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Bibliometrics-based foresight on renewable energy production

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Abstract

Purpose –The purpose of this study is to investigate whether news media as a form of social communication regarding pressing, important, and contemporary issues could be used as a leading indicator of technology adoption. For technology foresight, monitoring and analyzing energy technologies is in the spotlight due to their strategic importance to the agenda of competitive and sustainable economic growth.
Design/methodology/approach – The trends in renewable energy production and news media are determined and compared to draw inferences in foresight concerning the use of renewable energy technologies in energy production. Consequently, our data concerns wind and solar energy production and their representation in news media in Germany and the UK. Our analysis proceeds as a quasi-experiment treating each yearly observation of energy production as a function of news media data with lagged variables.
Findings – Our study reveals consistent dynamics in the lag in the primary production of energy in related technologies compared to the media visibility of the respective technologies.
Originality – This study explores the prospects of using news media data in foresight analysis concerning renewable energy production and provides many fruitful avenues for foresight research in investigating relationships between technology adoption and media exposure.
Keywords Renewable energy, Technology foresight, Bibliometric
Paper type Research paper

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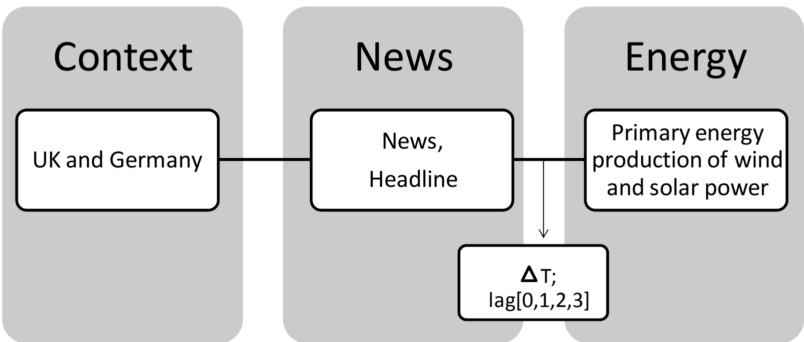
1. Introduction

Foresight may provide information about the future (Cuhls, 2003). Via foresight results, general directions for the unknown future can be reasonably dealt with. Technological foresight purports to provide timely insight into the prospects for technological change (Watts and Porter, 1997). In technology foresight, bibliometrics—among other foresight and forecasting methods (Martino, 2003)—has evolved, inter alia, for advances in data processing and storage capabilities (Linstone, 2011) during the course of the past decade. Watts and Porter (1997) argue that the data sources selected in a bibliometric study depend on the phase of the technology's life cycle, and news media reflect the application phase and social impacts of an innovation. In previous research, most diffusion studies based on the Life Cycle Indicators used patents (Järvenpää *et al.*, 2011; Ernst, 1997; Daim *et al.*, 2006; Chang *et al.*, 2009) or scientific publications (Chao *et al.*, 2007), typical data sources in the early phases of a technology's life cycle (Martino, 2003).

News media as a data source have not been used as extensively, even though newspapers and the popular press are acknowledged as appropriate data sources in the application phase of a technology (Martino, 2003; Okubo, 1997). Consequently, this study focuses on analyzing news media data. In previous studies that used news media data in diffusion analysis (Järvenpää *et al.*, 2011; Järvenpää, 2009; Järvenpää and Mäkinen, 2007), the examined technologies had a durable nature different from the investment one used in energy production. The purpose of this study is to investigate whether news media as a form of social communication regarding pressing, important, and contemporary issues could be used as a leading indicator of technology adoption. Thus, our research question is as follows: To what extent does renewable energy production lag news activity? Consequently, we examine news media data for two renewable energy forms—wind and solar energy production in two European countries assessed with bibliometrics—and further test the lag variables. Our research setting is presented in Figure 1.

Figure 1 Research setting



In this study, the UK and Germany, two European countries, are the focus. Thus, we collected German and UK news media data from LexisNexis for the period 1995-2008 and data on the production of solar energy in 1999-2010 and wind energy in 1995-2010 in both countries from EuroStat. We further analyzed the data to see if determining and comparing the trends in renewable energy production and news media could lead to inferences concerning renewable energy production and news publication activity. Therefore, the descriptive statistics and correlations between news media data and energy production data were calculated. Our data analysis proceeds as a quasi-experiment treating each yearly observation of energy production as a function of news media data with lagged variables.

We found that news media visibility and renewable energy production are significantly correlated for wind energy and solar photovoltaic energy technologies. Importantly, our study reveals that in three out of our four cases the two years of lagged media visibility dominates in explaining the energy production figures. This result is rather remarkable given the complex institutional environments, for instance, political and investment decision-making. As a conclusion, we drew inferences about the prospects that in foresight analysis news media visibility could anticipate investments in renewable technologies.

Our paper is constructed as follows. First, the theoretical foundations of bibliometrics as a technology foresight method are presented. Then, the Methodology section explicates the data collection and data analysis. Results of the paper are discussed in section 4. Finally, the discussion and conclusion conclude the paper indicating avenues for the future studies.

2. Theoretical background: bibliometrics as a technology foresight method

The definitions of forecasting, foresight, and technology forecasting vary to a certain extent, but they all have a view into the future in common. Foresight includes aspects of networking and preparing decisions concerning the future, and thus goes further than forecasting (Cuhls, 2003). The roots of the field are in the 19th century (Linstone, 2011); however, the term "technology foresight" was not brought up until 1983 (Martin, 2010). Technology foresight has been defined as systematically looking into the future over the long-term and in collaboration with experts to identify technologies that would bring the greatest economic and social benefits (Martin, 1995; Georghiou, 1996; Smith and Saritas, 2011). Technology foresight has gained ground since the 1990s as more and more countries have launched national technology foresight programs (Miles, 2010). Through foresight, multiple possible futures may be revealed, and by making the right decisions, the desired future state can be attained (Martin, 1995).

Foresight could be seen as about identifying potential future innovations by examining the complex situations and factors leading up to today with analytical methods; furthermore, the belief is that it is possible to predict changes in the future—and intervene—as similar patterns begin to emerge (Carleton *et al.*, 2011). Although the future is unpredictable, some developments can be foreseen, and alternative methods can be thought of. Common techniques taught in technological forecasting include environmental scanning, models, scenarios, Delphi, extrapolation, probabilistic forecasts, and technology measurement (Martino, 2003) among others, such as trend analysis and pattern analysis to garner information on technology life cycle status (Watts and Porter, 1997). Hence, multiple analytical methods are available, and the methodology in technology foresight can be classified by making distinctions between quantitative versus qualitative, exploratory versus normative, predictive versus open, and creativity- versus evidence-based methods (European Commission, 2011). Exploratory methods are used to look into the future based on current technological capabilities (Bengisu and Nekhili, 2006).

In technology foresight, bibliometrics—among other foresight methods—has evolved, inter alia, due to advances in data processing and storage capabilities (Linstone, 2011) during the past decade. Bibliometric analysis is an evidence-based, exploratory method used to increase understanding of the examined topic (Smith and Saritas, 2011; Change, 2004). Bibliometrics is about using history data from publications—for example, patents, newswires, blogs, scientific articles, press releases, or news articles—as an indicator of scientific or technological activity (Okubo, 1997). The publications can be examined in terms of the word counts, attributes, information contained, links, co-occurrences, and networks between them (Kostoff, 2001; Gupta and Bhattacharya, 2004). The studied topic can also be visualized to see who the leading authors are, how the terminology has developed, or how the research in the field is related to other fields (Su and Lee, 2010). Bibliometrics can also be used to draw inferences from the development phase of a research field or technology, and the directions they may be heading to in the future by using publication, patent, or citation data (Martino, 2003).

The publication activity, or the visibility, of an innovation first builds up in scientific arenas. The majority of studies use patents (Järvenpää *et al.*, 2011; Ernst, 1997; Daim *et al.*, 2006; Chang *et al.*, 2009) or scientific publications (Chao *et al.*, 2007), typical data sources in the early phases of a technology's life cycle (Martino, 2003). As the innovation moves on in the life cycle to the phase of applied research, the patent activity grows, and further, as the life cycle advances, the activity proceeds to public arenas, such as newspapers, and the business and popular press (Watts and Porter, 1997), as presented in Table 1. Watts and Porter (1997) argue that selecting data sources in a bibliometric study depends on the phase of the technology's life cycle, and news media reflect the application phase and social impacts of an innovation, but have rarely used as a data source in bibliometric studies (Järvenpää *et al.*, 2011).

Table 1 Technology Life Cycle Indicators (Watts and Porter, 1997).

Factor	Indicator
R&D Profile	
Fundamental research	Number of items in databases such as *Science Citation Index*
Applied research	Number of items in databases such as *Engineering Index*
Development	Number of items in databases such as *U.S. Patents*
Application	Number of items in databases such as *Newspaper Abstracts Daily*
Societal impacts	Issues raised in the Business and Popular Press abstracts
Growth rate	Trends over time in number of items
Technological issues	Technological needs noted
Maturation	Types of topics receiving attention
Offshoots	Spin-off technologies linked

The technology life cycle is central regarding bibliometric diffusion analysis, and the majority of bibliometric diffusion studies are based on Watts and Porter's (1997) life cycle indicators. Bibliometric data can be used in determining the stage of the technology life cycle, as the growth of scientific knowledge has been observed as resembling the diffusion process, more precisely the diffusion S-curve (Gupta *et al.*, 1997). Rogers defined the diffusion of an innovation as a process in which the innovation spreads into a social system in time, through communication between individuals (Rogers, 1962). The technology diffusion process is partially influenced by the media (Bass, 1969), which explains the use of media data in diffusion analysis. The external effect also contains the media impact, which explains the assumption that media influence the diffusion process.

Accordingly, studies that have used news media data in diffusion analysis have examined technologies such as the minidisc and digital camera (Järvenpää and Mäkinen, 2007), Bluetooth (Järvenpää, 2009), and biodiesel, laser cladding, and light-emitting diodes (LED) (Järvenpää *et al.*, 2011). In previous studies that have used news media data in diffusion analysis (Järvenpää *et al.*, 2011; Järvenpää, 2009; Järvenpää and Mäkinen, 2007) the examined technologies used were durable products, and thus were of a different nature than the ones used in energy production, which could be seen as an investment.

Foresight not only looks into the future by using all instruments of futures research but also includes the use of implementations for the present (Cuhls, 2003). Indeed, technology foresight scholars have noticed that the increase in scientific knowledge resembles diffusion process, as ideas are communicated from one individual to another (Gupta *et al.*, 1997) and the publication or citation activity of a technology generally follows an S-shaped growth pattern (Daim *et al.*, 2006; Bengisu and Nekhili, 2006) similar to the technology adoption S-curve.

3. Methodology

Data collection

For technology foresight and energy monitoring, energy statistics are in the spotlight due to the strategic importance to the agenda of competitive and sustainable economic growth of institutional environments. Consequently, two types of data on renewable energy—wind and solar photovoltaic—were collected: primary energy production data and news media data. The annual data for the analysis was collected using two sources: EuroStat for the primary energy production data for wind energy for 1995-2010 and solar energy for 1999-2010 and LexisNexis for the news media data for 1995-2008.

Primary energy production data was collected from the EuroStat webpages (Eurostat, 2011). The term "primary energy production" refers to the "extraction of energy products in a useable form from natural sources," and primary energy can be produced by exploiting natural sources—such as coal, crude oil, or water resources—or by fabricating biofuels. Thus, primary production does not comprise transforming energy from one form to another. We refer here, within primary production, to wind energy as it covers the kinetic energy of wind converted into electricity in wind turbines and solar energy as it covers the solar radiation exploited for solar heat (hot water) and electricity production.

Eurostat is the statistical office of the European Union (EU) and has developed a coherent and harmonized system of energy statistics. Annual data collected by EuroStat covers the 27 Member States of the EU, the candidate countries Croatia and Turkey, and the European Economic Area countries Iceland and Norway; the time-series run back to 1985 for some countries but are more generally available from 1990 (Eurostat, 2011).

LexisNexis—our second data source—is a database portal owned by Reed Elsevier Inc. (LexisNexis, 2011), and is widely used as a data source in scholarly research. As described previously, bibliometric analysis is about analyzing documents, such as patents and publications, in terms of their attributes—for example, article titles, authors, origins, or dates. The documents can be examined using the information they contain, or the links, co-occurrences, and networks between them (Kostoff *et al.*, 2001). The studied topic can also be visualized to see who the leading authors are, how the terminology has developed, or how the research between different fields is related (Su and Lee, 2010).

The news media data were outlined at the headline level. The first phase of the data collection process involved defining search terms for the news media data searches. The search term contained different elements. First, it contained information about which part of the text search words are sought: from the headline. Second, the search term contained the country code for which Country/Region the search was for, and the time period from which the documents are sought. In addition, the Boolean connector OR was placed between the terms. For instance, the search clauses contained the following elements: information about from which part of the text search words were sought (from the headline), LexisNexis's country code for Germany (GC318), and the time period, from January 1 to December 31 each year during the period 1995-2008. The search terms are presented in Table 2.

Table 2 Search terms in news media coverage data collection

Energy form	Germany, search terms in German	UK, search terms in English
Wind energy	windenergie OR windkraft	wind energy OR wind power
Solar photovoltaic energy	sonnenenergie OR sonnenkraft OR solarenergie OR solarkraft	solar energy OR solar power OR photovoltaic energy OR photovoltaic power OR pv energy OR pv power

The terminology used, as presented in Table 2, in related articles was scanned to provide relevant search terms in the original languages. Collective terms that represent the production of each renewable energy form in general were chosen, and the terms were written down in German and English. Collected news included newswires and non-business articles covering all industries, subjects, and countries related to the news, thus including news for other countries in addition to Germany. The duplication option was on, meaning that with this selection Nexis UK made a similarity analysis of the search results by identifying documents that had similar content and grouped similar documents together.

Data analysis

The first step in the data analysis was presenting the news media and energy production data in line graphs to create a general view of the trends during the periods examined. The descriptive statistics and correlations between the news media data and energy production data were calculated. Our data analysis was a quasi-experiment treating each yearly observation of energy production as a function of news media data with lagged variables. Our dependent variable therefore was the primary production of kiloton oil equivalents in solar and wind energy production. Our independent variables were new hits in headline and body text, including yearly lagged variables of one, two, and three years. We followed traditional

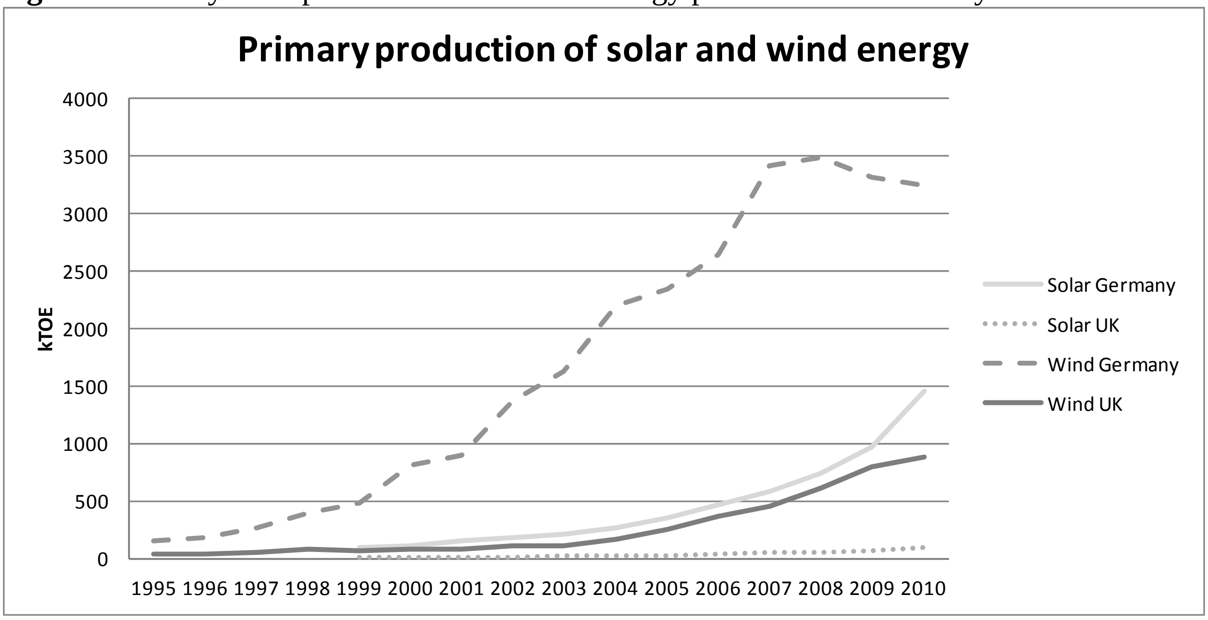
OLS multi-regression in analyzing our quasi-experimental data. We treated our data as quasi-experimental instead of time series modeling for two reasons; namely, the brevity of our time series limits the applicability of time series methods. Further, we expect the yearly production figures to be a function of news media hits in recent history (path-dependency), and at the same time, these data points represent in a sense quasi-experiments taking place each year whether we witness this path-dependency.

4. Results

Energy diffusion

The primary wind and solar photovoltaic energy produced during the reference periods is presented in Figure 2. In the figure, kTOE is an acronym for kilotons of oil equivalent.

Figure 2 Primary solar photovoltaic and wind energy production in Germany and the UK

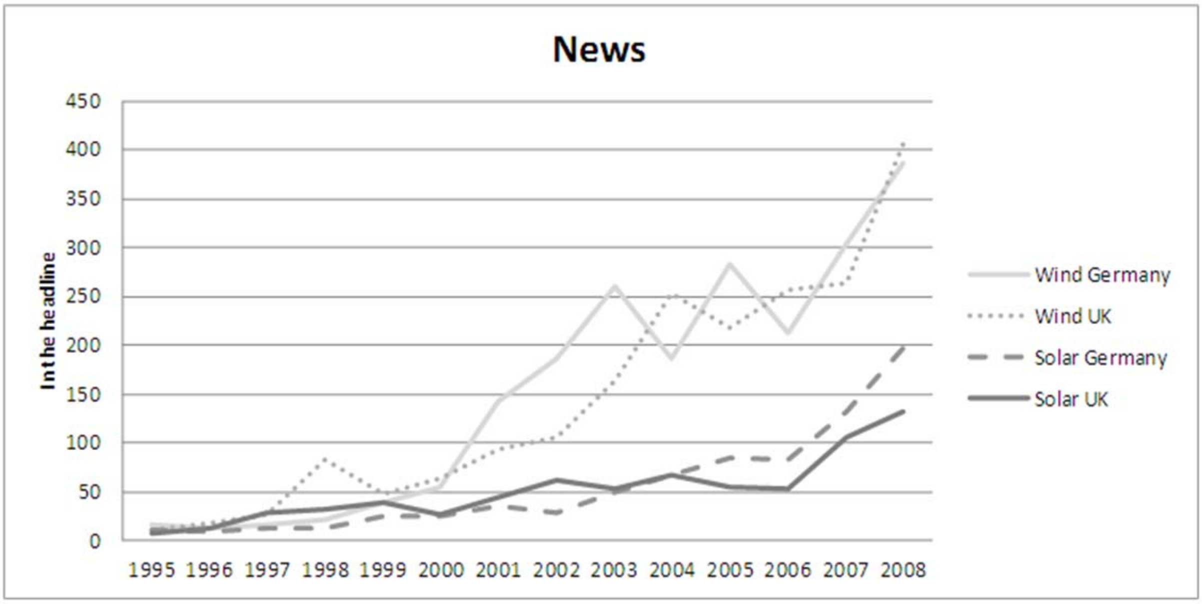


Germany saw substantial growth in wind energy production during the reference period, from 147 to 3,250 kilotons of oil equivalent (kTOE); meanwhile, wind energy production increased from 34 to 875 kTOE in the UK. Although the cumulative growth in wind energy in Germany during the reference period was larger than in the UK, annual growth rates (%) varied between 95% and 169% in Germany and similarly between 97% and 151% in the UK. Hence, Germany produces and has produced more wind energy than the UK. However, both countries saw similar increases in growth in percentages in their primary production of wind energy during the reference period. Germany saw substantial growth in solar energy production during the reference period, from 92 to 1,452 kilotons of oil equivalent (kTOE); meanwhile, solar energy production increased from 10 to 90 kTOE in the UK. Although the cumulative growth of solar energy in Germany during the reference period was larger than in the UK, substantial annual growth rates (%) varied between 117% and 135% in Germany and similarly between 110% and 127% in the UK.

News visibility

The news media trends in covering wind and solar photovoltaic energy during the reference periods are shown in Figure 3. News exposure includes headline-level type of data.

Figure 3 Annual headline-level news hits for wind and solar photovoltaic energy in Germany and the UK in 1995-2008



The headline-level news media activity varied in Germany and the UK, but the trend was an increase in news regarding all studied renewable energies during the reference period.

Articles about wind energy have been widely published in the UK and Germany. In Germany, the numbers of news hits increased from 16 to 387 per year in Germany and from 11 to 405 per year in the UK during the reference period. Annual growth rates (%) varied from 72% to 263% in Germany and from 58% to 307% in the UK. Although there were substantial variations, the cumulative amount of news reached more than 2,000 items in Germany and in the UK.

Articles on solar energy have also been widely published in the UK and Germany. In Germany, the number of news hits increased from 10 to 196 per year in Germany and from 7 to 131 items per year in the UK during the reference period. The accumulation of news items had similar paths in Germany and the UK. Annual growth rates (%) varied between 90% and 208% in Germany and 69% to 215% in the UK. In spite of the variations, cumulative growth in news increased to more than 700 items in Germany and in the UK.

Statistical analysis

The descriptive statistics and correlation table for the German wind energy–related variables are presented in Table 3. In Table 3, the variables are for Germany, wind-energy (GW), and news hits (HL) in headlines, with lags of one, two, and three years. The results show that the news hits in headline text correlate statistically significantly with one another, in addition to having statistically significant correlations with the wind energy primary production figures.

Therefore, our quasi-experimental analysis with multiple regressions examines only nested models with one variable explaining the variance in primary energy production, as multicollinearity would present difficulties in the full model.

Table 3 Descriptive statistics and correlation table for German wind energy

	Mean	Std. Deviation	1	2	3	4	5
1 GWHL	151.14	126.665	1				
2 GWHLlag1	151.14	126.665	.889**	1			
3 GWHLlag2	151.14	126.665	.873**	.889**	1		
4 GWHLlag3	133	111.304	.795**	.873**	.889**	1	
9 GWPro	1674.75	1271.955	.940**	.932**	.926**	.928**	1

** Correlation is significant at the 0.01 level (2-tailed).

Table 4 Multiple regression results for German wind energy (dependent variable primary energy production, standard errors in parentheses)

Variable	beta	beta	beta	beta
GWHL	8.811*** (0.924)			
GWHLlag1		9.001*** (1.010)		
GWHLlag2			8.852*** (1.039)	
GWHLlag3				9.686*** (1.169)
R2	0.883	0.869	0.858	0.862
Adj. R2	0.874	0.858	0.846	0.849
F-value	90.873	79.412	72.627	68.644

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

The results show that lagged variables show smaller explanatory power compared to the non-lagged regardless of whether we consider news hits in headlines. In addition, news hits in headlines (GWHL) explain 88.3% of the variation in the production figures. Therefore, there is a clear relationship between the overall discussion about wind energy in the news media and the wind-energy production figures, and the media coverage and production figures did not seem to have a strong lagging influence.

Similarly, Tables 5 and 6 present results for UK wind energy.

Table 5 Descriptive statistics and correlation table for UK wind energy

	Mean	Std. Deviation	1	2	3	4	5
1 UKWHL	143.64	118.822	1				
2 UKWHLlag1	143.64	118.822	.917**	1			
3 UKWHLlag2	143.64	118.822	.904**	.917**	1		
4 UKWHLlag3	123.54	95.734	.864**	.904**	.917**	1	
9 UKWPro	261.31	279.082	.922**	.935**	.941**	.935**	1

** Correlation is significant at the 0.01 level (2-tailed).

Similarly to the German wind-energy variables, we find high correlations between variables in the UK case between the independent variables and with the dependent primary production figures, which warrants using the nested models in our multiple regression analysis.

Table 6 Multiple regression results for UK wind energy (dependent variable primary energy production, standard errors in parentheses)

Variable	beta	beta	beta	beta
UKWHL	1.370*** (0.166)			
UKWHLlag1		1.861*** (0.205)		
UKWHLlag2			2.255*** (0.234)	
UKWHLlag3				2.810*** (0.322)
R2	0.849	0.873	0.886	0.874
Adj. R2	0.837	0.863	0.876	0.862
F-value	67.727	82.78	92.804	76.097

* p < 0.10; ** p < 0.05; *** p < 0.01

In contrast to the German modeling results, the lagging variables of the news hits better explain the variance in wind-energy production. The two-year lagging variable of the news hits in the headlines explains the highest amount of variance in production figures among the headline variables (88.6%). Therefore, our results suggest that wind-energy production follows media exposure in the UK.

Tables 7 and 8 show the results of our analysis of German solar energy variables. Similarly to the wind energy–related results, we find high multicollinearity among the variables.

Table 7 Descriptive statistics and correlation table for German solar energy

	Mean	Std. Deviation	1	2	3	4	5
1 GSHL	54.64	54.147	1				
2 GSHLlag1	54.64	54.147	.965**	1			
3 GSHLlag2	54.64	54.147	.926**	.965**	1		
4 GSHLlag3	43.77	37.189	.959**	.926**	.965**	1	
9 GSPro	465.33	412.749	.971**	.983**	.993**	.981**	1

** Correlation is significant at the 0.01 level (2-tailed).

Table 8 Multiple regression results for German solar energy (dependent variable primary energy production, standard errors in parentheses)

Variable	beta	beta	beta	beta
GSHL	3.797*** (0.330)			
GSHLlag1		5.056*** (0.311)		
GSHLlag2			7.445*** (0.275)	
GSHLlag3				10.836*** (0.676)
R2	0.943	0.967	0.987	0.963
Adj. R2	0.936	0.963	0.985	0.959
F-value	132.762	264.846	734.876	257.077

* p < 0.10; ** p < 0.05; *** p < 0.01

In Table 8, the news hits variables GSHL lagged by two years present the highest percentages of explanation of the variance in production figures, namely, 98.7% and 99.3%, respectively. Therefore, our data suggests that solar power production investments follow news media coverage with a two-year lag and visibility in body text seems to have better explanatory power.

Tables 9 and 10 present results of our analysis of the UK solar energy variables. Once again, we find high multicollinearity among the variables.

Table 9 Descriptive statistics and correlation table for UK solar energy

	Mean	Std. Deviation	1	2	3	4	5
1 UKSHL	51.07	33.735	1				
2 UKSHLlag1	51.07	33.735	.843**	1			
3 UKSHLlag2	51.07	33.735	.584*	.843**	1		
4 UKSHLlag3	44.92	25.682	.696*	.584*	.843**	1	
9 UKSPro	26.63	27.208	.924**	.930**	.937**	.881**	1

** Correlation is significant at the 0.01 level (2-tailed).

* Correlation is significant at the 0.05 level (2-tailed).

Table 10 Multiple regression results for UK solar energy (dependent variable primary energy production, standard errors in parentheses)

Variable	beta	beta	beta	beta
UKSHL	0.497*** (0.059)			
UKSHLlag1		0.606*** (0.069)		
UKSHLlag2			0.750*** (0.081)	
UKSHLlag3				0.912*** (0.148)
R2	0.854	0.865	0.878	0.776
Adj. R2	0.842	0.854	0.868	0.755
F-value	70.02	77.105	86.298	38.068

* p < 0.10; ** p < 0.05; *** p < 0.01

In Table 10, similarly to the results for German solar energy and UK wind energy, the two-year lagged variables dominate in explaining the variance in the production figures; namely, news hits in headlines UKSHLlag2 explains 87.8% of the variance.

5. Discussion and conclusions

The purpose of this study was to investigate whether news media as a form of social communication regarding pressing, important, and contemporary issues could be used as a leading indicator of technology adoption. We selected renewable energy technologies, namely, wind and solar energy technologies, as representative technological developments in today's economic environment. Further, we aimed to establish our empirical research in a restricted and (more or less) controlled environment; hence, we limited our study to inside the EU. However, concurrently our aim was to have heterogeneous institutional environments with differing national economic, social, and political environments with different approaches to renewable energy production. Therefore, we selected Germany and the UK for our sample. We collected German and UK news media data and identified the number of news items citing these technologies in headlines from the LexisNexis database for 1995-2008.

Our results show that the news media data and energy production data are significantly correlated for wind and solar photovoltaic energy and in both national contexts. Thus, we conclude that the news media visibility of wind energy and solar photovoltaic energy were in line with Life Cycle Indicators (Watts and Porter, 1997), as the news media portray the use of these technologies in energy production. Importantly, however, our study reveals lagged dynamics between news media visibility and energy production figures. We find that in three out of four cases the two-year lagged media visibility is the best model for explaining the primary energy production figures for these renewable technologies. This result is rather remarkable given the differing and complex institutional environments of political decision making, investment decision-making, technology development cycles, and shifting consumer preferences and national market conditions. However, it seems possible to anticipate the use of renewable technologies in energy production by looking at their news media visibility.

Our proposed method has several advantages compared to other methods used for foresight. Our proposed method is independent of expert or specialist opinions or views on technology evolution. Media visibility can be regarded as an unbiased source of data in this respect. In addition, the information regarding media visibility is readily available, compared to privately sourced technology information or other non-public information. This facilitates wide use of this type of method for various parties. At the same time, we acknowledge cautionary notes as our method has inherent limitations that warrant further empirical research. First, using key word searches is notoriously difficult, fault prone, contextually bounded, and easily misleading. As is typical for the limitations in bibliometrics, our analysis contains changes in terminology over time and noisy or lagging data. These challenges can be overcome with the use of various strategies documented in the literature. In our empirical setting, we attempted to have as representative key words as possible. Similarly, our production figures and the news media data show monotonically increasing functions, and finding these high correlations is not completely unexpected. Therefore, future studies should look for other technologies to see whether similar results are attained in different technological contexts. However, our result that the two-year lagged variable predominantly explains the renewable energy production figures is promising in the sense that this variable holds across technologies and national contexts. Further, future studies could examine the actual content of the news data more qualitatively and see whether the sentiment, the context, the technologies, or similar produce similar or differing patterns in relation to technology adoption data.

In conclusion, this study has produced preliminary promising results that news media visibility as measured by the number of news items citing particular renewable energy technologies is a leading indicator of energy production in that particular technology. Our empirical analysis showed that in two national contexts for two renewable energy technologies the leading indicator of news media visibility lagged by two years in three cases out of four, and therefore, news media visibility facilitates anticipative analysis of energy production. However, due to inherent limitations, our results provide many fruitful avenues for future foresight research on determining and comparing the trends in technology adoption in differing national contexts and their relation to news media visibility.

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