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Faster market growth of wind and PV in late adopters due to global experience build-up

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A B S T R A C T

Different perspectives on the diffusion of technologies have suggested that market growth of technologies in late adopter countries may be either slower (because the technology is adopted later in areas where the technology has poorer economic performance) or faster (because global experience has resulted in maturation and improved performance of the technology). We compare the pace of market growth of wind and PV power in early and late adopters. We use panel data analysis on a database spanning all countries of the world, and years 1980–2014. We find that late adopters manage to access the global experience with these technologies, and utilize it to accelerate domestic market growth. Despite their lower GDP, late adopter countries have managed market growth for wind power that was up to 4.7 times faster than it was in early adopters, and up to 16 times faster for PV. These results suggest increased development efforts of novel clean-tech may kick-start rapid global deployment. Beneficial effects are less for very late adopters and less developed economies, signalling attention is needed for these in global climate change mitigation efforts.

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1. Introduction

The technological development and deployment of modern renewables has long been concentrated in advanced economies [1,2]. Meeting stringent climate change mitigation targets requires that these technologies are transferred and diffused to emerging and developing economies [3]. There are indications that global transfer and diffusion of such modern renewables is taking place. By year end 2014, 89 countries had wind turbines, and 59 had PV panels installed, including a growing number of emerging and developing economies (Fig. 1). Some of the largest emerging economies, notably China and India, are even amongst the global top ten in terms of installed capacity, although their ranking in terms of per capita installations remains much lower [4]. These numbers, however, do not say much about the pace with which these technologies are being deployed in these late-adopter countries, or how this pace compares to that in early adopters.

Historical evidence shows that market shares of (energy) technologies follow logistic growth patterns [7,8] (Fig. 2). The slow growth in early phases is due to a long list of interconnected problems, including a lengthy phase of technological development, during which the novel technology has limited competitiveness versus conventional alternatives [9–11]. As the technology matures, competitiveness improves, and increasingly rapid market growth becomes possible.

This logistic growth pattern is repeated in individual countries (or other geographical units) [7,8,14]. The growth curve in late adopter markets, however, is not simply the same logistic curve found in early adopters, shifted right along the time axis (as scenario A in Fig. 3).

Emerging and developing economies tend to be among the later adopters [14,15], and their relatively lower GDP reduces deployment speeds [16]. In itself, these effects would be expected to lead to increasingly flat slopes for late adopter countries (scenario B in Fig. 3). Such a pattern is consistent with what Griliches, in 1957, identified for the diffusion of hybrid corn in the US, in one of the earliest studies using logistic growth curves to compare the diffusion of a technology in different geographies [7]. Griliches identified that the economic benefits of switching to hybrid corn differed by state, and that high economic benefits in some states stimulated

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Fig. 1. Global deployment of wind and PV. Countries with any wind or PV installations (top) and countries with at least 100 MW of wind or PV (bottom); status by year end 2014. Source:[1,5,6].

both early as well as rapid market uptake [7]. Similarly, Pry [17], as cited in Marchetti and Nakicenovic [8], identified that the substitution of basic oxygen furnace for open-hearth and Bessemer steel production techniques was most rapid in early adopters, less rapid in early followers, and less rapid still in lagging markets.

In contrast, other historical studies of technology have identified many cases, including a diverse range of energy technologies, infrastructure, consumer electronics etc., in which late adopter countries managed more rapid transitions to the new technology than early adopters did [14,15,18–23] (as scenario C in Fig. 3). The explanation for this accelerating effect is that late adopter countries may benefit from the substantial technological and industrial development that has previously occurred at the global level (ibid). This notion is also found in the literature on technological experience curves. These curves represent the reduction in costs of a technology with increasing production experience, usually measured as accumulated production output [24,25]. Studies have found differing experience curves for individual countries, suggesting that the build-up of experience is at least in part a national matter [26,27]. Concurrently, there is evidence that global experience build-up matters as well, similarly suggesting that this experience spills over into domestic development processes [24,28].

Studies comparing the diffusion of novel technologies in early versus late adopters have further identified that late adopters tend to end up with lower market saturation levels of these technologies [29–31]. For example, Grübler compared the switch from traditional biomass to coal in a number of European countries [32]. Countries that started switching to coal in the early 1800's or before, reached a maximum share of 90% coal in their energy mix, before switching again from coal to other fuels. Countries that started to switch to coal several decades later, had a peak share of 50–60% in their energy mix [32]. Ultimate levels of per capita car ownership has also turned out to be lower in countries where the technology was first introduced at a later point in time [31].

To correct for these differing levels of saturation, the usual metric for comparing transitions is the number of years it took to get from 10% to 90% of the ultimate level of market saturation (Δt, in years, sometimes called turnover time, or diffusion rate) [8,14,15,18,30–32]. Bento and Fontes [18] compared the development of wind power in Denmark and Portugal in this way, by fitting logistic growth curves to observed data. For less matured wind and

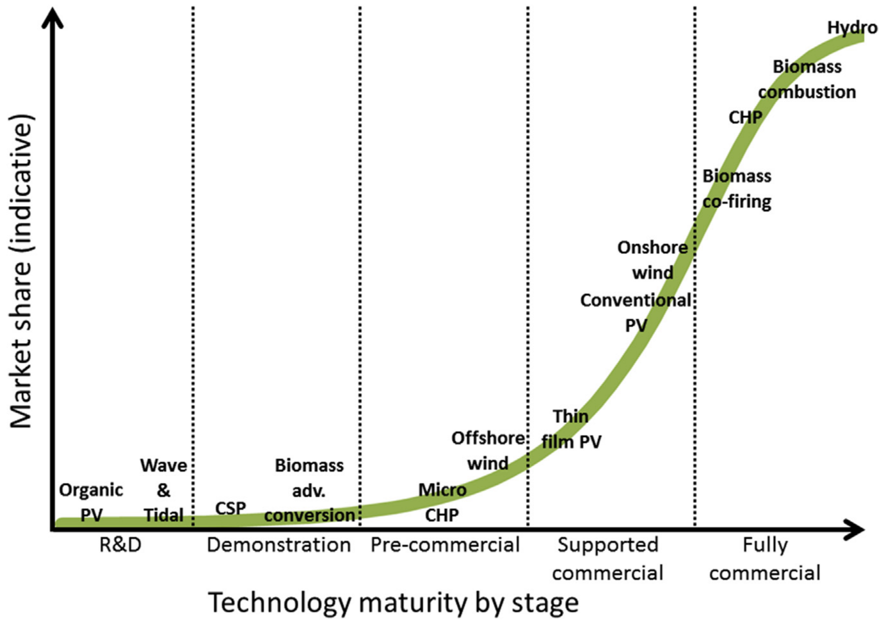

Fig. 2. Market development of maturing (renewable energy) technologies.
Source: adoption from Refs. [12,13].

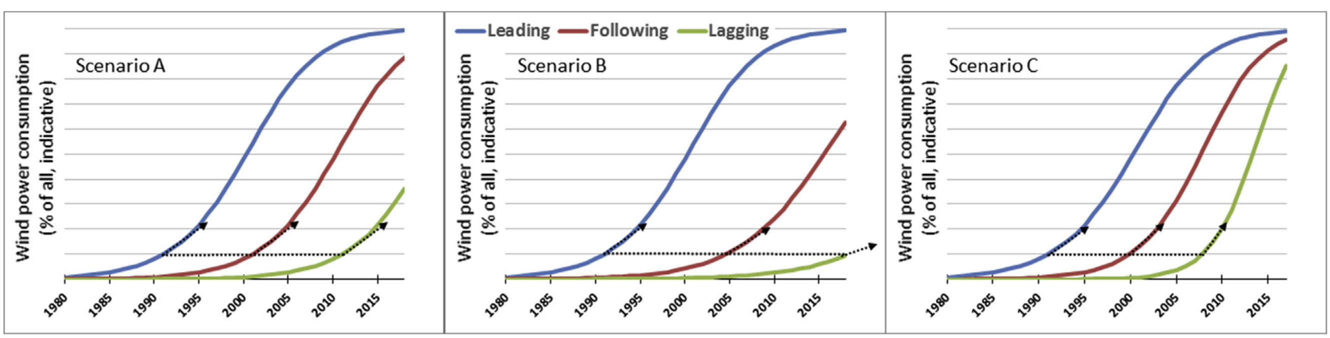

Fig. 3. Growth of renewables in early versus late adopter countries: 3 simplified scenarios. Scenario A: growth rates depend mostly on domestic experience build-up; countries manage similar growth rates; slopes are equal.Scenario B: economic development status matters most; poorer countries, which tend to be late adopters, also manage lesser growth rates. Alternatively, earliest adoption as well as fastest market saturation occurs in countries or areas where the technology offers the best financial performance; slopes are increasingly flat.Scenario C: global experience build-up matters most; late adopters manage to access this experience, and utilize it to accelerate domestic growth; slopes are increasingly steep.

PV markets that we aim to include in our analysis, this is not a credible method, as we do not know their ultimate market shares. Fitting logistic curves, and in particular predicting the upper asymptote is a highly imprecise exercise for such less mature markets. We can, however, compare absolute market shares of wind and PV, and the speed with which these grow. Such a comparison is at least as relevant in studying the spatial diffusion of low-carbon technologies.

Here, we analyse differences in the pace of market growth of wind and PV power in early and late adopters. The metric for comparison is annual increases of market share, as a percentage of total power production. Our database spans all countries, and years 1980–2014, although we limit our sample to market share increases in the deployment phase (here defined as starting when a country exceeds 100 MW of installations of wind or PV; more on this in the method section). We use panel data analysis to connect differences in annual market share increases to several explanatory variables.

We find that increased global experience has accelerated market growth in both early and late adopters. Market growth is more rapid in follower countries, possibly resulting from policy learning or technology transfer programmes. These beneficial effects far outweigh the negative effects from lower GDP typically found in late adopter countries. The net effects are that markets shares of wind power have been growing up to 4.7 times faster than markets in early adopters did, and up to 16 times faster for PV. The effects, however, are not linear. Relatively early followers were found to benefit the most from the build-up of global experience, whilst relatively late laggards benefit less.

2. Methods and data

In this section, we will explain:

- Our outcome variable, defined as annual market share increases of wind or PV (2.1);

- Our selection of key explanatory variables (economic development status, development of the domestic market, global experience build-up and country lag (2.2);
- Control variables selection, based on a review of earlier literature on factors determining renewable energy development (2.3);
- The need for a data filter to separate demonstration and deployment phases, which have strongly differing market mechanics (2.4), and;
- The selection of our estimation method (2.5).

Data collection is described in section 2.6, with an overview of the definition and data sources for the variables used provided in the appendix, Table A.1.

2.1. Outcome variable

The most common outcome variable in previous work using panel data analysis to determine what factors drive renewable energy development is the total share (%) of renewables in energy or electricity consumption [33–38]. As early adopters have had far longer periods of time to grow their market shares, it can be expected that these have (far) larger total markets shares of wind or PV.

We are interested in comparing the growth speed of market shares of wind and PV in early versus late adopters. We therefore regard annual market share increases, similar to growth speed variables used in a number of earlier analyses [39–42]. We use natural log transformed values of annual market share increases. The values of both market share and market share increases range over several orders of magnitude. As implied by the logistic growth curve, there is a linear relation between current market share and annual market share increases, when both are (natural) log transformed (this is also apparent in our data; see Supplementary Fig. S.1). Similar to Hitaj [39], we use logs of annual market share increases, defined here as:

$$'Market\ share\ increase'_{i,j,t} = \ln(market\ share_{i,j,t} - market\ share_{i,j,t-1})$$

where $market\ share_{i,j,t} = \frac{MWh\ power\ production_{i,j,t}}{MWh\ power\ consumption,\ all\ sources_{i,t}} \times 100\%$
and i: country identifier, j: technology (wind or PV), and t: year

2.2. Key explanatory variables

2.2.1. Economic development status

Higher levels of per capita GDP are expected to enable more rapid deployment. Higher GDP provides a better ability to afford modern renewables (which are more costly in early development phases in particular), and the economic stimulus measures often required for their development [33,35–37,43]. High income countries also have better technological capabilities to develop and deploy modern renewables [2,44]. Environmental concern and policy may or may not be stronger in these countries [45]; this effect is controlled for with emissions to air (section 2.3).

2.2.2. Current domestic market share of wind power

The logistic growth curve implies that higher market shares of wind or PV enable greater annual market share increases. At (very) high market shares, annual market share increases should slow down again, and eventually stall. To identify the former, we include the natural log of wind or PV's market share. To identify the latter effect, we include the untransformed value of this market share. Both variables are lagged one year, as we are interested in effects of current market shares on market shares increases in the following period.

2.2.3. Country lag and global development of the industry

To determine whether latecomer countries do indeed manage to deploy wind power more rapidly, we include the following variables:

- Country lag: the number of years a country was behind on the first nation to enter the (pre-commercial) deployment phase for wind or PV power (see section 2.5 for more on how we separate demonstration and deployment phases). This variable has a single, time-invariant, value per country.
- Global installed capacity (cumulative MW of installations, natural log). We expect accumulated global installations to accelerate domestic market growth. Cumulative installations have previously been used as a proxy for technological maturity and economic competitiveness in technological experience curves [24,25]. We use a log transformation of the original MW values, as these experience curves follow an inverse exponential form. Unit costs, the focal indicator of accumulated experience in modelling these experience curves, tend to drop by a certain factor (the ‘progress ratio’) with each doubling of installations [24,25].
- Interaction term between ‘Country lag’ and ‘Global installed capacity’. Included to identify whether latecomer countries in particular benefit from accumulated global industry experience. The reasoning is that these may ‘leap-frog’ many years of slow technical development by utilizing globally available technology, whereas early adopters may already have such developed industries that additional global experience does not boost further deployment much more.

2.3. Control variables

Based on a set of earlier studies on factors that drive the development of renewable energy [33,35–37,43,46–50], we included variables on the make-up of the electric power system, levels of air pollution and natural resource endowment.

Individual market shares of power generation are included for each of the most important alternative technologies (coal, hydro, nuclear, gas, oil, biomass and geothermal). These different energy types may affect the drive for renewables as they may or may not 1) result in energy import dependency [37,43,51]; 2) lead to concern over environmental impact [16,35,43]; and/or 3) make it easier or more difficult to integrate substantial shares of renewables into the power mix [52]. To identify if environmental concern drives deployment we also include per capita emissions of CO_2 (emissions related to climate change) and emissions of SO_2 (related to local air pollution).

High levels of per capita, or total volume of power consumption, may make it more difficult to attain rapid market penetration of renewables. There may be limiting factors to the growth speed of industries required to deploy renewables [53,54], so that these industries might not be able to scale up together with market demand in large markets as easily as they would in smaller markets. Growing power demand may create a larger market for wind or PV installations, although some analysts hold that countries with rapidly growing power demand tend to concentrate on construction of fossil and hydropower plants [43,51].

Lastly, wind and PV power generation can be expected to depend on natural resources, in these cases wind or solar irradiance [33,35,37,39,40]. We use indicators of natural resource endowment in MWh/km^2. For wind, we consider only areas with sufficiently high wind speeds (classes 3 and above), and in relative close proximity (<100 km) to existing energy infrastructure. For PV, we use the country wide average of solar energy potential (MWh/km^2). This selection provides an indicator of ‘readily available’ technical potential [40,50], whilst preventing bias towards countries with vast, scarcely populated landmasses.

2.4. Data filter: separating demonstration and deployment phases

We differentiate early and late adopters with a variable ‘country lag’, which is the number of years a country was behind on adopting the technology, relative to the first adopter. It would be most intuitive to regard the very first installation of a wind turbine or PV panel in determining such country lag. Here, however, we consider the first 100 MW of installations to be the demonstration phase, with pre-commercial deployment starting at 100 + MW. We exclude data from the period before a country exceeds 100 MW of installations in our analyses. Our variable country lag is determined as the moment a country exceeded this 100 MW threshold, compared to the first country to do so. Our reasons to do so are as follows.

It is theoretically well established that the demonstration phase is subject to very different market mechanics than the pre-commercial and supported commercial phases [11,55,56]. In the demonstration phase, small individual projects are developed for testing purposes or as lighthouse projects, etc. Such projects are much more stochastic events, because in these early ‘nursing markets’, market driving forces and institutional pressure or stimulus are still underdeveloped [56,57]. This is also what we see in our data. Demonstration in many countries consisted of individual projects, with little or no further projects for many years. The period required to get from 0 + MW to 100 MW was often a decade or more (Fig. S.2). This phase is where the mathematical model (the logistic growth curve) diverges from reality. The logistic growth model supposes a near constant year-on-year growth throughout the first half of the growth curve (e.g., 10% annual increases in total installations). Such market growth would be linear when graphed on a (natural) log scale. This is often not the case in real world data, where prolonged periods of no, or very few new installations in the demonstration phase result in very flat market development lines, even when graphed on a natural log scale. Rather than a constant year-on-year growth rate throughout (linear growth on a natural log scale), markets tend to see a distinct acceleration (higher year-on-year growth rates, with a kink in the linear growth pattern on a log scale) when market sizes exceed a certain threshold. A number of example graphs to clarify the issue are provided in Fig. S.3. Including data from the lengthy demonstration phase strongly flattens the development of annual market share increases, making it more difficult to find a statistical relationship with variables that do vary.

An additional issue is that the very slow (or no) growth in installations in the demonstration phase may lead to negative market share increases, when overall power consumption grows faster than wind or PV power output. Such negative values are dropped in the natural log transformation of our outcome variable. This means that years with relatively big growth spurts within the demonstration phase are preserved, whilst smaller values are dropped. These negative values of annual market share increase are strongly concentrated in the demonstration phase (Table S.2). This further flattens the development of our outcome variable, as this gives the appearance that average market share increases in the demonstration phase are as large as, or larger than, market share increases in larger, more matured markets.

The effect of this flattening was that a number of the relationships investigated here were less, or not, apparent when including data from countries and years with at least 0 + MW of installations. The threshold of 100 + MW as the distinction between demonstration and diffusion phases was based on visual inspection of individual countries' growth curves (examples in Fig. S.3) and comparison of regression results using different data filters. Below this threshold, the relationships investigated here were not apparent; above this threshold, the patterns in terms of significance and sign remained the same. Results using different data filters (0 + MW, 50 + MW, 100 + MW, 200 + MW, 500 + MW) are included in Tables S.3 & S.4.

2.5. Estimation method

Our data has a number of properties that require attention to the error structure. Our data is trending, with larger annual market increases over time. If we assume that variance increases with increasing levels of the observed outcome variable (annual market share increase), then there is a risk of heteroskedasticity as well as serial correlation of the disturbances. If we also assume that developments between countries may be linked (which we specifically do, as our model contains reference to global sector development), there is also a risk of contemporaneous correlation of the disturbances [58,59]. Tests confirmed the presence of both heteroskedasticity and serial correlation for both wind and PV models (Table S.5).

We performed estimations using a Prais-Winsten regression, with panel corrected standard errors (PCSE). This method corrects for heteroskedasticity, contemporaneous and serial correlation [60]. The Prais-Winsten regression uses the generalized least-squares (fGLS) method to estimate parameters in a linear regression model assuming the errors to be serially correlated (AR(1)) [61]. Removing this serial correlation is a prerequisite before calculating PCSE [58,59], which further correct for panel heteroskedasticity and contemporaneous correlation [58,59]. Simultaneously, PCSE prevent over-optimistic standard errors (particular with small time vs units (panels) dimensions, as is the case in our dataset) when compared with alternative estimation methods, including pooled OLS estimation [58,59]. The same dimensions of our dataset can result in over-optimistic standard errors when using panel-specific autocorrelation parameters [58], and we therefore choose to use the more conservative method of a common autocorrelation parameter.

This estimation was performed using Stata, version 13.1, using the xtpcse command [62], with first order autoregressive correlation structure specified.

To make sure that our results were not due to the specificity of the selected estimation method, we performed the same analysis using four closely related estimation methods; results were robust throughout (see Tables S.6 & S.7). This comparison included random effects but not fixed effect models. One of our key explanatory variables, country lag, has a single value for each country and would be dropped in such a model.

2.6. Data collection

Wind and PV development are well reported on in a number of databases. Because of differing data availability, we combined data from Eurostat [5], UN data [1], and the BP review [6]. Eurostat data was used for EU countries (availability 1990–2014); UN data for all other countries (availability 1990–2013); BP data to update 2014 values and for years prior to 1990. BP data was used for a number of countries for which data series were more complete than the UN data. The three sources were also checked for internal consistency (reporting on MW of installations versus MWh of power production), requiring a number of fixes (details in Table S.1).

3. Results

3.1. Domestic versus global determinants of renewables market growth speeds

Our first finding is that economic development status matters:

higher per capita GDP enables more rapid market growth of both wind and PV (Table 1). This relates to the question of early versus late adopters, as early adopters were, on average, wealthier countries (more in section 3.3). This result is in line with previous work on modern renewables [44,51]. Earlier analyses have also regularly used the share of all renewable energy as the outcome variable, and tended to find an insignificant relationship between GDP and renewable energy use [35–37]. We suspect that the difference is due to the inclusion of hydropower in these studies. This technology is far more mature, less costly than modern renewables, and strongly dependent on natural resource endowment, and therefore likely less related to income levels. This suggests that driving factors for the deployment of renewable power generation are not equal across all technologies, and supports the relevance of technology specific analysis.

Our second finding is that the development of the domestic sector matters. We find that larger market shares of wind and PV power enable more rapid market share growth, in line with the non-linearity in growth implied in the logistic growth pattern (Fig. 2). Domestic sector growth may lead to positive feedback loops, as the technology itself matures, but also because manufacturing and maintenance industries grow in size and become more competitive, and because societal support, user acceptance, and policy support, develops [8,15,57]. The variable with untransformed values of current market share, included to identify whether growth slows down again at very high market shares, was significant for PV, but not for wind. In effect, we identified an exponential growth pattern for wind, and a logistic growth pattern for PV. This is contrary to what we would expect, as wind markets are surely more matured than those for PV, making it more likely that those would already see some slowing effects of market saturation. We have no credible explanation as to why the slowdown shows up in PV but not wind markets.

Our third finding is that the build-up of global experience enables more rapid domestic market growth. This positive relation implies that countries are able to access and utilize this global experience. This indicates that technology transfer has occurred, at least if we consider a very wide definition of technology transfer (for a good overview of the many mechanisms considered under the umbrella of technology transfer see Reisman, 2005 [63]). In its simplest form, such technology transfer could have occurred through international sales of power generation equipment. Such equipment has become available at ever lower cost on the global market, making the technology more competitive in domestic markets. It is also possible that experience has been transferred between foreign and domestic manufacturing industries, for example through licensing of equipment designs, or in joint ventures for manufacturing [63]. Such mechanisms have, for example, been pointed to in the development of wind turbine manufacturing industries in China and India [64,65]. Note, however, that out of all the countries that have installed wind turbines (Fig. 1), only a limited number has domestic manufacturing or domestic wind turbine brands. Further channels for transfer include knowledge spill-overs in global production networks and/or research organizations, etc. [63,66]. It is difficult to determine which of such channels has provided the access to global experience. Such an exercise would likely involve investigation of developments in individual countries to a level of detail that is more suited to case study research. Here, we suffice it to say that domestic market growth speed depends in part on domestic sector development, and in part on global experience build-up.

Our fourth finding is that late adopters manage more rapid market growth, in addition to the beneficial effect from global technological experience. There is a positive effect from country lag. This indicates that there are beneficial effects of developments of the technological field, which are not accurately grasped by experience as measured with cumulative global installations. Within the literature on learning curves, analysts regularly suggest the use of R&D based knowledge stock as a complementary factor to cumulative production output, as parameters in the modelling of such curves [27]. Similarly, Coe and Helpman [67] identified that foreign R&D may stimulate domestic economic productivity, depending on

Table 1
Regression results for 'Market share increase' (wind & PV).

	Wind pcse, common AR(1)		PV pcse, common AR(1)	
Per capita GDP	0.499***	(0.007)	0.883***	(0.005)
Market share Wind or PV (%, ln, lag1)[a]	0.675***	(0.000)	0.448***	(0.002)
Market share Wind or PV (%, lag1) [a]	−0.003	(0.906)	−0.320***	(0.002)
Global installed capacity [a]	0.405**	(0.028)	0.715***	(0.000)
Country lag [a]	0.294***	(0.005)	0.263**	(0.011)
Global capac*ctry lag [a]	−0.025***	(0.004)	−0.024***	(0.006)
National power cons.	−0.151	(0.170)	−0.175*	(0.053)
Growth of power cons.	−0.055***	(0.000)	−0.004	(0.666)
Per capita power cons.	−1.025**	(0.030)	−1.825	(0.151)
Energy imports (%)	0.001	(0.345)	0.001	(0.695)
Coal power (%)	0.002	(0.668)	−0.003	(0.836)
Hydro power (%)	0.009*	(0.076)	−0.024*	(0.082)
Nuclear power (%)	0.008*	(0.079)	−0.004	(0.772)
Gas power (%)	0.001	(0.124)	0.004	(0.796)
Oil power (%)	−0.003	(0.587)	−0.002	(0.948)
Bio&Geo power (%)	−0.009	(0.730)	0.006	(0.917)
PV Power (%)	−0.192***	(0.001)	–	–
Wind Power (%)	–	–	−0.035	(0.143)
Emissions to air (CO2)	0.193	(0.650)	−0.333	(0.785)
Emissions to air (SO2)	0.300**	(0.016)	0.972***	(0.000)
Natural Resource Endowment[a]	0.000	(0.944)	−0.001***	(0.001)
Constant	−5.961**	(0.016)	−3.485	(0.318)
N	429		140	
groups (countries)	46		27	
R^2	0.521		0.747	

p-values in parentheses.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.
[a] Variable is technology specific: refers to market share, global capacity etc., of wind power in the wind model and to PV in the PV model.

openness to foreign trade. There may also be an effect of policy learning; late adopters may learn from successful experience with implementing favourable renewables policies elsewhere. The effect may also be due to the many bilateral and global programmes for technological cooperation and transfer in the area of renewable energy technologies.

Lastly, the interaction variable between global experience build-up and country lag has a negative coefficient, indicating that the global experience is not equally accessible to early and late adopters. Late adopters do not manage to benefit as much from global technological experience as early followers do. This is in line with conclusions from much of the literature on technological catch-up, which suggests that 'absorptive capacity', i.e., the ability to comprehend, utilize and manufacture technologies is much stronger in early followers than laggards [68,69]. Technology transfer programmes, including projects co-financed through the CDM mechanism, are also strongly concentrated in early follower countries [70,71].

3.2. Control variables

Most of our control variables had limited or no consistent effect on annual market share increases of wind and PV.

Market size and growth variables had insignificant effects on PV developments, although the total national volume of electricity consumption had a marginally significant negative effect on PV market share increases. For wind power, there was a clearer, and negative, effect on market share increases in markets with higher per capita consumption, and markets with growing power demand. This suggests upscaling of industry output to fulfil greater market demand has been more of an issue for wind than PV industries (more on this in section 3.4).

We find no effects from energy imports, suggesting that import dependency concerns are not a common or strong driver for rapid transitions to wind or PV power. Similarly, the shares of other energy sources for electricity production have little or no effect on market growth speeds of wind or PV. There are marginally significant effects from hydropower on wind and PV, but the sign of the effect is opposite for these two technologies. A marginally significant effect from nuclear power on wind markets is not replicated for PV. High shares of PV reduce market growth speeds of wind, which could be because both technologies contribute to the same societal goals, and successful PV market development therefore reduces the need to spur wind power development. Our data does not show that high shares of wind also reduce market growth speeds of PV, however. The limited significance, or inconsistency over technologies, for these variables, makes it difficult to make statements with much certainty about connections with market growth speeds.

With regard to environmental concerns, it appears countries with higher levels of local air pollution are more rapidly transitioning to wind and PV, whilst there appears to be no difference in how rapidly countries with low or high carbon dioxide emissions are working on such transitions.

We find no effect of natural resource endowment on wind power market growth, and a negative effect on PV market growth. The latter in particular may seem surprising, but other studies have regularly reported positive, insignificant, as well as negative effects (cf. [33,35,37,72]). Here, we would explain it because of a strong negative correlation between GDP and solar resources, i.e., wealthier countries are concentrated in latitudes with less solar irradiance (see Fig. S.4, and note that no such relation exists for wind resources).

3.3. Net effects on deployment speeds for early versus late adopters

The effects of key variables described in 3.1 require some framing before their relevance can be properly assessed. Statistical significance does not say much about the size of the effect of a variable [73]. Further, some of these variables had positive effects for late adopters, whilst others had negative effects. To help clarify, we graph the development of these effects over time. Global installed capacity of wind and PV in any year is known. We know the value of country lag for a country that starts deploying the technology in a certain year, and we can derive the value of the interaction term between it and cumulative global capacity. To account for the lower average per capita GDP in late adopter countries, we use the values of the linear trend line between GDP and country lag (Fig. S.5). Effect sizes are calculated by multiplying coefficients from the regressions (Table 1) with the value of corresponding variables in each year.

Results in Fig. 4 show that the negative effect of lower average GDP in late adopter countries is outweighed by beneficial effects from global industry experience, and initially positive effects of country lag.

For wind power, the net effect on annual market share increases of these variables has reached a maximum in 2001. Countries that started to deploy wind power around the year 2001, ceteris paribus, have done so at a pace 4.7 times greater than the earliest adopters managed (calculated as $e^{1.55}$, 1.55 being the maximum value of the net effects on 'annual market share increase', which was natural log transformed). Countries that have started to deploy wind power past this point still manage more rapid deployment than the earliest of adopters, but not as rapid as countries that started around 2001. For countries that have recently started to deploy wind power, deployment speeds are approximately 2.0 times as high as those realised by the earliest adopters.

For PV, the pattern is similar. Here, however, net beneficial effects have started to plateau but not yet fall. Further, the magnitude of effects is larger; deployment speeds for countries that have recently adopted the technology are approximately 16 times higher than they were for the earliest adopters.

These values are largely in accordance with observed ranges of annual market share increases in early versus late adopters. Indicative of this is that early adopters of wind power, in their first five years of deployment, managed average annual market share increases of approximately 0.05–0.1% points per year, whereas late adopters regularly managed increases of 0.2–0.4% points per year. The stronger effects for PV are largely due to the fact that early adopters managed only very slow initial growth, in the range of 0.005–0.02% points per year, whereas late adopters also managed 0.2–0.4% points per year (Fig. S.6; note that we regard only the first five years of deployment to roughly correct for the fact that more mature markets grow faster). Further, residuals plots confirm that these extremes are not due to over- or underestimation for some periods or values of country lag (Figs. S.7 & S.8). Still, the fact that our outcome variable is natural log transformed does make these estimates quite sensitive. A more proper summary of these findings is that late adopters have managed deployment speeds that were several times higher than for early adopters for wind, and more than a dozen times higher for PV.

3.4. Comparison of effects on deployment speed for wind and PV

Regression results and net effects of key variables showed similar patterns for wind and PV, but there are important differences as well.

For both, domestic market growth speed depended on the size of the domestic market as well as on accumulated global experience. For wind, domestic sector build-up has been more important than the global experience, whilst for PV, it is the other way around. A doubling of the domestic market share enables 68% larger annual market size

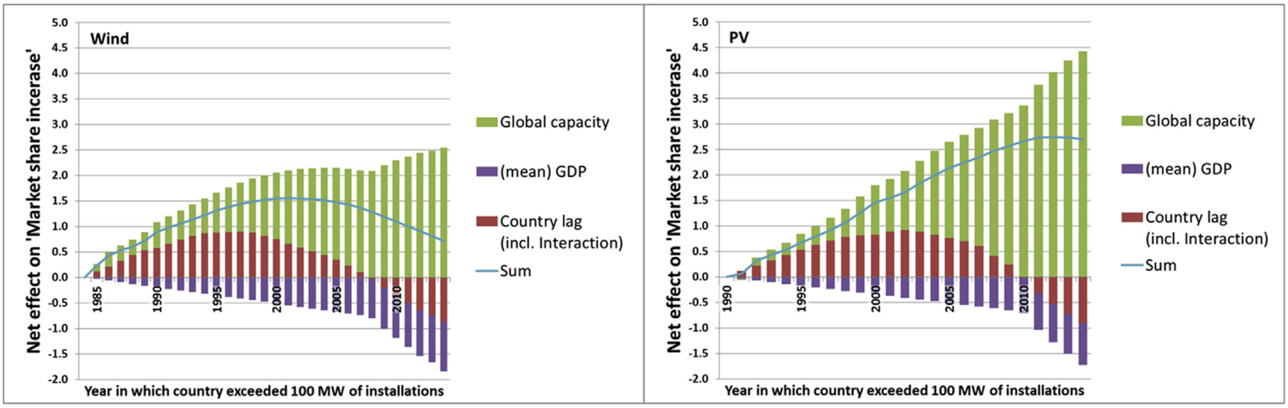

Fig. 4. Net effect of key variables on annual market share increases. Note: values relative to first country exceeding 100 MW of installations. The variable 'market share increase' is the natural log of annual increases in markets share. Effect of country lag and its interaction with cumulative global capacity were summed as the two were quite large but opposite.

increases for wind versus 45% larger increases for PV. A doubling of global industry experience enables 41% larger annual market size increases for wind, versus 72% larger increases for PV. The difference could be due to the relative ease with which PV panels are shipped to foreign markets, whilst a number of wind turbine components are quite costly to transport. Further, analysts using concepts form the literature of technology life-cycles have characterized PV panels as (mostly comparable to) mass-produced goods, whereas wind turbines are closer in characteristics to 'complex products and systems' technologies. This has effects on industry localization, with evidence suggesting that substantial wind power deployment requires the development of domestic technological capabilities, equipment production capacity and maintenance industries, to a higher extent than is the case for PV panels [74,75].

The same mechanisms may also explain why there is less of a problem with scaling up PV development for the larger demand in large or rapidly growing electricity markets (as reported in section 3.2).

Per capita GDP is a much stronger determinant of deployment speed for PV than for wind. This is not very apparent from the net effects graphed in Fig. 4, because the relationship between per capita GDP and country lag is less pronounced for PV than for wind (Fig. S.5). For both wind and PV, high income countries were the initial users of the technology. The difference is that fewer low income countries have started using PV. Fig. 4 reflects differences in mean GDP between early and late adopter countries, but there is a relatively large spread around this mean (Fig. S.5).

Users of wind power had GDP per capita between roughly \$2800 and \$50,000 (10^{th} vs. 90^{th} percentile). Countries toward the upper end of that spread will manage deployment speeds of 4.2 times greater than countries at the lower end (calculated as $e^{0.499*\ln((\$50,000)-\ln(\$2,800))}$, with 0.499 being the coefficient for GDP from Table 1). Per capita GDP of users of PV varied roughly between \$7000 and \$50,000, indicating that the richest of countries manage deployment speeds 5.7 times greater than the poorest of countries did.

Both the lower usage and lower deployment speeds in poorer countries indicate that PV, still the more expensive technology [76], remains a technology for wealthier nations; more so than wind power.

4. Discussion

Our analysis of developments in the PV sector rests on a relatively small sample (N = 140, 27 countries). In itself, this may have been too little to ensure sufficient reliability of the results. We would argue, however, that such scrutiny should be reduced by the very similar pattern found in the far larger data sample for wind (N = 429, 46 countries). Further studies on other technologies are required before we could comment on the generic nature across technologies of the patterns identified here.

Below, we further discuss the potential role of energy prices (4.1), renewable energy policy (4.2), alternative model specifications that might have explained the result on country lag (4.3), and compare our results with earlier work on the timing and speed of transitions (4.4).

4.1. Energy prices

Earlier analyses have regularly included energy prices as an explanatory factor of renewable energy deployment [33,35–37,48]. This work was focused on OECD countries, for which energy pricing statistics are readily available via the IEA. For our dataset, which includes a wider variety of countries, we did not manage to find a sufficiently exhaustive set of domestic energy prices for all major fuel types and years, and we therefore decided to exclude these. We have considered using global or regional energy prices as a proxy, but did not find significant effects, except for a negative effect of natural gas prices on the pace of wind power development (results included in Table S.8). Energy prices in international markets are likely a rather rough proxy for cost to domestic users, as they ignore taxes and domestic supply. Lacking data quality may therefore be as much of a reason for the presence or absence of significance as the existence of an actual relationship between the energy price and outcome variables.

4.2. Renewable energy policy

Many earlier analyses of renewables development have regarded policy support [33,37,43,50,51,77–80], something that we entirely agree to be an important driving factor. It is, however, exceptionally difficult to operationalize the strength or effectiveness of policies, and results have often been inconclusive (for an excellent overview see e.g., [81]). Earlier work has operationalized policy support with either a binary variable (indicating the presence of a certain support policy type), or the number of policies implemented [33,37,43,50,51,79,80], or with a proxy for political orientation of the government [50,78,82]. Policy count data can be extracted from IRENA's renewable energy policy database [83], which catalogues different policy types and year of implementation for a long list of countries. We used such a variable for the number of policies implemented, for several different policy types, and found a significant and positive effect for only a single policy category for wind, and a negative effect for a single policy category for PV (Table S.9). We have decided to exclude these policy variables in our results, as we are unconvinced that this count data is the best way to operationalize the effect of policy measures, and oppose drawing conclusions based on them. The lacking significance for most policy categories should, in our view, not lead to the conclusion that these are not important. Better operationalization, for example the volume of R&D funding, the level of feed-in-tariffs, resulting levelized cost of electricity etc., might result in different conclusions. Such improved policy variables have been used in a small number of earlier analyses for EU countries or US states, for which data is relatively easily available [34,41]. These studies have also focused on individual types of policy (e.g., FIT, targets, renewable portfolios). For the expanded country group regarded here, such data is much more difficult to obtain, in particular or a wide range of policies. Including such variables would require data collection efforts that are outside the scope of most analyses, including ours.

4.3. Alternative explanations for the result on country lag

The variable country lag, and its interaction with cumulative global experience are somewhat of a 'catch-all' variable, and do not specify very well what is different about these late adopters. We attempted two different model specifications to establish or rule out our results being due to unobserved variable bias.

A prime candidate to substitute the country lag variable, in its interaction term with cumulative global experience, was per capita GDP. GDP was found to be positively related with deployment speeds. We included an interaction between per capita GDP and cumulative global experience to establish whether poorer countries were less capable of accessing and utilizing the global experience pool. This interaction was found to have no significant relationship with market growth speed, for either wind or PV (Table S.10).

Secondly, Pan and Köhler [84] have criticised the use of exponential formats for global experience curves, and rather argue that these follow an inverse logistic growth curve. That is: they agree that technological costs have often been observed to fall by a certain fraction with every doubling of cumulative global experience (the so-called 'progress ratio'), but they argue that this progress ratio starts to decline with technologies reaching maturity. This could be an alternative explanation for the drop-off in beneficial effects from growing global experience that we found for late adopter countries. To test whether this was the case, we added a quadratic term of cumulative global installations. This alternative for the interaction term was not found to have a significant relationship with market growth speed, for either wind or PV (Table S.11).

4.4. Comparison with earlier work on timing and speed of adoption

Results presented here are not exactly equivalent to the shorter 'turnover times' identified in studies that concluded that transitions in late adopters were quicker, but also less pervasive [8,14,15,18,29–32]. Here, we regard absolute levels of market shares, without adjustment relative to the (unknown) ultimate market shares. Whereas those earlier analyses concluded that latecomer countries required a shorter amount of time to reach their lower level of ultimate market penetration (most clearly demonstrated in Ref. [31]), we conclude that they require a shorter amount of time to reach an equal market share, e.g., 1% of all power production from wind or PV.

Because we do not use the same metric for comparison as in much of the earlier literature, it is not possible to identify anything particular about the technologies studied here. There are, however, reasons why the development of wind or PV may not follow the exact same patterns as older energy technologies such as coal, hydro, nuclear, natural gas fired plants, etc. Although the development of different energy sources has always been highly influenced by policy making (in addition to relative pricing), the renewable energy technologies studied here are currently being pushed by a rather particular set of climate policy goals. The Clean Development Mechanism, climate finance agreements, and other policy programs stimulating the transfer of such technologies to less developed countries, are likely to affect the global diffusion of these technologies. Already, although the very earliest of adopters of wind and PV were still the richer countries, early followers have been a mix of relatively rich and emerging economies, in particular for PV (Fig. S.5). Further, one explanation for the lower ultimate shares of coal consumption by late adopters, was that they were so much later in switching (100 years or more), that alternative energy technologies had become available and/or competitive [32]. The global diffusion of wind and PV are far more rapid. Global markets are much more interconnected than they were when England switched from traditional biomass to coal, and "international economic integration eases access to environmentally friendly technologies and leads to earlier adoption" ([85]: p.16). This means that the (set of) available energy technologies and their maturity is now far more similar for early and late adopters of wind and PV. Further comparison between current and historical transitions, as well as follow-up on ongoing transitions, may help clarify if these sorts of differences substantially affect global diffusion patterns or not.

5. Conclusion

Our results show that late adopters have managed substantially higher market growth speeds of wind and PV. Late adopter countries appear to be able to access global experience with these technologies and utilize this experience to accelerate domestic market growth. Despite their lower GDP, late adopter countries have managed market growth for wind power that was up to 4.7 times faster than it was in early adopters, and up to 16 times faster for PV.

These results imply that development efforts for novel renewable energy technologies, by technologically advanced countries, may kick-start their global deployment. Even if such efforts have only small immediate effects on domestic market growth, these effects may multiply manifold by accelerating market growth in a large number of late adopter countries.

The beneficial effects, however, are non-linear. Early followers benefit most, whilst late adopters benefit increasingly less. This suggests that late adopters have more difficulties accessing and/or utilizing the global experience pool, which suggests this requires attention in multi-lateral technology transfer programmes.

In addition, per capita GDP remains to have a strong effect on market growth speeds. This suggest renewable energy development in low income countries may be sped up with co-financing, through reinvigorating global carbon markets or other forms of climate finance assistance.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.energy.2017.05.046.

Appendix A

Table A.1
Variables definition and data sources.

Variable	Definition	Notes and data source
Per capita GDP	per capita GDP, 2010 USD (ln)	Source [86]
Market share Wind/PV (%, ln, lag1) Market share Wind/PV (%, lag1)	Market share; production (MWh) from individual sources as a percentage of total power consumption	Sources [1,5,6,87], see Table S.1 for further details.
Country lag	Year of first deployment, minus year in which first nation started to deploy the technology	Sources [1,5,6,87]
Global wind capacity (cumulative)	Cumulative global wind capacity, year end, MW (ln)	
Interaction: Ctry Lag*Glob wind cap.	Interaction term, multiplication of above two variables	
National power cons.	National level power consumption, total MWh (ln)	Source [86]
Per capita power cons.	Per capita power consumption, MWh/capita (ln)	Source [86]
Growth of power cons.	Year on year growth of national power consumption (% increase)	Calculated from above sources
Energy imports (%)	Percentage of primary energy consumption imported	Source [86]
Coal power (%) Hydro power (%) Nuclear power (%) Gas power (%) Oil power (%) Bio&Geo power (%)	Market share of individual power sources; production from individual sources as a percentage of total power consumption	The World Bank reports production, not consumption, per source only. A small number of countries have significant power exports. We are interested in production (per source) as a share of domestic consumption. Source [86], Bio&Geo source [88]
Emissions to air (CO_2)	Emissions of CO_2 from energy use, t/capita (ln)	Source [86]. Updates 2014 [88], or if not available with growth factors in energy use
Emissions to air (SO_2)	Emissions of SO_2, t/capita (ln)	Source: years 1980–2011 [89]. Extrapolation through 2014 with growth factors in coal based power production from Ref. [86], 5 year average growth rates for other sectors.
Natural Resource Endowment: Wind	Maximum generation potential from wind sources (MWh/km^2). Includes only onshore, classes c3 and up, and areas with 'distance to load' of <100 km	Source [90]
Natural Resource Endowment: PV	Maximum generation potential from PV sources (MWh/km^2), country-wide average irradiation	Source [91]
Policy and energy prices variables used in estimations reported in Tables S.11 & S.12		
Price of Steam coal	Price of Steam coal, 2010 USD per ton	Country specific values for IEA countries [92], others global prices [93]
Price of Oil	Price of Oil, 2010 USD per barrel, average of Brent, Dubai and WTI	Global average prices [93]
Price of Natural gas	Price of Natural gas, 2010 USD per mmbtu	Northern America: Henry hub spot prices; Europe: average import border prices (Europe); rest of world: LNG import prices [93]
Policy variables, several categories	Cumulative number of policies enacted.	Categories of policy types as reported by IRENA [83]

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