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Increasing inequality between countries in key renewable energy costs

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Highlights

- There is much optimism around the fact global renewable costs have declined rapidly
- We explore country-level costs to understand differences and implications
- We find rising inequality between countries in renewable energy installed costs
- Investment costs faced by countries based on these disparities vary significantly
- Countries with lower emissions and income, and in the global south face higher costs

Abstract

There is growing optimism that the energy transition will be strongly aided by the reduction in global renewable technology costs. We use trends in solar PV and onshore wind costs and related factors to explore differences between countries and consider how cost inequalities might affect the energy transition. We show that, despite average costs falling, technology cost inequality between countries is increasing over time. The impacts of this could be severe as certain countries and investors face higher costs to implement green technologies. Countries with historic developmental disadvantages, and lower emissions, face higher costs, reinforcing potential injustices in the energy transition. We also show that demand pull factors (e.g., income, ease of doing business), renewable industry competitiveness, and policy portfolios are significant explanatory factors for cost differences.

Keywords: renewable energy, solar energy, wind energy, technology costs, just transition

1. Introduction

In recent years, there has been growing optimism around the rapidly reducing costs of key green energy technologies (Timilsina, 2021; Way et al. 2022). Low-cost renewables such as solar and wind have the potential to accelerate the energy transition through market signals and commercial private sector behaviour, rather than relying on government policy. However, there are many practical constraints which might undermine this optimism. Many of these constraints are technical, economic, regulatory, or social (Moorthy, Patwa, and Gupta, 2019; Spiess and De Sousa, 2016). There also remains a large open question about how decreases in costs at the global level are felt by different countries, and what this means for distributional impacts of the transition between countries and their development.

Costs of green technologies have implications for innovation, energy security, and economic inequality. Renewable energy technologies traditionally must compete on costs as the main indicator of innovation since all firms sell a nearly identical product - energy (Grubb, 2014). Costs are increasingly relevant in national energy security debates (Ang, Choong, and Ng, 2015). And, at the household level, solar PV is afforded by the rich (Rahut et al., 2018) while the poor are vulnerable to energy poverty (Halkos and Gkampoura, 2021). Internationally, green technology costs can affect development outcomes (Adom et al., 2021).

This paper investigates how country-level solar PV and onshore wind costs are trending through time. We find that technology cost inequality (TCI)[1], measured by the coefficient of variation, increases over time. When we adjust costs for national price level, the driving factors of disparities across countries (demand pull, policy, and

[1] We refer to the variation or the dispersion in installed costs (i.e., the full start-up costs) between countries for a technology as 'Technology Cost Inequality' (TCI). Similar studies such as Gillingham et al. (2016) and Nemet et al. (2021) use the term 'price dispersion' (which is mathematically equivalent to TCI), however, we believe this term is inadequate to capture the full gravity of cost disparities, particularly for crucial energy technologies. The term inequality alone would be misleading because it is conventionally used in the context of economic inequality. Instead, we use the term Technology Cost Inequality because it captures some justice elements and potential social science implications and is therefore more suitable for our research.

renewable industry competitiveness) are clearly observed. We comment on these drivers and the just transition implications.

1.1. Energy justice: the issue of distributional justice

Our study of country-level differences means we implicitly focus on the distributional idea of justice – justice that is concerned with the asymmetric allocation of benefits and costs along spatial and temporal contexts. Distributional justice can be studied across multiple geographical levels (Walker, 2009; Carley and Konisky, 2020), and extended beyond the more dominant debates localised to sub-national scales (Bouzarovski and Simcock, 2017). We can conceptualise distributional justice at the level of nation-states. We are forced to ask ourselves questions about participation and responsibilities, and cost inequality leading to vulnerability or well-being (Walker, 2009).

We acknowledge that there will be inherent differences in how the energy transition occurs for different countries as there are several factors including historical and choice-based factors (Markard, 2018). However, our goal is to highlight areas that might lead to the transitions occurring in a manner that exacerbates unequal outcomes and slows down the global transition unnecessarily and identify potential remedies.

1.2. What influences technology costs?

1.2.1. Learning-by-doing and learning-by-searching

Several studies have postulated a strong relationship between declining costs of green technologies and learning-by-doing combined with research and development. There is an intuitive symbiotic relationship between cost reductions and deployment, however it is difficult to prove learning rates are based on a direct causal relationship, nonetheless it can be argued that causal relations can be inferred (Grubb et al., 2021).

Learn-by-searching (R&D) effects have become less important than deployment-induced innovation, particularly in the renewable energy sector. Initially cost reductions were driven by R&D (1980-2000, half of cost reductions were from R&D) but there was a shift from the early 2000s to costs being driven by economies of scale or learning-by-doing (R&D approximately 25%, deployment nearly 50%) (Kavlak, McNerney, and Trancik, 2018).

In addition to module cost decreases, learning-by-doing effects can be seen in the support costs for renewables installation; these are balance-of-system costs (support hardware, installation, and inspection) and other costs such as the cost of capital, permitting, customer acquisition etc. Support costs can be as large as module costs and follow different trends over time (Barbose, Darghouth, and Wiser, 2010). Elshurafa et al. (2018) analysed learning rates across 20 nationalities for these supporting costs and solar PV modules noting that prices have declined over time for both, however, the rates of decrease for the modules have been faster than those of the support costs. It is also noted that the support costs vary across countries and have decreased at varying rates and learning rates have varied by installation type (residential vs utility-scale). Therefore, studying installation costs should include both technology and support costs as these might account for the variations across countries.

1.2.2. Policy's impact on costs

Policy measures may greatly stimulate deployment of renewables. Liu et al. (2019) analysed fiscal and financial incentives (strong effect), market-based instruments (strong effect), direct investments (weak effect), policy support i.e., institution building and strategic planning (strong effect), regulation and information and education (weak effect) and R&D (strong effect). These results were similar to those identified by Polzin et al., (2015) who conducted a similar study to investigate the impact of policy on investments. Abolhosseini and Heshmati (2014) studied FiTs[2], tax incentives, and tradeable green certificates as investment mechanisms that could stimulate private investment and increase deployment but only postulated that this might also decrease costs.

[2] FiT=Feed in Tariff

There are three additional insights about policymaking that have potential relevance to costs. Firstly, it matters at which level policy mechanisms are set, for example in the US, local permitting procedures (Burkhardt et al., 2015) and city level policies (Dong and Wiser, 2013) impact solar PV costs. Secondly, general environmental policies may be complemented by technology-specific policies (Groba and Breitschopf, 2013), however, there are diminishing marginal returns from increased complexity and quantity of policies (Zhao, Tang, and Wang, 2013). Lastly, commitment to policies and stringency might be more crucial than the policy portfolio proposed (Lipp, 2007; Johnstone et al. 2012).

Policy instruments are crucial but the relationships between costs and policies are much less straightforward than with other variables. Peñasco, Anadón, and Verdolini (2021) reviewed the impact of ten individual types of decarbonization instruments and showed their cost, distributional, and other outcomes were varied e.g., there was a high level of disagreement in cost related outcomes of quotas whereas the opposite was true for R&D funding. Policy mixes affect green technology diffusion however, quantitative studies of these impacts are scant (Schmidt and Sewerin, 2019), and there are none that focus on technology costs.

1.2.3. Market dynamics and macroeconomic context

Energy technology market's competitiveness, structure, and maturity, the heterogeneity of consumers, and firm costs influence price variation (Baye et al., 2006). The technology type and innovative ability of firms are also relevant (Groba and Breitchopf, 2013).

The macroeconomic environment shares a strong link with costs and deployment of green technologies and renewables in particular. GDP as a measure of overall economic strength, population as an indicator of demand, labour, and resource costs have been considered critical factors influencing the cost of renewables (Dai et al., 2016; Yao et al., 2021).

The relationship between the renewables industries and the economy is symbiotic. As the macroeconomic environment influences renewables industries, the industries themselves impact the macroeconomic environment (e.g., employment Proença and Fortes (2020) or industrial goals Komor and Bazilian (2005) and Schmidt, Schmid and Sewerin (2019)). The result has been that cost reduction in renewables industries has been linked to several attempts by governments to bolster macroeconomic conditions. The potential link between the macroeconomic environment and installed cost disparities, therefore, deserves inquiry.

2. Methods and data

We collected data from a series of sources, iteratively adding to separate time-series and cross-sectional datasets. Time series data is used to show the trends in technology cost inequality. The cross-sectional data is for 2021/2, and made up of categorical classifications (i.e., income, renewable industry competitiveness, emissions, geographical location, and policy clusters) and continuous variables (i.e., GDP, Population, Patents, etc.) We use these for comparisons between country groups and regression analysis of the drivers of technology cost differences.

2.1 Data collection and preparation

A useful contribution of this study is the creation of a cross-sectional dataset containing a set of indicators obtained from theory on technology costs as explanatory variables for Installed cost differences between countries. We collected this data systematically from multiple sources in an iterative fashion. In particular, the collection of explanatory factors was driven by existing literature and theory on technology costs, as well as preliminary results. We then cleaned and merged the data and performed a statistical power analysis (see Appendix A for details). Missing variables, particularly for costs, were handled either by using previous year values, where available, or dropping the country from the dataset.

Table 1: List of data categories and sources

Data category	Source	Citation/link
Installed costs - Time series data - Disaggregated costs	IRENA 2022	IRENA, 2022. Renewable Power Generation Costs in 2021, *International Renewable Energy Agency (IRENA)*, Abu Dhabi.
Renewable energy deployment	IRENA 2022	IRENA, 2022. Renewable capacity statistics 2022, *International Renewable Energy Agency (IRENA),* Abu Dhabi
Policy and Incentives and Public Financing	REN21 2021 GSR Table 6	REN21, 2022. Renewables global status report. *REN21*. Available at: https://www.ren21.net/reports/global-status-report/
Economic complexity - *Proximity* - Revealed Competitive Advantage	Green transition Navigator	Andres, P and Mealy, P, 2021. *Green Transition Navigator,* Available at: www.green-transition-navigator.org.
Renewables patenting	IRENA	IRENA, 2021. *INSPIRE Platform,* Available at: www.irena.org/INSPIRE
GDP per capita, GDP, Population	Our World in Data	Ritchie, H., 2019. 12 key metrics to understand the state of the world. *Our World in Data*. Available at: https://ourworldindata.org/12-key-metrics (Accessed: 01 July 2022).
Human Development Index (HDI)	Our World in Data	Our World in Data, 2022. *Human Development Index,* Available at: https://ourworldindata.org/grapher/human-development-index (Accessed: 1 July 2022)
Doing business score	World Bank	World Bank, 2022. *Doing Business Scores,* Available at: https://archive.doingbusiness.org/en/scores (Accessed: 1 July 2022)
Price level	Our World in Data	Our World in Data, 2022. *Price levels relative to the US,* Available at: https://ourworldindata.org/grapher/gdp-price-levels-relative-to-the-us (Accessed: 1 July 2022)

We have a time-series dataset containing data for 40 countries for onshore wind and 17 countries for solar PV costs through 1984-2021 and 2010-2020 respectively. An additional cross-sectional dataset is used which contains costs in 2020/21 and explanatory variables for 37 solar PV and 36 onshore wind countries. There are several instances of missing data points for the onshore wind time series (measured from 1984) but is complete from 2010 (the start date for the solar PV time series). There are 27 explanatory variables (including three categorical classification variables and 11 policy situations reducible to 1). The countries represented "broadly" span all continents and the data is sufficient for the classifications we aim to make and the Kruskal-Wallis tests to run. However, the state of the data does present some limitations to the research (see 4.2 for deeper analysis).

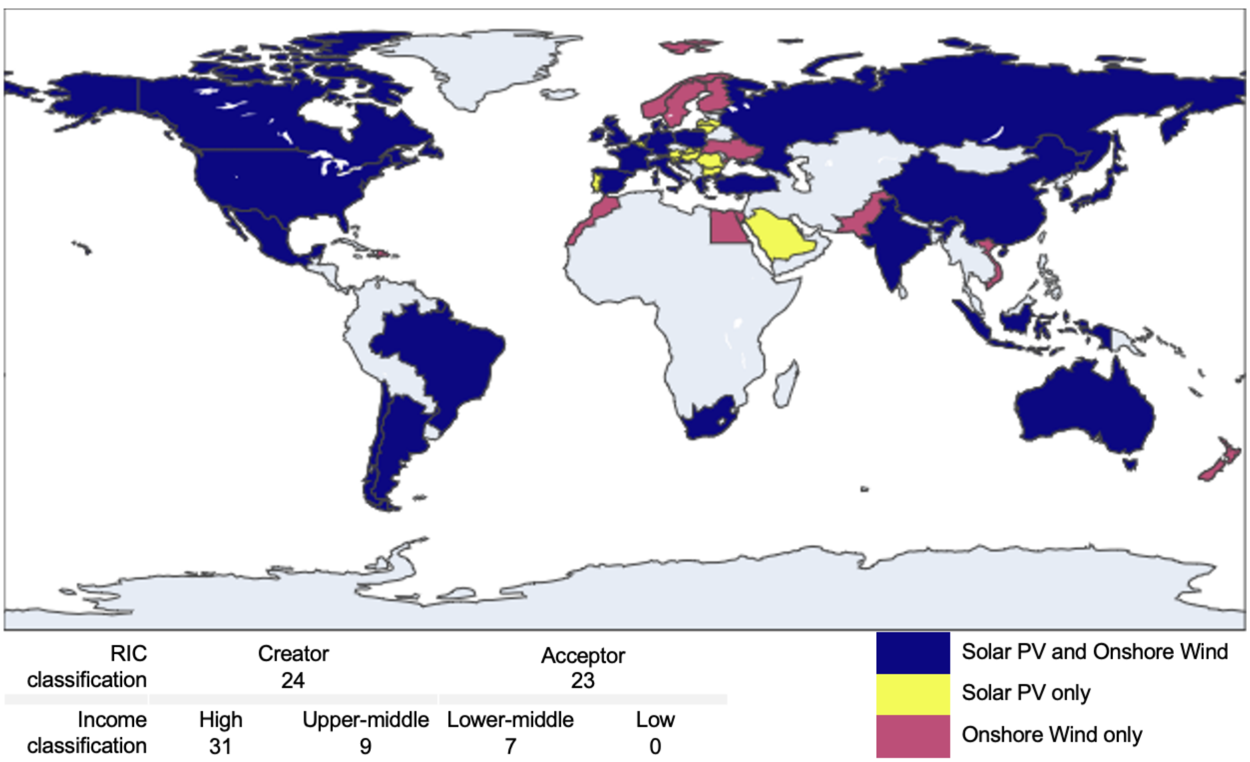

Figure 1: Geographic representation of the cost data and the number of countries represented in the RIC (explained below in 2.3) and Income classifications.

2.2 Assessing Technology Cost Inequality (TCI)

We chose the coefficient of variation (relative standard deviation) as a measure for TCI and the spread of costs across the different countries. The means are varying at each time interval where technology cost inequality in costs is measured, therefore, standard deviation alone would be insufficient. The coefficient of variation is a more suitable indicator as it determines the extent of variability in costs in relation to the mean. Coefficient of variation has been used as a measure of economic inequality (Champernowne and Cowell, 1998; Campano and Salvatore, 2006) and to highlight regional differences over time (Huang and Leung, 2009). Additionally, Nemet et al. (2021) used the coefficient of variation as a measure of price dispersion for residential solar PV installations in the US, showing that the metric is sufficient for this analysis.

For computing Coefficient of variation c_v:

$$c_v = \frac{\sigma}{\mu}$$

Where σ standard deviation and μ is the mean

For our time-series analysis of technology cost inequality, we compute c_v over time and fit an Ordinary Least Squares linear regression plot to the data. The slopes (i.e., larger slope means technology cost inequality is increasing faster) of the regression plots are then compared to analyse the change in costs.

We also acknowledge that raw total costs are not a good indicator of the relative costs facing investors in each regional market – as investors need to factor in local cost and local revenues in their analysis. Therefore, in our analysis we control for the Balassa-Samuelson[3] effect by adjusting total costs by price level (we indicate explicitly each time we make a price level adjustment).

[3] Countries with higher GDPs tend to have higher price levels – i.e., broader market basket (Balassa, 1964; Samuelson, 1964; Costa et al., 2019). Adjusting for price level allows for analysis where we have purchasing power parity across countries. The true impact of costs felt by investment and consumers can be observed.

2.3 Determining Renewable Industry Competitiveness (RIC)

We use three proxies for determining Renewable Industry Competitiveness: (1) innovation – patenting; (2) technology production – *proximity*; and (3) technology export – Revealed Comparative Advantage (RCA). We use IRENA data on patents filed in individual countries for solar and wind energy as indicators of R&D output. *Proximity* and RCA are indicators of economic complexity and competitiveness of renewable energy production and dispersal capabilities of a country. Specifically, *proximity* for renewables can be thought of as a computation of the similarity of renewable products to a country's productive capabilities and as correlated with the probability of developing future competitiveness in renewables – it, therefore, makes sense as a measure of internal renewable energy market strength. RCA for renewables is an indicator of whether a country exports renewables technology competitively. A more detailed description of how RCA and *proximity* are calculated is available from Mealy, Farmer, and Teytelboym (2019). Together, cumulative patenting, *proximity,* and RCA work to highlight the competitive strength of a country's renewables industry.

We classify countries as technology creator/acceptor countries using RCA as our principal indicator. According to Mealy and Teytelboym (2020), if RCA>1 for a country then, "the country is assumed to be competitive in the product, as it exports more than its 'fair share'". Therefore, our classification is as follows: RCA>1 tech-creator (green competitive strengths), RCA<1 tech-acceptor (green opportunities). A 5-year running average from 2016-2020 is used for the RCA and *proximity* data.

2.4 Working with varying policy situations

Analysing the policy data required several preliminary steps before it could be used to test our hypotheses on factors influencing installed cost differences. We work with a cross-sectional dataset that is coded for any one of 11 regulatory policy, financial incentives, and public financing categories (see *supplementary data)*. We make two attempts at dealing with this data and dimensionally reduce it to a smaller set of variables that are more useful for our analysis, (1) a cluster analysis to determine "policy families" and assessing the impact of being in one "family"; (2) using axiomatic policies i.e., Feed-in-Tariffs and Quotas to observe the effect of these policies.

For our cluster analysis, we use K-modes clustering which is an alternative to K-means clustering but for categorical variables, an extension developed by Huang (1998). Here, sets of categorical objects are matched to those that are most similar – which in our example are policy and incentives situation for each country (see appendix B for details). The clustered data is then used in the subsequent analysis (Kruskal-Wallis tests for observing whether there are statistically significant differences due to each policy situation and a regression analysis when all variables are combined).

2.5 Assessing potential drivers of Technology Cost Inequality

The analysis of potential drivers occurs at two levels. First, analysis of differences related to categorical classifications of countries (i.e., as technology creator/acceptors for RIC, as high/upper-middle/lower-middle/low-income countries for income classification and policy and incentives clusters). Here, we use the Kruskal-Wallis tests (a one-way Anova on ranks); the test data satisfies the assumptions for this non-parametric test.

Second, analysis using a multiple regression with fixed effects. In this section, we select appropriate variables that are indicators of the theory on factors that influence technology price. For policies (a categorical variable) we use dummies. We validate the final model by analysing the residuals and conducting robustness checks e.g., removing variables, adjusting controls etc.

$$Technology\ Installed\ Cost_{2020/21} = \left(\sum_{\mathrm{i}} \beta_i * V_i\right) + \delta_{Technology} + \epsilon$$

Where:

- V_i is the explanatory variable i
- β_i is the coefficient of the explanatory variable
- $\delta_{Technology}$ are technology specific fixed effects

- ϵ is an error term

3. Results

3.1 Solar PV and onshore wind energy costs are declining over time

Cost trends vary by country, and we plot the costs adjusted for price level to observe the costs experienced in a country (Figures 2-4).

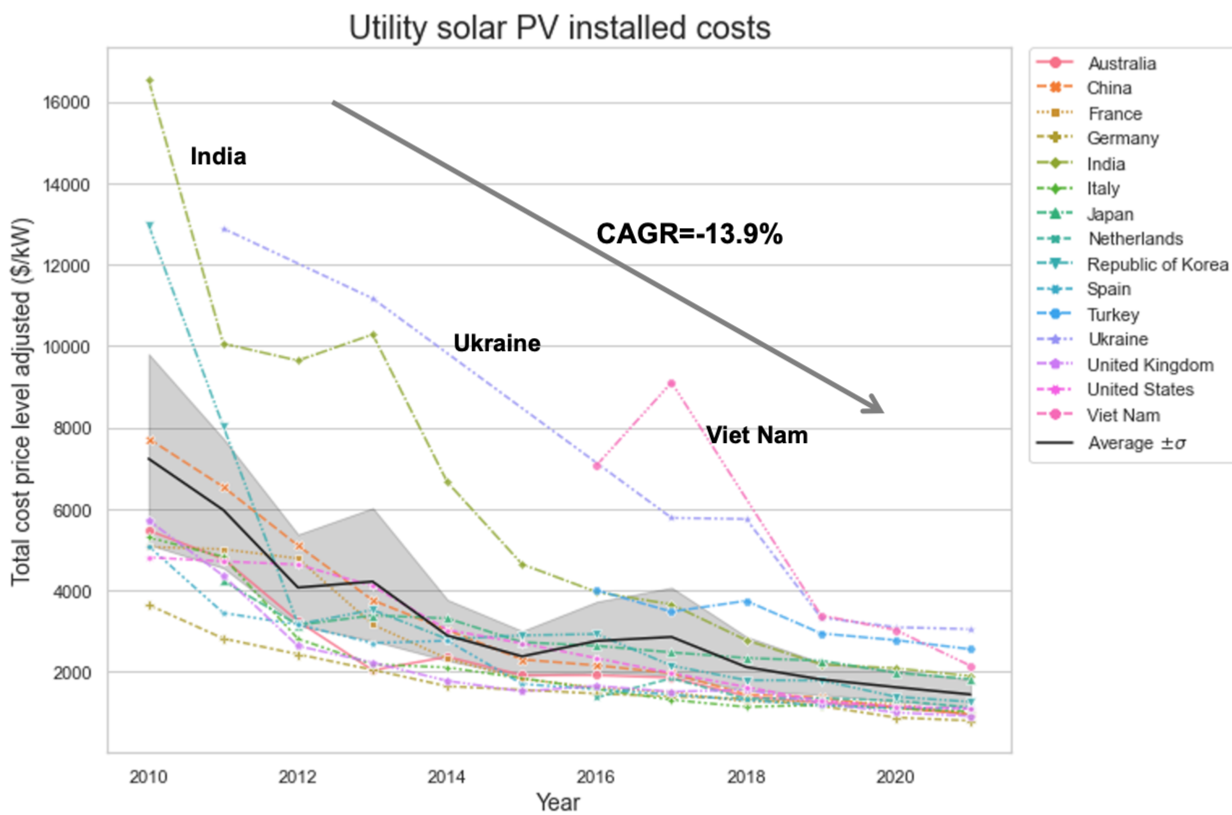

Figure 2: Average solar PV utility costs for 15 markets from 2010-2021. A mean line with +/- one standard deviation shading is shown[4]. CAGR[5] for the mean is computed and shown with a grey arrow indicating cost increase/decrease[6].

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[4] Here we plot the mean +/- standard deviation to demonstrate the interval that most costs should fall into as time progresses. This should not be taken as a measure of cost inequality or true price dispersion since average costs vary over time.

[5] CAGR=Compound annual growth rate

[6] The mean average installed cost for Residential, Commercial and Utility scale solar PV has decreased by mean CAGR=-12%,-14.3%,-13.9% respectively since 2010 (residential and commercial costs are not shown - see Appendix C for solar PV residential and commercial plots.)

For solar PV, we see a smooth downward cost trend for most countries, starting with more volatility early on e.g., Republic of Korea. The sharpest decrease can be seen in India, which has made significant strides in solar PV deployment. Vietnam was initially high and had a bump in 2017 but later joined the trend, whereas costs in Turkey remained relatively high from 2016. Broadly costs have gone down fast across solar PV segments.

The utility/residential/commercial solar PV split has varied over the years. Globally, utility solar PV is forecasted to dominate future deployment with residential and commercial solar PV growing to relatively lower levels (IEA, 2021). As of 2020, on average the segments make up 61%, 19% and 21% cumulative deployment across different regions around the world; utility largest in Russia, Sub-Sahara Africa, the UK, and China (92%, 73%, 73% and 69% respectively), commercial largest in the EU and ASEAN (47% and 42% respectively), and residential dominant in Australia (55%) (see Appendix E). This means that, depending on the region of the world, different segments of solar PV costs will matter in the energy transition.

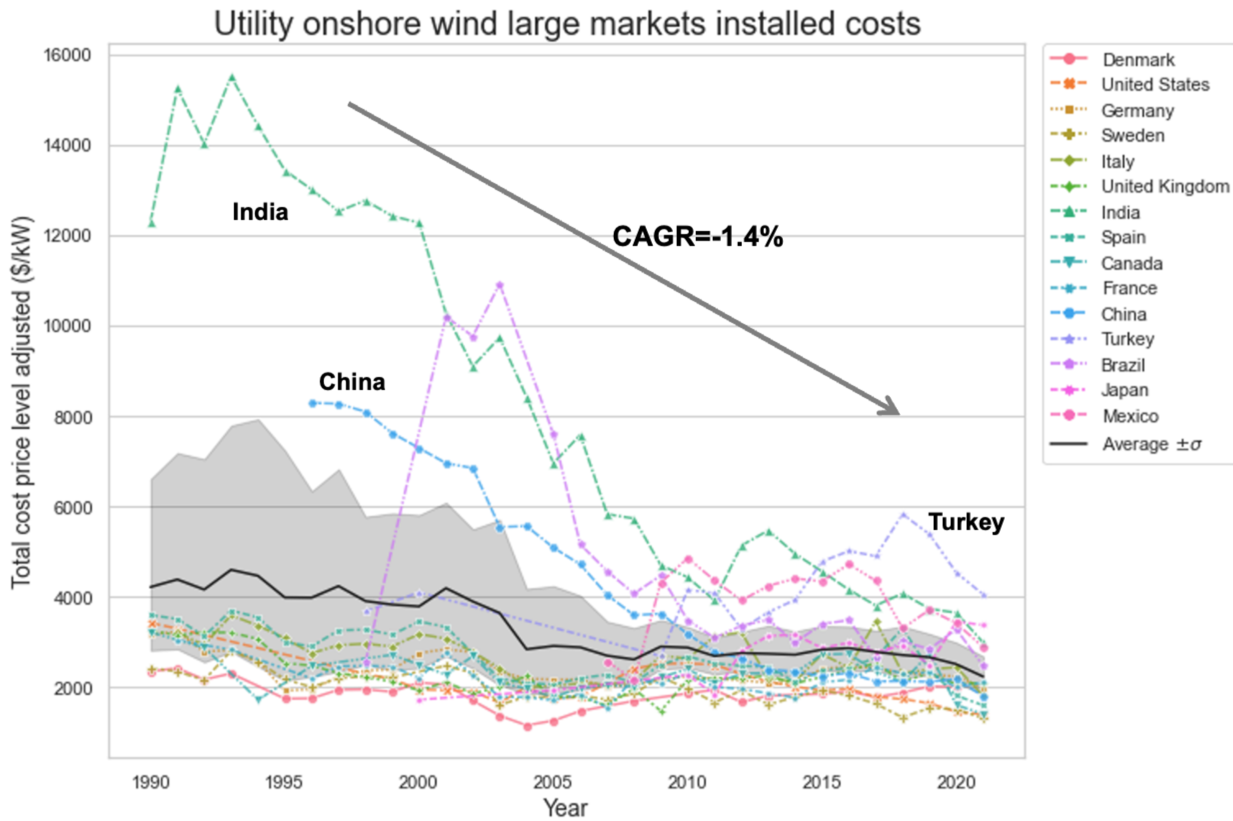

Figure 3: Average Onshore wind energy costs by country for 10 large wind energy markets from 1990-2021. Pre-1990 wind is dominated by just 4 countries so is not useful for a cross-national comparison. A mean line with +/- one standard deviation shading is shown; CAGR for the mean is computed and shown with a grey arrow indicating cost increase/decrease.

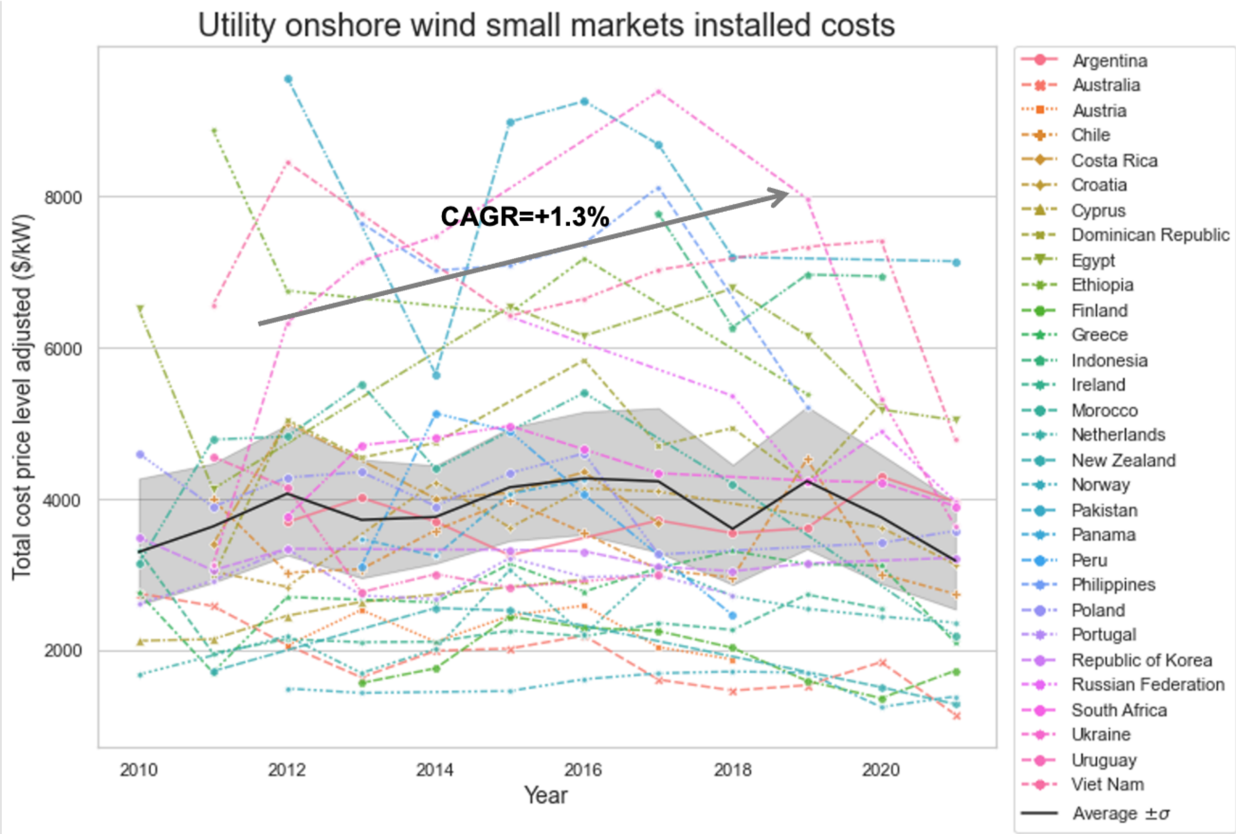

Figure 4: Average Onshore wind energy costs by country for small wind energy markets at a utility-scale from 2010-2021. Small markets data is only collected from 2010 onward. *A mean line with +/- one standard deviation shading is shown; CAGR for the mean is computed and shown with a grey arrow indicating cost increase/decrease.*

We can split onshore wind markets into large and small markets. For large markets, cost declines are small but continuous over time. There is more volatility as new countries enter the market (e.g. Mexico and Japan) with these countries eventually settling into the downward trend. Both India and China start as high-cost outliers. China succeeds in falling within the band by 2010, whereas India remains an outlier (though less so than at the start). Despite sizable renewable investments from both countries, there stills exists a disparity in outcomes. In small markets, costs have increased. The trajectories are more sporadic than in the large markets case or the solar PV case.

3.2 Technology Cost Inequality is increasing over time with varying rates

We use the trends in TCI (measured by coefficient of variation or relative standard deviation - c_v) to examine the differences in cost outcomes for countries by technology (Figure 5).

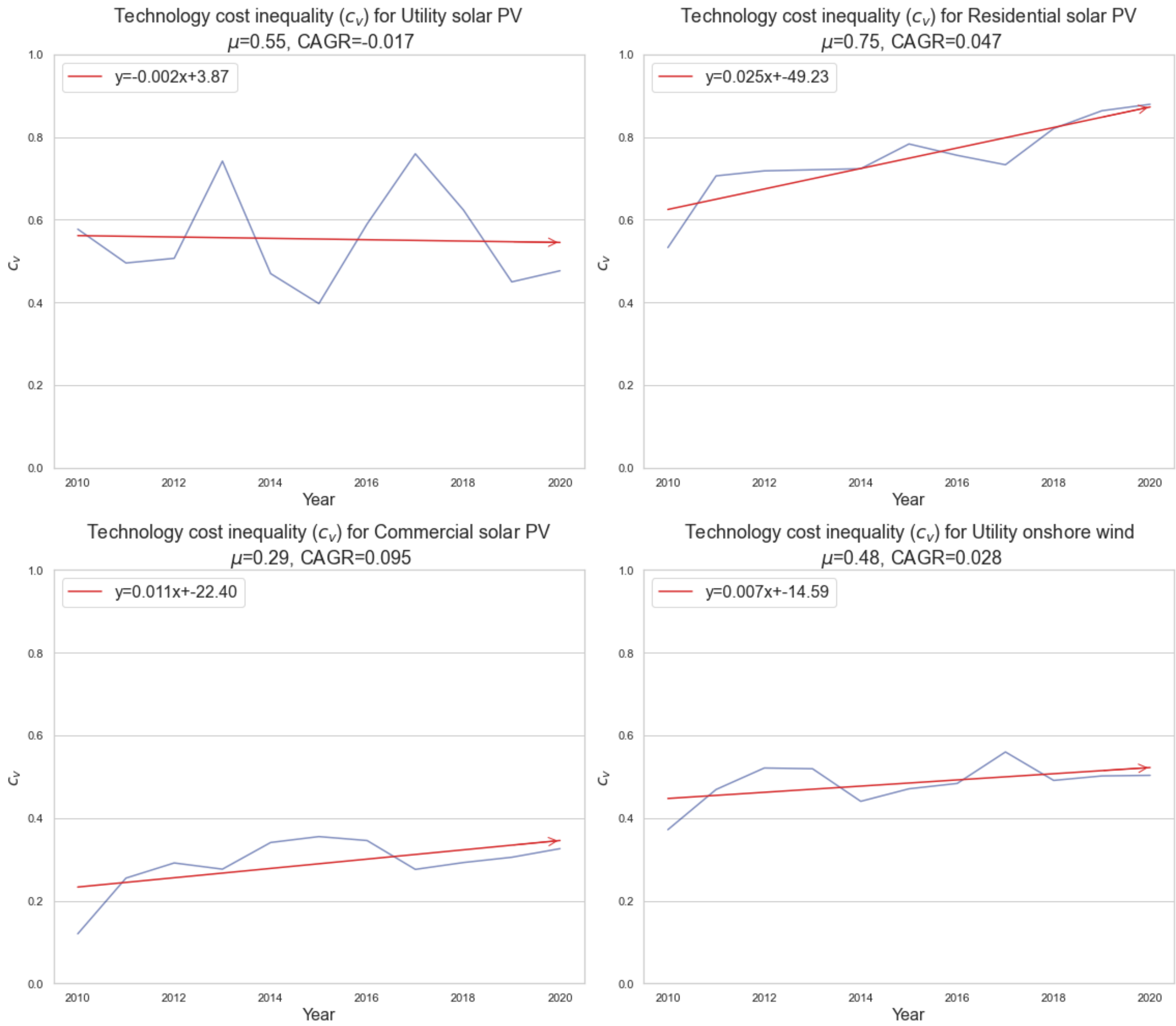

Figure 5: Coefficient of variation over time across solar PV and onshore wind and at multiple levels of implementation for solar PV (utility, residential, commercial). Red arrow shows the trajectory of TCI over the time period (best-fit line). Each of the plot shows a slope when a regression line is fitted to the c_v vs time, the μ - average for TCI over the time period, and the CAGR for c_v from 2010-2020.

For solar PV, TCI varies depending on the segment on which it is examined. Average TCI is highest in the residential segment, followed by utility scale then commercial solar PV (μ = 0.75, 0.55, 0.29 respectively). TCI is increasing at 4.7% and 9.5% per year in the residential and commercial segments while decreasing slightly by 1.7% in the utility segment. This suggests that under a “business-as-usual” scenario TCI in the commercial segment will catch up to the utility and residential segments. TCI in the utility segment is decreasing, however, it is useful to note that solar PV data was only recorded in lower-middle to high-income countries. In 2020 Indonesia, the second lowest income country, had the second highest price level adjusted utility installed costs. This suggests that significant utility solar PV cost disparities likely exist, but they could not be shown due to lack of data.

TCI for onshore wind varies depending on whether we consider large markets, small markets, or the combined case. In all three cases TCI increases. Across all markets CAGR = 2.8%, in large markets alone CAGR = 1.1%, small markets alone CAGR = 1.4%. This means countries that have recently entered the market are facing increasingly higher costs as a group, whereas incumbents have benefits from being in the market longer. Only rich countries such as Denmark, the United States, Germany, and Sweden had recorded onshore wind installed costs in earlier years. Other markets such as India, China, Brazil, and Mexico had onshore wind energy production only recorded in the 1990s, with much smaller markets only recorded from 2010. Over the last decade, TCI increase coupled with rising costs in small markets, increases the likelihood of unequal transition outcomes between countries.

3.3 The impacts of cost inequality can be severe

To understand the implications of these patterns in TCI on the potential costs countries will face in investing in these renewables, we explored several potential cost and investment measures (Figure 6).

Countries with high costs will face higher investment expenditure and the difference between being a low and high cost installing country can be high. For example, if Pakistan (a high-cost onshore wind country), installed at the lowest cost ($1282/kW vs $7571/kW) under the same deployment, the total investment would be $155M vs $920M, investing 0.011% vs 0.065% of GDP. Similarly, India (medium-cost utility solar PV country) has a $28B gap between the lowest and highest costs. China, a low-cost commercial onshore wind country, saves 0.04% GDP. And in the residential solar PV segment if Australia (low-medium cost country), installed at highest costs, would be a staggering $103B vs $8.2B (6.5% vs 0.5% of GDP.)

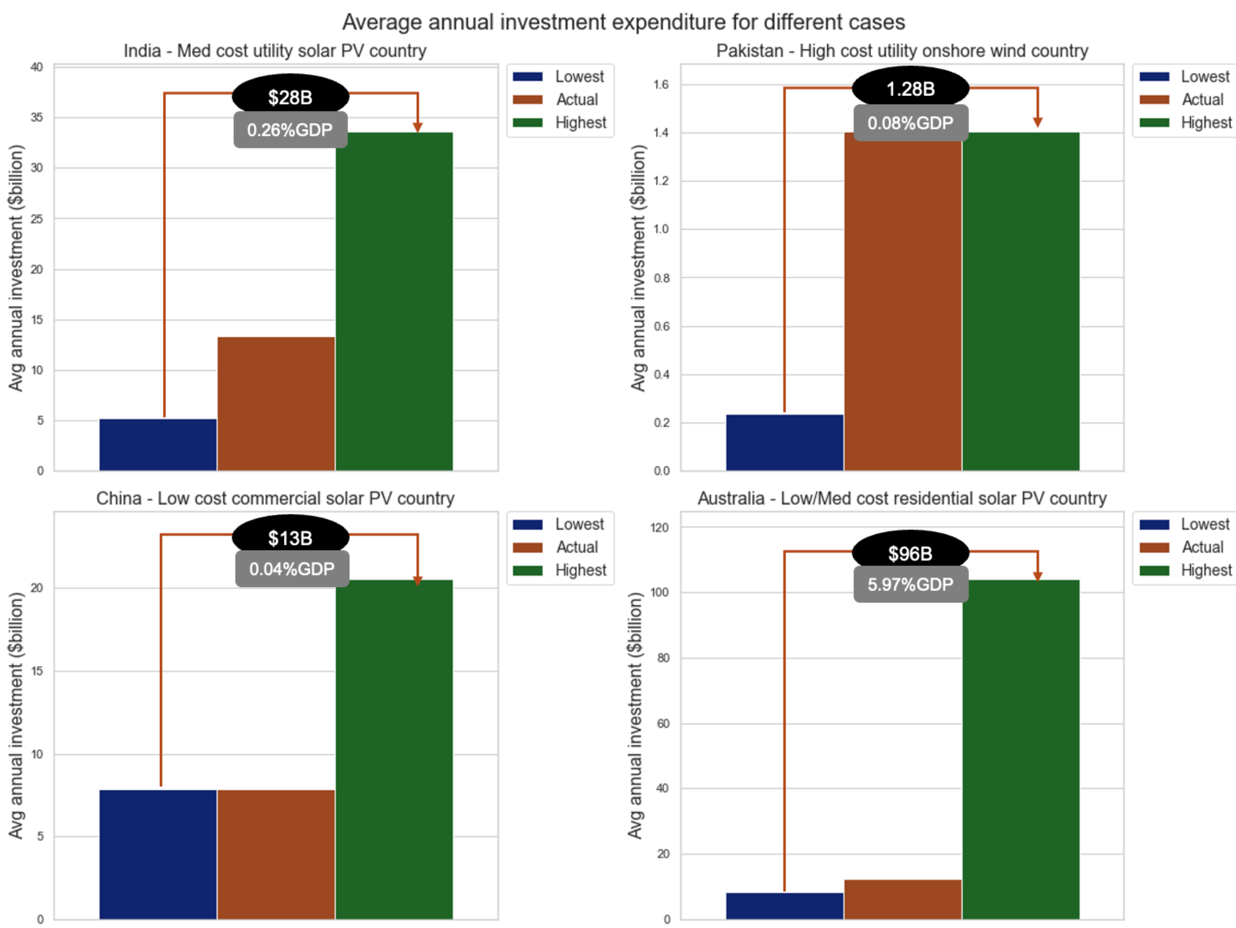

Figure 6: Average annual investment with best, worst, and actual cases for different technology/segment installation types. Average annual investment is taken as either the average over the last 5 years (2016-2021) or 2018/19 as an indicative year. Best cost - lowest in category, worst - highest in category. We show the difference between the best and worst case for each country and the proportion of GDP this represents.

3.4 Various country groupings further reveal installed costs patterns

We compare the relationship of country classifications for income, RIC, policies, and geographical location with costs. First, we show how disaggregated solar PV costs vary across technology acceptor and creator countries. Second, we derive policy groups. Third, Kruskal Wallis tests are conducted to determine if categorical classifications explain costs.

3.4.1 Disaggregated utility solar PV costs highlight TCI differently

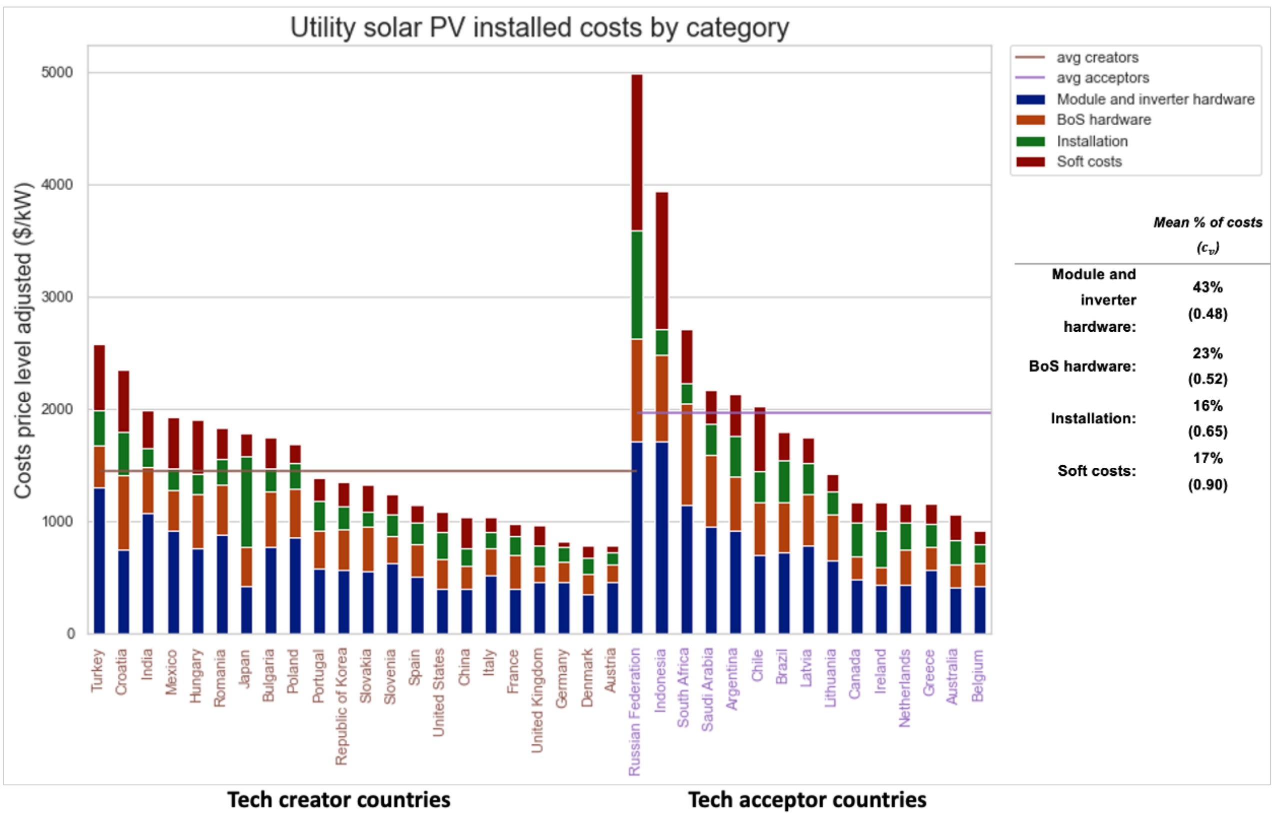

Figure 7: Installed costs disaggregated into sub-costs for module and inverter hardware, BoS hardware, Installation and Soft costs. We adjust costs for price level. Mean sub costs are shown with the corresponding c_v . These sub-costs are further disaggregated into 16 sub-sub-costs such that Modules and inverter hardware = Modules + Inverters; BoS[7] hardware = Racking and mounting + Grid connection + Cabling/ wiring + Safety and security + Monitoring and control; Installation = Mechanical installation + Electrical installation + Inspection; Soft costs = Margin +

[7] BoS=Balance of Systems

Financing costs[8] *+ System design + Permitting + Incentive application + customer acquisition (IRENA 2021).*

To understand where differences in costs may be coming from, we consider the disaggregated costs across countries. Historical installed costs are driven by module and inverter hardware costs (43%) which are relatively stable across countries (global commodities). The support costs are over half the total costs and tend to have greater dispersion across countries (i.e., higher c_v *);* BoS hardware (which might also be commoditized given that some countries may import many of the products) has the lowest TCI in support costs. These observations are consistent with Elshurafa et al. (2018) even though we adjust for price level. This variability is sufficient to warrant investigation into the driving factors.

[8] Financing costs included are the costs of capital acquisition not cost of capital. See a more detailed regional analysis of cost of capital acquisition and cost of capital in IRENA (2023)

3.4.2 Country policy portfolios fall into three categories

Policy clusters (i.e., groups of countries with similar policy and incentives situations) are obtained using a K-modes analysis on our policies dataset. Our analysis of the clusters reveals patterns described in *Table 2*. The diversity of policy situations is large, although all countries appear to have at least some policy relating directly to renewables. Our goal here is not to highlight the superiority of any one policy, but to highlight the effect that a particular portfolio of types of policy scenarios might yield on installed cost differences.

Table 2: Policy clusters obtained from policy situations (Regulatory Policy, Financial Incentives and Public financing). The proportion of countries that fit in each cluster is shown. Description of the policy cluster and a representative country is stated. Corresponding detail on policy analysis is available in Appendix B

Cluster name	% of countries in cluster	Description
Diverse set	40%	Regulation, market policies and incentives all used. We see RPS and quotas - regulation, FiTs, tradable Renewable Energy certificates (RECs) and Tendering - market, and Sales tax reductions - incentives. Policy options set at both national and sub-national levels. **Representative country: United States**
Market focussed	32%	Moderate policy diversity. Substantive use of financial incentives including sales tax credits and investment tax credits. Some tendering and regulatory policy occasionally employed e.g., through FiTs. **Representative country: Denmark**
Low use	28%	Very little use of regulatory policies or financial incentives for stimulating renewables. Some use of FiTs for regulatory policy tendering or sales tax credits for financial incentives. **Representative country: Turkey**

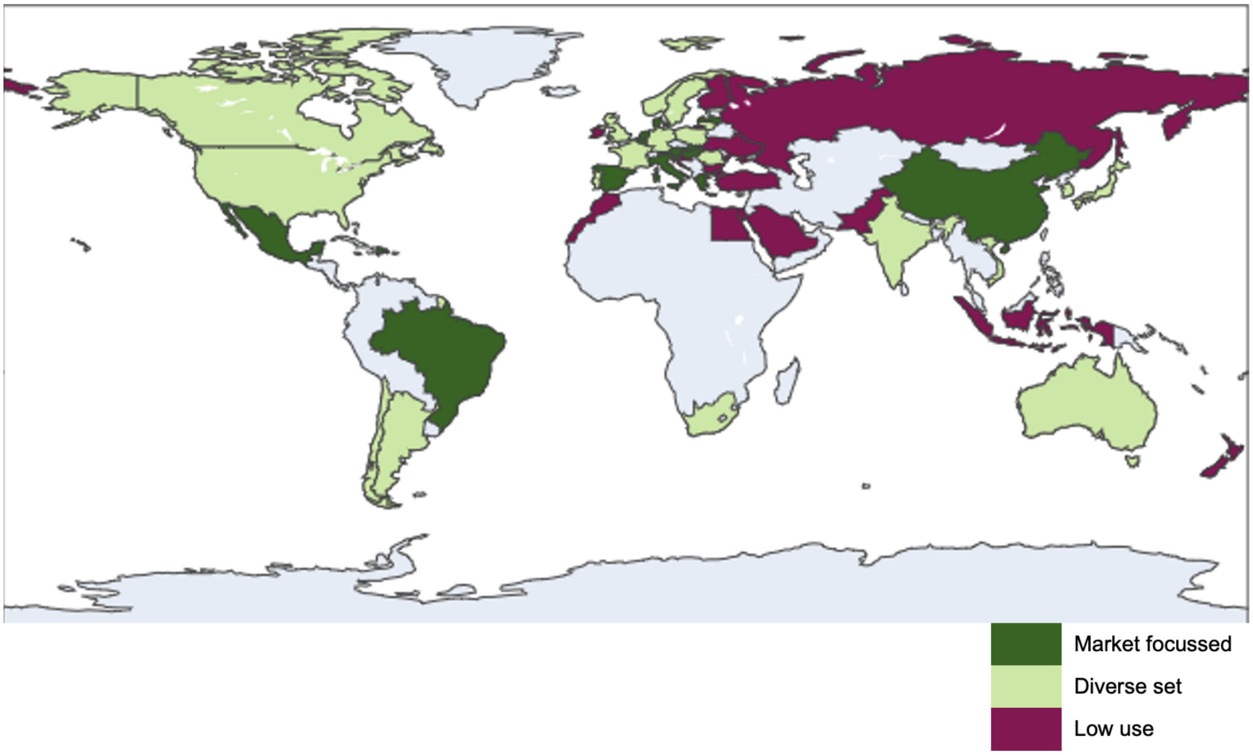

Figure 8: Geographical spread of the policy cluster classifications.

3.4.3 Cost differences exist across all country classifications

We conducted Kruskal Wallis tests and made box plots of country costs for both technologies together by country classifications (Figure 9). We can see that across all categories countries with worse historical conditions face higher costs (i.e., countries with below average emissions, technology acceptors, lower incomes, in the global South, and with less policy, tend to face higher costs).

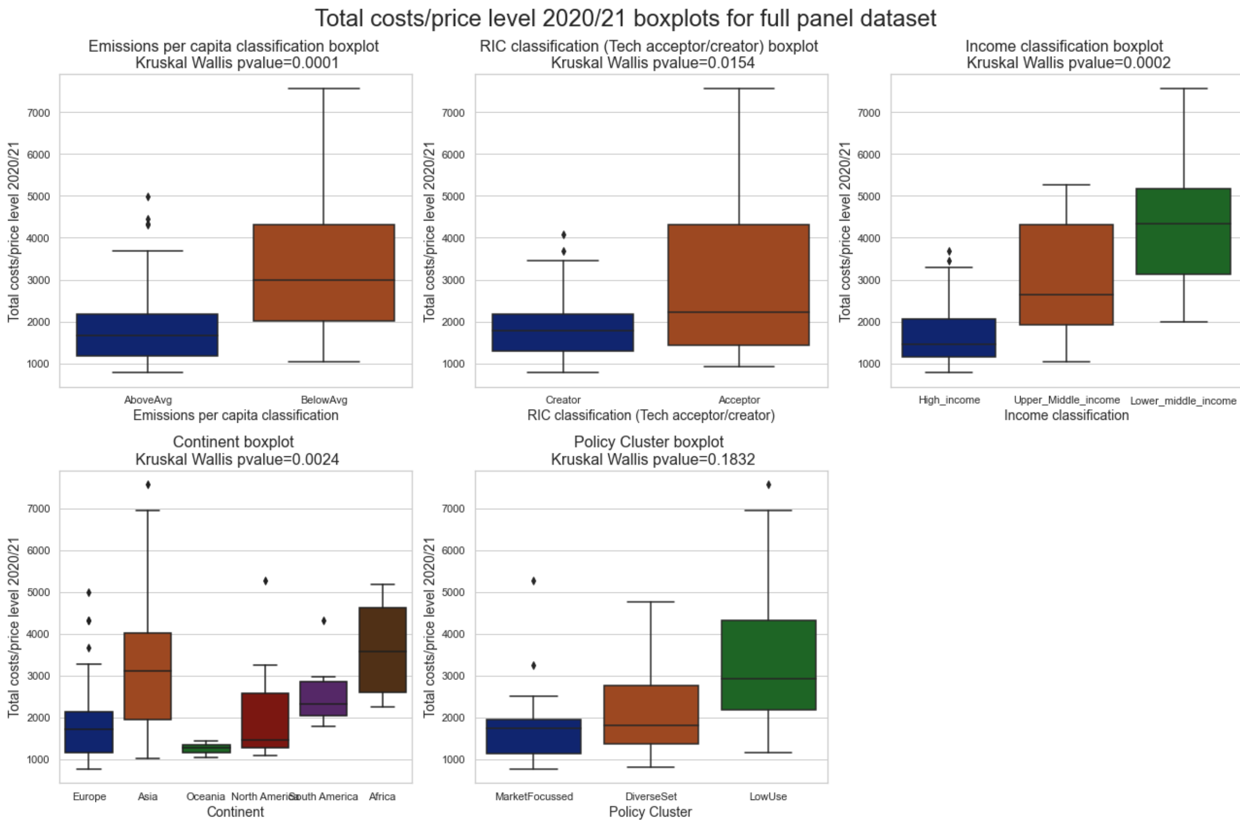

Figure 9: Boxplots for several categorical variables and Kruskal Wallis (KW) tests conducted on the differences in total installed costs based on the chosen categorical variable (i.e. we take costs for both solar PV and onshore wind combined to see the impact of categorical variables on cost independent of the technology). Categorical variables: Emissions, RIC (tech acceptor/creator), Income, Continent, Policy cluster. Output variable is Total costs price level adjusted. KW tests p-values shown such that pvalue < 0.5 – significant difference in the medians (otherwise insignificant). For solar PV data only where we have disaggregated costs, we can conduct KW/box plot tests to see which parts of the costs are influenced by the drivers. The results are mixed (see Appendix G)

We find that RIC is a strong determinant of green technology cost outcomes. Tech creators tend to have lower technology costs. These trends are broadly consistent across technologies albeit less pronounced when each technology is examined individually for the classification (lower levels of statistical significance for KW tests). This is concerning given that RIC correlates strongly with income and historical emissions.

Despite having only three income categories (low-income countries missing), we still observe cost inequalities across categories. Without adjusting for price level, total costs appear to be the same across income categories for countries. However, when we adjust for price level, we clearly see that high-income countries get a better deal. Total installed costs are lower in higher income countries and highest for lower-middle income countries. These results are consistent across technologies.

Continent or geographical location follows the same trends as income. We note that the African and Asian continents tend to have higher price level adjusted costs. These are the continents with the greatest proportion of lower-middle income countries. Again, we see the effect of adjusting for price level as we note that countries that have above average historical emissions per capita also have cheaper access to green technologies. This raises questions regarding the “historical responsibility" aspect of the energy transition.

The results show low statistical significance in cost differences across policy clusters when observed in isolation from other variables. We do note that the “Low use” cluster does tend to have higher costs across technologies. We also test for whether axiomatic policies such as FiTs or quotas impact costs (as an alternate approach to understanding policy effects). These two policy mechanisms have been known to stimulate renewables development with FiTs being more useful when renewables are still nascent in a market (control the price) and Quotas (control the quantity) being more powerful when a technology becomes more mature (Polzin et al., 2015). We find that these policies are also not statistically significant explanatory variables for cost differences.

3.5 Multi-variate exploration of relationships between costs and potential drivers

Here, we present a multivariate analysis to further unpick relationships between costs and potential technology cost drivers (Table 3). We use our insights from analysing the correlation between variables (see Appendix D) to reduce the variables so that we avoid collinearity in the regression. We use GDP per capita as the measure of income (demand pull) and the business/market environment, Patenting as a measure of R&D (learning by searching) and RCA/Proximity as measures of the renewables industry. Because RCA and Proximity are moderately correlated, we only use one of the variables in the regression at a time. The policy clusters are our policy variables. Nearly all the explanatory variables share a negative monotonic relationship with total costs adjusted for price level.

We control for GDP and population (we are interested in more than just economy size or the size of the country as explanatory variables). We also add deployment per capita to our control variables because the relationship has been shown in prior research (e.g. Way et al., 2022) (also shown in correlation analysis) and we want to examine costs independent of total technology stock.

Table 3: Regression analysis of drivers of TCI. Dependent variable = Total price level adjusted installed costs. Variables are scaled by normalising across the countries - we can observe the size of the effects from each factor using the coefficients (if a variable changes by 1 std then we observe the corresponding change in total costs). Dummies used for technology and policy categorical variables. Intercept is specified for each result (policy, technology). Impact on costs of different variables can be calculated from the intercept.

	(1) RCA		**(2) Proximity**		**(3) RCA no FE**		**(4) Proximity no FE**		**(5) RCA no Controls**		**(6) Proximity no Controls**	
Intercept	Low Use, SolarPV		Low Use, SolarPV		Low Use		Low Use		LowUse, SolarPV		LowUse, SolarPV	
	2336	***	2291	***	3174	***	3113	***	2387	***	2332	***
GDPperCap	-669	***	-686	***	-725	**	-755	**	-719	***	-737	***
RCA	-168				-245	.			-177	.		
Proximity			-100				-182				-122	
TotalRenewablePatents	-141		-124		-145		-112		-130		-97	
DiverseSet	-749	**	-672	*	-965	**	-843	*	-777	**	-685	*
MarketFocussed	-960	**	-955	**	-1285	**	-1262	**	-1024	**	-1006	**
OnshoreWind	*1301*	***	*1320*	***					*1263*	***	*1282*	***
Population	-92		-83		-59		-41					
GDP	92		94		108		114					
DeploymentperCapita	-138		-136		6		20					
Full set of control variables	Yes		Yes		Yes		Yes		No		No	
Technology FE	Yes		Yes		No		No		Yes		Yes	
R2	0.68		0.68		0.49		0.48		0.68		0.67	
Adj R2	0.64		0.63		0.43		0.41		0.65		0.64	

Significance levels: 0 '*', 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1**

Demand-pull and business environment variables have a strong relationship with TCI. GDP per capita has a negative coefficient and the second strongest relationship outside of policies even when we control for country size and cumulative deployment per deployment. These results are consistent even when we vary the macroeconomic variable we use in the regression (GDP per capita, HDI, Doing Business Score etc.) and the demand-pull variable remains highly statistically significant.

While there are no statistically significant differences in cost when policy clusters are examined in isolation (Figure 9), when we control for other variables, we note a significant increase in statistical significance (see all Table 3). Low-use policies cluster are associated with higher costs. When countries use a diverse set of policies, technology installation costs are roughly $700/kWh cheaper. And market-oriented policies tend to have the lowest installed costs being ≈$1000/kWh cheaper than the low-use case. When we control for other variables, policies have the largest relationship with technology costs.

RIC has a moderate association with TCI but varies depending on placement on the value chain; with activities higher up the chain being more significant. At the learning-by-searching level (R&D represented by patenting) we note that while patents are associated with lower costs, it is small (negative but small coefficient; the variable is also statistically insignificant). This is likely because 86% of renewable patents are produced by the top 5 countries China, USA, Japan, South Korea, and Germany. As we move up the chain, we see that proximity shares a weak monotonic relationship with costs but is insignificant in the regression (see Table 3 (2), (4) and (6)). RCA which is further up the chain shares a weak monotonic relationship but has a regression coefficient that is statistically significant at a 10% level (see Table 3 (1), (3) and (5)). Additionally, RCA which is our main measure for the RIC classification shows that costs are different for technology creators vs acceptors (see Figure 9).

4. DISCUSSION AND CONCLUSIONS

4.1 Key findings

The global energy transition has so far largely been driven by improvements in energy technologies and reductions in their costs. There is much optimism surrounding the large reductions in renewable costs that have been observed in recent years. This paper set out to explore the country-level trends in costs of solar PV and onshore wind, to better understand how different countries might be experiencing these global trends.

We have shown that regional differences exist, and technology installed costs disparities influence a country’s experience of the transition. Technology Cost Inequality exists and is broadly increasing. Utility onshore wind and residential and utility solar PV segments have seen increasing TCI, whereas utility scale solar PV is on a slight downward trend (CAGR = 2.8%,4.7%,9.5% and -1.7% respectively). Currently, solar PV installations are dominated by utility scale (58%) installations, but some parts of the world are likely to continue increasing the proportion of residential and commercial installations. Therefore, rising cost inequality is concerning. The impacts of TCI can be severe. Differences between a country deploying technology at the lowest vs highest cost can be high e.g. $1.2B (0.08% of GDP) of GDP for Pakistan a high-cost utility wind installer and $96B (6% of GDP) for Australia a low/medium cost installer of residential solar PV.

We also explored the association between a range of factors that have been theorised to impact technology costs. These also revealed several potential energy justice implications for the transition. Higher income countries with stronger demand-pull factors (e.g. Income, Doing Business Score etc.) tend to face lower costs. Countries with stronger renewable industries face lower costs though the relationship with renewable industry competitiveness is more pronounced further up the value chain. At the level of research and development, there are no significant cross-country differences, whereas when we examine the competitiveness of manufacturing and export capabilities, we see more advanced countries faring better. A country’s policy portfolio had the strongest association with cost differences. Countries with market-based policy mechanisms tend to have lowest costs, whereas countries with low policy use face higher costs (differences of over $900/kW). We also note that countries with lower historical emissions and in global south regions of the world i.e., Africa, Asia and South America face higher costs. These trends bring to question the agency that a country has to improve costs and whether cost differences might exacerbate the already low distributional justice in the energy transition.

4.2 The truth about Technology Cost Inequality

The coefficient of variation is a relative statistic for measuring dispersion which allows us to make comparisons across different datasets. In this case, we can compare TCI for each of our technologies (solar PV and onshore wind) across time, however, we can also use the statistic to compare across the technologies. It is unclear if we can derive any meaning from the coefficient of variation about TCI beyond using this metric to measure relative TCI across technologies and across time. Our values for solar PV c_v are in a similar range to those identified by Nemet et al. (2021) and broadly increasing over the last decade for 2 (out of 3) crucial solar PV segments. This suggests that TCI is increasing at multiple scales which raises larger questions about the drivers and impacts of this cost dispersion – if we continue this trend the world may continue to be more unequal.

If we assume there is some generalisability of the trends for TCI we have found, we can foresee increasingly unequal outcomes in the energy transition across a range of country contexts. Further study could examine sets of countries that fit the profiles for either benefiting or suffering from the TCI trends and observe the trends for a greater set of technologies. The magnitude of the impact of TCI for forecasted transitions can be computed and compared to the relative sizes of the economies of these countries.

4.3 The impact of variable data quality

The impact of data quality on our ability to do this type of analysis cannot be understated. While most geographical locations were covered by our data (i.e., we had data from countries on all continents for both solar PV and onshore wind), there was disproportionate representation. For example, only 1 (2%) and 3 (5%) countries from Africa were represented in solar PV and onshore wind data while 22 (42%) and 16 (31%) of European countries were represented in the data (see *Table 2*). This places severe constraints on the generalisability of the insights that we generate in the research, for example a Kruskal-Wallis test conducted with too few data points in one category would be unreliable. Moreover, it is reasonable to assume that these countries will face the highest costs following our analysis. Additionally, because developing countries are perpetually underrepresented in studies such as these, the recognition and procedural elements of justice are violated (Sovacool and Dworkin, 2015; Jenkins et al., 2016). Because these geographical areas are underrepresented in the research, solutions to the problems they face may also remain undiscovered, further exacerbating inequalities.

We also note that there were several missing data points for time series data across both solar PV and onshore wind datasets. The robustness of the coefficient of variation computation may be low for some years with very few data points, however, on the entire time series, the results were fairly reliable. Because wind energy costs were not disaggregated to sub-costs, we could not generalise the disaggregation insights from solar PV to onshore wind without postulating some inferences. Additionally, because the disaggregated data was unavailable for both solar PV and onshore wind on a time series, we could not observe how the various sub-costs have changed over time – such analyses would have been powerful.

4.4 Future work

Future research should include improved data collection, particularly from underrepresented countries and disaggregated installed costs for onshore wind energy. A fixed effects regression would have been possible if disaggregated cost data was available on a time series - we could note the stability of the explanatory variable coefficients over time. Further study of the agency that countries have to improve cost and deployment of renewables is needed. Such a study could focus on policy feasibility - understanding what policy portfolios are possible for some countries at a particular time given the country's attributes e.g., income, knowledge/skills capacity etc. By studying this we can further unpack the "justice" implications of the energy transition. Lastly, future work should unpack how TCI impacts forecasted energy transitions combining empirical cost forecasting (e.g., Way et al., 2022) and drivers of TCI. The "true" cost of the transition can be observed for different countries and compared to economy size to unpack new insights.

Data availability

A supplementary datafile is available that contains:

- Time series data
- Cross-sectional data
- Policy clustering data
- Solar PV Deployment data by segment

Tankwa, Brendon; Barbrook-Johnson, Pete (2023), "Data: Increasing inequality between countries in key renewable energy costs", Mendeley Data, V1, doi: 10.17632/stbmpm8kch.1
https://data.mendeley.com/datasets/stbmpm8kch/1

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Competing interests

The authors have no competing interests or conflicts of interest to declare.

Author contributions

Removed for anonymity

Appendix

Appendix A - Data cleaning and preparation details

Our final step after collecting IRENA Installed costs data and conducting regression tests was to verify data with statistical power analysis (a post hoc power analysis) to ensure that the tests will reject a false null hypothesis (not making a type II error). We use this to determine whether we have an adequate sample size for the analysis and to inform subsequent steps in our methodology. The significance criterion is maintained for the entirety of the analysis at 5% and with a Cohen's effect size determined from the R2 and 8 independent variables (the most that we use at a time) we note that our sample size (≈73 countries) yields a statistical power of ≈1 (100% chance that a false null hypothesis will be rejected in regression testing). This is higher than the desired statistical power of 0.8 (that satisfies the standard 5-80 ratio used by most researchers) (Soper, 2022).

Next, we cleaned the data and added it to the cross-sectional data used for the analysis of explanatory variables. This was done on an MS Excel workbook using a series of MS excel functions. Missing variables, particularly for costs (e.g. wind energy panel data had several missing cost values from the year 2021 for multiple countries), were handled either by using previous year values or dropping the country from the dataset.

Appendix B: K-modes clustering

Our steps in this analysis are as follows: (i) Determine the number of clusters using the elbow method (in our analysis we determine that there are 3 clusters). (ii) Cluster the policies for the combined solar PV and Onshore Wind countries since the policy dataset does not distinguish between the technologies. (iii) Review the results of the clustering analysis and create codes for each of the clusters based on the observed patterns in the policy and incentive situations. This step requires some subjective judgement on the part of the analyst.

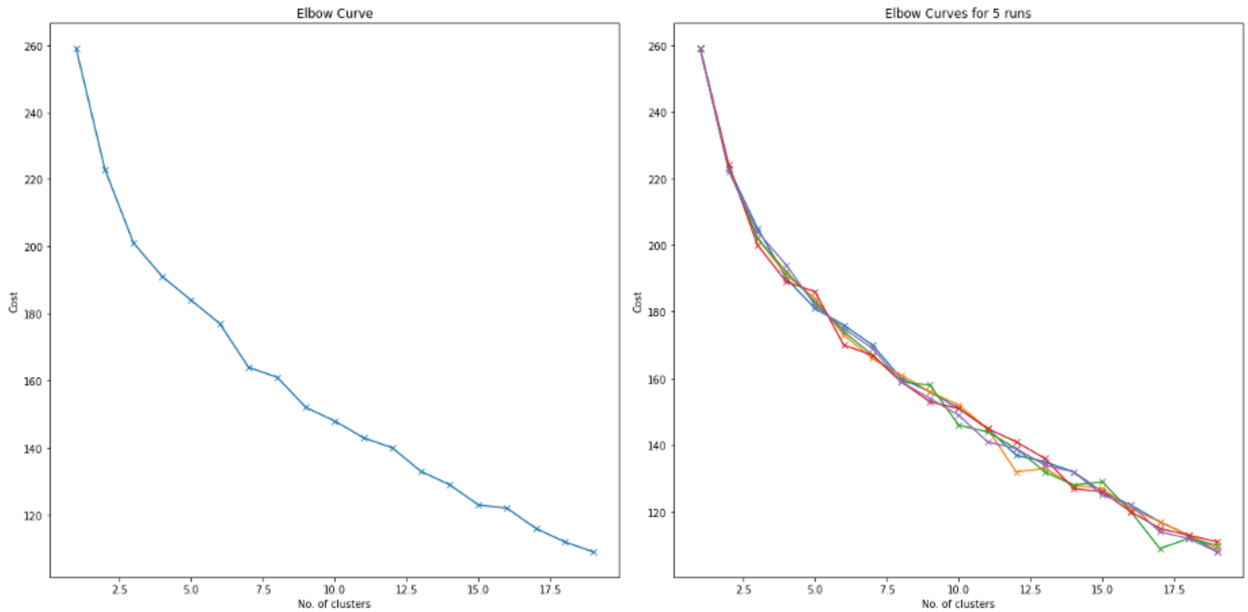


Figure 10: Elbow curve used to show the number of clusters coming from the data. Policy data used is policy categories from REN21 GSR (see supplementary data). Elbow shown at n=3 – robust for when we remove "Renewable energy in INDC or NDC" which all countries have and when we remove "Public investment, loans, grants, capital subsidies or rebates" which in general contains more options for each country.

B.1 Limitations of policy findings

We also note the limitations in using thematic approaches to thinking about policies and incentives. Governments tend to apply strategic thinking to policy formation and the mere presence of a specific type of policy may not indicate much. For example, according to REN21 "India put forward an expedited manufacturing plan to incentivise domestic solar cell manufacturing capacity and planned to impose new tariffs of 40% on imports of solar modules and 25% on solar cells starting in April 2022. The Indian government also approved a "production-linked incentive" plan to enhance the country's manufacturing capabilities and exports, including domestic high-efficiency solar PV module manufacturing and advanced chemistry cell batteries." (REN21, 2021). This type of policy proposal might have the effect of increasing the costs of renewables in the short term as the nation builds up its manufacturing capabilities as the price would be higher due to the tariff and possibly shorten supply before the domestic manufacturing market builds up capacity. Such nuance would not be captured in our type of analysis.

Appendix C: Residential and Commercial solar PV installed costs

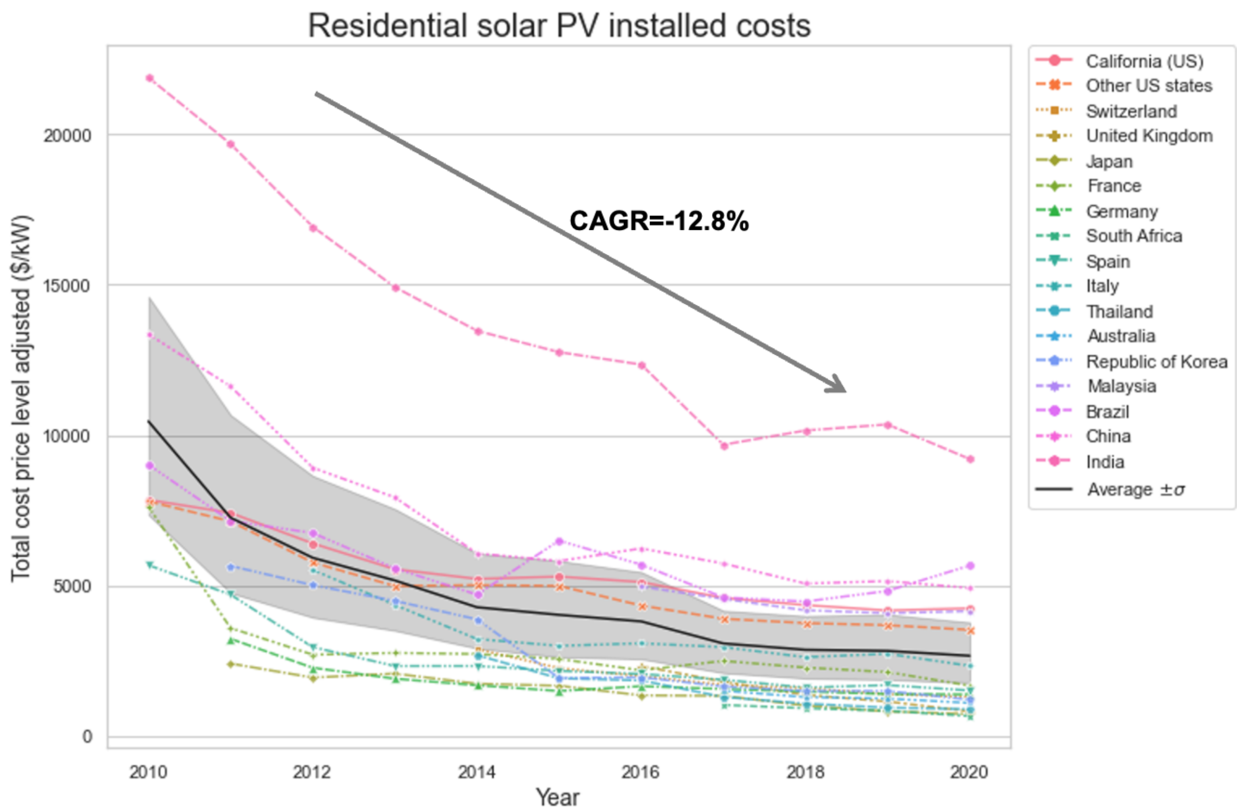


Figure 11: Average Onshore wind energy costs by country for 17 residential solar PV energy markets from 2010-2020. A mean line with +/- one standard deviation shading is shown. CAGR for the mean is computed and shown with a grey arrow showing cost increase/decrease.

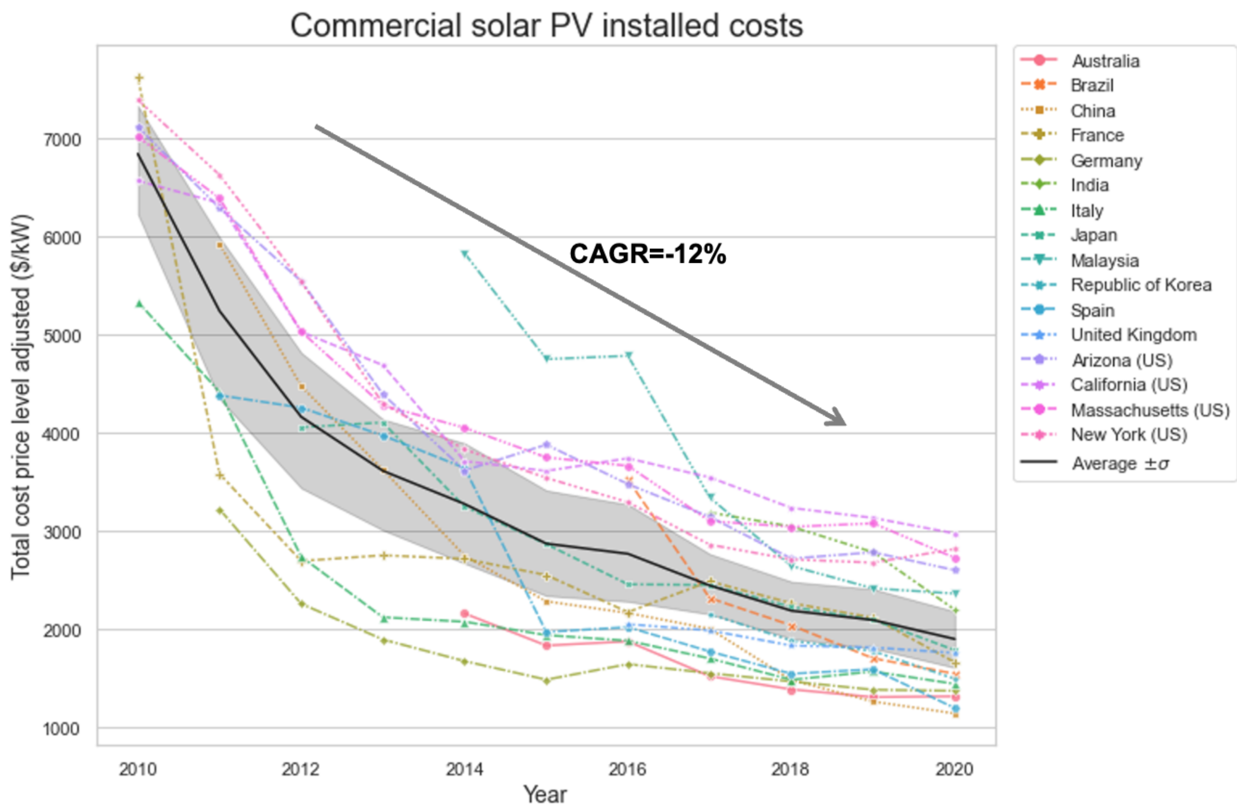


Figure 12: Average Onshore wind energy costs by country for 16 commercial solar PV energy markets from 2010-2020. A mean line with +/- one standard deviation shading is shown. CAGR for the mean is computed and shown with a grey arrow showing cost increase/decrease

Appendix D: Relationships between the variables

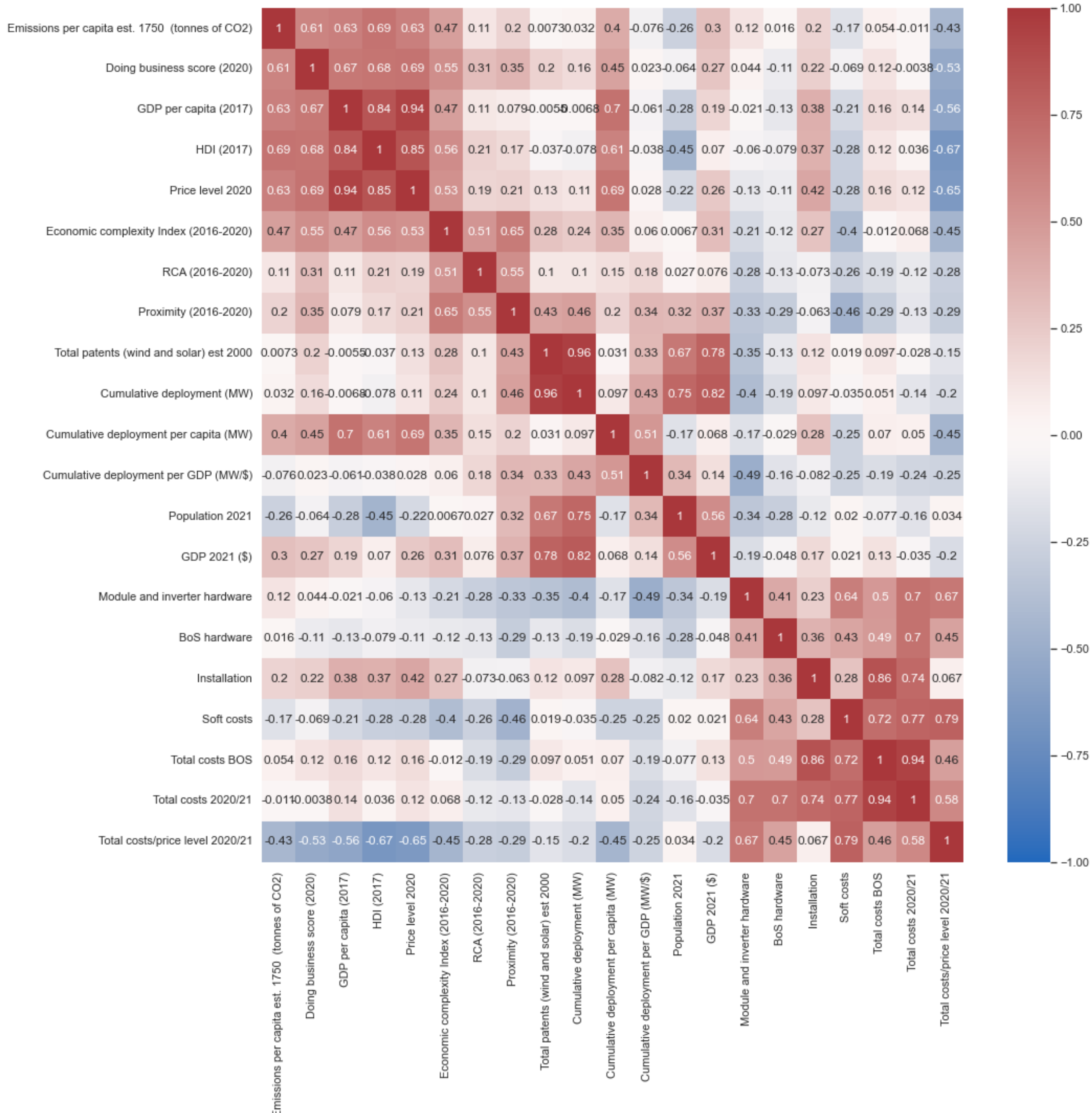


Figure 13: Pearson correlation plot of all continuous variables for cost data combined solar PV and onshore wind. BoS hardware, Installation and Soft costs that exist only in the solar PV dataset are examined for this case

Economic indicators tend to track well with each other across countries, but relationships gradually get weaker as we compare with more focussed industry variables. Ease of doing business, GDP per capita, HDI, and Price levels all have strong monotonic relationships with each other (ρ >0.6). We also note that as we begin to become more industry specific, we still see strong relationships. Economic Complexity Index, which is a measure of economy strength from an industry perspective (stronger/more advanced economies have greater economic complexity) has moderate monotonic relationships with economic variables 0.45< ρ <0.6. And as we focus on renewables industries (RCA and Proximity) we see much weaker correlation with economic strength (ρ <0.35 for all). Patenting, which is an indicator of innovation and R&D – which occurs much earlier in the lifecycle of a technology shares an even weaker monotonic relationship with economic variables.

Cumulative deployment has varying relationships with variables depending on how we adjust it. Raw cumulative deployment shares strong associations with patenting, population, and GDP =0.96, 0.75, and 0.82 respectively. The strong relationship with patenting is consistent because the top 5 countries producing renewable patents (China, United States, Japan, Republic of Korea, Germany) are also the top countries in deploying green technologies (excluding Republic of Korea). If we adjust deployment by population, we note strong positive associations with economy related variables (0.4<ρ<0.7) – meaning in rich countries each citizen has a higher chance of having renewables in their energy supply than their poorer counterparts. Surprisingly, RCA and Proximity share mostly weak associations with cumulative deployment adjusted by either population or GDP. We would expect that in countries with stronger renewable industries, there might be more deployment, however the relationship is only moderately positive monotonic relationship between raw cumulative deployment and proximity. This likely means that other variables other than the strength of the industry relative to peers explains cumulative deployment trends.

Appendix E: Solar PV segments by region

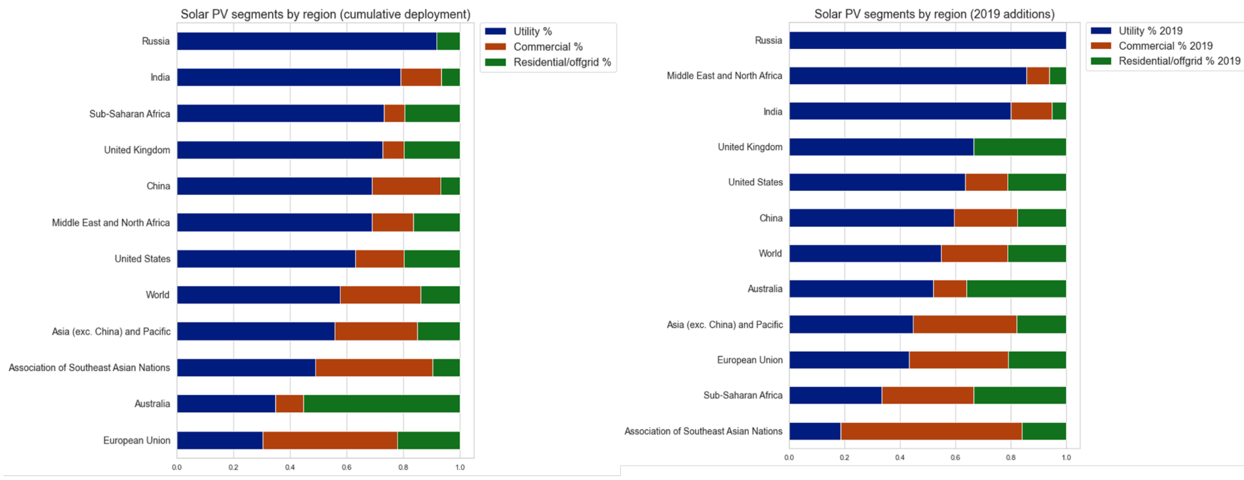
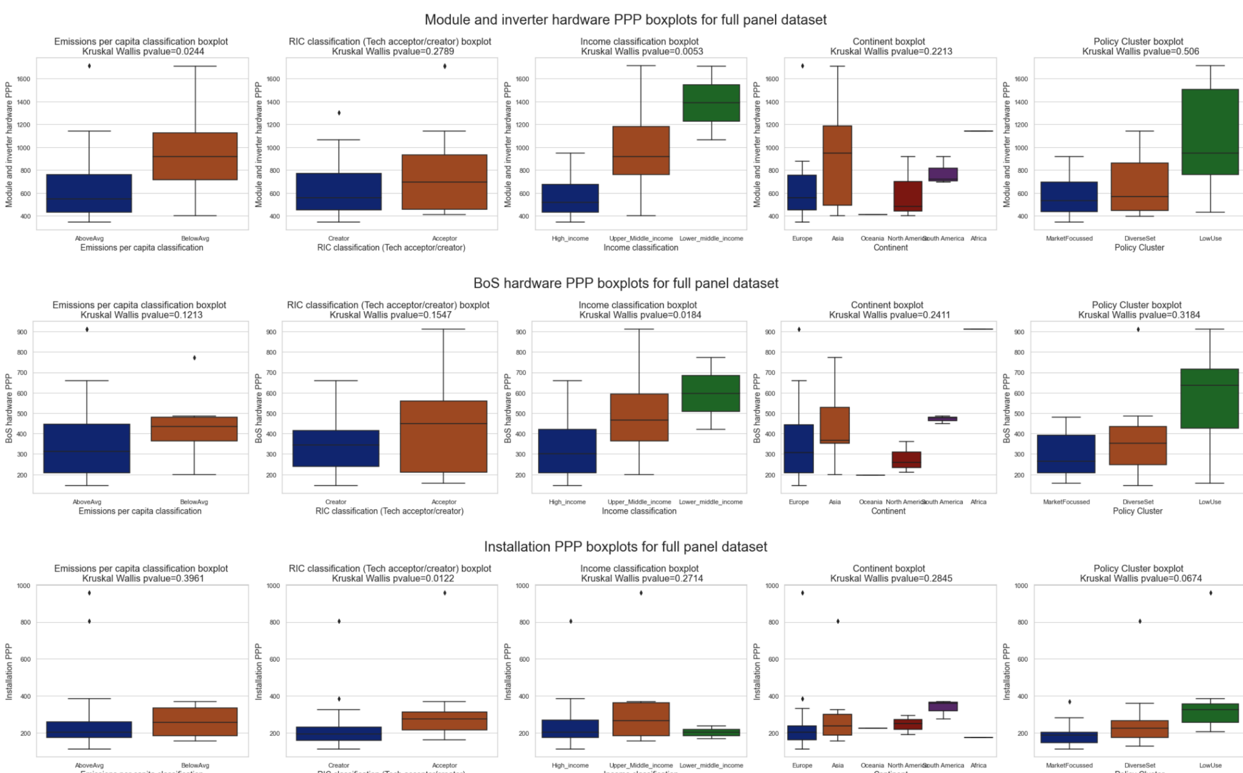
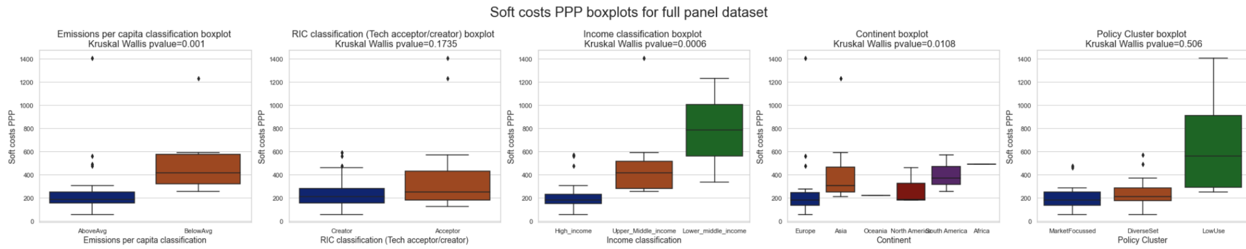
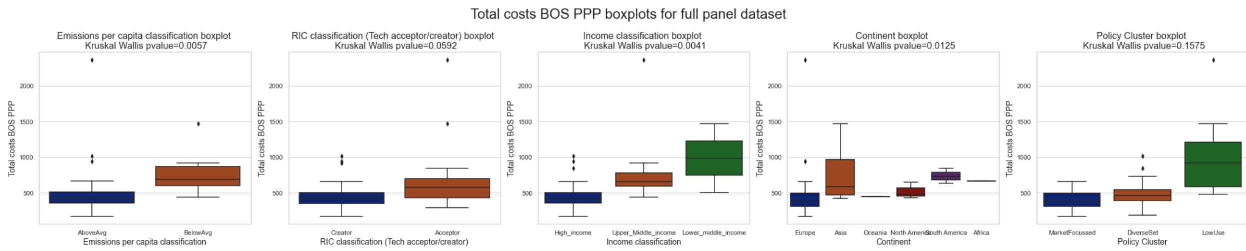
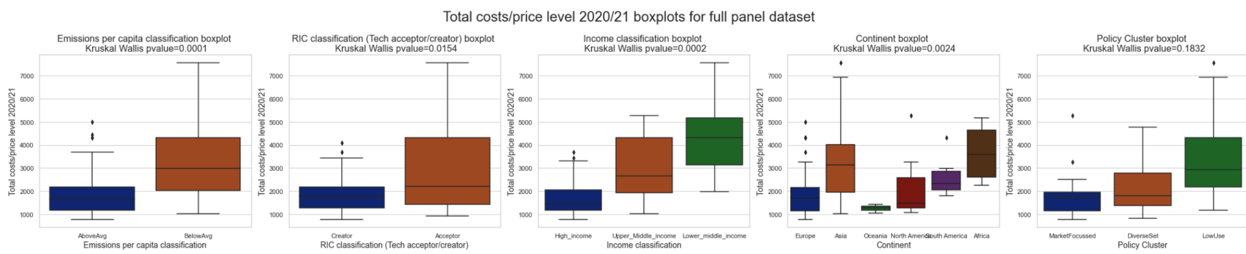


Figure 14: Solar PV segments representation (utility, commercial, residential) by region (cumulative deployment - left; 2019 deployment - right). 11 Regions and a "World" case are plotted

Appendix G: Box plots for the different sub costs




Soft costs PPP boxplots for full panel dataset
Emissions per capita classification boxplot
Kruskal Wallis pvalue=0.001
RIC classification (Tech acceptor/creator) boxplot
Kruskal Wallis pvalue=0.1735
Income classification boxplot
Kruskal Wallis pvalue=0.0006
Continent boxplot
Kruskal Wallis pvalue=0.0108
Policy Cluster boxplot
Kruskal Wallis pvalue=0.506
Soft costs PPP
AboveAvg
BelowAvg
Emissions per capita classification
Creator
Acceptor
RIC classification (Tech acceptor/creator)
High_income
Upper_Middle_income
Lower_middle_income
Income classification
Europe
Asia
Oceania
North America
South America
Africa
Continent
MarketFocussed
DiverseSet
LowUse
Policy Cluster

Total costs BOS PPP boxplots for full panel dataset
Emissions per capita classification boxplot
Kruskal Wallis pvalue=0.0057
RIC classification (Tech acceptor/creator) boxplot
Kruskal Wallis pvalue=0.0592
Income classification boxplot
Kruskal Wallis pvalue=0.0041
Continent boxplot
Kruskal Wallis pvalue=0.0125
Policy Cluster boxplot
Kruskal Wallis pvalue=0.1575
Total costs BOS PPP
AboveAvg
BelowAvg
Emissions per capita classification
Creator
Acceptor
RIC classification (Tech acceptor/creator)
High_income
Upper_Middle_income
Lower_middle_income
Income classification
Europe
Asia
Oceania
North America
South America
Africa
Continent
MarketFocussed
DiverseSet
LowUse
Policy Cluster

Total costs/price level 2020/21 boxplots for full panel dataset
Emissions per capita classification boxplot
Kruskal Wallis pvalue=0.0001
RIC classification (Tech acceptor/creator) boxplot
Kruskal Wallis pvalue=0.0154
Income classification boxplot
Kruskal Wallis pvalue=0.0002
Continent boxplot
Kruskal Wallis pvalue=0.0024
Policy Cluster boxplot
Kruskal Wallis pvalue=0.1832
Total costs/price level 2020/21
AboveAvg
BelowAvg
Emissions per capita classification
Creator
Acceptor
RIC classification (Tech acceptor/creator)
High_income
Upper_Middle_income
Lower_middle_income
Income classification
Europe
Asia
Oceania
North America
South America
Africa
Continent
MarketFocussed
DiverseSet
LowUse
Policy Cluster