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Financial development and renewable energy adoption in EU and ASEAN countries☆

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ABSTRACT

The shift from carbon-based to green energy is pivotal in addressing climate change. However, this transition is expensive, and the availability of financing sources is a necessary precondition for the green transformation of the economy. We therefore examine the role of financial institutions and capital markets in facilitating this change, focusing on a heterogeneous sample of 32 EU and ASEAN countries covering the years 2000 to 2020. Our findings reveal a persistent preference by financial institutions and banks for carbon-intensive energy production, negatively impacting renewable energy consumption. Contrarily, developed capital markets demonstrate a positive influence on green energy initiatives, especially pronounced in EU countries. The results highlight a dichotomy in financial support for green energy transition. While traditional financial institutions lag in supporting renewable energy, developed capital markets show a positive effect for green energy production. Concluding, we advocate for an increasing financialization of renewable energy markets and enhanced regulatory support for banks and financial institutions in supporting renewable energy business models.

1. Introduction

Up until now, all world climate conferences have ended without major progress to green energy production. The race to climate-friendly renewable energy production and consumption, away from carbon intensive energy sources, is a central challenge for humanity in the 21st century. Energy production, as one of the major emitters of greenhouse gases (GHG), which accounts for nearly two thirds of total emissions (Khan et al., 2017), plays an especially important role. At the same time, sufficient and affordable energy sources continue to be a fundamental basis for prosperity and economic welfare (Apergis and Danuletiu, 2014). Compared to other world regions, the European Union tries to be a pioneer in the development, but also in the promotion, of alternative energy sources. On the other hand, emerging economies, in particular the ASEAN countries, are also achieving significant progress in the introduction of modern green technologies. Especially after the Paris Climate Agreement, both regions put supranational efforts[1] in place to promote renewable energies and to facilitate challenges imposed by the necessary green transition. The comparison of these two regions can therefore present an important contribution to our understanding of how different political and financial environments contribute and support the green economic transformation. Surprisingly, this important topic has not yet been thoroughly analyzed. Therefore, we contribute to this gap in the in the literature.

At the current stage of discussion, it is still impossible to foresee the costs and time length of the transition to renewable energy sources.

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[1] The EU has largely introduced goals for renewable energies adoption within the Renewable Energy Directive 2018 (https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:02018L2001-20220607). The ASEAN has set an aspirational target to increase the component of renewable energy (RE) to 23% by 2025 in the ASEAN total primary energy mix within the ASEAN Plan of Action for Energy Cooperation (APAEC) 2016–2025 (https://asean.org/wp-content/uploads/2021/08/APAEC-2016-2025-Phase-I.pdf).

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Especially in the years since the Paris Climate Agreement in 2015, the first significant policy and financial efforts have been conducted. These include, for example, the European "Green Deal" and the ASEAN Plan of Action for Energy Cooperation. Furthermore, the Covid 19 pandemic with its massive restrictions and the associated initial lower energy consumption, has had a strong impact on price of renewable and fossil energy sources (Horky et al., 2022) and financial markets (Albrecht et al., 2023). Finally, since February 2022, Europe has been confronted with the war in Ukraine and unprecedented supply reductions causing energy shortages and corresponding price increases for fossil fuels. Nevertheless, there is general agreement both in the academic research and at the policy level that a sufficiently high level of financial development is a necessary precondition for the green- energy transition. It is generally accepted that renewable energy production requires high investment, while its short-term returns are lower than the returns on fossil energy (Kim and Park, 2016). Last but not least, the use of renewable energies is usually facing a higher risk because investors have less experience in this field and the technological development is still very dynamic.

There is already a large body of literature dealing with the financial development levels of different country samples and their impact on pollution, environmental degradation, and renewable energy production and consumption. However, the results are mixed due to several reasons, in particular the heterogeneity of the analyzed countries and applied methodological approaches. The definition of financial development plays a crucial role in these studies. Financial development can be proxied by a variety of different measures such as stock market measures, domestic credit supply, and different FDI related measures, usually taken as a percentage of GDP. Despite these differences, we must keep in mind that financial development includes a large variety of different aspects (Svirydzenka, 2016). The financial institutions and capital markets contain heterogenous agents with highly different motivation reasons and behavioral drivers or biases. The IMF financial development index for 2022 tries to address these complexities by designing different levels of financial development. Therefore, we prefer this new indicator to simple indicators of financial development. The structure of this indicator allows us to reflect that the financial system in the EU countries is strongly bank based, while the majority of ASEAN economies rely more strongly on capital markets (Allen et al., 2004).

Using the IMF data, we define financial development levels in two steps. We use the IMF indicators for financial institutions and capital markets. Thus, we can distinguish traditional banking and financing via capital markets. Furthermore, we exploit the heterogeneity of policies and cultures by using a highly diverse sample of 26 European and 6 ASEAN countries. Political and cultural factors, as well as green preferences and technological development, are crucial when it comes to the adoption of effective environmental policies (Mutascu et al., 2023). For the total of 32 countries, we consider the period from 2000 to 2020, which includes the major financial crisis of 2007/2008 as well as the period after the Paris Climate Agreement in 2015, and the beginning of the COVID-19 pandemic. Finally, we apply a set of different panel estimation techniques to ensure the robustness of our results. These include standard fixed-effects estimations and Fully Modified OLS (FMOLS), as well as a Pooled Mean Group Estimator, to uncover the long-run relationship.

Our paper endeavors to fill the literature gap in the following four areas: First, we are able to draw a more robust picture of the current energy transition process based on a heterogenous country sample and a variety of methodologies. In doing so, we contribute to the understanding of often earlier ambiguous results in the literature. Second, we capture a broad set of policy factors through a principal component analysis of sustainable development goals (SDGs) and their fulfillment levels. This approach allows us to address, at least partially, the endogeneity issues in the investigation of renewable energy adoption. Third, our results show strong negative effects of the development of financial institutions on renewable energy consumption in Europe and high-income countries. It seems that these financial institutions, in general, tend to promote carbon intensive, traditional industries. On the contrary, the development of capital markets shows positive effects on renewable energy consumption in the EU and in high-income countries. Furthermore, developed capital markets tend to have a negative effect on the carbon intensity of the energy production in these areas. Fourth, our results show completely diverging effects in the growth-oriented ASEAN countries. In that way, our study highlights the need to take into account different backgrounds and development stages of regions when investigating the progress towards sustainability.

The rest of the paper is structured as follows: Section 2 provides a literature review, and Section 3 describes the datasets. The methodological explanation follows in Section 4. Section 5 discusses the results and the robustness analysis, and Section 6 concludes and derives policy implications.

2. Literature review

Currently, hardly any other field is as vital as energy economics in scientific research, as it is a groundbreaking field of research for dealing with the challenges of climate change and energy transition. It is well known that energy production is an extremely capital-intensive process due to the high level of investment in production and power plants and R&D. Furthermore, climate-relevant finance is a key for reaching the 1.5 °C goal and contributes to multiple SDGs (Iacobuţă et al., 2022). For renewable energy producers it is often easier to obtain public funds than private funds, especially in the initial phase of investment (Przychodzen and Przychodzen, 2020).

We can therefore assume that high-tech energy production requires a high level of industrial development, but also a certain degree of financial development. Deregulation, new technologies, and political-economic crises, however, impose great risks to producers and wholesale energy buyers (Paraschiv et al., 2015). Renewable energies, in particular, are associated with a significant degree of financial risk due to high investment costs in technologies, and their future prospects are often ambiguous (Kim and Park, 2016). At the same time, a higher level of financial development, and thus better information, flows between the relevant agents. In addition, broader investment opportunities should reduce the costs of renewable energy investments and thus support the energy transition (Shahbaz et al., 2021). In fact, the analysis of the topic is complex due to the interplay of economic, geo-political, cultural, and methodological aspects (Mutascu, 2023). Therefore, the literature often shows ambiguous results regarding financial development. There are also opposing streams present: First, there is literature that postulates a reduction of emissions through financial development. Second, there is research that finds an increase of emissions through financial development. Third, there are authors who show ambiguous or weak and insignificant effects (Khan et al., 2019). For the overview, we focus on the research that examines panel data, similar to our analysis. Additionally, there is a broad literature of single-country studies, usually examined with ARDL models. Reflecting the methodological differences, these results are not reviewed here.

To begin with, we take a look at the strand of literature that documents a reduction of emissions, or an environmental improvement related to better financial development. This strand of literature especially focuses on the fact that economic policies try to increase renewable energies by stronger financialization (Horky et al., 2022). The availability of affordable loans and investments for renewable technologies motivates production and consumption of these technologies. Tamazian et al. (2009) find evidence that financial liberalization is an important factor in combating environmental degradation in BRICS countries from 1992 to 2004. Saud et al. (2019) examine a large panel of 56 Belt and Road Initiative countries and find that, from 1980 to 2016, financial development enhances environmental quality by negatively influencing CO_2 emissions. For their analysis they use 3 different indicators of financial development provided by the World Bank. Al-

Mulali et al. (2015a) examine a large sample of 93 countries covering the period 1980–2008. They find that financial development reduces environmental degradation with a significant negative effect on the ecological footprint for higher income countries, while it shows no significant impact on the ecological footprints of lower income countries.

Up to now, the developed countries have received the main attention in the literature. Zafar et al. (2019) investigate 27 OECD countries from 1990 to 2014. They find in these countries, that in the long run, financial development significantly decreases CO2. This is also in line with the findings of Anton and Nucu (2020) who investigate the 28 current and former member states of the EU during the period from 1990 to 2015. They provide one of the few papers that explicitly looks at the development of different financial sectors and find that both the banking sector and the bonds and capital market have a positive effect on renewable energy consumption. They also emphasize that it is one of the major strategic objectives of the European Union to increase the renewable energy consumption level. Another study, investigating 23 countries listed in the renewable energy country attractiveness from 1985 to 2011, also concludes that financial development (domestic credit to the private sector) has a negative impact on CO2 emissions (Dogan and Seker, 2016). These countries reflect the top countries regarding the attractiveness of their renewable energy investment and deployment opportunities. Raheem et al. (2020) investigate the G7 countries from 1990 to 2014, and find a negative, but weak, effect of financial development on CO2 emissions on these countries.

The emerging economies are also frequently analyzed. Usman and Hammar (2021) investigate 16 Asian countries from 1990 to 2017 where they find that financial development accelerates environmental quality. However, they mention that no strong effect can be seen. Haldar and Sethi (2022) investigate a panel of 16 emerging countries from 2000 to 2018, with a specific emphasis on CO2 emissions from information and communication technologies. They also find evidence for a mitigating influence of financial development on CO2 emissions.

Summarizing this branch of literature, we can see that particularly strong positive effects are found for middle- and high-income countries. One of the reasons for this pattern is that financial development in low-income countries is generally still too weak compared with middle- and high-income countries (Al-Mulali et al., 2015a). Several studies also highlight the importance of political strategy, which is particularly pronounced in the EU (Anton and Nucu, 2020; Zafar et al., 2019).

The second major stream of literature takes the opposite perspective, arguing that financial development is associated with increased CO2 emissions and degraded environmental quality. One of the most seminal papers in this regard comes from Sadorsky (2010), who argues that financial development is an important driver of growth, and thus of energy consumption and CO2 emissions. Examining the BRICS countries with data from 1980 to 2007, Pao and Tsai (2011) find evidence that financial development, like economic growth, causes additional energy demand and thus additional emissions. Their analysis therefore directly contradicts the results of Tamazian et al. (2009) and confirms the assumptions postulated by Sadorsky (2010). It should be noted that they use FDI inflows as a measure of financial development. Usman and Balsalobre-Lorente (2022) come to the same conclusions, looking at a sample of 10 newly industrialized countries (NIC) over the period from 1990 to 2019. They also identify financial development as a driver of further industrial development and thus of emissions. This finding is confirmed by Wang et al. (2020) who also use a sample of newly industrialized countries. In another study, Al-Mulali et al. (2015b) specifically examine CO2 emissions in 23 European countries from 1990 to 2013, and conclude that financial development increases these emissions. Compared to their other study (Al-Mulali et al., 2015a) they focus explicitly on CO2 emissions and not on the broader topic of environmental degradation. Acheampong et al. (2019) investigate a sample of 46 sub-Saharan African countries for the period 1980 to 2015. By using fixed- and random-effects panel estimations they find that different measures of financial development significantly increase carbon emissions in these countries. Khoshnevis Yazdi and Ghorchi Beygi (2018) find similar long-run results for a sample of African countries by investigating the period from 1985 to 2015, utilizing Pooled Mean Group estimation. Yang et al. (2021) investigate the 6 GCC countries from 1990 to 2017, and find a negative impact of financial development, measured by the IMF Index, on environmental sustainability. Their result is significant for the single countries as well as for the overall panel. It is striking that many of the studies that find a positive relationship between financial development and environmental degradation look at relatively specific world regions (BRICS, GCC, NICs).

The third strand of literature to be presented finds ambiguous and nonsignificant effects of financial development on environmental degradation. Acheampong et al. (2020), for example, come to a differentiated conclusion when examining a broader panel. They use data from 83 countries over a period from 1980 to 2015, and find that financial development reduces CO2 emissions in developed and emerging countries, but increases them in frontier financial countries. Ehigiamusoe and Lean (2019) find a similarly ambivalent result in a panel of 122 countries from 1990 to 2014. In their study, they find that financial development has a negative effect on carbon emissions in high-income countries, but a positive effect on carbon emissions in low- and middle-income countries. Their result is striking when considering the first two strands of literature, and furthermore provides a nice link to what should be expected by the environmental Kuznets curve (EKC) hypothesis. Earlier, Khan et al. (2017) find a similar result. In their study of 34 countries from different continents, they find a positive effect of financial development on GHG emissions in Europe and a significant reduction in Asia and the Americas. By employing system-GMM, Omri et al. (2015) investigate 12 MENA countries from 1990 to 2011. In their panel, they find no significant relationship between financial development and carbon emissions. Similarly, Jamel and Maktouf (2017) find no significant causality for financial development and carbon emissions in a sample of 40 European countries from 1985 to 2014.

Actually, ambiguous results seem to dominate the literature. This is largely due to the heterogeneity of the country samples used, especially with regard to the level of development and cultural factors, but also with regard to the heterogeneous definition of financial development. The present paper addresses these issues by using a country sample consisting of two world regions and a multilayered approach to measure financial development.

3. Data

We use data covering 32 countries from 2000 to 2020. Our country sample consists of countries from regions of the world, EU countries and ASEAN countries, which are characterized as having large heterogeneity with regard to their cultures and economic policies. However, in the aftermath of the Paris Climate Agreement, both the ASEAN and the EU have put major intergovernmental policy efforts in place to promote and develop renewable energies. Therefore, these two world regions provide a fruitful ground for a comparative evaluation of the role of financial development for renewable energy adoption. The similarities in the dimensions “timing”, “clear goals” and “intergovernmental character” make these world regions an especially interesting natural experiment. We do not include other Asian countries such as China and India due to the lack of intergovernmental cooperation in the renewables sector, coherency issues, and lack of significant data availability. We include data from 26 EU countries and 6 ASEAN countries (see Table A1 in the Appendix). We could not include Malta, Brunei Darussalam, Laos, Cambodia, and Myanmar due to similar data reliability issues. While many earlier studies focus on highly homogenous country samples, the heterogeneity of our country sample can contribute new insights on energy transition in a comparative perspective. In addition, we use two different characteristics for the energy sector, namely the renewable-energy consumption per capita (RC) and the carbon intensity of electricity production (CI) in order to cover a broader picture of the energy transition. Per capita consumption of renewable energy is defined as the sum of energy consumed, in megawatt, from hydropower, wind, solar, geothermal, wave and tidal, and bioenergy. Carbon intensity is measured in grams of carbon dioxide equivalents emitted per kilowatt-hour of electricity produced.

Another major contribution of the analysis is the use of the IMF's new multifaceted financial development index. The overall IMF financial development indicator takes values between zero (0) and one (1). Compared to the traditional indicators used as proxies for financial development (e.g., domestic credit to private sector), this indicator exhibits several advantages. First, it has a very broad coverage and provides a multidimensional measure of financial development using eight financial variables (Svirydzenka, 2016). In addition, it provides sub-indicators of financial market development that include accessibility, efficiency, and depth of the financial development's dimensions. In particular, we use the subindices to measure financial institutions (FI) and capital markets (CM). The subindices themselves cover the depth and the accessibility of the financial institutions and markets.

Renewable energy is also a core element of the Sustainable Development Goals (SDG). We capture this dimension by incorporating an extensive dataset with indices for the achievement of each SDG[2] for each country. Therefore, we use index data from the SDG Tracker project (SDG Tracker, 2018). The achievement of each of the 17 SDGs is measured by several indicators, adding up to a list of 232 unique indicators. Within the SDG Tracker project, an index signifying the progress towards the unique goal is calculated for every country and year in our sample. Moreover, we include standard macroeconomic controls, i.e., data on GDP (in current USD), unemployment, and inflation retrieved from the World Bank Database (World Bank Group, 2023). A descriptive overview of the variables and the abbreviations can be found in Table 1. In the Appendix (Tables A1 to A4), the descriptive statistics for our country subsamples can be found. For the income split, we follow the World Bank Classification, combining lower-middle and upper-middle income into one group. The sample does not contain any low-income countries.

4. Methodology

4.1. Principal component analysis

We consider 17 different variables that describe the various aspects of SDGs, which are highly correlated (see Table 2). To overcome the problem of multicollinearity and to include as much information in our analysis as possible, we apply a two-step procedure. First, out of the extensive SDG dataset, we calculate principal components (PCs), using the loadings of the major PCs as additional covariates in our regression. The main target of the principal component analysis (PCA) is to find a smaller set of orthogonal variables, i.e., PCs, that can explain as much of the variation in the original variables as possible without being correlated.

As can be seen in Table 2, except for Goals 12 (Responsible Consumption and Production), 13 (Climate Action), and 14 (Life below Water), all the SDGs are strong and positively correlated. Oppositely, the three mentioned goals show strong negative correlations within the other goals (as in the case of SDGs 12 and 13) or barely any correlation (as in the case of SDG 14). A descriptive overview over the single SDG Index values can be found in Table A6 in the Appendix.

[2] The 17 Goals are: 1. No Poverty, 2. Zero Hunger, 3. Good Health and Well-Being, 4. Quality Education, 5. Gender Equality, 6. Clean Water and Sanitation, 7. Affordable and Clean Energy, 8. Decent Work and Economic Growth, 9. Industry, Innovation and Infrastructure, 10. Reduced Inequalities, 11. Sustainable Cities and Communities, 12. Responsible Consumption and Production, 13. Climate Action, 14. Life Below Water, 15. Life on Land, 16. Peace, Justice and Strong Institutions, 17. Partnerships for the Goals

Now, as the raw data are presented, the PCs can be calculated. The weights of the first PC, in order to satisfy the variance maximization, are given as:

$$\boldsymbol{w_1} = \underset{|w|=1}{\operatorname{argmax}} \left\{ \mathbf{w}^T Cov(\mathbf{SGDSGD}) \mathbf{w} \right\}, \tag{1}$$

therefore, the loadings $\boldsymbol{t_{1(i)}}$ of the first PC are given as:

$$\mathbf{t_{1(ii)}} = \mathbf{w_1} {}^* \mathbf{SDG_i} \tag{2}$$

Here, **SDG** is the matrix of our SDGs and $\boldsymbol{w}$ is the weight of the first PC. The subsequent PCs can be found by subtracting the sum of the previous PCs from the original data vector and extracting the next weight to maximize the variance of the new data matrix:

$$\widehat{\boldsymbol{SDG}}_k = \boldsymbol{SDG} - \sum_{pc=1}^{k-1} \boldsymbol{SDG}^* \mathbf{w_{pc}} {}^* \mathbf{w_{pc}^T}, \tag{3}$$

and subsequently repeating Eq. (1) with $\widehat{\boldsymbol{SDG}}_k$.

A scree plot, identifying the importance of the single principal components can be found in Fig. 1 in the Appendix. Based on the plot and the respective variance explained, we include the loadings of the first two principal components as covariates to our dataset. The respective loadings can be found in Table A7 in the Appendix. The most important deviation between the two principal components is that PC1 is negatively correlated with Goals 5 to 8, while PC2 is strongly positively correlated with these goals. Especially, Goals 6 to 8 can be connected to comparably high levels of economic and financial development. Furthermore, Goals 12 to 15 are strongly positively correlated with PC2, which are strongly policy-related goals. Considering these patterns, it seems that one of the principal components captures Western, policy-driven developments in high income countries, while the second principal component seems to capture more emerging-economies features. Having a look at the distribution of the weights for PC1 and PC2 across the subsets (Tables A2 to A5 in the Appendix), we can see mostly negative values for PC1 in the EU and high-income countries, while we can see positive values in the ASEAN and middle-income countries. Given this distribution and the correlations of the goals with the PCs (negative correlation and negative PC value results in positive absolute contribution), we could argue that PC1 and PC2 capture the developments in high-income countries and in the emerging economies (e.g., stronger needs of institutions and policies), respectively.

4.2. Empirical strategy

The analyzed time series are generally considered to be non-stationary, which is confirmed by standard panel unit root tests (Table 3). As we have a panel dataset with largely differing cultural, institutional, and economic factors, it is appropriate to apply the heterogenous autoregressive coefficients. Therefore, we apply two sets of unit root tests, the Im-Pesaran-Shin (IPS) test which allows for heterogenous autoregressive parameter (Im et al., 2003). The IPS-Test tests the H0 of "all panels contain unit roots", against the H1 of "some panels are stationary". For the sake of robustness, we further apply the Harris-Tzavalis (HT) unit root test with the assumption of a fixed-time dimension T, as we have a comparatively short time span of $T = 21$ (Harris and Tzavalis, 1999). The HT-Test tests the H0 of "panels contain unit roots" against the H1 of "panels are stationary."[3]

The results for both the original series as well as the first differences suggest the presence of unit roots for most series (except for CM and IR).

[3] The exact formulation of the H0 and H1 is important in unit root tests and slightly differs across the different tests. However, this can lead to important deviations in the results.

Table 1
Descriptive statistics.

	Obs	Mean	Std. Dev.	Min	Max	Jarque-Bera	Weak CD-Test
Renewables consumption (RC)	672	4.151	5.420	0.000	31.257	2269***	70.028***
Carbon Intensity (CI)	672	396.076	240.926	0.000	1060.820	24.512***	24.893***
Financial Institutions (FI)	672	0.607	0.178	0.137	0.927	29.392***	18.827***
Capital Markets (CM)	672	0.452	0.247	0.018	0.949	40.087***	12.67***
GDP per capita	672	25,958	22,351	390.09	124,081	585.47***	88.217***
Inflation rate (IR)	672	2.710	3.449	−4.478	45.667	71820***	57.412***
Unemployment rate (UR)	672	7.722	4.579	0.250	27.470	311.30***	17.317***
SDG – Principal Component 1 (PC1)	672	−0.677	2.386	−4.715	6.240	67.978***	94.941***
SDG – Principal Component 1 (PC2)	672	0.100	1.242	−3.726	2.723	31.949***	38.96***

Note: *, **, *** denote significance at the 10%, 5% and 1% level respectively. For testing the weak cross-sectional dependency (CD), we rely on Pesaran (2015), with H0: cross-sectional independence / weak cross-sectional dependence and H1: Strong cross-sectional dependence.
Source: own estimation.

Thus, there is a need to determine whether a long-run relationship exists between the analyzed variables. For this purpose, we perform the heterogenous panel cointegration test, according to Pedroni (1999, 2004) under the following specifications:

$$RC_{it} = \alpha_i + \delta_i t + \gamma_{1i} FI_{it} + \gamma_{ni}\mathbf{Z}_{it} + \varepsilon_{it} \tag{4}$$

$$CI_{it} = \alpha_i + \delta_i t + \gamma_{1i} FI_{it} + \gamma_{ni}\mathbf{Z}_{it} + \varepsilon_{it}, \tag{5}$$

with $i = 1, \ldots, N$ representing the countries in the panel and $t = 1, \ldots, T$ referring to the time period. The included variables are described above (see also Table 1). The parameters α_i and δ_i allow for country-specific fixed effects and deterministic trends. Furthermore, ε_{it} denotes the residuals that represent deviations from the long-run relationship. **Z** represents the vector of control variables (except IR) with γ_n being the respective parameters, $n = 3, \ldots, 7$. The GDP per capita is included as natural logarithms in all our estimations.

The panel cointegration tests are based on the within-dimension approach, including four test statistics and the between-dimension approach, including three test statistics (see Table 4). The within-dimension statistics are the *panel v, panel ρ, panel PP*, and *panel ADF*-statistics that take into account common time factors and heterogeneity across the countries in the data. The between-dimension statistics are the *group ρ, group PP*, and *group ADF*-statistics, that are based on the averages of the autoregressive coefficients given by the unit root tests of the residuals for the countries in the panel.

In summary, the panel cointegration tests confirm a long-run relationship among the analyzed variables. However, the results are somewhat mixed, and given the unit root test results as well as our general panel structure, no single methodology can be identified as being the best-fitting one. This is confirmed in the literature, as several different estimation methods have been used in similar settings. Considering the results of our PCA, we estimate a set of different models, with the following specifications:

$$RC_{it} = \beta_1 FI_{it} + \beta_2 FM_{it} + \beta_3 log\left(GDP\_capita\right) + \beta_{ni}\boldsymbol{Z}_{it} + \varepsilon_{it} \tag{6}$$

$$CI_{it} = \beta_{1i} FI_{it} + \beta_{2i} FM_{it} + \beta_3 log\left(GDP\_capita\right) + \beta_{ni}\boldsymbol{Z}_{it} + \varepsilon_{it} \tag{7}$$

$$RC_{it} = \beta_{1i} FI_{it} + \beta_{2i} FM_{it} + \beta_3 log\left(GDP\_capita\right) + \beta_{ni}\boldsymbol{PCA}_{it} + \varepsilon_{it} \tag{8}$$

$$CI_{it} = \beta_{1i} FI_{it} + \beta_{2i} FM_{it} + \beta_3 log\left(GDP\_capita\right) + \beta_{ni}\boldsymbol{PCA}_{it} + \varepsilon_{it} \tag{9}$$

Z identifies a standard set of controls (i.e., unemployment and inflation), while ***PCA*** identifies the artificially created set of Principal Components used to account for a multitude of influences. Unemployment and Inflation are important topics, directly measured and therefore included in the SDG indices. To avoid multicollinearity and to further see the robustness of our results, we do not use ***PCA*** and ***Z*** in one specification.

In the first step, we estimate a standard fixed-effects panel model with additional country and time effects. Subsequently, we estimate the fully modified OLS Estimator (FMOLS) for heterogenous panels as proposed by Pedroni (2001). The FMOLS technique for estimating the long-run relationship between the variables is used in various similar studies.[4] For the sake of robustness, we finally apply another technique for estimating the long-run relationship between the variables, i.e., the pooled-mean-group estimator proposed by Pesaran et al. (1999). Regarding the size of our sample splits, the FMOLS Estimator is superior to the maximum likelihood based PMG estimator in investigating the long-run relationship due to algorithmic convergence issues in small samples.

To address the challenges posed by our limited sample size, particularly in our subsamples, we supplement our analysis with kernel regression utilizing the Epanechnikov kernel. This non-parametric method does not require the assumption of asymptotic normality, making it suitable for small sample sizes. Furthermore, kernel regression offers additional insights into the relationships within our heterogeneous country sample regarding, e.g., possible non-linearities.

5. Results

Based on the presented tests, we can continue with the estimation of the long-run relationship between the variables. First, we present the results of the fixed-effects estimation in Table 5. Contrary to frequent public declarations, we can see that financial institutions still seem to favor the traditional, i.e., carbon-based energy industry. A higher degree of financial development in terms of financial institutions reduces the amount of renewable energy consumption per capita and increases the carbon intensity of energy production. A higher development of capital markets on the other hand seems to increase the renewable energy consumption and reduces the carbon intensity of energy production. However, these effects are only evident in the full sample and the EU countries. For the ASEAN countries, we see fundamentally different dynamics. In the fixed-effects models, the results for financial institutions and financial market developments are not significant.

Considering the results with our standard set of controls in Table A8 in the Appendix, the results are broadly confirmed. However, in the specification with the standard controls, capital markets exhibit significant positive effects for both renewable energy consumption and the carbon intensity of energy production. This finding is potentially in line with the ASEAN countries being mostly market-based emerging economies, i.e., capital markets facilitate cheap energy growth for the purpose of economic development. In Table A11 in the Appendix, we present the results for the sample, split by income class. For the high-income countries, we again find that financial institutions negatively affect environmentally-friendly energy, while capital markets positively affect renewable energy consumption.

[4] See, for instance, Shabaz et al. (2021) and Al-Mulali et al. (2015b), among others.

Table 2
Correlations of the SDGs.

	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10	G11	G12	G13	G14	G15	G16
G1																
G2	0.52***															
G3	0.86***	0.54***														
G4	0.80***	0.47***	0.85***													
G5	0.46***	0.41***	0.58***	0.45***												
G6	0.77***	0.55***	0.75***	0.67***	0.59***											
G7	0.54***	0.43***	0.54***	0.51***	0.58***	0.68***										
G8	0.65***	0.47***	0.66***	0.62***	0.66***	0.67***	0.59***									
G9	0.61***	0.50***	0.85***	0.63***	0.72***	0.66***	0.49***	0.65***								
G10	0.49***	0.51***	0.55***	0.36***	0.49***	0.54***	0.31***	0.65***	0.53***							
G11	0.70***	0.37***	0.82***	0.77***	0.52***	0.66***	0.46***	0.59***	0.71***	0.33***						
G12	−0.68***	−0.48***	−0.83***	−0.69***	−0.54***	−0.62***	−0.31***	−0.66***	−0.78***	−0.56***	−0.76***					
G13	−0.43***	−0.25***	−0.68***	−0.60***	−0.33***	−0.37***	−0.16***	−0.50***	−0.60***	−0.41***	−0.77***	0.79***				
G14	0.01	−0.06	−0.07	−0.01	0.23***	0.29***	0.25***	0.22***	0.07	−0.03	0.07*	0.05	0.05			
G15	0.55***	0.42***	0.52***	0.47***	0.49***	0.57***	0.49***	0.62***	0.43***	0.56***	0.49***	−0.47***	−0.38***	0.38***		
G16	0.71***	0.54***	0.81***	0.66***	0.59***	0.69***	0.43***	0.72***	0.77***	0.65***	0.63***	0.83***	−0.57***	0.060	0.51***	
G17	0.35***	0.18***	0.48***	0.38***	0.60***	0.47***	0.45***	0.48***	0.51***	0.30***	0.44***	−0.38***	−0.34***	0.15***	0.31***	0.35***

Source: own estimation.

Table 6 contains the results of our FMOLS estimation for our whole country sample. As in the fixed effects estimation, we find that financial institutions tend to have a negative impact on renewable energy consumption per capita in the full sample and the EU subsample, while we see a positive effect on carbon intensity. Contrary to this, especially in the EU, the development of capital markets seems to boost the transition to renewable energies by a significant negative effect on the carbon intensity. In the ASEAN countries, we see opposite effects. Exceptionally, financial institutions and capital markets foster the carbon intensity of energy production. Most interestingly, in this country sample, the development of capital markets even reduces the renewable energy consumption share. The results are confirmed in the specifications with the standard set of controls (Table A9 in the Appendix). These effects become even more pronounced when considering income levels (Table A12 in the Appendix). Generally, the FMOLS results strengthen the assumption that capital markets in the ASEAN countries boost cheap energy for growth purposes, while the capital markets in the EU countries are increasingly also characterized by smaller investors who seek long-run benefits in the green- energy sector. Finally, the main results are again confirmed by FMOLS for country income levels (Table A8 in the Appendix).

For the sake of robustness, we apply another alternative technique to estimate the long-run relationship of our variables as well as the short-run dynamics. For this purpose, we use the Pooled Mean Goup Estimator using maximum likelihood. However, this technique converges only for the whole sample and the largest sample subsamples, i.e., the EU and the high-income countries (see Table 7 with the PCs and also Table A10 in the Appendix with the standard controls).

The parameters of the long-run relationship in this model are particularly important. They show a significant negative effect of financial institutions on renewable energy consumption in the entire sample and across nearly all subsamples. We see similar positive coefficients for the capital markets, implying an adverse relationship, similar to the FMOLS results.

We can further observe positive parameter values for carbon intensity, which are, however, augmented by negative parameters in the short-run relationship. Although the results are somewhat weaker in the PMG Estimation, the findings strengthen the assumption that in ASEAN countries, financial institutions and capital markets may be generally committed more strongly to economic growth, thereby fostering cheap energy production. Furthermore, cultural and policy differences in investing actions and targets on capital markets could be an additional reason for this effect.

We extend our analysis by employing kernel regression, which allows us to deal with the relatively low number of observations, especially in the ASEAN and middle-income country subset. The results can be found in Tables A13 to A15 in the Appendix. Although some parameters differ in terms of significance, the kernel regression especially confirms the positive impact of capital markets on renewables production and consumption. Furthermore, the negative effect of financial institutions on renewables consumption is confirmed, especially for the standard set of control variables (Table A14 in the Appendix).

Summing up, the following Fig. 2 shows the average parameter values for all estimation strategies with the standard controls. The overall results show that the development of capital markets in the full set and the EU countries exerts a positive effect on the share of renewable energy consumption. In some specifications, we can find decreasing effects on the carbon intensity of energy production in these countries. On the contrary, financial institutions have stronger negative effects on the renewable energy consumption share. It seems that financial institutions, i.e., banks, support traditional business models for energy production. For the ASEAN countries, which are mainly middle-income countries, both financial institutions and capital markets exert a negative effect on environmentally friendly energy production and consumption. These countries are presumably characterized by economic growth and ensuring economic benefits. This is also in line with what

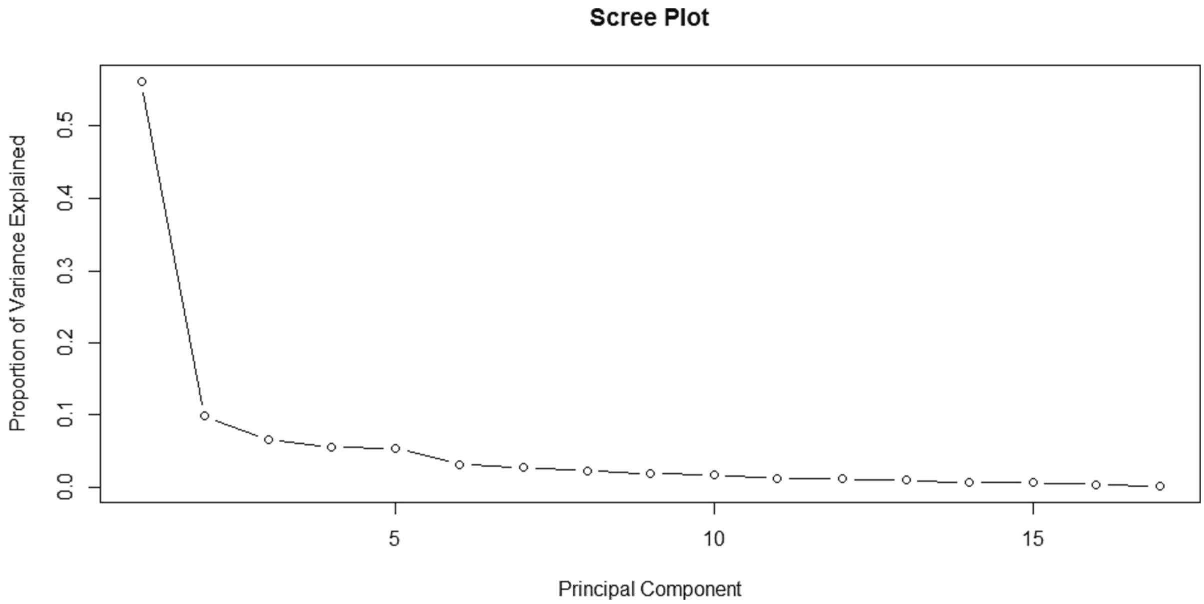

Fig. 1. Scree plot of the principal components.
Source: own estimation.

Table 3
Panel unit root tests.

	IPS	HT		IPS	HT
RC	−0.257	−0.768	ΔRC	−4.709***	−44.670***
CI	−1.167	−2.020**	ΔCI	−5.209***	−43.359***
FI	−1.479	1.301	ΔFI	−4.099***	−29.719***
CM	−2.262***	−7.878***	ΔCM	−5.240***	−38.949***
lnGDP_capita	−1.590	0.059	ΔlnGDP_capita	−3.502***	−27.956***
IR	−3.014***	−11.509***	ΔIR	−5.316***	−39.642***
UR	−1.330	0.790	ΔUR	−3.115***	−15.338***
PC1	−0.708	4.639***	ΔPC1	−5.093***	−39.908***
PC2	−1.512	1.137	ΔPC2	−4.564***	−36.200***

Note: *, **, *** denote significance at the 10%, 5% and 1% level respectively. For the IPS-Test, we report the *t*-bar statistic with thresholds of −1.690, −1.730, −1.820 for the 10%, 5% and 1% level of significance. For the HT-Test we report the respective *z*-values.
Source: own estimation.

could be expected by the environmental Kuznets curve theory.

Finally, our results clearly show that the relationship between financial development and the sustainability of energy consumption and production are influenced by regional specifics, i.e., a clear sustainability agenda, a focus on growth, a market or bank-based system, and the preferences of individual investors. Moreover, especially in the EU, we further see an effect of risk-averse financial institutions and more risk-taking capital markets. Financial institutions in the EU tend to favor traditional, and therefore safe, energy business models, while capital markets investors promote and invest in renewables with a potentially riskier, but higher, return given the political environment.

6. Conclusions

The production and use of renewable energies and the related reduction of GHG emissions is a central element in counteracting the progressive climate change. However, the transition to renewable energy is an expensive venture due to high development costs and high complexity of the necessary facilities. Access to financial resources is therefore essential. This paper examines the impact of financial development in a culturally heterogeneous country sample. In particular, it presents an analysis of differences between the development of financial institutions and capital markets.

The results suggest that financial institutions (banking) tend to prefer traditional, i.e., carbon- intensive, energy production and thus negatively influence renewable energy consumption. This is in line with the argument that financial institutions, as providers of safe deposits and investments, tend to be risk averse. The development of capital markets, on the other hand, seems to promote renewable energy consumption, at least in financially developed countries with a large population of small investors. In principle, the agents for the capital markets can take greater risks than financial institutions and are also influenced by behavioral factors such as individual (green) preferences. However, one can clearly see that cultural- or policy-induced factors seem to play a major role. ASEAN and EU countries appear to have fundamentally different dynamics. The analysis thus not only provides a deeper insight into the role of various aspects of financial development, but also clearly illustrates that general statements based on specific country samples can be difficult due to different non-observable factors.

Several policy implications can be derived from the results shown: The first and most important implication is to support financial institutions in promoting research and potentially perceived risky investment in the renewable energy sector. This can be done, for example, through clear policy requirements on ESG criteria in the area of bank lending and investment. Given the declining prospect of traditional energy industry, the risk assessment of this sector should be adjusted as soon as possible. Governmental default insurance for financial institutions in case of failure of innovative strategies, up to a certain

Table 4
Energy transition, panel cointegration tests.

Within Dimension	Test statistic	Between Dimension	Test statistic
Specification 1 for the whole sample			
Panel *ν*	−0.070		
Panel *ρ*	1.923*	Group *ρ*	4.128***
Panel *PP*	−5.621***	Group *PP*	−6.147***
Panel *ADF*	5.551***	Group *ADF*	6.231***
Specification 2 for the whole sample			
Within Dimension	Test statistic	Between Dimension	Test statistic
Panel *ν*	−0.466		
Panel *ρ*	2.105**	Group *ρ*	4.107***
Panel *PP*	−6.216***	Group *PP*	−7.630***
Panel *ADF*	5.055***	Group *ADF*	4.920***
Specification 1 for the EU sample			
Within Dimension	Test statistic	Between Dimension	Test statistic
Panel *ν*	−0.527		
Panel *ρ*	1.252	Group *ρ*	3.265***
Panel *PP*	−7.062***	Group *PP*	−7.938***
Panel *ADF*	5.675***	Group *ADF*	8.049***
Specification 2 for the EU sample			
Within Dimension	Test statistic	Between Dimension	Test statistic
Panel *ν*	−0.904		
Panel *ρ*	1.474	Group *ρ*	3.350***
Panel *PP*	−7.257***	Group *PP*	−8.784***
Panel *ADF*	−0.058	Group *ADF*	2.744***
Specification 1 for the ASEAN sample			
Within Dimension	Test statistic	Between Dimension	Test statistic
Panel *ν*	0.220		
Panel *ρ*	1.283	Group *ρ*	2.230**
Panel *PP*	−2.161**	Group *PP*	−2.242**
Panel *ADF*	1.350	Group *ADF*	1.921*
Specification 2 for the ASEAN sample			
Within Dimension	Test statistic	Between Dimension	Test statistic
Panel *ν*	−0.772		
Panel *ρ*	1.535	Group *ρ*	2.639***
Panel *PP*	−0.155	Group *PP*	0.071
Panel *ADF*	3.912***	Group *ADF*	3.904***

Note: *, **, *** denote significance at the 10%, 5% and 1% level respectively. We used Stata's xtpedroni command to calculate the test statistics. Inference is straightforward as the test statistics are N(0,1) distributed.
Source: own estimation.

degree, can also be considered. Second, the innovative potential of the capital markets should be exploited. The core element here, however, is an awareness among potential investors, of the issues of climate change. Particularly in the EU, with its free western-style capital markets, it is clear that investment in the renewable energy sector is dependent on capital markets to raise funds.

Given the existing differences observed between the ASEAN and EU countries, a deeper investigation covering more world regions could shed more light on this important issue. Especially, Africa and Latin America as emerging world regions, could be interesting cases. Another significant avenue for further research is to conduct a comparative analysis of different renewable energy sources within diverse financial landscapes. This study could compare the financial viability and attractiveness of various renewable energy sources – such as solar, wind, hydro, and bioenergy – in different financial contexts. This analysis could explore how the capital intensity and business models of these energy sources interact with the financial development stage of a country or region. For example, future research could further investigate whether the solar energy might be more appealing in countries with robust capital markets, while hydropower requiring significant state involvement and is geographically determined, might be more feasible in countries with strong government backing and suitable geographical features.

The time series used in this paper covers a comparably long period from 2000 to 2020, and thus includes major social and political changes in the framing of climate change, such as the Paris Climate Agreement and the Fridays-for-Future movement. However, the roles of financial development and capital markets should be continuously monitored in the future to account for more recent developments such as the COVID-19 pandemic and the Russian invasion of Ukraine. For future research, it is also worth looking at other underlying factors such as possible cultural differences.

CRediT authorship contribution statement

Florian Horky: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Visualization, Writing – original draft, Writing – review & editing. **Jarko Fidrmuc:** Conceptualization, Project administration, Validation, Writing – review & editing.

Table 5
Energy transition, fixed effects estimation with the PCs.

	Full Sample		EU		ASEAN	
	RC	CI	RC	CI	RC	CI
Financial	−5.338***	125.670***	−5.545***	84.975	−0.309	52.370
Institutions (FI)	(0.651)	(46.042)	(0.778)	(55.666)	(0.768)	(72.455)
Capital	2.362***	33.827	2.049***	23.276	0.745	43.015
Markets (CM)	(0.572)	(40.506)	(0.684)	(48.925)	(0.555)	(52.404)
Log of GDP per	0.035	60.022***	0.460	70.722***	0.408*	−2.250
Capita	(0.249)	(17.590)	(0.317)	(22.682)	(0.239)	(22.518)
SDG - Principal	0.436***	−45.007***	0.780***	−21.749	−0.123	−70.013***
Component 1 (PC1)	(0.164)	(11.590)	(0.221)	(15.816)	(0.106)	(10.022)
SDG - Principal	0.734***	−70.422***	0.748***	−51.119***	−0.474***	−64.234***
Component 2 (PC2)	(0.114)	(8.054)	(0.143)	(10.257)	(0.128)	(12.091)
Observations	672	672	546	546	126	126
Panels	32	32	26	26	6	6
R^2 (within)	0.653	0.477	0.684	0.499	0.675	0.652

Note: Values in the table represent regression coefficients. We use Stata's xtreg command to calculate the estimations. The dependent variables are RC – renewable consumption and CI – carbon intensity. *, **, *** denote significance at the 10%, 5% and 1% level respectively. Robust standard errors are reported in parentheses.
Source: own estimation.

Table 6
Energy transition, FMOLS estimation with the PCs.

	Full Sample		EU		ASEAN	
	RC	CI	RC	CI	RC	CI
Financial	−3.150***	164.390***	−3.900***	200.080***	0.130***	9.720***
Institutions (FI)	(−45.110)	(21.700)	(−38.620)	(21.590)	(−23.800)	(5.170)
Capital	0.370***	−186.720***	0.580***	−265.380	−0.520***	154.14***
Markets (CM)	(−20.020)	(5.050)	(−15.250)	(0.060)	(−14.490)	(11.54)
Log of GDP per	−0.630***	15.940***	−0.740***	21.780***	−0.160***	−9.35***
Capita	(−13.520)	(8.230)	(−6.500)	(10.410)	(−17.690)	(−2.67)
SDG - Principal	−1.360***	61.100***	−1.540***	75.730***	−0.600***	−2.290***
Component 1 (PC1)	(−111.500)	(30.880)	(−73.760)	(29.610)	(−103.950)	(9.680)
SDG - Principal	1.440***	−54.420***	1.720***	−58.140***	0.240***	−38.330
Component 2 (PC2)	(25.750)	(−40.080)	(23.750)	(−44.18)	(10.020)	(−0.600)
Observations	672	672	546	546	126	126
Panels	32	32	26	26	6	6

Note: Values in the table represent regression coefficients. We use Stata's xtcointreg command to calculate the estimations. The dependent variables are RC – renewable consumption and CI – carbon intensity. *, **, *** denote significance at the 10%, 5% and 1% level respectively. *t*-statistics are reported in parentheses.
Source: own estimation.

Table 7
Pooled Mean Group Estimation for the whole sample, the EU and the high-income countries with the PCs.

	Full Sample		EU		High-Income	
	RC	CI	RC	CI	RC	CI
	Short-Run Relationship					
Δ Financial	0.414	290.691**	0.665	285.983	0.871	329.812
Institutions (FI)	(1.127)	(144.801)	(1.412)	(196.838)	(1.438)	(210.074)
Δ Capital	1.583*	−153.487	1.987**	−167.627	2.278**	−181.785
Markets (CM)	(0.816)	(119.927)	(0.976)	(163.987)	(0.953)	(172.395)
Δ Log of GDP per	0.883**	15.388	1.196**	16.504	1.291**	0.121
Capita	(0.448)	(23.215)	(0.557)	(29.313)	(0.569)	(28.576)
Δ SDG - Principal	−0.877*	−9.416	−0.970*	−24.628	−1.026*	−29.620
Component 1 (PC1)	(0.470)	(23.468)	(0.574)	(32.102)	(0.596)	(34.417)
Δ SDG - Principal	1.194***	−59.340***	1.499***	−68.034**	1.514***	−67.095**
Component 2 (PC2)	(0.394)	(20.584)	(0.481)	(26.687)	(0.497)	(28.009)
EC	0.371***	0.375***	0.418***	0.395***	0.393***	0.369***
	(0.059)	(0.053)	(0.064)	(0.066)	(0.068)	(0.068)
	Long-Run Relationship					
Financial	−3.641***	20.208	−3.566***	−67.638	−3.859***	−44.765
Institutions (FI)	(0.649)	(45.067)	(0.736)	(54.399)	(0.766)	(57.389)
Capital	1.343***	−17.542	1.185***	119.703**	1.458***	158.005***
Markets (CM)	(0.380)	(42.727)	(0.445)	(53.059)	(0.493)	(51.864)
Log of GDP per	−0.666***	44.202***	−0.319*	2.105	−0.499***	−15.485
Capita	(0.131)	(15.116)	(0.184)	(16.596)	(0.183)	(16.308)
SDG - Principal	−1.314***	46.291***	−1.102***	41.219***	−1.189***	32.286***
Component 1 (PC1)	(0.070)	(8.430)	(0.125)	(9.442)	(0.130)	(10.085)
SDG - Principal	0.323***	−70.536***	0.314**	−59.408***	0.203	−74.510***
Component 2 (PC2)	(0.092)	(9.013)	(0.138)	(10.950)	(0.155)	(12.460)
Obs.	640	640	520	520	500	500
Log Likelihood	87.745	−2849.886	−84.494	−2245.971	−22.373	−2244.867

Note: Values in the table represent regression coefficients using Stata's xtpmg command. For CI in the EU sample, we set the "difficult" option to achieve convergence of the ML algorithm. The dependent variables are RC – renewable consumption and CI – carbon intensity. *, **, *** denote significance at the 10%, 5% and 1% level respectively. Standard errors reflecting common correlated effects in fixed-*T* panels (Westerlund et al., 2019) in parentheses.
Source: own estimation.

Appendix A. Appendix

Table A1
Country list of the respective subsamples.

	Countries
EU	Austria, Belgium, Bulgaria, Cyprus, Czech Republic, Germany, Denmark, Spain, Estonia, Finland, France, Greece, Croatia, Hungary, Ireland, Italy, Lithuania, Latvia, Luxembourg, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Sweden
ASEAN	Indonesia, Malaysia, Philippines, Singapore, Thailand, Vietnam
High-Income	Austria, Belgium, Cyprus, Czech Republic, Germany, Denmark, Spain, Estonia, Finland, France, Greece, Croatia, Hungary, Ireland, Italy, Lithuania, Latvia, Luxembourg, Netherlands, Poland, Portugal, Singapore, Slovakia, Slovenia, Sweden
Middle-Income	Indonesia, Malaysia, Philippines, Thailand, Vietnam, Bulgaria, Romania

Source: own World Bank, own presentation.

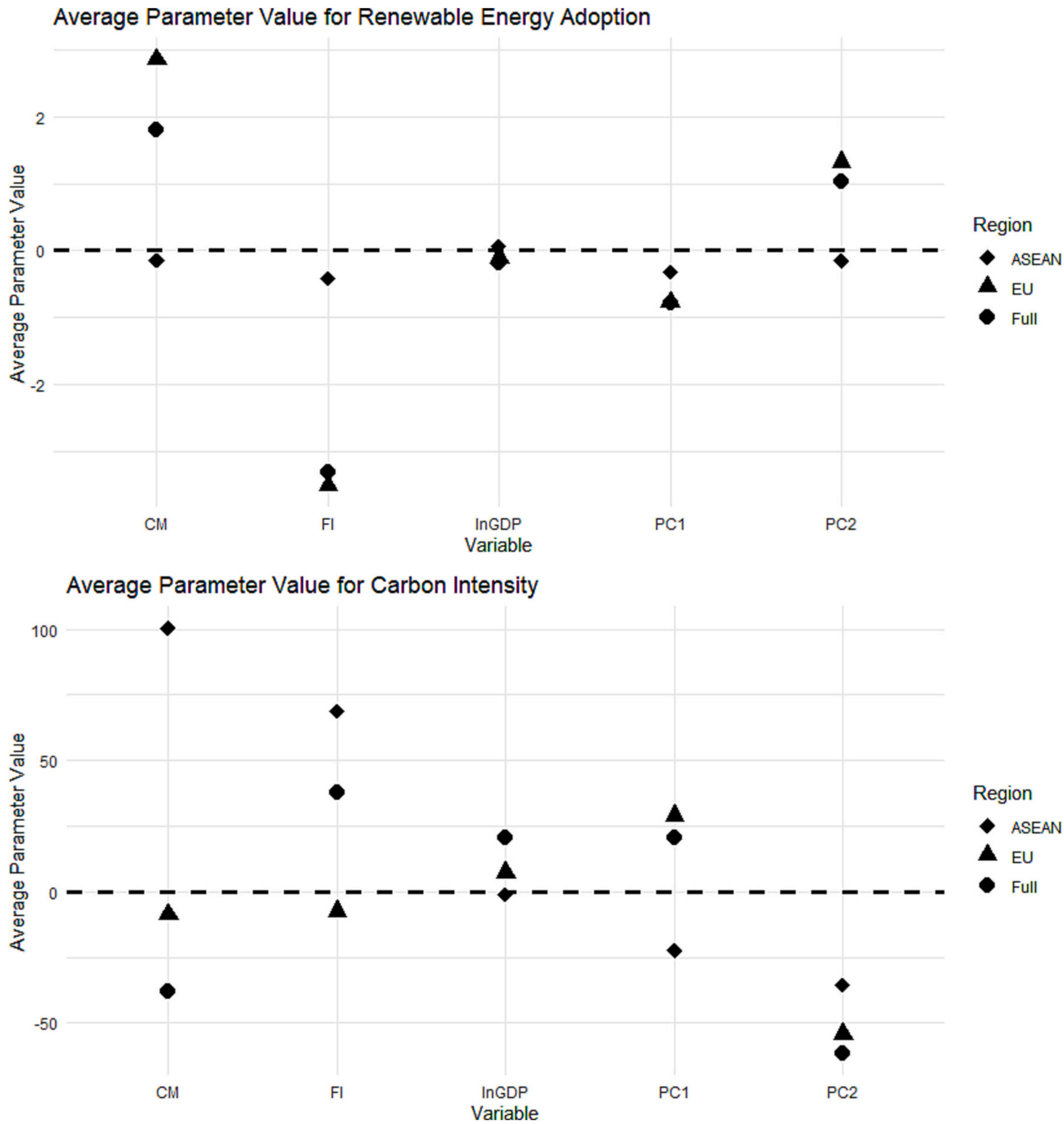

Fig. 2. Average parameter values for the renewable energy adoption and carbon intensity across regions.
Note: The averages are calculated using the parameter values from the estimations in Tables 5 to 7 and Table A13, capturing all estimations with the standard controls.

Table A2
Descriptive statistics for the EU countries.

	Obs	Mean	Std. Dev.	Min	Max
Financial Institutions (FI)	546	0.637	0.164	0.137	0.927
Capital Markets (CM)	546	0.440	0.261	0.018	0.949
GDP per Capita	546	29,496	22,035	1656	124,081
Inflation Rate	546	2.500	3.376	−4.478	45.667
Unemployment Rate	546	8.751	4.416	1.810	27.470
Renewables Consumption	546	4.934	5.729	0.000	31.257
Carbon Intensity	546	370.851	257.848	0.000	1060.820
SDG – Principal Component 1	546	−1.464	1.618	−4.715	2.703
SDG – Principal Component 2	546	0.156	1.139	−2.959	2.723

Source: own calculation.

Table A3
Descriptive statistics for the ASEAN countries.

	Obs	Mean	Std. Dev.	Min	Max
Financial Institutions (FI)	126	0.475	0.178	0.216	0.734
Capital Markets (CM)	126	0.503	0.170	0.262	0.895
GDP per Capita	126	10,626	16,525	390.09	65,479
Inflation Rate	126	3.623	3.625	−1.710	23.115
Unemployment Rate	126	3.266	1.699	0.250	8.060
Renewables Consumption	126	0.758	0.560	0.194	2.522
Carbon Intensity	126	505.382	82.991	263.983	654.281
SDG – Principal Component 1	126	2.736	2.165	−1.151	6.240
SDG – Principal Component 2	126	−0.146	1.598	−3.726	1.778

Source: own calculation.

Table A4
Descriptive statistics for the high-income countries.

	Obs	Mean	Std. Dev.	Min	Max
Financial Institutions (FI)	525	0.651	0.154	0.261	0.927
Capital Markets (CM)	525	0.480	0.250	0.018	0.949
GDP per Capita	525	31,895	21,799	3291	124,081
Inflation Rate	525	2.126	2.058	−4.478	15.402
Unemployment Rate	525	8.609	4.474	1.810	27.470
Renewables Consumption	525	4.964	5.860	0.000	31.257
Carbon Intensity	525	371.105	262.587	0.000	1060.820
SDG – Principal Component 1	525	−1.649	1.456	−4.715	1.407
SDG – Principal Component 2	525	−0.062	1.289	−3.726	2.723

Source: own calculation.

Table A5
Descriptive statistics for the middle-income countries.

	Obs	Mean	Std. Dev.	Min	Max
Financial Institutions (FI)	147	0.447	0.166	0.137	0.717
Capital Markets (CM)	147	0.347	0.209	0.029	0.736
GDP per Capita	147	4754	3323	390.09	12,995
Inflation Rate	147	4.797	5.819	−1.710	45.667
Unemployment Rate	147	4.557	3.412	0.250	19.920
Renewables Consumption	147	1.247	0.943	0.203	3.660
Carbon Intensity	147	485.259	95.124	232.925	654.281
SDG – Principal Component 1	147	2.796	1.735	−0.163	6.240
SDG – Principal Component 2	147	0.676	0.836	−0.752	2.396

Source: own calculation.

Table A6
Descriptive statistics for the single SDGs.

	Obs	Mean	Std. Dev.	Min	Max
SDG1	672	95.87	10.62	47.4	100.00
SDG2	672	66.99	6.57	42.96	78.39
SDG3	672	83.27	10.25	51.56	95.91
SDG4	672	92.84	7.49	57.12	99.93
SDG5	672	69.36	10.53	43.74	91.69
SDG6	672	81.55	8.51	57.00	95.06
SDG7	672	72.97	7.26	50.00	94.63
SDG8	672	76.44	7.49	52.28	89.92
SDG9	672	55.82	25.33	7.39	97.33
SDG10	672	80.38	17.09	27.17	100.00
SDG11	672	84.11	8.34	56.21	98.61
SDG12	672	71.31	12.14	46.7	95.03
SDG13	672	66.34	15.38	33.33	96.73
SDG14	672	61.89	10.55	34.94	89.68
SDG15	672	73.00	16.47	30.21	97.89
SDG16	672	78.75	8.97	54.90	94.24
SDG17	672	60.05	10.60	35.73	89.59

Note: The SDGs are measured in an index composed of the available data for the respective sub-goals. The values can range from 0 to 100 with 100 meaning that the goal, as defined by the UN, is fully achieved.
Source: own calculation.

Table A7
Loadings for the first two PCs.

	PC1	PC2
Goal 1	−0.271	−0.057
Goal 2	−0.202	−0.007
Goal 3	−0.301	−0.179
Goal 4	−0.266	−0.148
Goal 5	−0.235	0.257
Goal 6	−0.273	0.189
Goal 7	−0.210	0.357
Goal 8	−0.268	0.152
Goal 9	−0.277	−0.069
Goal 10	−0.214	0.005
Goal 11	−0.268	−0.154
Goal 12	0.277	0.262
Goal 13	0.220	0.342
Goal 14	−0.038	0.594
Goal 15	−0.217	0.273
Goal 16	−0.278	−0.101
Goal 17	−0.181	0.196

Source: own estimation.

Table A8
Energy transition, fixed effects estimation with the standard controls.

	Full Sample		EU		ASEAN	
	RC	CI	RC	CI	RC	CI
FI	−4.875***	97.247**	−4.584***	22.818	0.135	−23.548
	(0.676)	(48.174)	(0.803)	(56.181)	(0.751)	(93.457)
CM	2.409***	21.378	2.426***	−9.763	1.063	199.165
	(0.592)	(42.198)	(0.703)	(49.169)	(0.485)	(60.328)
lnGDP	−0.788***	144.952***	−0.275	100.650***	0.806	117.760
	(0.227)	(16.212)	(0.337)	(23.547)	(0.165)	(20.550)
IR	−0.018	5.089***	0.003	4.143***	0.011	0.422
	(0.013)	(0.962)	(0.017)	(1.195)	(0.011)	(1.327)
UR	−0.021	1.513	−0.007	−1.159	0.198	5.607
	(0.014)	(1.027)	(0.017)	(1.223)	(0.042)	(5.170)
Observations	672	672	546	546	126	126
Panels	32	32	26	26	6	6
R^2 (within)	0.631	0.435	0.664	0.491	0.702	0.446

Source: own estimation.

Table A9
Energy transition, FMOLS estimation with the standard controls.

	Full Sample		EU		ASEAN	
	RC	CI	RC	CI	RC	CI
FI	−5.960***	412.560***	−7.440***	424.51***	0.470***	360.74***
	(−29.530)	(26.380)	(−49.890)	(25.630)	(35.640)	(7.590)
CM	1.550***	−91.400***	1.970***	−126.78***	−0.280***	61.91***
	(−2.770)	(6.690)	(4.780)	(3.390)	(−16.350)	(8.380)
lnGDP	1.470***	−49.010***	1.670***	−57.450***	0.600***	−12.420***
	(67.410)	(−26.560)	(58.530)	(−19.470)	(33.840)	(−20.820)
IR	−0.140***	4.860***	−0.160***	5.580***	−0.030***	1.730***
	(−41.730)	(23.320)	(−32.300)	(18.400)	(−29.130)	(15.540)
UR	−0.010***	1.020**	−0.060***	−0.110**	0.230***	5.900***
	(11.490)	(−2.350)	(5.920)	(2.370)	(14.210)	(−10.350)
Observations	672	672	546	546	126	126
Panels	32	32	26	26	6	6

Note: *, **, *** denote significance at the 10%, 5% and 1% level respectively. We used Stata's xtcointreg command to calculate the test statistics. t-statistics are reported in parentheses.
Source: own estimation.

Table A10
Pooled mean group estimation for the whole sample, the EU and the high-income countries with the standard controls.

	Full Sample		EU		High-Income	
	RC	CI	RC	CI	RC	CI
	Short-Run Relationship					
ΔFI	2.729*	175.752	3.104*	101.535	2.253	158.480
	(1.417)	(125.932)	(1.839)	(114.473)	(1.476)	(150.027)
ΔCM	1.028	−30.745	0.702	−113.127	1.887**	−73.809
	(0.824)	(110.330)	(1.009)	(127.869)	(0.842)	(136.402)
ΔlnGDP	0.966**	14.387	1.317**	−0.020	1.298**	1.088
	(0.463)	(32.361)	(0.564)	(39.373)	(0.616)	(40.190)
ΔIR	0.020	0.418	0.030	0.656	0.028	1.091
	(0.022)	(1.512)	(0.027)	(1.607)	(0.027)	(1.824)
ΔUR	0.107**	−3.773	0.140***	−5.470**	0.142***	−2.984
	(0.044)	(2.510)	(0.053)	(2.593)	(0.054)	(2.151)
EC	0.296***	0.266***	0.345***	0.313***	0.362***	0.305***
	(0.060)	0.053	(0.073)	(0.060)	(0.073)	(0.064)
	Long-Run Relationship					
FI	−6.325***	−88.265	−6.802***	126.067**	−10.379***	−100.293
	(1.053)	(86.912)	(0.942)	(55.594)	(0.707)	(88.169)
CM	−1.224	305.725***	−2.936***	−20.553	1.758**	346.665***
	(0.877)	(59.989)	(1.073)	(56.430)	(0.800)	(65.316)
lnGDP	1.072***	−97.828***	1.907***	28.601	1.686***	−101.041***
	(0.169)	(16.018)	(0.191)	(17.563)	(0.171)	(16.659)
IR	−0.160***	10.069***	−0.122***	1.084	−0.088***	8.731***
	(0.032)	(2.714)	(0.042)	(2.950)	(0.032)	(2.959)
UR	−0.011	−1.628	−0.028	−4.590**	0.051***	−1.609
	(0.022)	(1.731)	(0.023)	(1.862)	(0.017)	(1.772)
Obs.	640	640	520	520	500	500
Log Likelihood	43.834	−2910.902	−112.800	−2287.740	−52.381	−2298.001

Note: *, **, *** denote significance at the 10%, 5% and 1% level respectively. We used Stata's xtpmg command to calculate the estimations. For CI in the EU sample, we specified Stata's "difficult" option to achieve concave convergence in the ML algorithm. Standard errors reflecting common correlated effects in fixed-T panels (Westerlund et al., 2019) in parentheses.
Source: own estimation.

Table A11
Fixed-effects estimation results for the sample split by income.

	High-Income				Middle-Income			
	RC	CI	RC	CI	RC	CI	RC	CI
FI	−5.299***	115.522**	−4.840***	69.649	−0.573	−33.730	−0.391	−148.360
	(0.825)	(57.371)	(0.870)	(59.564)	(0.741)	(73.569)	(0.780)	(92.299)
CM	2.969***	28.774	3.331***	−6.046	−0.686	−13.361	−0.639	72.364
	(0.705)	(49.047)	(0.719)	(49.254)	(0.642)	(63.746)	(0.666)	(78.796)
lnGDP	0.241	82.353***	−0.685*	108.254***	0.669***	−32.988	0.103	102.890***
	(0.358)	(24.910)	(0.367)	(25.100)	(0.239)	(23.747)	(0.229)	(27.115)
IR			0.038	5.062**			−0.012	4.754***
			(0.029)	(2.017)			(0.008)	(0.915)
UR			−0.011	−0.452			−0.024	7.303***
			(0.018)	(1.257)			(0.022)	(2.652)
PC1	0.438**	−14.301			0.556***	−87.066***		
	(0.217)	(15.094)			(0.146)	(14.493)		
PC2	0.885***	−47.834***			0.156*	−77.804***		
	(0.170)	(11.836)			(0.085)	(8.409)		
Obs.	525	525	525	525	147	147	147	147
Panels	25	25	25	25	7	7	7	7
R^2 (within)	0.673	0.497	0.656	0.487	0.692	0.600	0.655	0.363

Note: *, **, *** denote significance at the 10%, 5% and 1% level respectively. Robust standard errors are reported in parentheses.
Source: own estimation.

Table A12
FMOLS estimation results for the sample split by income.

	High-Income				Middle-Income			
	RC	CI	RC	CI	RC	CI	RC	CI
FI	−3.680***	125.860***	−7.48***	387.27***	−1.23***	301.99***	−0.51**	502.88***
	(−25.54)	(16.740)	(−34.73)	(19.30)	(−48.18)	(14.77)	(2.48)	(19.94)
CM	1.10***	−276.93	2.2***	−123.31***	−2.22***	135.44***	−0.77***	22.58***
	(−7.03)	(1.2)	(3.25)	(3.88)	(−29.510)	(8.53)	(−12.07)	(6.96)

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Table A12 (*continued*)

	High-Income				Middle-Income			
	RC	CI	RC	CI	RC	CI	RC	CI
lnGDP	−0.78***	21.920***	1.69***	−56.41***	−0.10***	−5.42**	0.68***	−22.60***
	(−7.14)	(8.22)	(66.02)	(−34.48)	(−15.41)	(2.06)	(19.36)	(8.36)
IR			−0.16***	5.38***			−0.05***	2.99***
			(−35.24)	(20.9)			(−22.62)	(10.36)
UR			−0.05***	−1.10			0.14***	8.58***
			(9.04)	(0.01)			(7.48)	(−5.04)
PC1	−1.49***	67.82***			−0.92***	37.10***		
	(−44.59)	(27.56)			(−154.12)	(13.94)		
PC2	1.79***	−57.17***			0.19***	−44.63***		
	(33.09)	(−42.82)			(−7.49)	(−4.78)		
Obs.	525	525	525	525	147	147	147	147
Panels	25	25	25	25	7	7	7	7

Note: *, **, *** denote significance at the 10%, 5% and 1% level respectively. We used Stata's xtcointreg command to calculate the test statistics. *t*-statistics are reported in parentheses.
Source: own estimation.

Table A13
Kernel regression results.

	Full Sample		EU		ASEAN	
	RC	CI	RC	CI	RC	CI
FI	−1.157	−159.287**	−1.072	−247.610***	−1.090	143.979
	(1.132)	(75.221)	(1.426)	(93.746)	(0.695)	(145.497)
CM	3.159***	18.597	7.614***	88.053	−0.661*	104.331***
	(0.584)	(48.604)	(1.062)	(66.209)	(0.381)	(36.486)
lnGDP_capita	0.503*	−37.278	0.176	−65.110*	−0.062	8.447
	(0.298)	(23.302)	(0.456)	(36.807)	(0.101)	(18.119)
PC1	−0.909***	20.486**	−1.247***	20.783*	−0.235***	4.711
	(0.130)	(8.186)	(0.17)	(11.787)	(0.091)	(13.971)
PC2	1.668***	−52.251***	2.528***	−48.459***	−0.233*	−3.718
	(0.130)	(7.263)	(0.184)	(9.296)	(0.129)	(17.114)
Observations	672	672	546	546	106	106
Panels	32	32	26	26	6	6
R^2	0.982	0.924	0.985	0.936	0.975	0.978

Source: own estimation.

Table A14
Kernel regression results with the standard controls.

	Full Sample		EU		ASEAN	
	RC	CI	RC	CI	RC	CI
FI	−8.147***	−60.049	−9.441***	−97.951	0.380	191.212**
	(1.969)	(80.842)	(2.116)	(84.376)	(0.939)	(75.475)
CM	4.509***	77.280	6.678***	119.012*	−0.681	59.685
	(0.798)	(51.919)	(1.261)	(61.033)	(0.535)	(45.641)
lnGDP_capita	2.630***	−74.982*	2.496***	−117.370***	−0.306*	5.433
	(0.320)	(12.418)	(0.460)	(20.798)	(0.160)	(14.915)
IR	−0.056	−0.541	−0.147*	−0.833	0.006	1.483
	(0.049)	(2.945)	(0.075)	(5.035)	(0.022)	(1.463)
UR	0.063*	−1.781	−0.034	−2.401	0.164**	8.306
	(0.034)	(2.146)	(0.038)	(2.436)	(0.070)	(7.063)
Observations	672	672	546	546	116	117
Panels	32	32	26	26	6	6
R^2	0.056	0.056	0.035	0.018	0.966	0.977

Source: own estimation.

Table A15
Kernel regression results for the sample split by income.

	High-Income			Middle-Income				
	RC	CI	RC	CI	RC	CI	RC	CI
FI	−2.122	−234.791*	−11.598***	−120.511	−0.075	−114.900	1.900***	34.420
	(1.812)	(133.693)	(2.253)	(96.344)	(0.399)	(73.930)	(0.504)	(82.464)
CM	4.733***	233.524***	4.432***	161.016**	−2.379***	230.665***	−2.692***	239.461***
	(0.888)	(71.763)	(1.172)	(65.148)	(0.755)	(49.278)	(0.622)	(63.186)
lnGDP	0.500	−36.597	4.359***	−158.082***	−0.202	45.879***	0.146	7.847

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Table A15 (*continued*)

	High-Income			Middle-Income				
	RC	CI	RC	CI	RC	CI	RC	CI
_capita	(0.509)	(33.516)	(0.565)	(26.451)	(0.142)	(14.147)	(0.105)	(16.503)
IR			−0.361**	11.813			−0.020	2.309
			(0.141)	(9.329)			(0.016)	(1.620)
UR			0.147**	−9.028***			0.216***	4.671
			(0.057)	(3.460)			(0.052)	(5.394)
PC1	−1.281***	−77.864***			−0.369***	18.569*		
	(0.193)	(20.396)			(0.083)	(10.152)		
PC2	1.932***	−67.738***			−0.286***	−13.855		
	(0.150)	(18.691)			(0.066)	(11.312)		
Obs.	525	525	525	525	147	147	147	147
Panels	25	25	25	25	7	7	7	7
R^2	0.986	0.951	0.182	0.210	0.981	0.964	0.979	0.973

Source: own estimation.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2024.107368.

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