wind technology and FIT for BGH. However, we find no statistically significant impact for either the wind FIT or BGH FIT. The results and possible explanations are presented in the next section.

[5] We use FIT rate averages per country and per RE technology. FIT rates usually vary not only by country and RE technology, but also by project capacity. Thus, firms can receive different FIT rates across their projects. We do not have information either on whether a firm is a FIT recipient (i.e., a FIT contract has been signed).

4. EMPIRICAL FINDINGS

4.1 Baseline Regression Results: Renewable Energy Technology

In this section, we show the impacts of FITs on firms' RE investments. The estimated results are reported in Table 5. We find that an RE FIT positively affects investments in RE and the impact is highly significant once we address the endogeneity using country-level carbon emissions intensity as the IV. Specifically, the point estimate is 0.388, demonstrating that the introduction of an RE FIT increases firm investments in RE projects (as a share of total assets) by 38.8%. The positive impact of FITs on RE investments is well documented by the existing literature. The endogeneity test indicates that an RE FIT is indeed endogenous; therefore, using the two-stage least-squares regression approach is appropriate. In addition, we demonstrate that carbon emissions intensity is not a weak instrument as suggested by the weak instrument test of Stock and Yogo (2005).[6]

We further examine the impacts of FITs across different RE technologies on firm investments in RE. The results are displayed in Columns (2), (3), and (4) of Table 5. We find that a solar FIT has a statistically significant and positive impact on firms' investments in solar energy. This means that a solar FIT boosts investments in solar technology, as shown in Column (3). Specifically, firm investments in solar energy (as a share of total assets) increase by approximately 36.1% after a solar FIT is implemented in the country. This finding is in line with previous literature that also indicates the positive impact of FIT policy on solar PV installations (see, for example, Ahmad et al. 2015; Tantisattayakul and Kanchanapiya 2017; and Do et al. 2020). Meanwhile, we find no statistically significant evidence of the impact of wind and BGH FITs on investment in wind and BGH technologies, respectively.[7] This also implies that the general significant effects of FITs on RE investments in Southeast Asia are largely driven by solar energy.

There are several potential explanations for the effectiveness of solar FITs and relatively less effectiveness of wind and BGH FITs. First, solar irradiance is very high in Southeast Asia. Second, solar technologies require less minimum capacity, have fewer geographical requirements, and need less space than wind, hydro, and geothermal. While the region is also well endowed with windy conditions, developing wind technologies requires sufficiently large space and investments. Hydro and geothermal energy also require very specific local geographical conditions and land. Land acquisition is one of the barriers and could benefit from policy support (such as the simplification of the land acquisition and permitting process) in ASEAN (International Energy Agency and Imperial College London 2023). Third, average solar FIT rates are greater than wind and BGH FIT rates in Southeast Asia (Table 1).

---

[6] Note also that although we do not report it here, we treat RE FIT as exogenous and estimate the impacts of RE FIT using the fixed-effect regression. The fixed-effect model, however, does not capture how these RE FIT policies have led to increases in private support for RE technologies.

[7] In the interest of brevity, we do not report the results from the fixed-effect models for FITs on different RE technologies. The results from fixed-effect models are not statistically significant. However, once we address the potential endogeneity, we obtain significant results for the solar FIT as shown above. In addition, we conduct some statistical tests for our IV. The results from the endogeneity test indicate that our variable is not exogenous; thus, the IV regressions are required. Furthermore, the Stock and Yogo statistics (across all models) indicate that our IV is not weak.

We find that the difference between the levelized cost of electricity generated from RE sources and its prevailing price does not affect investments when the endogeneity is addressed. The insignificant impact of electricity price could be due to FITs. When FIT contracts are signed, firms sell electricity at a predetermined price (tariff rate) as in their FIT contract, thus they are not affected by the electricity price. The insignificant impact of the levelized cost of electricity (LCOE) generated from RE sources can be explained as follows. The LCOE of RE has two impacts on investment in RE: positive and negative. On the one hand, a lower LCOE of RE makes investments in RE more attractive and bankable, and thus has a positive impact. On the other hand, a lower LCOE of RE requires less funds for the same amount of power capacity. Even if firms do not increase investments (same level) after the LCOE has declined, the newly installed capacity is increased. Both positive and negative driving forces might result in overall negative, positive, or no impact.[8]

Table 5: Feed-in Tariffs and Renewable Energy Investments Using a 2SLS Regression

Dependent Variable = RE	**(1)**	**(2)**	**(3)**	**(4)**
RE FIT	0.388**			
	(0.157)			
Solar FIT		0.361***		
		(0.139)		
BGH FIT			2.127	
			(1.750)	
Wind FIT				–59.223
				(924.362)
SIZE	–0.002	–0.002	0.001	0.129
	(0.002)	(0.002)	(0.009)	(2.070)
BETA	–0.031**	–0.032***	–0.021	–1.020
	(0.013)	(0.012)	(0.027)	(15.569)
LEV	–0.061*	–0.036	0.034	–0.042
	(0.033)	(0.024)	(0.089)	(1.851)
AGE	–0.016	–0.007	–0.092	–0.895
	(0.010)	(0.006)	(0.077)	(13.966)
ROA	–0.001	–0.001	–0.002	–0.095
	(0.001)	(0.001)	(0.002)	(1.468)
Renewable electricity cost difference	–0.032	–0.262	0.071	–21.799
	(0.435)	(0.352)	(1.090)	(320.651)
Year dummies	Yes	Yes	Yes	Yes
Observations	906	906	906	906
Chi-square	37.61	39.91	8.503	0.0627

BGH = biomass, geothermal, and hydro; FIT = feed-in tariff; RE = renewable energy; 2SLS = two-stage least-squares regression.

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors are in parentheses. Instrumental variables in 2SLS include carbon dioxide emissions (kilogram per dollar of gross domestic product at 2015 prices).

Source: Authors' own calculations.

---

[8] Although we do not report it here, our key above-mentioned results are unchanged for models with sector-year dummies. The detailed results of these models are available upon request for interested readers.

4.2 The Impacts of FITs on RE Investment: Firm Characteristics

This section explores how the impacts of FITs on RE investments vary across various firm characteristics. The results are displayed in Table 6. Compared to larger firms, smaller firms are more responsive to the introduction of a FIT. Specifically, as shown in Column (1), smaller companies invest nearly 33% more in RE projects (as a share of total assets) relative to bigger firms after a FIT is implemented. This could be because FIT rates are often differentiated across energy capacity, with higher rates for smaller-scale installations, and also because we measure the dependent variable (RE investments) as a share of total assets. As shown by Roslan et al. (2022), increased returns on investment due to the implementation of FIT policies drive increases in PV capacity among smaller participants, especially at the residential level, while the opposite is observed in bigger participants that provide energy on a commercial scale. In addition, younger firms are highly likely to invest more in RE projects than older firms. Our estimated results show that young firms experience 23.5% more investment in RE (as a share of total assets) than older firms. The potential explanation for this is that FITs encourage the establishment of new firms. This is consistent with the finding of Sreenath et al. (2022) that FIT policies help boost the early stages of PV development. Favorable FIT rates allow the entry of new participants into the local electricity market.

Aside from firm size and firm experience, differences in other major firm characteristics—such as financial leverage and profitability—do not result in a significant difference in responding to an RE FIT, as shown in Columns (2)–(4).

Table 6: Impact of FIT on RE Investments—Role of Firm Characteristics (2SLS)

	(1)	(2)	(3)	(4)
Dependent Variable = RE	**Small**	**Low Level**	**Young**	**Low ROA**
RE FIT*Small	0.329**			
	(0.132)			
RE FIT*Low Leverage		0.105		
		(0.130)		
RE FIT*Young			0.235**	
			(0.106)	
RE FIT*Low ROA				–0.068
				(0.148)
RE FIT	0.208*	0.365**	0.233*	0.438*
	(0.118)	(0.157)	(0.123)	(0.232)
Renewable electricity cost difference	–0.044	0.047	–0.086	–0.019
	(0.422)	(0.469)	(0.433)	(0.460)
Firm Controls	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Observations	906	906	906	906
Number of Firms	109	109	109	109
Chi-squared	39.50	35.65	43.41	36.70

FIT = feed-in tariff, RE = renewable energy, ROA = return on assets, 2SLS = two-stage least-squares regression.

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors are in parentheses. Instrumental variables in 2SLS include carbon dioxide emissions (kilograms per dollar of gross domestic product at 2015 prices).

Source: Authors' own calculations.

Since the general impact of FITs on RE investment is largely driven by solar, we further investigate how the impact of a solar FIT on RE investment might change with major firm characteristics. Table 7 shows the estimated results. Similarly to the results of a general RE FIT, we find that smaller and younger firms significantly invested more (38.2% and 27.2%, respectively) than bigger and older firms after a solar FIT was introduced.[9]

Table 7: Solar Feed-in Tariffs and Firm Characteristics (2SLS)

	(1)	**(2)**	**(3)**	**(4)**
Dependent Variable = RE	**Small**	**Low Level**	**Young**	**Low ROA**
Solar FIT*Small	0.382***			
	(0.144)			
Solar FIT*Low Leverage		0.179		
		(0.159)		
Solar FIT*Young			0.272**	
			(0.115)	
Solar FIT*Low ROA				–0.030
				(0.150)
Solar FIT	0.156	0.325**	0.185*	0.382*
	(0.097)	(0.134)	(0.106)	(0.203)
Renewable electricity cost difference	–0.290	–0.141	–0.313	–0.261
	(0.341)	(0.406)	(0.368)	(0.357)
Firm Controls[a]	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Observations	906	906	906	906
Number of Firms	109	109	109	109
Chi-squared	41.47	37.36	49.03	39.89

FIT = feed-in tariff, RE = renewable energy, 2SLS = two-stage least-squares regression.

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors are in parentheses. Instrumental variables in 2SLS include carbon dioxide emissions (kilograms per dollar of gross domestic product at 2015 prices).

Source: Authors' own calculations.

4.3 Alternative for Feed-in Tariffs Variable: FIT Rates

The use of a dummy variable for feed-in tariffs can lead to biased estimates and/or be misleading. Therefore, in this section, we provide the estimated results using the average FIT rates as an alternative proxy for the FIT variable. The estimated results are reported in Table 8. Overall, our key findings do not change. Specifically, when FIT rates are treated as exogenous, the model cannot capture the policy's positive impact on private investments in renewable technology projects. Assuming endogeneity and using carbon emissions as the IV, we find that each additional $0.01 in the overall FIT rate per kWh translates to a 2.1% increase in RE investments (as a share of total assets), while each additional $0.01 in a solar FIT rate per kWh translates to a 3.5% increase in investments in solar energy (as a share of total assets). This supports the

---

[9] Although we do not report the results here, we observe impacts of the interaction between a wind FIT (and a BHG FIT) and firm characteristics that are not statistically significant. However, this is not surprising as we mentioned earlier that vast areas and large-scale investments are required to advance wind technologies. Unique geographic criteria are also required for the development of hydro and geothermal technologies.

claims of industry experts in Viet Nam that have identified favorable FIT pricing as one of the reasons for the country's rapid solar expansion (Do et al. 2021).[10]

Table 8: Feed-in Tariff Rates and Renewable Energy Investments (2SLS)

Dependent Variable = RE	**(1)**	**(2)**	**(3)**	**(4)**
RE FIT Rates	0.021***			
	(0.008)			
Solar FIT Rates		0.035**		
		(0.015)		
BGH FIT Rates			0.946	
			(2.677)	
Wind FIT Rates				0.583
				(1.098)
SIZE	–0.005***	–0.005**	–0.020	–0.021
	(0.001)	(0.002)	(0.046)	(0.028)
BETA	–0.007	–0.010	0.087	0.051
	(0.006)	(0.008)	(0.262)	(0.150)
LEV	–0.014	0.026	–0.041	0.187
	(0.013)	(0.027)	(0.076)	(0.324)
AGE	0.001	–0.001	–0.088	0.045
	(0.003)	(0.005)	(0.263)	(0.082)
ROA	–0.001	–0.000	–0.005	0.006
	(0.001)	(0.001)	(0.017)	(0.011)
Renewable electricity cost difference	–0.192	0.760	4.945	3.865
	(0.383)	(0.904)	(18.028)	(9.808)
Year Dummies	Yes	Yes	Yes	Yes
Observations	906	906	906	906
Chi-square	56.44	30.71	4.750	6.607

BGH = biomass, geothermal, and hydro; FIT = feed-in tariff; RE = renewable energy; 2SLS = two-stage least-squares regression.

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors are in parentheses. Instrumental variables in 2SLS include carbon dioxide emissions (kilograms per dollar of gross domestic product at 2015 prices).

Source: Authors' own calculations.

5. ROBUSTNESS CHECKS

The previous section demonstrates that our main findings remain unchanged with regard to an alternative proxy for the FIT variable. In this section, we further check the sensitivity of our results using two main estimation sets. First, we re-estimate our models using the IV regression with fixed effects. Second, we employ a lagged FIT variable as an additional IV and check our main findings.

5.1 Plausibly Exogenous IV

To bolster our assertion regarding the trustworthiness of the instrument, we examine the sensitivity of our results to departures from the assumption of perfect exogeneity. This involves evaluating the stability of our findings when the country-level carbon

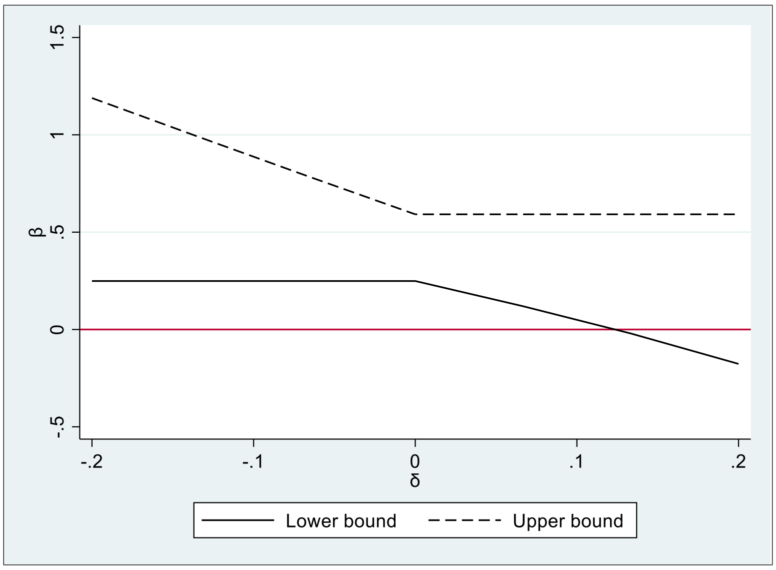
---

[10] Furthermore, FIT rates for BGH and wind technologies do not significantly affect RE investments, which is in line with our main findings.

intensity, which serves as our instrumental variable, has a direct effect on firm investment in RE projects. To do this, we utilize the method proposed by Conley, Hansen, and Rossi (2012) and allow the country-level carbon intensity to be included with a linear coefficient δ in the second stage.

Figure 3: Effects of FIT on RE Investment (Allowing Country-Level Carbon Emission Intensity to Have a Direct Impact on RE Investment)

a. RE FIT dummy



3b. RE FIT rates

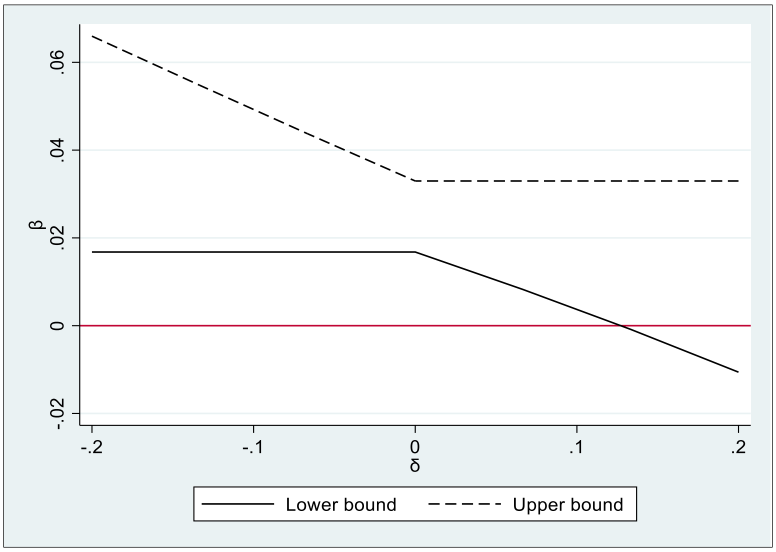


Figure 3a presents the estimated effects of the FIT dummy on firm investment in RE projects when allowing IV to directly impact RE investments. When δ is negative, the constraints on the estimated effect of the FIT dummy are further way from 0 in comparison to 2SLS estimates, which indicates that the conventional 2SLS estimates underestimate the effects of FIT on firm investments in RE projects. In addition, we still confirm the significant and positive impact of FIT as long as δ is less than 0.11. It is worth mentioning that the estimated effect of carbon emission on RE investments in a reduced form is 0.108. Therefore, our limit of 0.11 is appropriate as it accounts for 100% of the direct effect of carbon emission. Guo (2020) permits substantially lower departures (25% of the reduced-form coefficient) from perfect exogeneity. Similar findings are obtained when the FIT rates are employed as an alternative proxy for carbon pricing policy (Figure 3b).

5.2 Instrumental Variable Regressions with Fixed Effects

In this section, we incorporate the fixed effects into the IV regression approach. The estimated results are provided in Table 9, with Columns (1) and (2) being the results for FIT dummies and Columns (3) and (4) being those for FIT rates. In this series of regressions, we reach the same overall conclusions. Although the estimated coefficients of our FIT dummy variables are slightly higher than those under the IV regression without fixed effects, the signs of the coefficients remain unchanged and also those that were statistically significant remain so. We again demonstrate a significant and positive nexus between the implementation of an overall FIT (as well as a solar FIT) and firm investments in RE projects. Similarly, the results of FIT rates under the IV regressions with fixed effects are inconsistent with the previous findings. Although we do not report the results here, we also find no empirical evidence on the impact of wind and BGH FITs on RE investments, which is in line with our key findings. This confirms that the effectiveness of FITs in guiding RE investment is more pronounced for solar technology in Southeast Asia.

Table 9: Robustness Check—Feed-in Tariffs and Renewable Energy Investments (FE G2SLS)

	FIT Binary		**FIT Rates**	
Dependent Variable = RE	**(1)**	**(2)**	**(3)**	**(4)**
RE FIT	0.734*		0.017**	
	(0.400)		(0.008)	
Solar FIT		0.618**		0.034*
		(0.307)		(0.020)
SIZE	–0.062*	–0.034	–0.004	0.003
	(0.037)	(0.022)	(0.005)	(0.006)
BETA	–0.039*	–0.025*	–0.005	0.002
	(0.023)	(0.014)	(0.008)	(0.011)
LEV	–0.000	–0.013	0.034	0.163
	(0.059)	(0.053)	(0.037)	(0.134)
AGE	0.348	0.217	0.062*	0.110
	(0.222)	(0.135)	(0.033)	(0.083)
ROA	0.000	–0.000	0.000	0.000
	(0.002)	(0.002)	(0.001)	(0.001)
Renewable electricity cost difference	–0.132	–0.183	–0.335	0.712
	(0.503)	(0.474)	(0.365)	(1.102)
Year Dummies	Yes	Yes	Yes	Yes
Observations	906	906	906	906
Chi-square	51.49	60.19	44.76	25.34

FE = fixed effects, FIT = feed-in tariff, G2SLS = generalized two-stage least-squares regression, RE = renewable energy.

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors are in parentheses. Instrumental variables in 2SLS include carbon dioxide emissions (kilograms per dollar of gross domestic product at 2015 prices).

Source: Authors' own calculations.

5.3 Lag of Feed-in Tariffs as an Additional Instrument Variable

In this section, we further evaluate our main findings by employing the lagged FIT variable as an additional IV. The estimated results are provided in Table 10. Overall, the results from this exercise remain the same. The estimates of our FIT variables are lower than those under the IV regression without the lagged FIT variables, but the signs of the estimates are unaltered. We find that the implementation of an overall FIT (as well as a solar FIT) has a significant and positive effect on firm investments in RE projects. Meanwhile, we find no empirical evidence of the impact of wind and BGH FITs on RE investments. This confirms that the impact of FITs on RE investment mostly comes from solar technology. Similarly, the results of FIT rates under the IV regressions with fixed effects are consistent with the previous findings. Furthermore, the statistical tests indicate that our IV is not weak and overidentified. Although we do not report the results here, we obtain similar findings when employing the IV regressions with either fixed effects or random effects.

Table 10: Robustness Check—Feed-in Tariffs and Renewable Energy Investments (Additional IV)

	FIT Binary		**FIT Rates**	
Dependent Variable = RE	**(1)**	**(2)**	**(3)**	**(4)**
RE FIT	0.019*		0.017**	
	(0.011)		(0.008)	
Solar FIT		0.032**		0.031*
		(0.016)		(0.017)
SIZE	–0.003***	–0.003***	–0.004	0.003
	(0.001)	(0.001)	(0.005)	(0.006)
BETA	–0.010**	–0.011**	–0.005	0.001
	(0.005)	(0.005)	(0.008)	(0.010)
LEV	0.000	0.000	0.034	0.153
	(0.008)	(0.008)	(0.037)	(0.123)
AGE	0.001	0.001	0.062*	0.102
	(0.003)	(0.003)	(0.033)	(0.073)
ROA	–0.000	–0.000	0.000	0.000
	(0.000)	(0.000)	(0.001)	(0.001)
Renewable electricity cost difference	–0.976***	–0.959***	–0.334	0.560
	(0.155)	(0.155)	(0.366)	(0.932)
Year Dummies	Yes	Yes	Yes	Yes
Observations	906	906	906	906
Chi-square	68.86	69.77	44.42	28.87

FE = fixed effects, FIT = feed-in tariff, G2SLS = generalized two-stage least-squares regression, RE = renewable energy.

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors are in parentheses. Instrumental variables in 2SLS include carbon dioxide emissions (kilograms per dollar of gross domestic product at 2015 prices) and lag of FIT.

Source: Authors' own calculations.

5.4 Using Total Equity to Scale Renewable Energy Investments

As a further robustness check, we evaluate our key findings by using the renewable energy investments relative to a firm's total equity as a dependent variable. Table 11 provides the estimated results for both FIT dummies and FIT rates. Our main results remain unchanged, with an overall FIT and a solar FIT positively affecting firm investments in RE projects. Though we do not report them here, similar conclusions are reached when using fixed effects (or random effects) within IV regressions.

Table 11: Feed-in Tariffs and Renewable Energy Investments—Renewable Energy Investments Relative to Total Equity

	FIT Dummies		**FIT Rates**	
Dependent Variable = RE	**(1)**	**(2)**	**(3)**	**(4)**
RE FIT	1.007***		0.043***	
	(0.363)		(0.016)	
Solar FIT		0.938***		0.086*
		(0.320)		(0.045)
SIZE	–0.003	–0.004	–0.000	0.018
	(0.006)	(0.004)	(0.011)	(0.013)
BETA	–0.076**	–0.078***	–0.008	0.008
	(0.033)	(0.029)	(0.018)	(0.027)
LEV	–0.127	–0.062	0.115	0.438
	(0.084)	(0.063)	(0.098)	(0.327)
AGE	–0.043*	–0.020	0.160**	0.272
	(0.023)	(0.015)	(0.078)	(0.197)
ROA	–0.001	–0.001	–0.000	–0.000
	(0.002)	(0.002)	(0.001)	(0.002)
Renewable electricity cost difference	0.517	–0.078	–0.318	2.298
	(1.015)	(0.832)	(0.766)	(2.568)
Year Dummies	Yes	Yes	Yes	Yes
Observations	906	906	906	906
Chi-square	32.22	34.81	55.81	21.77

FE = fixed effects, FIT = feed-in tariff, G2SLS = generalized two-stage least-squares regression, RE = renewable energy.

Notes: *** p < 0.01, ** p < 0.05, * p < 0.1. Robust standard errors are in parentheses. Instrumental variables in 2SLS include carbon dioxide emissions (kilograms per dollar of gross domestic product at 2015 prices) and lag of FIT.

Source: Authors' own calculations.

6. CONCLUSIONS AND POLICY RECOMMENDATIONS

This paper investigates the impact of FIT policies on RE investments using firm-level data from six Southeast Asian countries—Indonesia, Malaysia, the Philippines, Singapore, Thailand, and Viet Nam. The above six countries accounted for 88% of RE investments in the ASEAN region in 2021. This study provides the following key results on the impact of FIT on RE investments and offers relevant policy recommendations. First, the implementation of a FIT has a significant and positive effect on firms' investments in RE projects (as a share of firms' total assets). Second, our results show that the effect of RE FITs on investments in renewable energy in ASEAN is largely driven by FITs in solar projects. This is not surprising, as more than half of RE investments in ASEAN (2012–2021) are in solar (Figure 2). However, we find no empirical evidence of the impacts of either wind or BGH FITs on firm investments in RE projects. Third, FIT programs for different technologies show different degrees of effectiveness in boosting RE investments among various firm cohorts. Compared to bigger and older firms, smaller and younger ones are more responsive to FITs. This could be because FIT rates are often differentiated across energy capacity with higher rates for smaller-scale installations. Our findings are robust to different model specifications and different measures of FIT variables.

These findings have the following policy implications for promoting RE investments. First, policymakers from Southeast Asian economies that have not implemented a FIT can consider doing so to boost RE investments, due to their effectiveness. The implementation of FITs is associated with a 38.8% increase in RE investments (as a share of total assets) (Table 5). Second, a higher FIT rate has stronger impacts. For example, investment in solar energy and smaller-scale installations are particularly responsive to FITs, probably due to their relatively higher rates. While the implementation of FITs and higher FIT rates have succeeded in encouraging private investments in solar technology, for other technologies (i.e., biomass, geothermal, hydro, and wind) FITs did not have a significant impact, probably due to the greater barriers that exist (e.g., land acquisition), thus other technologies require more policy support. A variety of different types of renewable energy (i.e., solar, wind, geothermal, hydro, and biomass) can help with the intermittency of renewable energy.

This paper has some limitations mainly due to data availability. Some explanatory variables, such as firms’ foreign ownership or state ownership, are missing due to a lack of such data in Southeast Asia. The exact FIT rates per project and information on whether a firm is benefiting from a FIT (i.e., whether a FIT contract has been signed) are also not available. Therefore, instead of firm-level FIT rates, this study uses country and RE technology averages.

REFERENCES

ACE. 2018. ASEAN Feed-in-Tariff (FIT) Mechanism Report, ASEAN Centre for Energy. http://go.aseanenergy.org/nb7Qq.

———. 2022. ASEAN Energy in 2022: Outlook Report, ASEAN Centre for Energy. http://go.aseanenergy.org/gcXzn.

Ahmad, S., R. M. Tahar, F. Muhammad-Sukki, A. B. Munir, and R. A. Rahim. 2015. Role of Feed-in Tariff Policy in Promoting Solar Photovoltaic Investments in Malaysia: A System Dynamics Approach. *Energy* 84: 808–815.

Aivazian, V. A. Y., Ge, and J. Qiu. 2005. The Impact of Leverage on Firm Investment: Canadian Evidence. *Journal of Corporate Finance* 11(1–2): 277–291.

Azhgaliyeva, D., J. Beirne, and R. Mishra. 2022. What Matters for Private Investment in Renewable Energy? *Climate Policy* 23(1): 71–87.

Azhgaliyeva, D., and R. Mishra. 2022. Feed-in Tariffs for Financing Renewable Energy in Southeast Asia. *Wiley Interdisciplinary Reviews: Energy and Environment* 11(3): e425.

Bai, R., B. Lin, and X. Liu. 2021. Government Subsidies and Firm-level Renewable Energy Investment: New Evidence from Partially Linear Functional-coefficient Models. *Energy Policy* 159: 112610.

Barroco, J., and M. Herrera. 2019. Clearing Barriers to Project Finance for Renewable Energy in Developing Countries: A Philippines Case Study. *Energy Policy* 135: 111008.

Carley, S., E. Baldwin, L. M. MacLean, and J. N. Brass. 2017. Global Expansion of Renewable Energy Generation: An Analysis of Policy Instruments. *Environmental and Resource Economics* 68: 397–440.

Chang, K., Y. Zeng, W. Wang, and X. Wu. 2019. The Effects of Credit Policy and Financial Constraints on Tangible and Research & Development Investment: Firm-level Evidence from China’s Renewable Energy Industry. *Energy Policy* 130: 438–447.

Conley, T. G., C. B. Hansen, and P. E. Rossi. 2012. Plausibly Exogenous. *Review of Economics and Statistics* 94 (1): 260–272.

Criscuolo, C., and C. Menon. 2015. Environmental Policies and Risk Finance in the Green Sector: Cross-country Evidence. *Energy Policy* 83: 38–56.

Do, T. N., P. J. Burke, K. G. Baldwin, and C. T. Nguyen. 2020. Underlying Drivers and Barriers for Solar Photovoltaics Diffusion: The Case of Viet Nam. *Energy Policy* 144: 111561.

Do, T. N., P. J. Burke, H. N. Nguyen, I. Overland, B. Suryadi, A. Swandaru, and Z. Yurnaidi. 2021. Vietnam’s Solar and Wind Power Success: Policy Implications for the Other ASEAN Countries. *Energy for Sustainable Development* 65: 1–11.

Eyraud, L., B. Clements, and A. Wane. 2013. Green Investment: Trends and Determinants. *Energy Policy* 60: 852–865.

García-Álvarez, M. T., L. Cabeza-García, and I. Soares. 2017. Analysis of the Promotion of Onshore Wind Energy in the EU: Feed-in Tariff or Renewable Portfolio Standard? *Renewable Energy* 111: 256–264.

Guo, S. 2020. The Legacy Effect of Unexploded Bombs on Educational Attainment in Laos. *Journal of Development Economics* 147: 102527.

International Energy Agency and Imperial College London. 2023. ASEAN Renewables: Opportunities and Challenges. https://www.iea.org/reports/asean-renewables-investment-opportunities-and-challenges.

IRENA. 2021. Renewable Power Generation Costs in 2020, International Renewable Energy Agency, Abu Dhabi. https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2021/Jun/IRENA_Power_Generation_Costs_2020.pdf?rev=c9e8dfcd1b2048e2b4d30fef671a5b84.

IRENA and ACE. 2022. Renewable Energy Outlook for ASEAN: Towards a Regional Energy Transition (2nd ed.), International Renewable Energy Agency, Abu Dhabi; and ASEAN Centre for Energy, Jakarta. https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2022/Sep/IRENA_Renewable_energy_outlook_ASEAN_2022.pdf?rev=ef7557c64c3b4750be08f9590601634c.

Kim, H. D., T. Kim, Y. Kim, and K. Park. 2019. Do Long-term Institutional Investors Promote Corporate Social Responsibility Activities? *Journal of Banking & Finance* 101: 256–269.

Koerner, S. A., W. S. Siew, A. A. Salema, P. Balan, S. Mekhilef, and N. Thavamoney. 2022. Energy Policies Shaping the Solar Photovoltaics Business Models in Malaysia with Some Insights on Covid-19 Pandemic Effect. *Energy Policy* 164: 112918.

Lang, L., E. Ofek, and R. Stulz. 1996. Leverage, Investment, and Firm Growth. *Journal of Financial Economics* 40(1): 3–29.

Lee, C. Y. 2010. A Theory of Firm Growth: Learning Capability, Knowledge Threshold, and Patterns of Growth. *Research Policy* 39(2): 278–289.

Nicolini, M., and M. Tavoni. 2017. Are Renewable Energy Subsidies Effective? Evidence from Europe. *Renewable and Sustainable Energy Reviews* 74: 412–423.

Polzin, F., F. Egli, B. Steffen, and T. S. Schmidt. 2019. How Do Policies Mobilize Private Finance for Renewable Energy? A Systematic Review with an Investor Perspective. *Applied Energy* 236: 1249–1268.

Rodríguez, M., I. Haščič, N. Johnstone, J. Silva, and A. Ferey. 2015. Renewable Energy Policies and Private Sector Investment: Evidence from Financial Microdata. *Environmental and Resource Economics* 62: 163–188.

Romano, A. A., G. Scandurra, A. Carfora, and M. Fodor. 2017. Renewable Investments: The Impact of Green Policies in Developing and Developed Countries. *Renewable and Sustainable Energy Reviews* 68: 738–747.

Roslan, F., Ș. C. Gherghina, J. Saputra, M. N. Mata, F. D. M. Zali, and J. M. Martins. 2022. A Panel Data Approach towards the Effectiveness of Energy Policies in Fostering the Implementation of Solar Photovoltaic Technology: Empirical Evidence for Asia-Pacific. *Energies* 15(10): 3775.

Setiawan, A. D., M. P. Dewi, B. A. Jafino, and A. Hidayatno. 2022. Evaluating Feed-in Tariff Policies on Enhancing Geothermal Development in Indonesia. *Energy Policy* 168: 113164.

Sreenath, S., A. M. Azmi, N. Y. Dahlan, and K. Sudhakar. 2022. A Decade of Solar PV Deployment in ASEAN: Policy Landscape and Recommendations. *Energy Reports* 8: 460–469.

Stock, J. H., and M. Yogo. 2005. Testing for weak instruments in Linear IV regression. In *Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg* (pp. 80-108). Cambridge University Press. https://doi.org/10.1017/CBO9780511614491.006.

Tantisattayakul, T., and P. Kanchanapiya. 2017. Financial Measures for Promoting Residential Rooftop Photovoltaics under a Feed-in Tariff Framework in Thailand. *Energy Policy* 109: 260–269.

Zhao, G., P. Zhou, and W. Wen. 2021. Feed-in Tariffs, Knowledge Stocks and Renewable Energy Technology Innovation: The Role of Local Government Intervention. *Energy Policy* 156: 112453.