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SPECIAL ISSUE ARTICLE

Can Banks Sustain the Growth in Renewable Energy Supply? An International Evidence

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Abstract

Confronted with rapidly deteriorating climate change resulting from the use of fossil fuels, the transition to renewable energy has now become imminent. But this shift to renewable energy requires massive financial support from banks, affecting their default risk. Responding to the growing environmental concerns and reluctance among banks to increase their exposure in the renewable energy sector, this study presents unique and novel insights on the relationship between the share of renewable energy in the total energy supply of a country and banking risk. To this end, we obtained data for a sample of 80 international banks from 20 countries in the 2006–2017 period. On this data, we implemented a two-stage least squares (2SLS) regression analysis model. Our findings reveal that increasing the share of renewable energy in the total energy supply of a country significantly reduces banks' default risk. To check the robustness of the results, we performed several tests which also endorsed the validity of our results.

Keywords Renewable energy · Banking risk · 2SLS · Distance-to-default

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Résumé

Face à l'aggravation rapide du changement climatique à cause de l'utilisation des énergies fossiles, la transition vers les énergies renouvelables est désormais imminente. Mais ce passage aux énergies renouvelables nécessite un soutien financier conséquent de la part des banques, ce qui affecte leur risque de défaut. En réponse aux préoccupations environnementales croissantes et à la réticence des banques à augmenter leur implication dans le secteur des énergies renouvelables, cette étude présente des informations uniques et inédites sur la relation entre la part des énergies renouvelables dans l'approvisionnement énergétique total d'un pays et le risque bancaire. À cette fin, nous avons obtenu des données pour un échantillon de 80 banques internationales de 20 pays sur la période 2006–2017. Sur ces données, nous avons mis en œuvre un modèle d'analyse de régression des moindres carrés en deux étapes (2SLS). Nos résultats révèlent que l'augmentation de la part des énergies renouvelables dans l'approvisionnement énergétique total d'un pays réduit considérablement le risque de défaut pour les banques. Pour vérifier la robustesse des résultats, nous avons effectué plusieurs tests qui ont également confirmé la validité de nos résultats.

Introduction

Energy is considered as the driver of the world economy and demand for this resource is continuously increasing. But its generation and consumption using fossil fuels are resulting in climatic change which not only polluting our water, air, and soil but also posing safety risks to the food and health quality (Martí-Ballester 2017). With time, this climatic change has transformed from an environmental to an economic threat (Zouabi 2021) affecting macroeconomic factors including the financial systems (Battiston et al. 2017). These issues have sparked a sense of concern among various stakeholders who are mounting pressure on the corporate sector to implement renewable energy (Hepbasli 2008).

Large multinational firms are already using renewable energy to "become a carbon–neutral company" (Unilever 2019), "combat climate change" (Apple 2018), "solve the world's most pressing environmental challenges" (P&G 2019), or "contribut[e] to the reduction of carbon [emissions]" (Nestle 2018). But this transition to renewable energy is a capital-intensive decision requiring immense participation from the financial institutions. Banks are expected to play a key part in assisting a country's shift to renewable energy and strengthening its financial resilience to environmental risks (Mazzucato and Semieniuk 2018). However, high exposure of the banking sector to renewable energy could be a cause of concern for their survival that may hinder their active engagement in this sector (Safarzyńska and van den Bergh 2017a). Unless this fear of default is addressed, the required financial participation of banks in renewable energy can never be ensured.

Motivated by the growing environmental concerns, increasing corporate interest in renewable energy, and the reluctance of banks to increase their exposure to renewable energy, we explore the relationship between the share of renewable energy in the total energy supply of a country (REN) and bank's default risk measured through distance-to-default (DD). In this regard, we collected the REN data on 20 countries and selected four banks from each country to calculate their DD. After controlling for various bank-specific and country-level confounding variables, our results based on Two-Stage Least Squares (2SLS) regression analysis indicate that increase in REN significantly reduces banks' default risk. We performed several tests to ensure that our results are robust to the selection of model estimation technique, alternate proxies for a bank's default risk, and exogenous shock of the global financial crisis (GFC). All the robustness tests validated a statistically significant positive relationship between REN and banks' default risk.

The paper contributes to the broader literature on the relationship between environmental performance and the financial stability of banks. To the best of our knowledge, it is the first empirical analysis of the impact of renewable energy use on the banks' default risk based on three measures of risk i.e., distance-to-default, distance to insolvency and distance to capital. The capital-intensive nature of renewable energy projects renders banks one of the most influential players in determining the growth and success of renewable energy usage and has intensified the researchers' heed to deal with the risks and risk management of renewable energy projects (Gatzert and Kosub 2016; Tsao and Thanh 2021; Das and Basu 2020; Zhou and Yang 2020; Taghizadeh-Hesary and Yoshino 2020). We contribute to this debate from the lens of banks' default risk based on an international sample of 20 countries. Findings are expected to motivate the banking sector to play their much-needed role in replacing pollution-creating and depleting energy sources with renewable energy. The study is insightful for managers and policymakers at the national and international level to design such policies that simultaneously focus on stimulating both the demand and supply side of renewable energy. By encouraging the participation of banks in financing renewable energy, it can help countries to achieve the United Nations' 2015 Sustainable Development Goals which are of major importance for worldwide sustainable development (Briant Carant 2017).

The rest of the paper is structured as follows. Section 2 presents the literature review and research hypotheses to be tested. Section 3 discusses the methodology including the measurement of variables, model estimation, and data analysis. In Section 4, various robustness tests are presented. Finally, Sect. 5 concludes the study with a discussion of results and policy implications.

Literature Review

Besides the importance of energy in residential life, its role is critical in the growth and viability of economic development. The extraordinary demand and consumption of energy during the 1970's energy crisis brought the world's attention to both climatic change and energy shortage (Nie and Yang 2016). But more serious efforts for preserving the environment by reducing emissions were initiated after Kyoto Protocol was signed in 1997 (Nie et al. 2016). Since then, there is a consensus among researchers and practitioners that switching to renewable energy is the most effective solution in this regard (Capasso et al. 2020).

The latest United Nations Intergovernmental Panel on Climate Change (IPCC) report (IPCC 2018) highlights that due to human activities, the current global warming level has already increased by 1 °C compared to the pre-industrial era. And based on a business-as-usual scenario, this increase may jump to 1.5 °C between 2030 and 2052. To sustain the environment, the report suggests reducing CO_2 emissions by approximately 45% until 2030 and achieving a net-zero mark by 2050. But these highly ambitious targets demand equally large financing. The report projects an annual allocation of USD 2.4 trillion in clean energy until 2035 and between USD 1.6 to 3.8 trillion in the energy system supply side until 2050. Committing such a large investment in renewable energy projects and achieving sustainable development through it appears unrealistic unless banks support such projects through financing solutions such as carbon financing (Zhang and Li 2018) or green financing (Taghizadeh-Hesary and Yoshino 2020).

Although banks could be cautious in financing renewable energy, literature shows that such financing can improve the financial stability of the banks reducing their credit risk (Cui et al. 2018). To portray the relationship between macro (country) level renewable energy and bank risk, we should take into account the interlinked activities of major stakeholders involved in the process. In this regard, we are building our arguments based on the macroeconomic model developed by Safarzyńska and van den Bergh (2017b). The schematic representation of the model is given in Fig. 1.

Today, it is fairly clear that the corporate sector being the largest contributor to the world's emission, needs to replace fossil fuels with renewable energy if the world wants to bring CO_2 emissions down (Martí-Ballester 2017). According to Safarzyńska and van den Bergh (2017b) model, for committing this structural transformation, each firm has two primary options. First, generating its own renewable energy by installing the required equipment, and second, buying renewable energy directly from energy-producing power plants (Depoorter et al. 2015). But in either case, the energy producer (the firm itself or power plant) will require financing from the banks (shown as loans arrow in Fig. 1). Considering the financial magnitude of the renewable energy project and associated financing need, the bank may seek funds from other financial institutions through interbank lending (shown as IB loans). The firm will use this renewable energy in selling its products and services to the public (consumers) which in return generates profit for the firm. The public (consumers) also include the workers who provide labor to both the firm and the power plant in return for wages. These consumers could even be the capital owners or energy producers themselves. All three key stakeholders; consumers, power plants, and firms are the primary source of deposits for the bank out of which it advances loans. If the borrower (firm or power plants) bankrupts, it will also increase the bank's probability of default (Thurner and Poledna 2013). However, if the borrower (firm or power plants) can use renewable energy to increase their profits, it could potentially increase their ability to repay bank loans which will ultimately decrease the bank's default risk (Safarzyńska and van den Bergh 2017a).

Building on Safarzyńska and van den Bergh (2017b) macroeconomic model, we argue that investing in renewable energy could help a bank to lower its default probability. A review of the literature reveals that renewable energy can enhance a firm's profitability and ability to pay back bank loans in various ways. First, the theory of product differentiation in a profit-maximization framework presented by Rosen

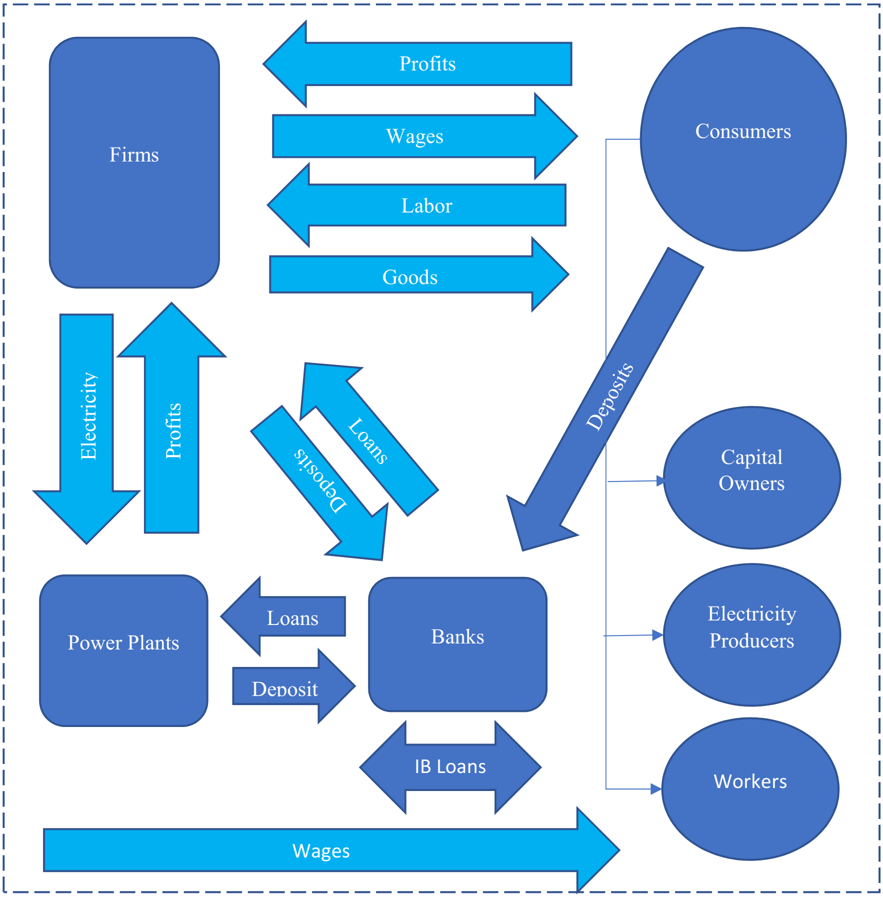

Fig. 1 Schematic representation of the macroeconomic model by Safarzyńska and van den Bergh (2017b)

(1974) provides the most appropriate theoretical ground to explain the profit relevance of renewable energy. According to this, employing renewable energy enables a firm to build a better reputation in the eyes of the public (Siegel and Vitaliano 2007) and helps it in differentiating itself from competitors (Hulshof and Mulder 2020). This differentiation-based competitive advantage allows a firm to charge a higher price which increases its profitability (Galdeano-Gómez et al. 2008). Second, when a firm switches to renewable energy, it discloses this transition in its environmental disclosures. These disclosures are expected to enhance the profitability of the firm because customers who demand rational energy use would prefer its products considering them more valuable (Kang et al. 2016).

Third, by integrating renewable technologies in their core business operations, firms don't have to count on unreliable conventional energy supply. This can improve firms' profitability in the long run (Martí-Ballester 2017). Fourth, investment in

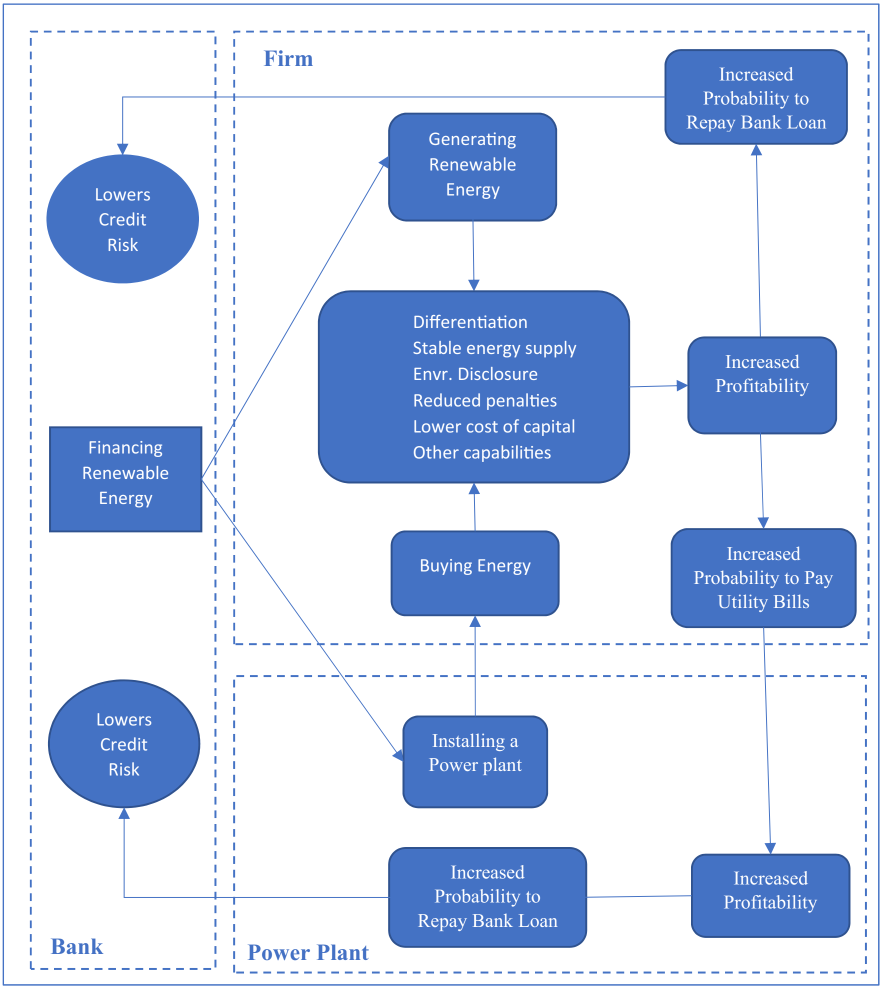

Fig. 2 Schematic flow of interconnected activities among a firm, bank, and power plant

such environment-friendly projects could also prevent a firm from governmental penalties or fines (Carroll and Shabana 2010). Fifth, Martí-Ballester (2017) argued that implementing renewable energy requires the adoption of advanced management systems which improve the organizational processes. It helps a firm to develop such resources and capabilities that could be non-substitutable, rare, valuable, and imperfectly imitable (Crowe and Brennan 2007). These resources would eventually help a firm to improve productivity and generate higher profits. Sixth, during the appraisal of loan applications, banks also consider the environmental implications of their financing and charge a lower interest rate for environment-friendly projects (Zhang and Li 2018). The reduced cost of capital will increase the profitability of the firm.

Figure 2 depicts all the above-discussed factors connecting it with the firm's profitability and the bank risk.

According to Safarzyńska and van den Bergh (2017b) model, the increased profitability will enhance a firm's probability to repay a bank loan which will reduce the bank's default risk. On the other hand, if the firm buys renewable energy from power plants instead of generating its own energy, the firm's higher profitability will enhance its probability to pay the energy bills that will increase the profitability of the power plants. Eventually, these power plants will be in a sound position to pay back the bank which will also reduce the bank's default risk. So, either way, financing renewable energy could ultimately help a bank in lowering its default risk. Based on the discussion above, we hypothesize the following relationship.

Hypothesis 1 Increase in the share of renewable energy in the total energy supply of a country (REN) reduces the banks' default risk.

The variable that links renewable energy to bank risk in Fig. 2 is firm profitability and the underlying assumption that supports Hypothesis 1 is the positive relationship between renewable energy and firm profitability. However, empirical evidence also exists against the profit relevance of renewable energy indicating an insignificant relationship between renewable energy and firm profitability (Hulshof and Mulder 2020). Consequently, lacking the prerequisite link of increased profitability in Fig. 2 could disconnect the nexus between renewable energy and bank risk leading to the following alternate hypothesis.

Hypothesis 2 Increase in the share of renewable energy in the total energy supply of a country (REN) may not have any significant impact on the banks' default risk.

Methodology

This section presents the measurement of variables, data collection, model estimation, and data analysis.

Measurement of Variables

Dependent Variables

Among the various approaches employed to estimate the probability of banks' default, structural techniques such as distance to default (DD) or distance to insolvency (DI) are the most popular ones among researchers (Capasso et al. 2020). These indicators are widely used by international organizations and financial authorities as well to monitor the risk of financial institutions (Harada et al. 2013). The seminal work by Merton (1973) introduced the concept of distance to default (DD) referring to it as the distance between the current market-based position of a financial organization and its hypothetical default position (Fiordelisi and Marqués-Ibañez

2013; Choudhury et al. 2021). It is an inverse measure of a bank's default risk that means a larger distance between the two or higher value of DD suggests a lower probability of a firm to default. Theoretically, it indicates the level where corporate liabilities exceed its assets (Dar and Qadir 2019) and is widely employed by international financial regulatory authorities for supervising financial institutions (Chan-Lau and Sy 2007). Based on the assumption made by Merton (1974), we followed Daly (2019) to calculate the yearly distance to default (DD) values for each bank in our sample as per Eq. 1.

$$\mathrm{DD}_t \quad = -\frac{\ln\left(L_t\right) - \left\{\ln\left(A_t\right) + \left(R_{\mathrm{f}} - \frac{\sigma_A^2}{2}\right)\cdot(T-t)\right\}}{\sigma_{\mathrm{A}}\cdot\sqrt{T-t}} \tag{1}$$

The distance to default (DD) for T–t maturity in Eq. 1 uses the natural logarithm of the market value of assets (LnA_t) and the natural logarithm of the value of liabilities (LnL_t) at time t taking into account the risk-free rate (R_{f}) and volatility of asset value σ_{A}. We used annual data from Bloomberg and Thomson Reuters DataStream to calculate DD for each bank in our sample.

Independent Variable

To measure the share of renewable energy in the total primary energy supply (REN) in a country, the SDGs database from the official website of the United Nations was used. Renewables which have been incorporated to calculate this variable include the primary energy equivalent of hydro (excluding pumped storage), wind, geothermal, solar, wave and tide sources. Energy resources obtained from other sources such as biodiesels, solid biofuels, liquid biofuels, the renewable fraction of municipal waste, biogases, and biogasoline are also included in this measure.

Control Variables

To account for the potential impact of various confounding variables, we included several bank-specific and country-level controls in our model. Firms with larger size and more leverage are more susceptible to default hence following Capasso et al. (2020), we controlled bank size (natural logarithm of total assets) and firm leverage (debt ratio) in this study. Similarly, return on equity (Trad et al. 2017) and price-to-book ratio (Switzer et al. 2018) can affect firms' probability of default. So, both the accounting-based (ROE) and market-based (PB ratio) measures of profitability are controlled in this study. Lastly, the volume of revenue can also be a determinant of bank risk (Stiroh 2006) hence we also incorporated revenue growth as a control variable.

Among the country-level factors, literature has identified various factors that can affect banks' risk such as level of corruption in a country (Chen et al. 2015), political system and its stability (Eichler and Sobański 2016), government effectiveness (Klomp 2013), accountability (Andrieş et al. 2020) and rule of law and regulatory quality (Laeven and Levine 2009, 2006). We controlled all these six country-level determinants of bank risk in this study. The data on bank-specific controls were collected from Bloomberg and Thomson Reuters DataStream. For country-level controls, the database of the World Bank, Heritage Foundation's Index of Economic Freedom, World Governance Indicators (WGIs) was used.

Data

To analyze the relationship between REN and DD, we selected an international sample of 80 banks from 20 countries for the year 2006 to 2017. To avoid any sample selection bias, we included 4 banks from each country in the final sample. The list of all the banks with their corresponding country name and Bloomberg tickers are given in Table 1. We followed Kinateder et al. (2021) to select the top 4 banks from each country in our sample based on their total assets.

Model Estimation and Analysis

Table 2 summarizes the descriptive statistics of the variables used in this study. It indicates that the mean DD is 7.127 with a maximum of 278.02 and a minimum of -12.678. For REN, the mean is 10.699 with a maximum of 42.65 and a minimum of 0.55.

In addition, to assess the potential of multicollinearity, the Pearson correlation matrix for all the variables in our study is illustrated in Table 3. The results depict no serious issues concerning multicollinearity except for country-level controls. However, given the nature of those variables i.e., control, high multicollinearity can safely be ignored (Troilo et al. 2016; Allison 2012).

The exactitude of the model estimation technique and accuracy of results depends on the underlying relationship among the variables. We started assuming the linear relationship between REN and DD and estimated the linear model (Eq. 2) using pooled OLS regression.

$$\mathrm{DD}_{it} = \alpha + \beta X_{it} + \Omega_{it} + \eta_i + \varepsilon_{it} \tag{2}$$

here "i" represents the bank under observation, "t" shows time, "X_{it}" indicates the independent variable (REN), Ω_{it} is a vector of control variables (bank size, bank leverage, bank profitability, market value, revenue growth, corruption control index, political stability index, government effectiveness, voice, and accountability index, rule of law and regulatory quality), η_i represents unobserved time-invariant bank-specific effects and ε_{it} is the random error term. The results of OLS regression in Table 4 (model 1) indicate that REN has a statistically insignificant relationship with DD.

As pooled OLS regression estimates the model assuming the underlaying relationship as static, its results could be invalid if the actual relationship among the variables is found to be dynamic. To test the nature of the relationship between REN and DD, we estimated the dynamic model (Eq. 3) using OLS regression after controlling the same bank-specific and country-specific variables.

Table 1 List of banks in final sample

Sr. #	Country	Name	Bloomberg Ticker	Sr. #	Name	Bloomberg Ticker
1	Australia	AUS and NZ Banking Group	ANZ AU Equity	3	Commonwealth Bank of Australia	CBA AU Equity
2		Westpac Banking Corporation	WBC AU Equity	4	National Australia Bank	NAB AU Equity
5	Belgium	Banque Nale De Belgique	1413118D BB Equity	7	KBC Group	KBC BB Equity
6		Dexia	BEXB BB Equity	8	Keytrade Bank	KEYT BB Equity
9	Brazil	Brb Banco De Brasilia	BSLI3 BZ Equity	11	Banco Estado Espirito Santo	BEES3 BZ Equity
10		Banco Do Nord On	BBAS3 BZ Equity	12	Amazonia	BAZA3 BZ Equity
13	China	Agricultural Bank of China	601,288 CH Equity	15	China Construction Bank	601,939 CH Equity
14		Bank of China	601,988 CH Equity	16	Industrial & Coml. Bk. of China	601,398 CH Equity
17	Denmark	Danske Bank	DANSKE DC Equity	19	Spar Nord Bank	SPNO DC Equity
18		Jyske Bank	JYSK DC Equity	20	Sydbank	SYDB DC Equity
21	France	Bnp Paribas	BNP FP Equity	23	Natixis	KN FP Equity
22		Credit Agricole	ACA FP Equity	24	Societe Generale	GLE FP Equity
25	Germany	Deutsche Bank	DBK GR Equity	27	Oldenburgische	OLB GR Equity
26		Commerzbank	CBK GR Equity	28	Umweltbank	UBK GR Equity
29	India	Bank of Baroda	BOB IN Equity	31	ICICI Bank	ICICIBC IN Equity
30		HDFC Bank	HDFC IN Equity	32	State Bank of India	SBIN IN Equity
33	Italy	Unicredit	UCG IM Equity	35	Intesa Sanpaolo	ISP IM Equity
34		Banco Popolare	BAMI IM Equity	36	Unione Di Banche Italian	UBI IM Equity
37	Japan	Mitsubishi Ufj Finl. Gp	8306 JP Equity	39	Sumitomo Mitsui Finl. Gp	8316 JP Equity
38		Mizuho Finl. Gp	8411 JP Equity	40	Chiba Bank	8331 JP Equity
41	Korea	Hana Financial Group	086,790 KP Equity	43	Kb Financial Group	0,105,560 KP Equity
42		Industrial Bank of Korea	024,110 KP Equity	44	Shinhan Finl. Group	055,550 KP Equity
45	Malaysia	Cimb Group Holdings	CIMB MK Equity	47	Rhb Bank	RHB MK Equity
46		Malayan Banking	MAY MK Equity	48	Alliance Financial Gp	ABMB MK Equity
49	Mexico	Banregio Grupo Financiero	6145695Z MM Equity	51	Grupo Financiero Inbursa	GFINBURO MM Equity
50		Gpo Finance Banorte	GFNORTEO MM Equity	52	Santander Mexico	BSMXB MM Equity

Table 1 (continued)

Sr. #	Country	Name	Bloomberg Ticker	Sr. #	Name	Bloomberg Ticker
53	Netherland	Ing Group	INGA NA Equity	55	Kas Bank	KA NA Equity
54		Binckbank	BINCK NA Equity	56	Van Lanschot	VLK NA Equity
57	South Africa	Firstrand	FSR SJ Equity	59	Capitec Bank	CPI SJ Equity
58		Nedbank Group	NED SJ Equity	60	Standard Bk. Gp	SBK SJ Equity
61	Spain	Banco Santander	SAN SM Equity	63	Banco De Sabadell	SAB SM Equity
62		Bbv. Argentaria	BBVA SM Equity	64	Banco Popular Espanol	POP SM Equity
65	Sweden	Nordea	NDA SS Equity	67	Svenska Handbkn	SHBA SS Equity
66		Seb	SEBA SS Equity	68	Swedbank	SWEDA SS Equity
69	Swiss	Credit Suisse Group	CSGN SW Equity	71	St Galler Kantonalbank	SGKN SW Equity
70		UBS	UBSG SW Equity	72	Banque Canton. De Geneve	BCGE SW Equity
73	UK	Barclays Bank	BARC LN Equity	75	Royal Bank of Scotland	RBS LN Equity
74		HSBC	HSBA LN Equity	76	Standard Chartered Bank	STAN LN Equity
77	USA	Wells Fargo & Company	WFC US Equity	79	JPMorgan Chase	JPM US Equity
78		Citigroup	C US Equity	80	Bank of America Corporation	BAC US Equity

This table shows the country-wise distribution of banks from 20 countries for the period of 2006–2017. The table also reports their corresponding Bloomberg ticker names

Table 2 Descriptive statistics

Variable	Obs	Mean	Std. Dev	Min	Max
Dependent variables					
Distance to default risk (DD)	816	7.127	19.281	− 12.678	278.023
Independent variable					
Renewable energy (REN)	720	10.699	8.966	.55	42.65
Control variables					
Bank size	891	13.328	3.396	1.117	19.879
Bank leverage	888	17.509	10.472	1.214	81.873
Bank profitability (ROE)	888	9.08	11.591	− 161.222	41.812
Market value (PB ratio)	890	1.449	1.072	.121	9.959
Revenue growth	888	5.531	20.38	− 58.395	272.463
Corruption control index	960	76.885	21.378	16.346	100
Political stability index	960	60.075	22.853	10.427	98.578
Government effectiveness	960	81.696	15.926	41.827	100
Voice and accountability index	960	76.715	24.119	4.695	100
Rule of law	960	78.207	20.521	29.808	100
Regulatory quality	960	79.718	17.822	34.615	100

This table reports descriptive statistics of the dependent, independent, and control variables for the period of 2006–2017

$$\mathrm{DD}_{it} = \alpha + \gamma \mathrm{DD}_{it-1} + \beta X_{it} + \Omega_{it} + \eta_i + \varepsilon_{it} \tag{3}$$

Lagged estimator (DD_{it-1}) was added in the regression model to test the dynamic nature of the model (Nadeem et al. 2017) and results in Table 4 (model 3) indicate two key findings. Firstly, the adjusted R^2 in the dynamic model has increased significantly compared to the static OLS model (from 0.12 to 0.858). Secondly, the lagged estimator (DD_{it-1}) has a coefficient of 1.153 which is statistically significant at 1% level. These two significant findings confirm the dynamic nature of the relationship between REN and DD and also endorse the presence of reverse causality and endogeneity in the model (Nadeem et al. 2017). Hence, the results of the OLS model assuming a static relationship between REN and DD in model 1 (Table 4) are invalid.

To account for the dynamic endogeneity in the models, researchers have suggested various techniques. Among those, Two-Stage Least Square (2SLS) is considered as one of the most effective ones (Zaman et al. 2018). We estimated the 2SLS model as per Eq. 4.

$$\ln(R_{i,t}) = \varphi_0 + \sum_{j=1}^{n} \theta_j X_{j,i,t} + \sum_{k=1}^{m} \delta_k C_{k,i,t} + \varepsilon_{i,t} \tag{4}$$

Here $\ln(R_{i,t})$ is the bank risk (DD) for "*i*" bank at "*t*" year; $X_{j,i,t}$ represents the explanatory variable (REN); $C_{k,i,t}$ represents all the control variables; φ_0 is a constant; θ_j is the coefficient of the explanatory variable (REN) and δ_k represents the

Table 3 Pearson correlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) Distance to Default Risk	1.000												
(2) Renewable energy	– 0.024	1.000											
(3) Bank size	– 0.153*	– 0.027	1.000										
(4) Bank leverage	– 0.077	0.078	0.238*	1.000									
(5) Bank profitability	– 0.111*	0.031	0.125*	– 0.196*	1.000								
(6) Market value	– 0.113*	0.068	0.032	0.049	0.452*	1.000							
(7) Revenue growth	– 0.066	– 0.083	0.044	0.002	0.370*	0.299*	1.000						
(8) Corruption control index	– 0.093*	0.202*	– 0.037	0.195*	– 0.195*	– 0.216*	– 0.215*	1.000					
(9) Political stability index	– 0.025	0.328*	– 0.034	0.195*	– 0.210*	– 0.228*	– 0.206*	0.878*	1.000				
(10) Government effectiveness	– 0.076	0.214*	0.002	0.222*	– 0.247*	– 0.202*	– 0.224*	0.928*	0.866*	1.000			
(11) Voice and accountability index	– 0.032	0.335*	– 0.110*	0.074	– 0.197*	– 0.190*	– 0.189*	0.839*	0.725*	0.706*	1.000		
(12) Rule of law	– 0.101*	0.183*	0.024	0.194*	– 0.226*	– 0.208*	– 0.217*	0.963*	0.852*	0.929*	0.847*	1.000	
(13) Regulatory quality	– 0.040	0.213*	– 0.088*	0.146*	– 0.246*	– 0.233*	– 0.232*	0.926*	0.864*	0.925*	0.816*	0.912*	1.000

This table reports the results for the Pearson correlation matrix among all pairs of variables employed in our study. * indicates a significance level of 5%. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4 Baseline regression results (dependent variable: distance to default risk)

Variables	Model 1 Pooled OLS	Model 2 Fixed Effects	Model 3 Dynamic OLS	Model 4 2SLS
Renewable energy (REN)	− 0.061	0.551*	0.010	0.977**
	(0.104)	(0.322)	(0.046)	(0.427)
Bank size	0.842**	− 0.502	0.077	− 0.536
	(0.341)	(0.416)	(0.154)	(0.435)
Bank leverage	− 0.042	0.011	− 0.013	0.011
	(0.074)	(0.058)	(0.034)	(0.058)
Bank profitability (ROE)	0.038	0.093	− 0.020	0.116
	(0.099)	(0.080)	(0.043)	(0.081)
Market value (PB ratio)	0.323	0.197	0.294	1.543**
	(1.319)	(0.637)	(0.645)	(0.680)
Revenue growth	− 0.048	− 0.081	− 0.024	− 0.063
	(0.035)	(0.071)	(0.017)	(0.059)
Corruption control index	− 0.860***	− 0.547	− 0.177*	− 0.514
	(0.231)	(0.369)	(0.104)	(0.343)
Political stability index	0.330***	− 0.196	0.015	− 0.095
	(0.070)	(0.133)	(0.032)	(0.109)
Government effectiveness	− 0.687***	1.157*	− 0.058	1.050*
	(0.258)	(0.628)	(0.121)	(0.549)
Voice and accountability index	0.507**	0.416	0.249**	0.453
	(0.256)	(0.630)	(0.120)	(0.648)
Rule of law	0.614***	1.428	0.040	1.456
	(0.228)	(0.927)	(0.102)	(0.897)
Regulatory quality	− 0.263	− 0.697	− 0.074	− 0.574
	(0.239)	(0.512)	(0.107)	(0.441)
Lagged DD			1.153***	

Table 4 (continued)

Variables	Model 1	Model 2	Model 3	Model 4
	Pooled OLS	Fixed Effects	Dynamic OLS	2SLS
			(0.023)	
Constant	33.924**	− 132.071*	− 1.035	
	(15.162)	(73.473)	(7.044)	
Observations	564	564	511	558
R^2	0.120	0.613	0.858	0.106
Bank fixed effect	No	Yes	No	Yes
Year fixed effect	No	Yes	No	Yes
F-test *p*-value	0.000	0.000	0.000	0.001
Kleibergen–Paap rk LM statistic *p*-value (under identification test)				0.000
Cragg–Donald Wald *F* statistic (weak identification test)				141.161
Kleibergen–Paap rk Wald *F* statistic (weak identification test)				112.214
Hensen J statistic *p*-value (overidentification test of all instruments)				0.3472

This table presents the results of OLS regression estimation (Model 1, 2, and 3) and 2SLS estimation (Model 4) of the relationship between renewable energy (REN) and bank risk (distance to default (DD)). The standard errors in model 2 (reported in parentheses) are based on the Windmeijer correction for heteroscedasticity and clustering. Asterisks ***, ** and * indicate significance at 1%, 5% and 10%, respectively. *p*-values are based on robust standard errors. Tests in Model 4 also include Hansen *J* Test, Kleibergen–Paap LM Test *p*-value, Cragg–Donald Wald Test, Kleibergen–Paap Wald *F* Test and Hensen J statistic *p*-value coefficient of control variables. Residual of the model is represented by $\varepsilon_{i,t}$. The model incorporates both bank and year fixed effects and results are reported in Table 4 (model 4). The coefficient (0.977) between REN and DD confirms a statistically significant positive relationship between the two accepting our research hypothesis 1 at 5% level of significance. Among the control variables, only PB ratio and government effectiveness were found to have a significant and positive relationship with DD at 5% and 10% levels of significance, respectively.

Given the first stage of the 2SLS involves creating a new variable (computing estimated values of the problematic predictor) based on the instruments, the reliability accuracy of 2SLS estimators is contingent on the validity of the instruments used in the model. In case the instruments are invalid, the potential bias in 2SLS estimates could even exceed the OLS bias (Hahn and Hausman 2005). To confirm the validity of our instruments in the 2SLS model, we have reported several post-estimation results in Table 4. The first test in this regard is for the under identification of instruments [i.e., Kleibergen and Paap (2006) rk statistic]. Its *p*-value is less than 0.05 which rejects the null hypothesis that the excluded instruments are not correlated with the endogenous variables. Next, we tested the overidentification of instruments based on Hansen's J statistic. The *p*-value greater than 0.05 for Hansen's J statistic validates our instruments rejecting the null hypothesis that the excluded instruments are valid. We also reported heteroskedasticity-robust Kleibergen–Paap Wald rk F statistic to test the weak identification hypothesis and compared the value of F statistic to the Stock and Yogo (2005) IV critical values at 5% significance level.[1] As the value of F statistics is greater than the critical value (10% maximum IV size bias), we conclude that our IV estimators have a maximum relative size distortion of 10% rejecting the null hypothesis at 5% significance level.

For comparative purposes, we also reported the results of the fixed effects model incorporating both bank and year fixed effects. The results reported in Table 4 (model 2) also indicate the positive relationship between REN and DD. However, fixed effects estimation is considered to have very limited ability in handling dynamic endogeneity (Wintoki et al. 2012).

Robustness Tests

We performed several tests to confirm the robustness of our results as discussed below.

[1] Based on Stock and Yogo (2005), Stock-Yogo weak ID test critical values for Cragg–Donald *F* statistic and i.i.d. errors are: 5% maximal IV relative bias: 16.85; 10% maximal IV relative bias: 10.27; 20% maximal IV relative bias: 6.71; 30% maximal IV relative bias: 5.34; 10% maximal IV size: 24.58; 15% maximal IV size: 13.96; 20% maximal IV size: 10.26; 25% maximal IV size: 8.31.

Robustness Test with the Alternate Proxy for Bank Risk

We re-estimated our baseline results using two alternate measures of bank risk i.e., distance to insolvency (DI) and distance to capital (DC).

Distance to Insolvency (DI)

Building on Merton's model of DD (Merton 1974), and incorporating insights from Leland's structural model of credit risk (Leland 1994), Atkeson et al. (2017) introduced a more robust approach to measuring corporate financial soundness referred to as the distance to insolvency (DI). This measure indicates the distance between the insolvent condition and the current position of a firm with due consideration to equity volatility. For calculating distance to insolvency (DI) for T-t maturity, we used Eq. (2) for each year from 2006 to 2017.

$$DI_t = \left(\frac{A_t - L_t}{A_t}\right) * \frac{1}{\sigma_A} \tag{5}$$

here A_t and L_t represent assets and liabilities at time t whereas R_f and σ_A indicate risk-free rate and volatility of assets value.

We re-estimated the same, pooled OLS, fixed effects, dynamic OLS, and 2SLS models for DI, and results are reported in Table 5. To ensure the comparability of results, we incorporated the same bank-specific and country-specific controls in all the models. Like DD, the relationship of DI with REN is dynamic hence the results of OLS are not reliable. 2SLS estimation which is capable of handling dynamic endogeneity confirms the robustness of our results with alternate measure (DI) at 5% level of significance. We have reported various post-estimation tests to confirm the validity of our instruments in the 2SLS model.

Distance to Capital (DC)

Similar to DI, distance to capital (DC) is another derivation of the DD measure. It adjusts the DD for the Basel framework's capital adequacy ratio and Prompt Corrective Action (PCA) framework. The Basel Committee on Banking Supervision (BCBS) recommends banks keep some buffer capital above the regulatory requirements for more effective risk management. Secondly, instead of the face value of a bank's liabilities, its consideration of capital thresholds (as suggested by the PCA framework) allows banking regulators to intervene timelier (Aggarwal and Jacques 2001). Following Liu et al. (2006), we used Eq. 6 to calculate DC.

$$\mathrm{DC}_t = \left[Ln\left(\frac{A_t}{\frac{1}{1-\mathrm{CAR}_t}L_t}\right) + \left(\mu - 0.5\sigma_A^2\right)T\right]\left(\sigma_A\sqrt{T}\right)^{-1} \tag{6}$$

Table 5 Robustness test (alternate proxy for bank risk: distance to insolvency risk)

Variables	Model 1 Pooled OLS	Model 2 Fixed Effects	Model 3 Dynamic OLS	Model 4 2SLS
Renewable energy (REN)	0.014	0.435	− 0.005	0.934**
	(0.089)	(0.277)	(0.039)	(0.364)
Bank size	0.465	− 0.440	0.092	− 0.491
	(0.292)	(0.336)	(0.129)	(0.362)
Bank leverage	− 0.047	0.004	0.011	0.007
	(0.063)	(0.049)	(0.029)	(0.049)
Bank profitability (ROE)	0.004	0.081	0.001	0.095
	(0.085)	(0.068)	(0.036)	(0.069)
Market value (PB ratio)	0.255	0.121	0.011	0.898
	(1.130)	(0.529)	(0.541)	(0.559)
Revenue growth	− 0.049	− 0.071	− 0.017	− 0.057
	(0.030)	(0.060)	(0.014)	(0.050)
Corruption control index	− 0.755***	− 0.466	− 0.163*	− 0.452
	(0.198)	(0.315)	(0.087)	(0.291)
Political stability index	0.202***	− 0.205*	0.023	− 0.115
	(0.060)	(0.113)	(0.026)	(0.093)
Government effectiveness	− 0.551**	0.833	− 0.053	0.717
	(0.221)	(0.537)	(0.102)	(0.470)
Voice and accountability index	0.670***	0.301	0.160	0.361
	(0.220)	(0.538)	(0.101)	(0.553)
Rule of law	0.389**	1.252	0.072	1.217
	(0.195)	(0.787)	(0.086)	(0.762)
Regulatory quality	− 0.162	− 0.725*	− 0.060	− 0.573
	(0.205)	(0.434)	(0.090)	(0.374)
Lagged DI			1.154***	

Table 5 (continued)

Variables	Model 1 Pooled OLS	Model 2 Fixed Effects	Model 3 Dynamic OLS	Model 4 2SLS
			(0.022)	
Constant	20.670	− 84.652	0.684	
	(12.986)	(62.241)	(5.899)	
Observations	564	564	511	558
R^2	0.115	0.617	0.863	0.110
Bank fixed effect	No	Yes	No	Yes
Year fixed effect	No	Yes	No	Yes
F-test p-value	0.000	0.000	0.000	0.008
Kleibergen–Paap rk LM statistic p-value (under identification test)				0.000
Cragg–Donald Wald F statistic (weak identification test)				141.161
Kleibergen–Paap rk Wald F statistic (weak identification test)				112.214
Hensen J statistic p-value (overidentification test of all instruments)				0.446

This table presents the results of OLS regression estimation (Model 1, 2, and 3) and 2SLS estimation (Model 4) of the relationship between renewable energy (REN) and bank risk (distance to default (DD)). The standard errors in model 2 (reported in parentheses) are based on the Windmeijer correction for heteroscedasticity and clustering. Asterisks ***, ** and * indicate significance at 1%, 5% and 10%, respectively. p-values are based on robust standard errors. Tests in Model 4 also include Hansen J Test, Kleibergen–Paap LM Test p-value, Cragg–Donald Wald Test, Kleibergen–Paap Wald F Test and Hensen J statistic p-value

To compare the results, we re-estimated the same pooled OLS, fixed effects, dynamic OLS, and 2SLS models for DC and reported the results in Table 6. All the models incorporate the same bank-specific and country-specific controls.

After the confirmation of the dynamic nature of the relationship between DC and REN in model 3, the results in model 1 (static OLS) and model 2 (fixed effects) are irrelevant. Model 4 (2SLS) shows a statistically significant relationship between DC and REN and corroborates our main results that an increase in REN significantly reduces banks' default risk by increasing DD. We have reported various post-estimation tests to confirm the validity of our instruments in the 2SLS model.

Robustness Test with the Alternate Model Estimation Technique

Although 2SLS is acknowledged as an appropriate technique to account for dynamic endogeneity, the dynamic panel generalized method of moments (GMM) estimator GMM is sometimes considered more reliable. To ensure that our baseline results are robust to the choice of estimation method, we estimated the relationship between REN and DD using system GMM as per Eq. 7.

$$\mathrm{DD}_{it} = \alpha + \beta_1 \mathrm{DD}_{it-1} + \beta_2 \mathrm{REN}_{it} + \Omega_{it} + T \cdot \lambda + \eta_i + \varepsilon_{it} \tag{7}$$

here Ω_{it} is a vector of control variables (bank size, bank leverage, bank profitability, market value, revenue growth, corruption control index, political stability index, government effectiveness, voice and accountability index, rule of law, and regulatory quality). $T \cdot \lambda$ is the vector of year dummies, η_i is unobserved bank-specific effects and ε_{it} represents error term. The results in model 4 (Table 7) validate our baseline findings at 5% level of significance and confirm that an increase in REN significantly increases DD. However, the results of GMM cannot be trusted unless the instruments are proved to be valid (Stock et al. 2002). Similarly, the presence of autocorrelation can also lead to biased estimates. To test the validity of instruments and absence of autocorrelation, we included several diagnostic tests as suggested by Arellano and Bond (1991) which are Henson eJ test of overidentifying restriction and the Arellano-Bond Test for second-order serial correlation [the AR (1) and AR (2)]. To ensure that model is free from any bias due to first- and second-order autocorrelation, we reported AR1 and AR2 in our results for system GMM. Following the criteria suggested by Roodman (2009), we are rejecting the null hypothesis of no serial correlation for AR1 (p-value of 0.002) but not for AR2 (p-value of 0.313). To test the null hypothesis that the instruments are correctly identified, we reported p-value for Henson eJ test of overidentifying restriction. Its p-value (0.588) doesn't reject the null hypothesis that the instruments are correctly identified. According to Roodman (2009), if the number of groups in the model is greater than the number of instruments, it is another indication of the reliability of instruments. Our model successfully satisfies this diagnostic test as well.

Table 6 Robustness test (alternate proxy for bank risk: distance to capital risk)

Variables	Model 1	Model 2	Model 3	Model 4
	Pooled OLS	Fixed effects	Dynamic OLS	2SLS
Renewable energy (REN)	− 0.213*	− 0.191	− 0.073	1.326**
	(0.122)	(0.567)	(0.104)	(0.516)
Bank size	0.681*	− 0.086	0.556	− 0.169
	(0.399)	(0.600)	(0.342)	(0.557)
Bank leverage	− 0.093	0.004	− 0.071	− 0.051
	(0.087)	(0.068)	(0.076)	(0.067)
Bank profitability (ROE)	0.041	0.058	− 0.047	0.124
	(0.116)	(0.088)	(0.097)	(0.096)
Market value (PB ratio)	− 1.251	− 0.900	0.094	1.501
	(1.542)	(0.905)	(1.443)	(0.919)
Revenue growth	− 0.053	− 0.081	− 0.038	− 0.058
	(0.041)	(0.074)	(0.038)	(0.061)
Corruption control index	− 0.813***	− 0.184	− 0.310	− 0.395
	(0.270)	(0.359)	(0.232)	(0.338)
Political stability index	0.288***	− 0.370	− 0.050	− 0.186
	(0.083)	(0.285)	(0.072)	(0.228)
Government effectiveness	− 0.373	1.105	0.214	0.973*
	(0.302)	(0.685)	(0.271)	(0.588)
Voice and accountability index	1.146***	0.264	0.834***	0.567
	(0.300)	(0.809)	(0.269)	(0.790)
Rule of law	0.270	0.460	− 0.147	0.437
	(0.268)	(0.591)	(0.229)	(0.544)
Regulatory quality	− 0.705**	− 0.529	− 0.448*	− 0.247
	(0.280)	(0.473)	(0.240)	(0.341)
Lagged DC			1.031***	

Table 6 (continued)

Variables	Model 1	Model 2	Model 3	Model 4
	Pooled OLS	Fixed effects	Dynamic OLS	2SLS
			(0.056)	
Constant	29.604*	− 55.445	− 13.672	
	(17.830)	(98.167)	(15.901)	
Observations	560	560	507	556
R^2	0.096	0.506	0.470	0.049
Bank fixed effect	No	Yes	No	Yes
Year fixed effect	No	Yes	No	Yes
F-test p-value	0.000	0.000	0.000	0.000
Kleibergen–Paap rk LM statistic p-value (under identification test)				0.000
Cragg–Donald Wald F statistic (weak identification test)				139.143
Kleibergen–Paap rk Wald F statistic (weak identification test)				109.239
Hensen J statistic p-value (overidentification test of all instruments)				0.4479

This table presents the results of OLS regression estimation (Model 1, 2, and 3) and 2SLS estimation (Model 4) of the relationship between renewable energy (REN) and bank risk (distance to default (DD)). The standard errors in model 2 (reported in parentheses) are based on the Windmeijer correction for heteroscedasticity and clustering. Asterisks ***, ** and * indicate significance at 1%, 5% and 10%, respectively. p-values are based on robust standard errors. Tests in Model 4 also include Hansen J Test, Kleibergen–Paap LM Test p-value, Cragg–Donald Wald Test, Kleibergen–Paap Wald F Test and Hensen J statistic p-value

Table 7 Robustness tests (exogenous shock and alternate estimation technique)

	Model 1	Model 2	Model 3	Model 4
	2SLS	2SLS	2SLS	System GMM
Variables	Year 2007	Year 2008	Year 2009	
Renewable energy (REN)	0.768**	0.757*	0.747**	0.033**
	(0.341)	(0.426)	(0.368)	(0.016)
Bank size	− 0.284	− 0.476	− 0.551	− 0.033
	(0.371)	(0.456)	(0.438)	(0.146)
Bank leverage	0.016	0.011	0.008	− 0.089
	(0.057)	(0.060)	(0.055)	(0.081)
Bank profitability (ROE)	0.143	0.153	0.117	− 0.010
	(0.088)	(0.108)	(0.099)	(0.029)
Market value (PB ratio)	1.693**	1.363**	1.528**	− 0.714
	(0.810)	(0.666)	(0.746)	(1.028)
Revenue growth	− 0.126	− 0.078	− 0.076	− 0.010
	(0.095)	(0.071)	(0.070)	(0.008)
Corruption control index	− 0.516	− 0.669	− 0.520	− 0.083
	(0.317)	(0.417)	(0.343)	(0.096)
Political stability index	− 0.081	− 0.072	− 0.154	0.035
	(0.109)	(0.117)	(0.140)	(0.039)
Government effectiveness	0.856**	1.129*	1.077*	− 0.091
	(0.424)	(0.637)	(0.602)	(0.119)
Voice and accountability index	0.736	0.488	0.379	0.079
	(0.594)	(0.733)	(0.682)	(0.134)
Rule of law	1.347	1.964*	1.635*	0.022
	(0.851)	(1.121)	(0.958)	(0.062)
Regulatory quality	− 0.664	− 0.764	− 0.755	0.026
	(0.459)	(0.500)	(0.501)	(0.104)
Lagged DD			1.148***	

Table 7 (continued)

	Model 1 2SLS	Model 2 2SLS	Model 3 2SLS	Model 4 System GMM
			(0.014)	
Constant				4.364
				(5.354)
Observations	509	509	509	467
R^2	0.129	0.119	0.114	
Bank fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
F-test	0.007	0.037	0.003	0.000
Kleibergen–Paap rk LM statistic *p*-value (under identification test)	0.000	0.000	0.000	
Cragg–Donald Wald *F* statistic (weak identification test)	133.843	129.067	141.112	
Kleibergen–Paap rk Wald *F* statistic (weak identification test)	83.742	79.662	92.302	
Hensen J statistic *p*-value (overidentification test of all instruments)	0.176	0.323	0.3684	0.588
Number of instruments				49
Number of groups				55
AR-2 *p*-value				0.002
AR-2 *p*-value				0.313
Difference-in-Hansen J. for GMM style (*p*-value)				0.411
Difference-in-Hansen J. for IV style (*p*-value)				0.566

This table presents the results of 2SLS estimation (Model 1, 2 and 3) and System GMM estimation (Model 4) of the relationship between renewable energy (REN) and bank risk [distance to default (DD)]. The standard errors in model 2 (reported in parentheses) are based on the Windmeijer correction for heteroscedasticity and clustering. Asterisks ***, ** and * indicate significance at 1%, 5% and 10%, respectively. *p*-values are based on robust standard errors. Tests in Model 4 also include Hansen *J* Test, Kleibergen–Paap LM Test *p*-value, Cragg–Donald Wald Test, Kleibergen–Paap Wald *F* Test and Hensen J statistic *p*-value (overidentification test of all instruments). GMM model (4) also report on *F*-test, AR-1 and AR-2, Hansen J. test, Difference-in-Hansen J. for GMM style (*p*-value), Difference-in-Hansen J. for IV style (*p*-value), number of groups and number of instruments

Robustness to Exogenous Shock (Global Financial Crisis) and effectiveness of results during COVID-19

The novel coronavirus disease (COVID-19) has caused a shock in both developed and developing economies by pushing millions of people under lockdown, throwing the global supply chains into disarray, and bringing economic activities to a standstill (Carlsson-Szlezak et al. 2020). Considering the time span of this study i.e., 2006–2017, we couldn't accommodate COVID-19 span or test the validity of our results to COVID-19 exogenous shock. However, due to its similarity with GFC in causing economic upheaval and posing an enormous risk to the financial markets (Kinateder et al. 2021; Hassan et al. 2021), we tested the robustness of our results to the exogenous shock of GFC which started in 2007 and lasted until mid-2009. To this end, we estimated 2SLS models after excluding 2007, 2008, and 2009 separately in three models. The results for each model are given in models 1, 2 & 3 in Table 7. The relationship between REN and DD is significant in all the models.[2] Post-estimation tests confirm the validity of instruments in all three models. Based on these findings, we assume that our results are equally relevant and effective during the current pandemic as well for risk management in the banks and worldwide sustainable development.

Discussion of Results and Conclusion

The corporate sector is one of the most critical players in sustaining the environment and defining its future. It not only consumes more than 40% of the total electricity supply in the world but also burns tons of fossil fuels to perform its operations. Merely these two factors resulted in 66.72% of global CO_2 emissions during the 2008–2013 time span (Martí-Ballester 2017). This rapidly deteriorating climatic quality is mounting pressure on the corporate sector to reduce carbon emissions by adopting renewable energy.

But the capital-intensive nature of this transition renders financial institutions particularly banks the most influential players whose serious contribution can facilitate a smooth transition to sustainable development. But this much-needed financial support from banks is difficult to secure unless they are ensured that such investments would not risk their own survival. This motivated us to investigates the relationship between the share of renewable energy in the total energy supply of a country and banks' default risk. To this end, we obtained data on 80 international banks from 20 countries in the 2006–2017 period. After establishing the dynamic nature of the relationship between REN and DD, we used the 2SLS estimation technique and found a positive relationship between REN and DD. To confirm the robustness of our results, we also employed other proxies of the bank's default risk i.e., DI and DC, and re-estimated our model with system GMM. Moreover, the robustness of the results was also ensured for each of the three GFC years as an exogenous shock.

[2] At 5% in model 1 & 3 and at 10% in model 2.

Our results imply that when banks finance the corporate sector to implement renewable energy, the transition to renewable sources enhances borrowing firms' profitability and ultimately their probability to pay back bank loans. These findings can also be interpreted in the light of various theoretical perspectives. For example, according to stakeholder theory (Freeman 1984), apart from shareholders, a firm has an extended responsibility to look after the interests of a wider set of stakeholders. As discussed by Pfeffer and Salancik (1978), based on the resource dependence theory, a firm is dependent on these stakeholders to procure the resources which are indispensable for its operations. To gain stakeholders' support and operate successfully in a society, a firm must listen and respond to these stakeholders' concerns, one of which is environmental sustainability (Mathiesen et al. 2011). Investing in renewable energy can help a firm to align its business interests with the interest of the stakeholders. According to legitimacy theory (Dowling and Pfeffer 1975), this alignment of interests enhances a firm's acceptance in society. The higher acceptance and reputation of a firm ultimately enable it to charge a premium for its products that enhance its profitability (Miles and Covin 2000). Moreover, demand and consumption of its products can increase significantly (Hart and Ahuja 1996) as the consumers consider them more valuable (Spangenberg et al. 2010). This increased profitability of the firm enhances its capability to pay back bank loans.

Hence, financing renewable energy in the corporate sector reduces the default risk of banks. Otherwise, if the bank advances loan to energy producers for installing renewable energy projects, the energy producers sell their product (renewable energy) to the corporate sector. In this case, the higher profitability of firms due to renewable energy enhances their capability to pay their energy bills. Timely paid bills by the corporate sector which is the revenue/profitability for energy producers help them to pay back bank loans on time reducing lending bank's default risk.

The practical implication for those banks seeking to extend credit towards renewable energy projects is that lending the renewable energy sector can reduce their default risk. The research findings infer that the policymakers in the central banks should design banking policies and regulations to encourage the participation of subsequent banks in the renewable energy sector. Moreover, policymakers at the national level are suggested to initiate national programs to increase awareness, demand, and supply of renewable energy in a country as it will be a win–win situation for both the corporate and financial sectors. The transition to renewable energy is also a part of the 17 Sustainable Development Goals (SDGs) adopted by all United Nations Member States in 2015 for achieving the 2030 Agenda for Sustainable Development. Hence, our findings imply that international initiatives such as the SDGs by the United Nations should be welcomed and implemented more seriously by the member countries in the spirit of worldwide sustainability.

Several caveats of this study need to be mentioned which open up avenues for future research. The study used country-level data on renewable energy share to explore its impact on banks' risk. To look from the other perspective, a future study could be conducted using firm-level data on renewable energy borrowing to identify how it affects the profitability and risk of borrowing firms and lending banks. The study is limited by its scope on 4 banks from 20 countries. However, the study can be extended by taking a larger sample size and incorporating more countries. Lastly, future researchers may extend this study by investigating do the institutional factors, both formal and informal that vary from country to country play any role in establishing a relationship between REN and bank risk.

Appendix A

Variable Definitions

Variable	Definition	Source and references
Dependent variables		
Distance to default risk (DD)	The distance between a bank's given position and default position	Kinateder et al. (2021) and Daly (2019)
Distance to capital risk (DC)	The distance between a bank's given position and insolvent condition	Kinateder et al. (2021) and Daly (2019)
Distance to insolvency risk (DI)	The distance between a bank's given position and capital threshold based on Basel framework's capital adequacy ratio and Prompt Corrective Action (PCA) framework	Kinateder et al. (2021) and Daly (2019)
Independent variable		
Renewable energy (REN)	The share of renewable energy in the total primary energy supply in a country	Safarzyńska and van den Bergh (2017a) and Najm and Matsumoto (2020)
Bank-level controls		
Bank size	Natural logarithm of a bank's total assets	Kinateder et al. (2021)
Bank leverage	Total debt of a bank divided by the total equity	Capasso et al. (2020)
Bank Profitability	The net income before extraordinary items divided by the total equity (ROE)	Trad et al. (2017)
Market value	Market price of the company stock divided by the book value of its share (P/B ratio)	Kinateder et al. (2021)
Revenue growth	The percentage of growth in the net revenue of the bank compared to the past fiscal year	Kinateder et al. (2021)
Country-level controls		
Corruption control index	The extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites and private interests. Source: World Governance Indicator – World Bank	Kinateder et al. (2021)

Variable	Definition	Source and references
Political stability index	The likelihood that the government will be destabilized by unconstitutional or violent means, including terrorism. Source: World Governance Indicator – World Bank	Kinateder et al. (2021)
Government effectiveness	The quality of public services, the capacity of the civil service and its independence from political pressures; and the quality of policy formulation. Source: World Governance Indicator – World Bank	Kinateder et al. (2021)
Voice and accountability index	The extent to which a country's citizens are able to participate in selecting their government, as well as freedom of expression, freedom of association, and a free media. Source: World Governance Indicator – World Bank	Kinateder et al. (2021)
Rule of law	The extent to which agent have confidence in and abide by the rules of society, including the quality of contract enforcement and property rights, the police, and the courts, as well as the likelihood of crime and violence. Source: World Governance Indicator – World Bank	Kinateder et al. (2021)
Regulatory quality	The ability of the government to provide sound policies and regulations that enable and promote private sector development. Source: World Governance Indicator – World Bank	Kinateder et al. (2021)

Appendix A outlines measurements/definitions/references of all variables which are employed throughout this research

Declarations

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

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