Measuring the Impact of Clean Energy Production on CO_2 Abatement in Denmark: Upper Bound Estimation and Forecasting[*]

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Abstract

Using annual data from 1978 through 2016, and monthly data from January, 2005, through November, 2017, from Denmark, we provide a precise estimate of the upper bound on the potential impact of the adoption of wind energy on the reduction of CO_2 emissions from energy production. We separate causal impacts from endogenous effects in regressions using instrumental variables including average wind speed, and from spurious effects in dynamic systems using impulse-response analysis and cointegration techniques. A one percentage point increase in the share of wind in total energy production is found to cause a reduction in CO_2 emissions of the order .3%, based on endogeneity-corrected regression, and .5% over two years in a fractional vector error-correction model, after allowing the cumulative effects to take place. This corresponds to an upper bound estimate of .69 tonnes of CO_2 emissions avoided per additional MWh of wind energy produced. We find that after a structural break at the time of introduction of the EU ETS and the Kyoto Protocol in 2005, the country has been on track towards meeting its long term goals for emission reduction and green energy production, but not before.

JEL classification: Q20; Q54; C50

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1 Introduction

Carbon dioxide (CO_2) emissions constitute the largest part of all greenhouse gas (GHG) emissions[1] and are the main reason behind the observed global warming and climate change over the last decades (see, e.g., Stocker et al., 2013). CO_2 is mainly emitted when fossil fuels such as coal, oil, and natural gas are combusted for the purpose of generating energy. In recent years, CO_2 emissions have declined in a number of countries, including Denmark. This decline may be associated with several factors, such as warming, substitution of import for production, and adoption of clean energy sources, in particular wind, in place of fossil fuels. Many countries are stepping up their efforts to bring down CO_2 emissions and at the same time increasing investments in zero-emission power generation. Jacobson and Delucchi (2011) offer technical suggestions as how to provide worldwide energy from wind, water, and sunlight (WWS). Pieralli et al. (2015) adapt the regression techniques of Kneip et al. (2016) to assess the efficiency of wind energy production. Yet, few reliable tests have been conducted to assess whether the observed correlation between rising fossil-free power generation methods and decreasing emissions is mainly spurious or indeed reflects causality running from clean energy technologies to CO_2 emissions abatement. More precise information on the potential for reducing CO_2 by substituting wind for other energy production technologies would be valuable to policy makers choosing among energy production technologies while facing increasing environmental challenges stemming from continuing reports on GHG emissions and global warming.

In this paper, we investigate whether a causal and dynamic effect of wind energy production on CO_2 emissions can be found in Denmark. This country has been a pioneer in the wind power industry going back to the 1970s, and with policy makers announcing further investments in this direction around the time of the implementation of the European Union Emissions Trading Scheme (EU ETS)[2] and the Kyoto Protocol in 2005. Today, Denmark is the world leader in wind energy, with production corresponding to 41.8% of domestic electricity consumption in 2015, compared to 1.9% in 1990.[3] The country has stated policy goals of no-fossil energy production by 2050, in accordance with the 2015 Paris Agreement joined by most countries of the world, and a reduction in CO_2 emissions of 70% by 2030, relative to the UN base year of 1990.[4] The latter goal was announced in June, 2019, at the time of formation of the new government, following general elections.

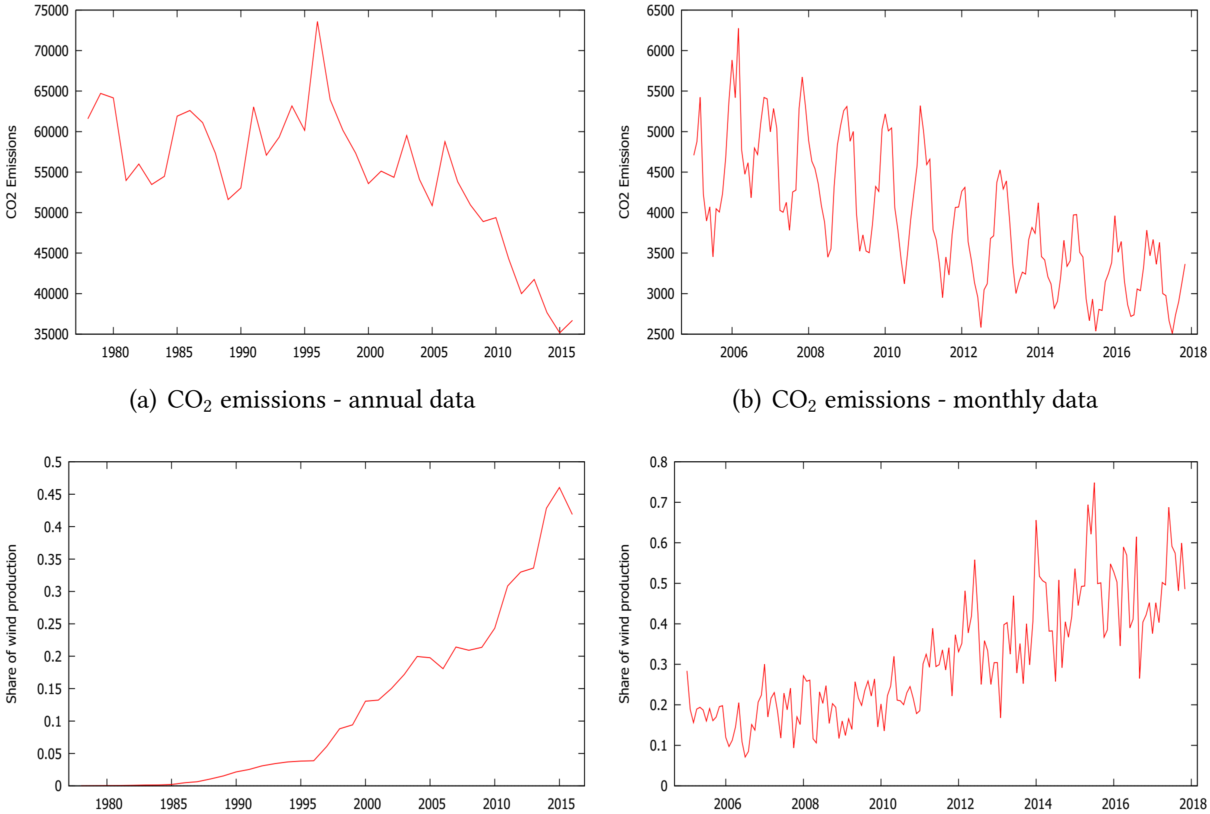
From Figure 1, annual CO_2 emissions from energy production have been trending down in Denmark in recent years, since 1996. In our empirical analysis, we test for breaks in the emissions series. The figure also shows the increase in the annual share of wind energy in total

[1]Other GHG emissions include methane (CH_4) and nitrous oxide (N_2O).

[2]For empirical analyses of the European carbon markets, see, e.g., Chevallier (2009) and Koop and Tole (2013).

[3]Based on official government statistics, Energistatistik 2015, Energistyrelsen, available at: https://ens.dk/sites/ens.dk/files/Statistik/energistatistik2015.pdf.

[4]The 2015 Paris Agreement advocates limiting the global temperature rise to 1.5 °C above pre-industrial levels. According to the Intergovernmental Panel on Climate Change (IPCC, 2019), this requires cutting global CO_2 emissions to net zero by 2050.



(a) CO_2 emissions - annual data

(b) CO_2 emissions - monthly data

(c) Wind energy share - annual data

(d) Wind energy share - monthly data

Figure 1: The time series of CO_2 emissions and wind share in energy production at annual and monthly frequencies. See Sections 3.1 and 3.2 for construction of the wind share and emissions series, respectively.

energy production. Focusing on the relation between the series, we separate the causal impact of wind share on emissions from effects of the potential endogeneity of wind adoption using instrumental variable (IV) regressions, and from spurious effects in dynamic systems using impulse response function (IRF) and cointegration techniques. The instruments used to control for the potential endogeneity of wind energy are variables affecting the efficiency of wind energy production, including climate measures such as average wind speed in Denmark, fluctuations in wind strength and direction, as captured by North Atlantic oscillation patterns, sunshine hours, and precipitation. In a dynamic system analysis, we use a vector autoregressive (VAR) model of emissions and wind energy to derive IRFs and long term forecasts. We investigate long run equilibrium properties of the system, and derive the impact on estimated IRFs of accounting for long memory and co-movement (fractional cointegration) among series.

Our analysis should essentially yield a relatively precise upper bound estimate of the potential impact of wind energy adoption on CO_2 emissions abatement, for three reasons. First, Denmark is at a comparative advantage, being in a unique position to exploit wind energy. A temperate climate and a location close to stable oceanic wind flows enable optimal harvesting of wind, e.g., through off-shore wind farms. Second, proximity to large hydro facilities in

Norway and Sweden mitigates shortfalls stemming from turbulence and intermittency in wind production. Third, the long history of production enables an investigation over a sufficient time span to allow a relatively precise estimation. We use annual data from 1978 through 2016, and monthly data from January, 2005, through November, 2017.

Several controls included make our results informative in relation to other countries. Specifically, we investigate the importance of accounting for (i) variations in heating and cooling demand, by conditioning on temperature, (ii) access to the energy source, by conditioning on wind strength, and (iii) access to replacement energy during intermittencies, by conditioning on net electricity import. In addition, some of our specifications accommodate an environmental Kuznets curve (see, e.g., Grossman and Krueger, 1995) by including output and its square, the hypothesis being that emissions increase at a decreasing rate with economic development, here output. Thus, estimated coefficients indicate how our results can be expected to relate to those for other countries characterized by different climate, import patterns, and degree of development.

From our empirical results, adoption of clean energy is an important contributor to the observed decline in CO_2 emissions, even after controlling for rising temperatures and increasing electricity imports from neighboring countries. A one percentage point increase in the share of wind in total energy production is found to cause a reduction in CO_2 emissions of the order 0.3%, based on endogeneity-corrected regression, and .5% over two years in a fractional vector error-correction model, after allowing the cumulative effects to take place. In the estimated long-run equilibrium, we find a displacement emissions factor of .69, in tonnes of CO_2 emissions avoided on the margin, per additional MWh of wind energy produced, which is in the high end of the range reported in the international literature. Although effects are system dependent and could be even higher in regions where wind replaces more heavily polluting power generation, the potential impact in most other countries is expected to be subject to an upper bound given by this estimate from Denmark. This country is found to have been on track towards meeting its long term goals for emission reduction and no-fossil energy production following the introduction of the EU ETS and the Kyoto Protocol in 2005, but not before.

The paper proceeds as follows. Related literature is described in Section 2, and data sources and methodology in Section 3. Modelling and estimation strategies are presented in Section 4, along with resulting regression estimates. Section 5 provides an analysis of the dynamic system and forecasting results. Section 6 concludes.

2 Related literature

The literature on emission control effects of wind generation is divided into two branches, dealing with simulation and statistical approaches, respectively. We follow a statistical approach, estimating effects using actual historical data from a particular country over a long period of time. The resulting estimates are used to predict effects of policy changes (e.g., adoption of additional wind power), as well as future developments in emissions and wind energy production. This is in contrast to the literature using simulations to calculate effects based on engineering models of the power system, with coefficients set based on technical considerations, or detailed data over shorter periods. A key question is which fossil-based generator to shut down as wind production is increased, emission reductions being higher if wind replaces, e.g., coal rather than natural gas. The focus in the simulation approach is on operational feasibility and cost minimization within the power system at hand, not on what actually took place over the historical period. The statistical approach applied to long span data series delivers estimated relations that in part reflect changes over time in investments, technology, demand, and decision-making behavior, implicitly identifying the technology replaced through responses in emissions to changes in wind generation. Further, estimates and forecasts are accompanied by assessments of uncertainty, such as significance levels and confidence regions. Hence, the statistical approach can generate important additional insights, relative to the simulation approach. We briefly summarize some of the main contributions and findings in the simulation and statistical literatures, respectively, and relate these to our analysis.

2.1 The simulation literature

In the simulation literature, typically either a displacement approach, or a more sophisticated dispatch model, is considered. The displacement approach assumes that wind power replaces an equal amount of power generated by the existing system. In an average emissions rate analysis, emission reductions are calculated according to emissions factors (conversion coefficients) of technologies in place. A more refined version, the primary energy equivalent (PEE) method, is based on assumptions about the marginal technology replaced, see Kartha et al. (2004). The approach has been used by wind industry associations, governments, and international organizations, e.g., for the European Wind Energy Association (EWEA) by Corbetta et al. (2015), and for the Global Wind Energy Council (GWEC, 2016). Results imply displacement emission factors (DEFs) of the order .6 tonnes of CO_2 emissions displaced per MWh produced by wind.[5] The PEE method is used by the Sustainable Energy Authority of Ireland (SEAI, 2019), yielding a DEF around .4 for this country. While these studies assume constant DEFs, Hernandez et al. (2019) apply a dynamic displacement approach to the European Union, with DEFs periodically updated according to anticipated changes in the future generation portfolio, suggesting they are currently in the .4 to .7 range. This is in contrast to our statistical approach, using the observed time-varying energy mix to imply the emissions series, then estimating the impact of wind share on this from historical data.

Dispatch models use detailed information on the structure of the power system, and can be used, e.g., for counterfactual scenario analysis. Technologies (generators) are ranked in a production stack according to marginal cost, and unit commitment, dispatch, and power flow selected to minimize cost of meeting assumed demand, subject to system constraints, includ-

[5] Henceforth, DEFs are stated in tCO_2/MWh.

ing generator capacities, network constraints, etc. Sophisticated versions account for cost and emission effects of start-up, shut-down, part-load operation, cycling, ramping, etc. Early dispatch simulations were conducted by El-Sayed (2002) for Egypt, and Holttinen and Tuhkanen (2004) for the Nordic countries, the latter indicating DEFs of .3 or .7, depending on whether gas or coal is replaced. Several subsequent studies apply PLEXOS, a commercial power market simulation software solving the unit commitment and dispatch problems by mixed integer programming. Simulations for SEAI by Clancy and Gaffney (2014), and others for Ireland by Denny and O'Malley (2006) and Deane et al. (2013), imply a DEF around .5. A similar figure is indicated by the U.S. Department of Energy, the National Renewable Energy Laboratory (NREL, 2013), for the Western interconnection, consisting of the United States, Canada, and Mexico. Using analogous software, Delarue et al. (2009) present a detailed dispatch analysis for Belgium, as do Valentino et al. (2012) for Illinois, Weigt et al. (2013) for Germany, and Gutiérrez-Martín et al. (2013) for Spain, with DEFs largely ranging between .4 and .7. Simulations generally show that the additional emissions impact of start-up, cycling, etc., is small and does not offset the emission reductions from using wind, e.g., Clancy and Gaffney (2014) find that fossil-based generation pollutes less than 2% more when combined with wind. This reinforces the notion that the statistical approach, even using more aggregate data, and not explicitly accounting for dispatch decisions, can be used to implicitly identify the technology replaced in practice, and the resulting emission reductions.

2.2 The statistical literature

The statistical literature has considered regression models for emissions data, controlling for wind energy production, demand, weather conditions, etc. Cullen (2013) uses conventional power production as the dependent variable and includes wind generation, demand, temperature, and lags among the independent variables. Production data at 15-minute frequency for each generator on the ERCOT (Electricity Reliability Council of Texas) electricity grid in Texas over a two year period from 2005 to 2007 are regressed on aggregated (across generators) dependent variables. The model predicts the conventional (coal, natural gas, nuclear, etc.) production offset by wind, and emissions offset are obtained through multiplication by emissions factors. As wind is allowed to enter nonlinearly, marginal emissions avoided (MEA) are derived in terms of a partial derivative. Average MEA is estimated at .43, i.e., comparable to DEFs from the simulation studies (and likewise stated in tCO_2/MWh). Our approach is related, in that we compute emissions by multiplying conventional production by emissions factors (Section 3.2), then regress on wind generation, including temperature and demand indicators (in our case GDP) among our controls (Section 4), but we use data over a long time span, aggregated over generators and time (lower frequency), and supplement the regression methods by more elaborate time series analysis, including break analysis and long-run forecasting (Section 5). Whereas regression using high-frequency short-span data identifies the marginal generator replaced by wind in the existing system at the data frequency (say, within the day), estimated emission reductions from our long-span aggregate analysis reflect replacement over the month or year, and the change in generation portfolio over time.

Several contributions in the regression literature consider relevant variations to the basic framework from Cullen (2013). Kaffine et al. (2013) and Novan (2015) similarly consider ERCOT data, with a focus on heterogeneity across generation portfolios. Novan (2015) applies an instrumental variable (IV) correction for the potential endogeneity of wind production in the regression, using wind speed as an instrument for wind production, but finds that results are unaltered by IV. These studies report MEA below hypothetical reductions based on an average emissions analysis, i.e., the marginal generator replaced by wind pollutes less than the average generator.[6] Similar regression methods are applied to data for 2011 from Ireland by Wheatley (2013), who adds electricity imports to the set of regressors, and accounts for serial correlation by taking first differences of series as well as allowing for ARMA(1,1) errors. Other studies for Ireland address dynamics in different ways, e.g., Di Cosmo and Valeri (2018) allow for AR(1) residuals, O'Mahoney et al. (2018) for wind forecasting errors, and Oliveira et al. (2019) for serial correlation using Newey and West (1987) standard errors, following Kaffine et al. (2013) and Novan (2015). Regression studies for other regions include Amor et al. (2014), with a focus on congestion effects in the Ontario grid, and Thomson et al. (2017) for Great Britain. Although system dependent, MEA estimates in the regression literature tend to range between .3 and .7, with some concentration between .4 and .6, broadly consistent with Cullen (2013), and with DEF calculations from the simulation literature.

In our regression analysis in Section 4, we similarly use IV methods to adjust for potential endogeneity, with wind speed as one of our instruments, and include imports among our controls. In contrast to Novan (2015), we find that IV correction matters, consistent with the notion that wind energy production is a decision variable, and endogenous in the emissions regression. Furthermore, in Section 5, we considerably extend the battery of time series techniques to handle the dynamics in our long-span analysis for Denmark. Unlike all previous studies of emissions and wind energy, we allow for long memory (fractional integration) in the series. Ang (2007) considered integer (not fractional) integration and cointegration between emissions and total energy consumption, and included an environmental Kuznets curve (EKC), but did not consider wind energy. In relation to this, we include wind energy in the analysis, as well as an EKC in our regression analysis, and we allow for general fractional (non-integer) integration and cointegration in our dynamic analysis. We find that this is strongly significant, and the model with integer order of integration and cointegration is rejected in favor of the fractional one. This is clearly important for the estimation of long-run policy effects and forecasting at the horizons relevant for the stated policy targets, i.e., through 2030 and 2050. Furthermore, unlike previous studies, we document a regime shift around 2005. This may be related to the introduction of the EU ETS system and the Kyoto protocol, thus reinforcing the notion that

[6] Siler-Evans et al. (2012) consider more U.S. regions and find that in some, the marginal effect is below the average (in the region), while in others, the reverse applies.

policy changes matter, which should be relevant to other countries planning for how to meet emission and renewable energy targets. For marginal emissions avoided, we also have nonlinearity and so consider a partial derivative. Our final MEA estimates are in the high end of the range from the simulation and statistical literatures, consistent with the idea that the Danish case provides an upper bound (up to estimation error).

3 Data and Methodology

In this section, we present the data and methodology for construction of our energy and emissions series, as well as explanatory and instrumental variables.

3.1 Energy data

The Danish Energy Agency (DEA) under the Ministry for Energy, Utilities and Climate produces annual and monthly Energy Accounts of the official energy statistics for the country, which include data on energy production, consumption, and emissions.[7] The annual data on total energy production are split into various categories, including wind energy. The original source of the DEA wind energy production data is a national database known as the 'Stamdataregisteret', which contains information about production for all electricity-producing wind power production facilities. Annual data on wind energy production and total energy production from 1978 to 2016 are obtained from DEA. By forming the ratio, we compute the share of wind energy production in total energy production, i.e., wind penetration, for each year. The resulting annual series is shown in Figure 1(c).

In the monthly frequency data from DEA, total energy production is only split into categories including renewable energy (involving, in addition to wind, also solar, biogas, and solid biomass energy), but not wind alone. Instead, for our monthly wind energy series, we use electricity production from wind energy, also from DEA. Therefore, our monthly wind share series is calculated as relative to total monthly net electricity production (excluding electricity used in electricity production). The resulting series covers the period January, 2005, through November, 2017, and is exhibited in Figure 1(d).

Finally, we collect data on monthly consumption of coal, oil, and natural gas for energy production over the period January, 2005, through November, 2017, reported by DEA (see footnote 3 for the source). These data are used to calculate monthly emissions in the following.

3.2 Emissions data

Annual CO_2 emissions from energy production covering the period 1978 through 2016 are collected from DEA data.[8] DEA applies emissions factors from the EU ETS to calculate annual

[7] https://ens.dk/service/statistik-data-noegletal-og-kort/maanedlig-og-aarlig-energistatistik.

[8] https://ens.dk/service/statistik-data-noegletal-og-kort/maanedlig-og-aarlig-energistatistik. CO_2 emissions are available from 1972. Our analysis uses data starting in 1978, since all series are available from this year onwards.

CO_2 emissions from energy production arising out of usage of coal, oil, natural gas, and non-biodegradable waste in Denmark. The energy sector, and in particular the part of the sector relying on these fuels, is the largest source of CO_2 emissions in Denmark (Nielsen et al., 2016, p. 82). Furthermore, emissions from energy production is the portion of total emissions that the adoption of wind energy may have an impact on. Thus, we do not consider emissions from transportation, agriculture, or other sources.[9] Figure 1(a) shows annual CO_2 emissions from energy production.[10]

As a robustness check, to ensure that there is nothing unusual about our data, we also consider an alternative series for annual CO_2 emissions, obtained from the European Commission's EDGAR[11] database, which estimates anthropogenic GHG emissions on a country-by-country basis. We focus on the series for CO_2 emissions from fossil-fuel use and industrial processes emissions, excluding short-cycle/large-scale biomass burning and carbon emissions/removals of land-use, land-use change, and forestry (LULUCF).

To construct a monthly CO_2 emissions time series corresponding to the annual series from DEA, we apply the IEFs (implied emissions factors) computed by the EU ETS for the period 2006 through 2014 and used in Denmark's National Inventory Report 2015 and 2016 (Nielsen et al., 2016, henceforth DNIR) to monthly consumption of coal, oil, and natural gas for energy production, cf. Section 3.1. DNIR is prepared by the Danish Center for Environment and Energy, which is responsible for submitting Denmark's national emission inventory under the United Nations Framework Convention on Climate Change (UNFCCC) and the Kyoto Protocol.

The EU ETS conducts fuel analysis to construct IEFs based on data from all reporting plants. For the 2006-2014 period, IEF (including the oxygenation factor) is 94.17 kg CO_2 per GJ[12] for coal, 79.49 kg/GJ for residual oil combusted in public electricity and heat generation facilities, and 57.381 kg/GJ for natural gas, based on emissions from offshore turbines. We apply the IEFs for 2006-2014 to the monthly data on coal, oil, and natural gas consumption for 2005-2017, to construct monthly CO_2 emissions. The slight difference in time periods is inconsequential as time series variation in these emissions factors is negligible (DNIR, pp. 143-148). The resulting monthly series for CO_2 emissions from energy production appears in Figure 1(b).

3.3 Economic data

Along with increasing wind energy production over the study period, cf. Figures 1 (c)-(d), there has been rising import of electricity in Denmark, largely from Norway and Sweden, serving as

[9] Emissions from biomass burning are excluded, as this form of energy production is less important for Denmark over our study period, and in principle CO_2-neutral in the long run, although the latter argument requires the replanting of vegetation to absorb CO_2 in the future.

[10] As physical emissions factors based on fuel analysis are applied, with no accounting of international carbon market trading, the decline in emissions in later years reflects reductions in usage of fossil based fuels and waste, and is not subject to the problem of double counting of emission reductions by both the countries buying and selling carbon credits.

[11] Emission Database for Global Atmospheric Research.

[12] 1 kg CO_2/GJ = 0.0036 tCO_2/MWh.

replacement energy during intermittencies. DEA provides monthly and annual data on net electricity imports. Similarly to wind energy production, net electricity import is calculated as share of total energy production in the annual data, and as share of total electricity production in the monthly data, as reported in the DEA Energy Accounts.

As indicators for demand, and to allow for an EKC, GDP and its square are included in the model. GDP is measured as gross domestic product in real terms (2010 prices) in billions of Danish kroner (DKK). Annual figures are obtained from Statistics Denmark.[13] In the absence of GDP measurements at the monthly frequency, we consider the industrial production index for Denmark, available from Eurostat at the monthly frequency over the period 2005-2017, with base year 2010.

3.4 Climate data

Temperature is included to account for variations in emissions unrelated to wind energy. Global warming in the Northern hemisphere, improved housing methods and materials, and more efficient insulation methods have reduced the demand for energy for heating purposes. Although demand for air conditioning has simultaneously increased (Stocker et al., 2013), the net effect on energy demand is typically negative in cold countries. In Denmark, since much heating is generated from the burning of coal, natural gas, and biomass, with only a smaller fraction covered via by-products (excess heat) from electricity production, this would imply a reduction in CO_2 emissions through a direct effect of temperature on demand, unrelated to wind energy adoption. We treat temperature as an exogenous regressor, the assumption being that local temperature changes affect local emissions, e.g., warmer winters require less energy use and hence lower emissions, while local temperature itself is not affected by local emissions, but rather by accumulated global carbon emissions (Leduc et al., 2016). Annual and monthly temperatures (in °C) are obtained from the Danish Meteorological Institute (DMI) historic records (Cappelen, 2018), which have been maintained consistently since 1874 (cf. Cappelen and Jørgensen, 2011).

Explaining emissions by wind energy raises the issue of possible endogeneity of the latter, e.g., wind energy production may react to emissions, for policy reasons. We use exogenous variables that matter for wind energy generation, and the efficiency of this, as instruments for wind energy in endogenity correction by IV methods. Efficiency in generation is sensitive to local climatic parameters, including temperature, wind speed, turbulence, intermittency, precipitation, sunshine, and air density. As temperature is already included as explanatory variable for emissions, due to its direct effect on energy demand, its total effect will combine the direct demand effect and an efficiency adjustment. All else equal, higher temperatures reduce wind production, because they make the air less dense, and the thermodynamic cycle used to drive turbines thereby less effective, hence increasing emissions (Cullen, 2013). Thus, while the

[13] From the Stat Bank Denmark website, made publicly available by Statistics Denmark, see B.1*g, Gross domestic product, Stat Bank, Statistics Denmark, available at: http://www.statistikbanken.dk/ statbank5a/SelectVarVal /Define.asp?MainTable=NAN1&PLanguage=0&PXSId=0&wsid=cfsearch.

direct effect of temperature may be expected to be negative (lower heating demand reduces emissions), the efficiency adjustment may mitigate the measured effect.

Wind strength and fluctuations, precipitation, and sunshine hours clearly matter for wind energy production. On stormy days, more wind power will be generated, while on calm, sunny days, the opposite will occur, implying that a mix of wind and solar energy installations can complement each other where climate is variable (Jacobson and Delucchi, 2011). Similarly, shortfalls can occur on rainy days, and ice and snow can damage or slow down wind turbines (Lacroix and Manwell, 2000; Pieralli et al., 2015). Precipitation and sunshine hours affect wind energy production considerably more than they affect emissions from stationary combustion sites (plants) using coal, oil, and natural gas as fuels, so they are natural IVs. We obtain annual and monthly precipitation (in mm) and sunshine (in hours) from the DMI historic records. Further, we use the North Atlantic Oscillation Index (NAOI) to capture climatic intermittency and turbulence patterns affecting Northern Europe. NAOI oscillates between positive and negative values, depending on surface sea-level pressure differences between the Southern and Northern Atlantic regions. It is highly correlated with other measures of atmospheric circulation, such as dp(abs)24, which is the interdiurnal pressure-variability index, and with wind speed and storminess (Hanna et al., 2008). The NAOI index is available at the annual, monthly, and daily frequencies.[14]

Data on average wind speed specifically for Denmark are not available for our full analysis period. For the subperiod January, 2005, through December, 2010, we have been able to acquire monthly data on wind speed at three weather stations in Denmark (Thyborøn, located North-West, Esbjerg Airport in the South-West, and Holbaek Airport, East) from DMI. For this subperiod, we use average wind speed for Denmark, calculated as the monthly average across the three weather stations, as an alternative to the NAOI index in the instrumentation, following Novan (2015).

4 Modelling and estimation

4.1 Preliminary analysis and regression specification

We are interested in assessing the dynamic effect of the share of wind in energy production on CO_2 emissions within a time series regression framework. Write E_t for log CO_2 emissions in period t, and W_t for our wind energy measure, using the logit transform, $W_t = \log(w_t/(1-w_t))$, with w_t the share of wind in total energy production. The baseline regression specification is

$$E_t = a_0 + a_1 t + \sum_{i=1}^{p} a_{e,i} E_{t-i} + \sum_{j=1}^{q} a_{w,j} W_{t-j} + a_x' X_{t-1} + \varepsilon_t \,. \tag{1}$$

This setup allows for dynamics through the inclusion of lagged emissions and wind energy, as well as a time trend. In the empirical work, p and q are chosen sufficiently large to leave ε_t

[14] See http://www.cpc.ncep.noaa.gov/data/teledoc/nao.shtml.

serially uncorrelated. The use of wind energy and lags as conditioning variables follows Cullen (2013) and the subsequent regression literature, cf. Section 2.2.

The log and logit transforms were selected after empirical experimentation. The distribution of changes in emissions depends on the level. The log transform has a stabilizing effect on this, and avoids a truncated error distribution, as emissions are non-negative. Wind share or production mix is preferred over level of wind production for interpretation and policy purposes. The log-logit specification facilitates elasticity calculations and was preferred over the level-level specification and combinations based on misspecification checks for residual correlation, heteroskedasticity, and normality. Further, it accommodates a decreasing impact of wind energy on emissions for higher wind penetration.[15]

To investigate the possibility that other conditioning variables impact emissions, (1) includes a vector X_{t-1} of additional regressors, treated as exogenous, i.e., uncorrelated with ε_t. In the annual data analysis, X_{t-1} includes net electricity import, $\log(\text{GDP})$ and its square, and temperature. In the monthly data analysis, the contemporaneous seasonal terms $\sin(2\pi t/12)$ and $\cos(2\pi t/12)$ are included,[16] while GDP is replaced by industrial production (IP), which is available at the monthly frequency. GDP, IP, and temperature serve as indicators for demand, and the latter for generation efficiency, as well. Cullen (2013) included demand and temperature as regressors, Wheatley (2013) added electricity import, and the quadratic in GDP allows for an EKC.

The effect of wind share on emissions is represented by coefficients $a_{w,j}$. Negative coefficients are consistent with the hypothesis that an increase in wind power leads to a reduction in emissions. With both the emissions and wind share series trending in time, especially in the last part of the annual sample and in the monthly dataset, cf. Figure 1, there is a risk of estimating a spurious effect. Inclusion of the deterministic trend term and lagged dependent variables in (1) should mitigate the impact of this problem on the estimates of $a_{w,j}$. Nevertheless, the possibility of stochastic trends in the series remains, and we implement augmented Dickey-Fuller (ADF) tests to investigate this.

From the summary statistics, appearing in Table 1, the average share of wind production is about 12.4% over the period 1978-2016 for which we have annual data, and increases to 31.2% over the more recent monthly data period, 2005-2017, consistent with the overall increase in the share of wind production over the last decade evident from Figure 1 (c)-(d). Table 1 also reports results of ADF tests of the null of a unit root (non-stationarity), and thus a stochastic trend, against a stationary alternative. While all monthly series are stationary around a linear trend and a seasonal component modelled using monthly dummies (ADF p-values all below conventional levels), it appears that at the annual frequency both E_t and W_t (emissions and wind share) exhibit non-stationary behavior. The only other variable displaying non-stationary behavior is GDP. Hence, from here on, the term GDP refers to the residual after application of

[15] This may be seen from (8) below, and is consistent, e.g., with Valentino et al. (2012), Gutiérrez-Martín et al. (2013), O'Mahoney et al. (2018), and Oliveira et al. (2019).

[16] For a more elaborate treatment of seasonality in climate series, see Proietti and Hillebrand (2017).

Variable	Units	Annual				Monthly			
		Mean	Std. dev.	ADF	p-val	Mean	Std. dev.	ADF	p-val
CO_2	1,000 tonnes	54839	8453	−2.024	0.570	3932	819.5	−3.900	0.012
Wind	Share in nrgy prd.	0.124	0.137	−1.946	0.611	0.312	0.150	−5.987	0.000
Net Import	Share in nrgy prd.	0.024	0.161	−3.596	0.043	0.104	0.238	−5.346	0.000
GDP	Bllns DKK 2010	1510	305.7	−1.481	0.836	–	–	–	–
Ind. Prd.	Index (2010=100)	–	–	–	–	97.95	9.076	−3.972	0.012
Temperature	Degrees °C	8.289	0.881	−5.178	0.000	8.914	5.857	−4.533	0.001
Sunshine	Hours	1576	168.2	−5.594	0.000	143.8	79.24	−11.219	0.000
Precipitation	mm	737.7	93.58	−6.110	0.000	64.78	31.19	−11.322	0.000
NAOI	Index	-0.150	1.040	−6.547	0.000	-0.099	1.124	−8.863	0.000

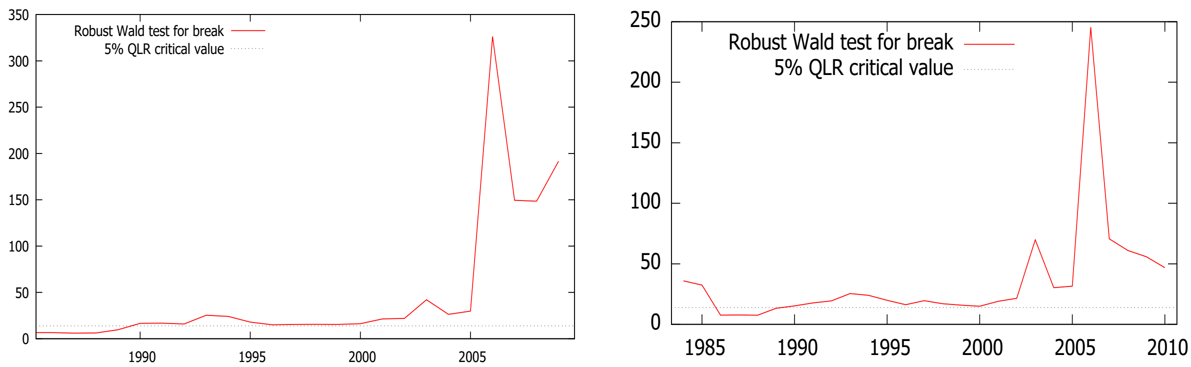
Table 1: Summary Statistics. The table reports summary statistics for the annual data series over the period 1978 through 2016, and for the monthly series over the period January, 2005, through November, 2017. The table also reports results from ADF regressions including a linear trend, a number of lagged first differences selected with AIC (maximum 3 lags), and, for the monthly data, seasonal dummies. In the ADF regressions, the variables CO_2, GDP, and industrial production are measured in logarithms, and the series Wind by the logit transform.

the Hodrick-Prescott (HP) filter, a proxy for the business cycle, to the original series.

Given the apparent non-stationarity of E_t and W_t, the regression setup in equation (1) is subject to the risk of leading to spurious results when the the parameters are estimated in annual data. Therefore, we investigate the possibility that the annual emissions series has been subject to structural breaks. Indeed, structural breaks are often found responsible for apparent non-stationary behavior of time series, see, e.g., Diebold and Inoue (2001) and Granger and Hyung (2004). The break analysis carried out in the annual data relies on the specification

$$E_t = a_0 + a_1 t + a_e E_{t-1} + \varepsilon_t \,, \tag{2}$$

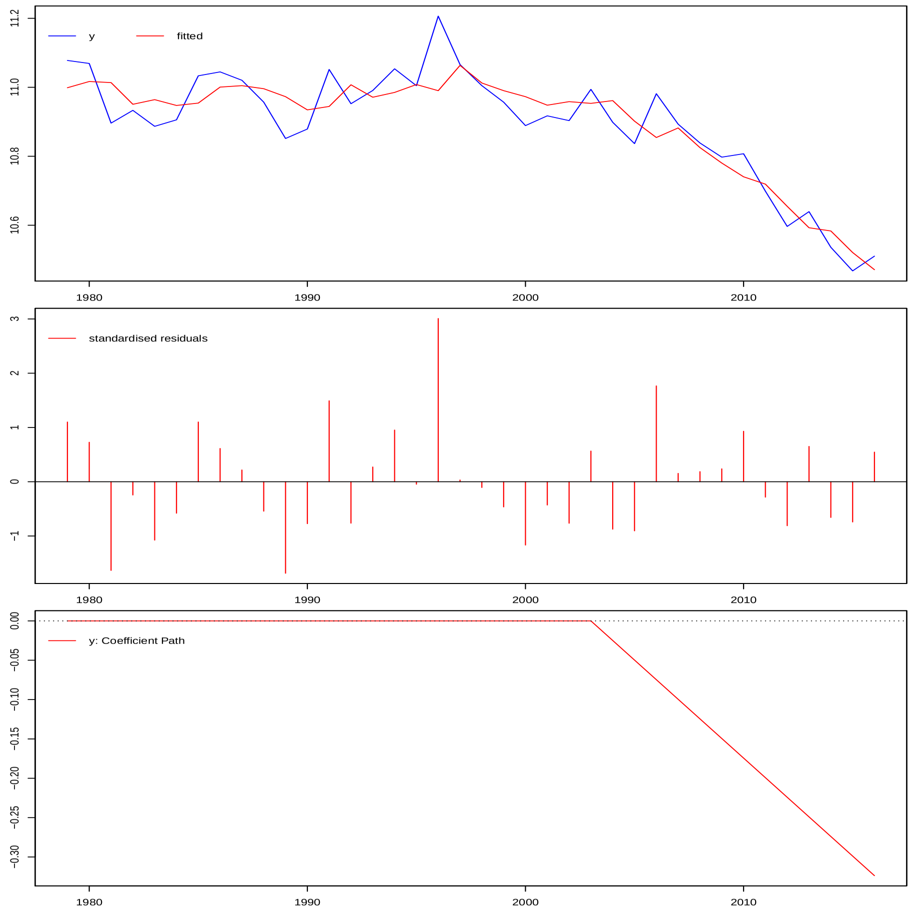
which is (1) with $p = 1, q = 0$, and $a_x = 0$. We first test for structural instability using the Quandt (1960) LR (QLR) or robust Wald test, as well as the *Autometrics* algorithm for automatic model



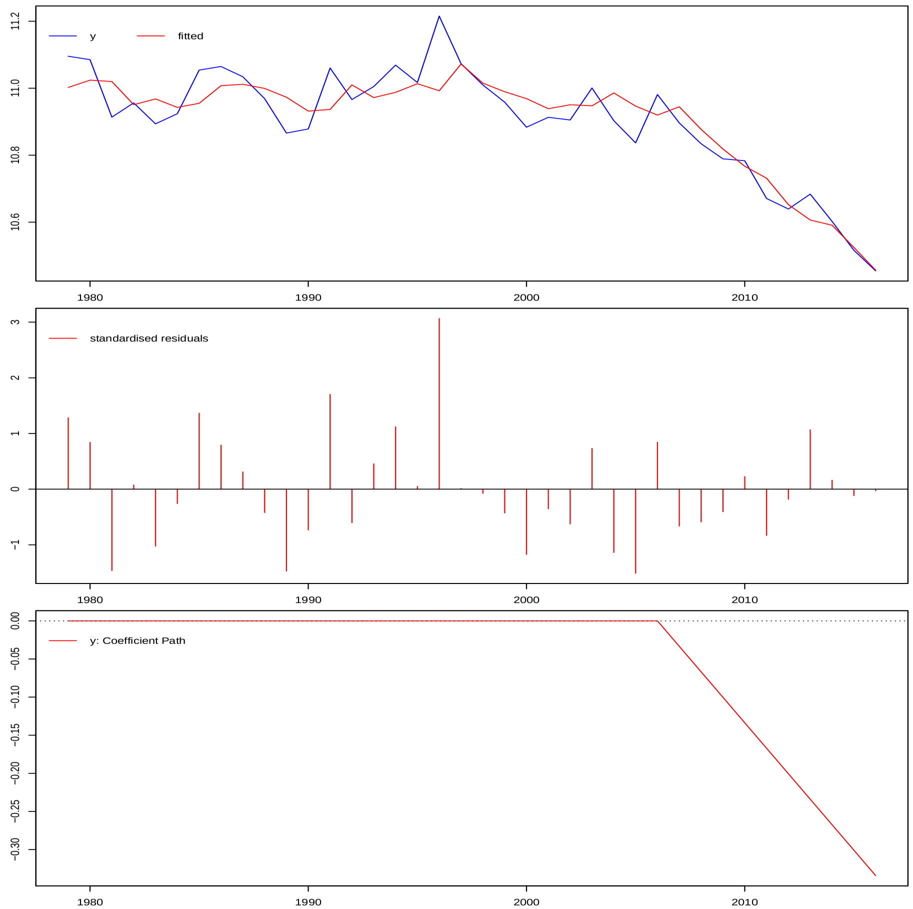
(a) QLR test - CO_2 DEA

(b) QLR test - CO_2 EDGAR

Figure 2: The figure reports the QLR test for parameter instability. Panel (a) shows the QLR test of a structural break in annual data on CO_2 from DEA under an AR(1) plus linear trend model, and Panel (b) shows the similar for the EDGAR data.



(a) Saturation test - CO_2 DEA



(b) Saturation test - CO_2 EDGAR

Figure 3: Autometrics - AR(1) model with linear trend. Panel (a) reports the structural break analysis with indicator saturation based on annual data on CO_2 from DEA under the AR(1) plus linear trend model (2), and Panel (b) shows the similar for the EDGAR data. The methodology follows Pretis et al. (2018). In each panel, the top figure shows observed (blue) and fitted (red) time series. The middle plot shows the standardized residuals, and the bottom plot shows the coefficient path relative to the intercept.

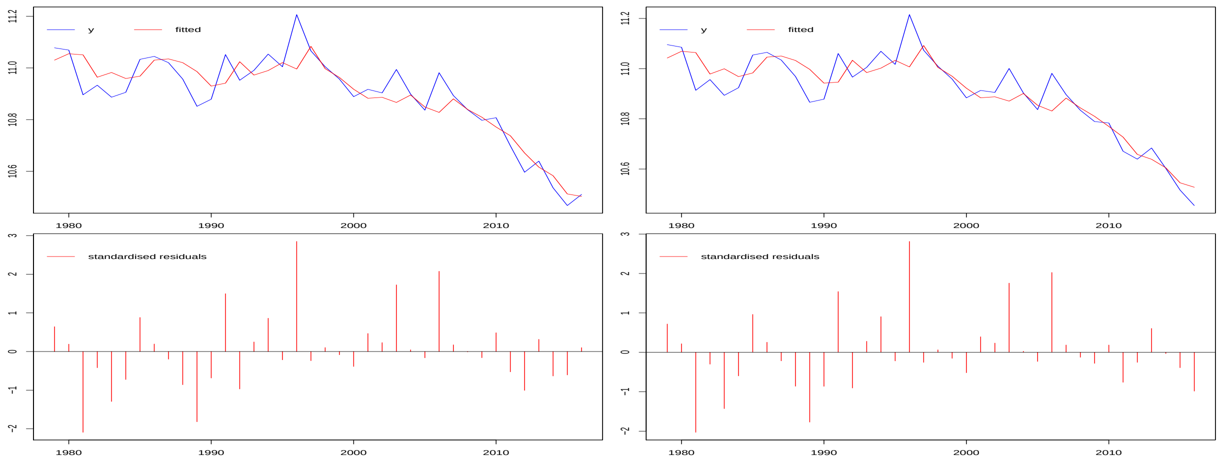
selection within the general-to-specific framework based on saturated regression analysis (see Santos et al., 2008, Castle et al., 2011, and the review in Doornik, 2009). An analogous analysis has been carried out by Pretis and Allen (2013) and Pretis et al. (2015) on climate series.

From Figures 2 and 3, it emerges that both QLR and Autometrics indicate structural instability in the last part of the sample, starting around the year 2005. A possible cause of the break is the implementation of the Kyoto Protocol and the EU ETS. Thus, following these events, the CO_2 emissions series has been moving around a negatively sloped trend, in contrast to the first part of the sample, when it fluctuated around a constant level. In addition to policy changes, trend breaks may also capture technological innovation, but we do not know of any particular emissions reducing technology introduced around 2005, and wind penetration had started increasing well before, cf. Figure 1(c). The presence of a structural break in emissions is confirmed in the EDGAR data, suggesting that there is nothing unusual in our DEA data. The break might be responsible for the apparent evidence of a unit root in the E_t series.

To allow for the impact of wind energy on emissions, we also investigate whether the inclusion of W_{t-1} in (2) would indicate a different dynamic behavior of the E_t series. Thus, we consider Autometrics analysis of the extended specification

$$E_t = a_0 + a_1 t + a_e E_{t-1} + a_w W_{t-1} + \varepsilon_t \,, \tag{3}$$

which is (1) with $p = q = 1$, and $a_x = 0$. Figure 4 displays the outcome of the analysis. Notably, with the inclusion of wind, there is no indication of a change in the drift of E_t after 2005. The



(a) Saturation test - CO_2 DEA　　(b) Saturation test - CO_2 EDGAR

Figure 4: Autometrics - AR(1) model with linear trend and wind. Panels (a) and (b) report the structural break analysis with indicator saturation based on annual data on CO_2 from DEA and EDGAR, respectively, under the AR(1) plus linear trend and wind model (3). The methodology follows Pretis et al. (2018). In each panel, the top figure shows observed (blue) and fitted (red) time series. The bottom plot shows the standardized residuals.

evidence shows not only that the relation between CO_2 and wind energy production has been changing over recent years, but also that the two series are likely to be related in the long run, at least in the later part of the sample. This motivates a long-run equilibrium analysis, pursued in Section 5.2 below, as well as a particular focus on the period after 2005. Indeed, the equilibrium analysis indicates cointegration, i.e., E_t and W_t move together in the long run. Here, we emphasize the role of the structural break, focusing on the findings obtained using the Autometrics method.

Overall, we conclude that regression (1) with $p, q \geq 1$ is a well specified framework within which to analyze the dynamic relation between E_t and W_t in both annual and monthly data. Cointegration (Section 5.2) implies that regression results are not spurious. Results from the break analysis, i.e., the shift in trend around 2005 in the univariate emissions data, and the disappearance of this in the bivariate data, support both (i) using the series jointly in the annual and monthly data regressions (Sections 4.2-4.3), and (ii) paying special attention to the period after the break in 2005 in the dynamic modelling using monthly data (Section 5).

4.2 Regression estimation

Estimates of the coefficients of regression (1) are reported in Table 2. The first four columns show the results of the annual data analysis, and the remaining two columns the monthly data results. From the first column, regression (1) with $a_x = 0$ using DEA data, the first lag of W_t loads positively on E_t in the annual data regression, $a_{w,1} = .04$, but the significance of W_{t-1} does not carry over when including other covariates, second column of table (robust two-sided p-values of t-test below estimates). The same evidence arises using EDGAR data (third and fourth columns). Instead, the regression based on monthly data over the period 2005-2017 (fifth column) suggests a negative relation between W_t and E_t. Both $a_{w,1}$ and $a_{w,2}$ are negative and strongly significant, indicating that an increase in wind penetration leads to a significant reduction in CO_2 emissions in the following periods. Furthermore, the impact remains negative and strongly significant in the monthly data, even after controlling for rising temperatures, industrial production, and net electricity import (sixth column).

Notably, in the monthly dataset, the impact of other covariates is largely as expected. An increase in net electricity import from neighboring countries significantly reduces emissions, which makes sense, since less domestic production is needed.[17]

The results indicate what can be expected for other countries, as well. The significance of the import coefficient for Denmark suggests that countries with poorer access to electricity import to counter the intermittency problem would have less potential to reduce emissions by adopting wind. Next, higher temperatures significantly reduce emissions, i.e., the reduction in heating demand dominates both the increase in cooling demand (air conditioning) and the mitigating effect of the efficiency adjustment (cf. Section 3.4) in Denmark. Warmer countries, where cooling demand dominates, would face stronger challenges in reducing emissions. Further, although insignificant, the point estimates are consistent with the existence of an environmental Kuznets curve, with emissions increasing at a decreasing rate in output (Grossman and Krueger, 1995).

[17] The one-sided test has p-value of 2.7%, half of the two-sided.

	Annual - DEA		Annual - EDGAR		Monthly	
	Baseline	Controls	Baseline	Controls	Baseline	Controls
Trend	−0.0136 0.0029	0.0009 0.8505	−0.0161 0.0004	0.0005 0.9291	−0.0015 0.0000	−0.0018 0.0000
E_{t-1}	0.6407 0.0000	1.3853 0.2286	0.5870 0.0000	1.4356 0.0000	0.2163 0.0013	0.0291 0.1012
W_{t-1}	0.0428 0.0202	0.0154 0.3639	0.0542 0.0030	0.0215 0.2305	−0.0417 0.0031	−0.0543 0.0000
W_{t-2}	–	–	–	–	−0.0391 0.0012	−0.0304 0.0144
Net Import	–	0.5285 0.0046	–	0.5453 0.0174	–	−0.0329 0.0542
Temperature	–	0.0051 0.6606	–	0.0032 0.7675	–	−0.0054 0.0030
Output	–	−0.3982 0.3375	–	−0.5901 0.1434	–	0.2241 0.9471
Output^2	–	−12.265 0.5652	–	−10.072 0.6603	–	−0.0022 0.9950
$\sin(2\pi t/12)$	–	–	–	–	0.0375 0.0042	0.0173 0.5672
$\cos(2\pi t/12)$	–	–	–	–	0.1276 0.0000	0.1286 0.0000
LB(6)	5.7764	5.7226	4.8462	4.1690	6.9400	6.3454
p-value	0.449	0.455	0.564	0.654	0.326	0.386

Table 2: Regression results. The table reports parameter estimates (and robust two-sided p-values computed using HAC standard errors) from regressions using the annual data series over the period 1978 through 2016 and monthly data from January, 2005, to November, 2017. The dependent variable is $E_t = \log(CO_{2,t})$. The regressors are the lags of E_t and $W_t = \log(w_t/(1-w_t))$ and the lagged control variables net import, temperature, output (HP filtered log(GDP) for annual data and log(industrial production) for monthly) and its square, and in monthly analysis the seasonal terms, $\sin(2\pi t/12)$ and $\cos(2\pi t/12)$. Lags of E_t and W_t selected by the AIC criterion. The bottom lines report the Ljung-Box (LB) test for six periods and the associated p-value.

In less developed countries, at steeper points on the EKC, further development would do more harm in terms of emissions than in Denmark (see Holtz-Eakin and Selden, 1995). Finally, the regressions are well specified, based on the Ljung-Box test for residual autocorrelation, which is insignificant throughout (last line of table).

Taken together, the results on wind and other covariates are more meaningful and believable in the monthly data starting in 2005 than in the longer annual series, consistent with the break analysis in the previous subsection. The analysis at the monthly frequency for the last decade suggests that the adoption of clean energy is an important contributor to the observed decline in CO_2 emissions.

4.3 Contemporaneous effect and endogeneity

Here, we explore the possibility that wind energy has a contemporaneous impact on CO_2 emissions. The analysis is based on the specification

$$E_t = a_0 + a_1 t + a_e E_{t-1} + a_{w,0} W_t + a_x' X_{t-1} + \varepsilon_t\,, \tag{4}$$

with current rather than lagged wind energy on the right hand side, compared to (1). If the wind power share W_t were exogenous, OLS estimation of (4) would lead to a consistent estimate of the causal effect of W_t on E_t, with a finding of $a_{w,0} < 0$ supporting the main hypothesis that wind power increases cause emission reductions. However, W_t may not be exogenous, and, consequently, OLS may be inconsistent. This complicates inference on the parameter $a_{w,0}$.

There are at least three reasons to expect that W_t may correlate with the shock to emissions, ε_t, and thereby be endogenous in (4). First, there may be endogeneity stemming from reverse causality. Indeed, high emissions may lead politicians and industry to shift to wind energy to reduce emissions. This is a political effect, driving a classical case of simultaneity. Since this relation induces a positive relation between emissions and wind energy, the resulting bias in the estimate of the expected main (negative) effect of interest, $a_{w,0}$, i.e., the causal impact of wind energy adoption on emissions, is in the opposite (positive) direction.

Second, there could be omitted variables affecting both emissions and wind energy. For example, global warming increases the demand for air conditioning (Stocker et al., 2013), and reduces the need for heating in cold countries, with uncertain net effect on emissions, while at the same time leading governments to pursue clean energy sources to reduce warming. This is a second policy-induced effect. In this case, the resulting bias in the estimate of $a_{w,0}$ would be negative, i.e., in the same direction as the expected main effect of interest, if the drop in heating demand dominates the increase in air conditioning, as suggested by the results in Table 2 (negative coefficient on temperature in monthly data regression), and again positive, i.e., of the opposite sign of $a_{w,0}$, if increased cooling demand dominates. To mitigate the possible bias from omitted global warming, we continue to include temperature among our controls X_{t-1}.

Third, there is likely a degree of measurement error in wind energy. DEA has become aware of a number of cases of imprecise or lacking data, and as a result has initiated a data quality control process, although not being financially liable for any losses incurred by users due to errors in data. Such errors imply a possible errors-in-variable (EIV) problem in W_t, and thus a potential attenuation bias towards zero in the estimate of $a_{w,0}$. The estimated standard error is biased towards zero, too, so the t-test of $a_{w,0} < 0$ is less biased than the parameter, but the EIV problem remains.

Besides including temperature as a control to mitigate possible omitted variable bias, we correct for possible endogeneity (stemming from simultaneity, omitted variables, EIV) by instrumental variable (IV) techniques, specifically, two-stages least squares (2SLS). The first stage regression is

$$W_t = b_0 + b_1 t + b_e E_{t-1} + b_x' X_{t-1} + b_z' Z_t + u_t \, . \tag{5}$$

This includes all the predetermined variables from (4), i.e., lagged emissions and explanatory variables X_{t-1}. In addition, sunshine, precipitation, and NAOI (Section 3.4) are used as instruments for W_t and collected in Z_t. The second stage regression is based on equation (4), with predicted values $\widehat{W_t}$ from the first stage regression (5) replacing W_t.

Table 3 reports the parameter estimates from both first and second stage regressions, together with a standard battery of test statistics relevant for the 2SLS analysis (Hausman, Sargan, and first stage F statistic). As a guideline, a first stage F statistic of at least 10 indicates that the IVs have adequate explanatory power for W_t (Staiger and Stock, 1997). The Sargan statistic is a test of overidentifying restrictions, with the null indicating that the IVs are valid (Z_t uncorrelated with ε_t). The Wu-Hausman statistic tests whether instrumentation is needed, i.e., whether there is a significant difference between the original (OLS) and instrumented (IV) specifications.

	Annual - DEA		Annual - EDGAR		Monthly - Full		Monthly - 2005-2010	
	First stage	Second stage	First stage	Second stage	First stage	Second stage	First stage	Second stage
Endogenous								
W_t	–	0.024	–	0.011	–	−0.083	–	−0.041
		0.7031		0.875		0.039		0.078
Exogenous								
Trend	0.297	−0.002	0.294	0.004	0.009	−0.002	0.001	−0.000
	0.000	0.869	0.000	0.859	0.000	0.002	0.541	0.567
E_{t-1}	7.883	1.232	8.591	1.524	−1.633	0.106	−1.217	0.183
	0.000	0.011	0.000	0.021	0.006	0.272	0.000	0.164
Net Import	3.532	0.432	3.717	0.583	−0.004	−0.113	−0.744	0.178
	0.014	0.052	0.007	0.056	0.993	0.053	0.095	0.291
Temperature	0.106	0.009	0.162	0.007	0.007	−0.003	−0.034	−0.004
	0.356	0.549	0.109	0.649	0.725	0.476	0.012	0.369
Output	−5.057	−0.285	−4.374	−0.652	34.24	0.308	35.86	−12.13
	0.364	0.598	0.321	0.215	0.210	0.929	0.098	0.079
Output^2	−124.8	−9.925	−211.1	−12.08	−3.663	−0.021	−4.000	1.359
	0.579	0.656	0.291	0.642	0.214	0.955	0.089	0.074
$\sin\left(\frac{2\pi t}{12}\right)$	–	–	–	–	0.427	0.015	−0.282	0.047
					0.002	0.667	0.051	0.419
$\cos\left(\frac{2\pi t}{12}\right)$	–	–	–	–	0.053	0.118	−0.230	0.161
					0.680	0.000	0.035	0.000
Instruments								
Precipitation	−0.001	–	−0.004	–	0.004	–	−0.000	–
	0.530		0.003		0.006		0.970	
Sunshine	0.001	–	−0.000	–	0.000	–	0.000	–
	0.318		0.986		0.968		0.772	
NAOI	0.141	–	0.035	–	0.033	–	–	–
	0.073		0.304		0.310			
Wind speed	–	–	–	–	–	–	0.344	–
							0.000	
R^2	0.963	0.818	0.967	0.812	0.765	0.914	0.775	0.847
DW	0.448	1.833	0.648	1.875	1.744	2.269	1.553	2.192
LB(6)	0.133	0.088	0.693	0.139	0.372	0.000	0.155	0.076
First stage F	2.211	–	3.200	–	5.520	–	79.46	–
Hausman p-value	–	0.695	–	0.939	–	0.653	–	0.001
Sargan p-value	–	0.126	–	0.102	–	0.023	–	0.921

Table 3: 2SLS regression results. The table reports the parameter estimates (and robust two-sided p-values computed using HAC standard errors) from regressions using the annual data series over the period 1978 through 2016, and monthly data from January, 2005, through November, 2017. The dependent variable is W_t in the first stage, and E_t in the second. In the first stage, W_t is modelled using the lags of E_t and other predetermined variables, as well as instrumental variables. At the monthly frequency, the predetermined variables also include the seasonal terms. The variables sunshine, precipitation, and NAOI are used as instruments for W_t. At the monthly frequency, W_t is also instrumented with average wind speed, available over the period January, 2005, through December, 2010.

At the annual frequency, the IV results in the first four columns of Table 3 are quite similar to those obtained in the OLS setup in Table 2, i.e., wind energy appears to cause no reduction in CO_2 emissions. However, although the IVs are formally valid (the Sargan test fails to reject at level 10%), they have little explanatory power, based on the first stage F statistic (2.2 and 3.2 for CO_2 and EDGAR, respectively), and really do not matter much (the Hausman test fails to reject at all conventional levels). In the monthly data, full sample, columns five and six, the estimate of $a_{w,0}$ is negative ($a_{w,0} = -0.08$) and significant at the 5% level, but in this case, the IVs appear invalid, as the Sargan test rejects at 5% ($p = 2.3\%$).

To get a well-specified 2SLS estimation of the causal effect of wind on emissions, we consider wind speed as an alternative instrument for wind energy, following Novan (2015). Thus, we resort to an analysis over the subperiod 2005-2010, for which monthly data on average wind speed in Denmark are available. We let this replace NAOI in the instrumentation. Based on a natural phenomenon, average wind speed should be uncorrelated with CO_2 emissions, but is expected to be highly correlated with wind energy production. This correlation is reflected in a very high first stage F statistic, at 79.5, well above the benchmark of 10, thus confirming adequate explanatory power. As expected, wind speed loads positively on wind share in production, with a coefficient that is significant at the 1% level in the first stage regression. The instrumentation is valid, now with much better Sargan statistic ($p = 92\%$). Further, it matters, as reflected in rejection of the null hypothesis of the Hausman test at level 1% ($p = .1\%$). This result is in contrast to that of Novan (2015), and consistent with the endogenous nature of the energy production decision. Using this successful instrumentation, the second stage regression appears well-specified, based on the Durbin-Watson and Ljung-Box statistics, and explains 85% of the variation in CO_2 emissions.

In this specification, last column of Table 3, the point estimate of $a_{w,0}$ is -0.04, and the parameter is significant, with a robust p-value of 3.9% in one-sided test, computed from the heteroskedasticity and autocorrelation consistent (HAC) standard error using residuals based on the second stage estimates, but original W_t (as opposed to $\widehat{W_t}$) data. The result suggests a causal effect of wind energy production on CO_2 emission reductions. The estimates further allow an assessment of the magnitude of this effect. As in Cullen (2013), since the relation is nonlinear, this is done in terms of partial derivatives. To this end, as $W = \log(w/(1-w))$, with w the wind share in energy production, we have

$$\frac{\partial W}{\partial w} = \frac{1}{w(1-w)} \,. \tag{6}$$

It follows that, to a first order of approximation, a change in wind share is associated with a proportional change in CO_2 emissions given by

$$\frac{\partial \mathrm{CO_2}/\partial w}{\mathrm{CO_2}} = \frac{\partial E}{\partial W} \cdot \frac{\partial W}{\partial w} = \frac{\partial E/\partial W}{w(1-w)} \,, \tag{7}$$

or $a_{w,0}/[(w(1-w)]$ in the regression model. From the estimate of $a_{w,0}$, with a 19% wind penetration over the period 2005 through 2010, and the series $1/w(1-w)$ averaging 7.11, a one percentage point increase in the share of wind in total energy production is found to generate a reduction in CO_2 emissions of the order 0.29%. For an assessment in absolute terms, write wind share as $w = \omega/\varpi$, where ω and ϖ are wind energy and total energy production, respectively, so that

$$\frac{\partial \mathrm{CO_2}}{\partial \omega} = \frac{\partial \mathrm{CO_2}/\partial w}{\mathrm{CO_2}} \cdot \frac{\partial w}{\partial \omega} \cdot \mathrm{CO_2} = \frac{\partial \mathrm{CO_2}/\partial w}{\mathrm{CO_2}} \cdot \frac{\mathrm{CO_2}}{\varpi} \,, \tag{8}$$

i.e., the displacement emissions factor (DEF) or marginal emissions avoided (MEA) by increasing wind energy production is estimated by multiplying the emission intensity EI = CO_2/ϖ onto the proportional impact (7). With EI at 1.442 tCO_2/MWh over the sample period, this corresponds to an emission reduction of .420 on the margin, very close to the estimate from Cullen (2013).

Finally, apart from the seasonals, other explanatory variables matter relatively little, based on the results in Table 3, and are left out when we turn to a more detailed analysis of the dynamic relation between wind energy and emissions in the following. We focus on the monthly data starting in 2005, as they have yielded the most meaningful results so far, and in line with the results from the break analysis.

5 Dynamic system analysis and forecasting

We extend the univariate regression framework of the previous section, building on equation (1), to a bivariate dynamic analysis of wind energy production and CO_2 emissions. The goal is threefold. First, we aim at accommodating feedback effects between the series when deriving the dynamic reaction of emissions to a shift in wind energy. We perform this analysis in a vector autoregressive (VAR) model. Earlier work has allowed dynamics through error terms in univarate regression models, e.g., ARMA(1,1) errors in Wheatley (2013). Second, in a multiple long-term forecasting analysis, we assess whether the structural break around 2005 had an impact on the share of wind production in Denmark, and whether the long-term policy goals of the Danish government appear feasible for energy production, given information in the data currently available. Third, in light of the indication from Section 4.1 that emissions and wind are related in the long run, as well as the evidence on the contemporaneous dependence in Section 4.3, we study the equilibrium between the series in a bivariate system, which allows for cointegration. Since both E_t and W_t are strongly dependent over time, we allow for the possibility of long memory in the series and study their co-movement in terms of fractional cointegration.

5.1 VAR analysis

We investigate the dynamic relation between emissions and wind power in an unrestricted VAR system at the monthly frequency. The system of equations is given by

$$\begin{bmatrix} E_t \\ W_t \end{bmatrix} = \begin{bmatrix} \psi_e \\ \psi_w \end{bmatrix} + \begin{bmatrix} \beta_e t \\ \beta_w t \end{bmatrix} + \sum_{i=1}^{p} \begin{bmatrix} \varphi_{ee,i} & \varphi_{ew,i} \\ \varphi_{we,i} & \varphi_{ww,i} \end{bmatrix} \begin{bmatrix} E_{t-i} \\ W_{t-i} \end{bmatrix} + \begin{bmatrix} \delta_{ex} \\ \delta_{wx} \end{bmatrix} X_t + \begin{bmatrix} \varepsilon_{e,t} \\ \varepsilon_{w,t} \end{bmatrix}. \quad (9)$$

Essentially, this combines (1) and (5), now with $p = q$ lags in both series, $b_z = 0$, and unrestricted seasonals in X_t, i.e., this holds eleven monthly indicators, with δ_{yx} of dimension 1×11, $y = e, w$.

Results of VAR analysis are reported in Table 4. The number of lags selected by AIC is $p = 2$. For this VAR(2) specification, the Ljung-Box tests highlight that the residuals do not display any significant autocorrelation (p-values above 20%), and departures from bivariate Gaussianity are insignificant, with a p-value of 84% in the Doornik and Hansen (2008) test, a multivariate extension of the Jarque-Bera normality test. Furthermore, both linear trend and seasonals are needed in the VAR specification (Wald tests, at 33.9 and 284.7, are significant at the 1% level).

	E_t				W_t			
	Est.	Std.Err.	t-stat	p-val	Est.	Std.Err.	t-stat	p-val
Estimates								
Const	4.8981	0.7836	6.251	0.0000	7.3506	5.2643	1.396	0.1649
Trend	-0.0011	0.0003	-4.242	0.0000	0.0064	0.0018	3.488	0.0007
E_{t-1}	0.3861	0.0907	4.257	0.0000	-0.4397	0.6092	-0.722	0.4716
E_{t-2}	0.0382	0.0863	0.443	0.6589	-0.5828	0.5800	-1.005	0.3167
W_{t-1}	-0.0172	0.0139	-1.247	0.2145	0.2085	0.0931	2.240	0.0267
W_{t-2}	-0.0401	0.0140	-2.857	0.0049	0.0964	0.0943	1.022	0.3086
S1	0.0043	0.0244	0.178	0.8590	0.2244	0.1640	1.368	0.1737
S2	-0.0705	0.0263	-2.683	0.0082	0.0001	0.1767	0.001	0.9996
S3	-0.0283	0.0266	-1.068	0.2875	0.1999	0.1786	1.119	0.2649
S4	-0.2042	0.0242	-8.435	0.0000	0.1782	0.1627	1.096	0.2751
S5	-0.2013	0.0287	-7.025	0.0000	0.2132	0.1926	1.107	0.2702
S6	-0.1947	0.0274	-7.104	0.0000	-0.0026	0.1842	-0.014	0.9888
S7	-0.2516	0.0286	-8.805	0.0000	-0.2054	0.1920	-1.070	0.2866
S8	-0.1236	0.0330	-3.751	0.0003	-0.1501	0.2215	-0.678	0.4990
S9	-0.1229	0.0306	-4.023	0.0001	-0.3526	0.2053	-1.718	0.0881
S10	-0.0421	0.0269	-1.565	0.1199	-0.1791	0.1809	-0.990	0.3239
S11	-0.0313	0.0246	-1.271	0.2059	-0.1588	0.1656	-0.960	0.3390
Misspecification tests								
LB(5)	2.659	–	–	0.752	3.478	–	–	0.627
LB(10)	13.209	–	–	0.212	8.953	–	–	0.537
No Trend	33.935	–	–	0.000				
No Seasonality	284.68	–	–	0.000				
Normality	1.399	–	–	0.844				

Table 4: VAR Results. The table reports VAR results using the monthly series E_t and W_t over the period January, 2005, through November, 2017. The number of lags selected by AIC is $p = 2$. The monthly indicators $S1, \ldots, S11$ account for unrestricted seasonality. The bottom lines report Ljung-Box (LB) tests for five and ten periods, the associated p-values, Wald tests for the absence of trend and seasonal dummies, and the Doornik and Hansen (2008) test of multivariate normality.

From the estimation of the equation for E_t, the first equation in (9), both E_{t-1} and W_{t-2} significantly affect current emissions. Both W_{t-1} and W_{t-2} load negatively on E_t, confirming the negative dependence of emissions on lagged wind energy production from the regression evidence in Section 4.2. For the six months from April through September, the seasonals are negative, large in magnitude, and significant, December being the left-out month, consistently with the notion that the reduction in heating demand over the summer dominates the increase in cooling demand and the efficiency adjustment, cf. Sections 3.4 and 4.2.

Moving to the equation for W_t, the second equation in (9), past values of E_t do not significantly affect wind energy, which only depends on its own first lag. This is consistent with W_t being chosen with discretion, not responding to changes in E_t according to any particular rule. Based on the policy angle, we might expect a positive relation, as declining emissions might reduce the apparent need to invest in green energy, but the (insignificant) coefficients on lagged emissions are in fact negative. Perhaps a better interpretation is that observed emission reductions confirm the value of the green technology and thus spur further investments, for a negative relation.

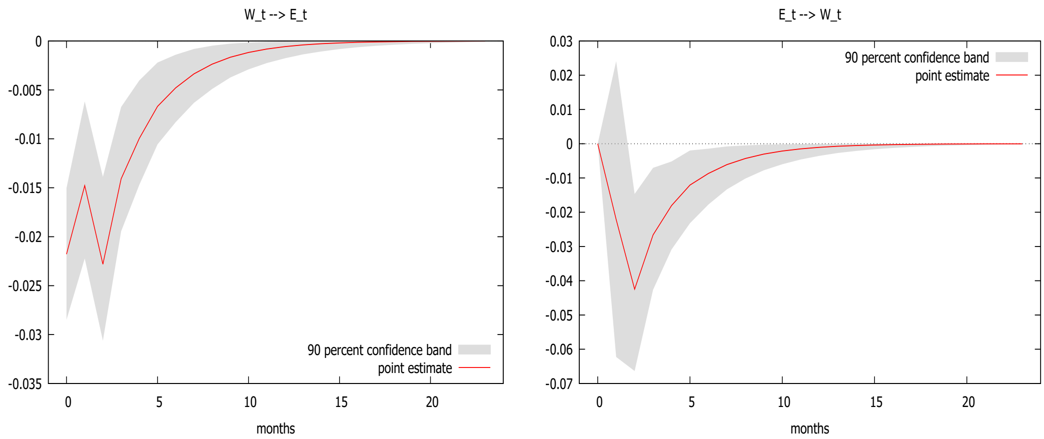
To get a more precise understanding of this dynamic relation, Figure 5 shows the impulse response functions (IRFs) from wind energy to emissions, and from emissions to wind energy. In both cases, a positive shock in one variable generates a negative reaction in the other. The impact is lasting for many periods, due to the strong persistence of the observed series. From Panel (a), the response of E_t to a W_t impulse starts within the month of the shock and remains significant nearly a year after. Based on this IRF, a one percentage point increase in the share of wind in total energy production is predicted to generate a reduction in CO_2 emissions of the order 0.06% within the first month, and a long-run cumulated reduction of the order 0.27%, corresponding to a MEA at .375, broadly consistent with the results from the regression analysis in the previous section.[18] In contrast, from Panel (b), W_t only responds with a lag to an E_t impulse, and the effect is significant only between two and six months after the shock, with a negative sign. This evidence might reflect a delayed policy response with respect to the construction and installation of new wind turbines, given an observed reduction in CO_2 emissions. In any case, that wind energy responds to emissions is consistent with our result in Section 4.3 that it is endogenous in the regression analysis, in contrast to the result in Novan (2015).

5.1.1 On track for 2030 and 2050 policy goals?

We now assess whether the structural break around 2005 (cf. Section 4.1) had an impact on the share of wind production in Denmark, and whether the country is 'on track' to meet the government's stated goals of 70% emission reduction by 2030 (relative to 1990) and no-fossil energy production by 2050. In particular, we forecast E_t and W_t using the VAR(2) specification from (9), including both trend and seasonals, i.e., we treat E_t and W_t as trend-stationary variables.

Clearly, fitting a linear trend over a relatively short in-sample period and projecting it into the distant future might give rise to misleading interpretations. In particular, the slopes of the linear trends are very likely influenced by the in-sample periods used to estimate the coefficients of the model, and particularly by possible structural breaks, cf. Section 4.1. For this reason, we

[18] The IRF shows the response after i periods, i.e., of E_{t+i}, to a W_t impulse, namely, a shock to $\varepsilon_{w,t}$ from (9), of size one standard deviation, $\sigma_W = \sigma(\varepsilon_{w,t})$: $\mathrm{IRF}_{W\to E}(i) = \sigma_W \frac{\partial E_{t+i}}{\partial \varepsilon_{w,t}}$. Using this for $\partial E/\partial W$ in (7), the proportional impact of wind share is estimated as $\partial E_{t+i}/\partial w_t = \mathrm{IRF}_{W\to E}(i)/[w(1-w)]$, for average wind penetration w at 31% over the period 2005 through 2017, and $1/[w(1-w)]$ averaging 5.66. The cumulated impact is found by summing over $i = 0, 1, 2, \ldots$ By (8), MEA is obtained via multiplication by EI = 1.399 tCO_2/MWh for the period.



(a) Response of CO_2 emissions to wind energy (b) Response of wind energy to CO_2 emissions

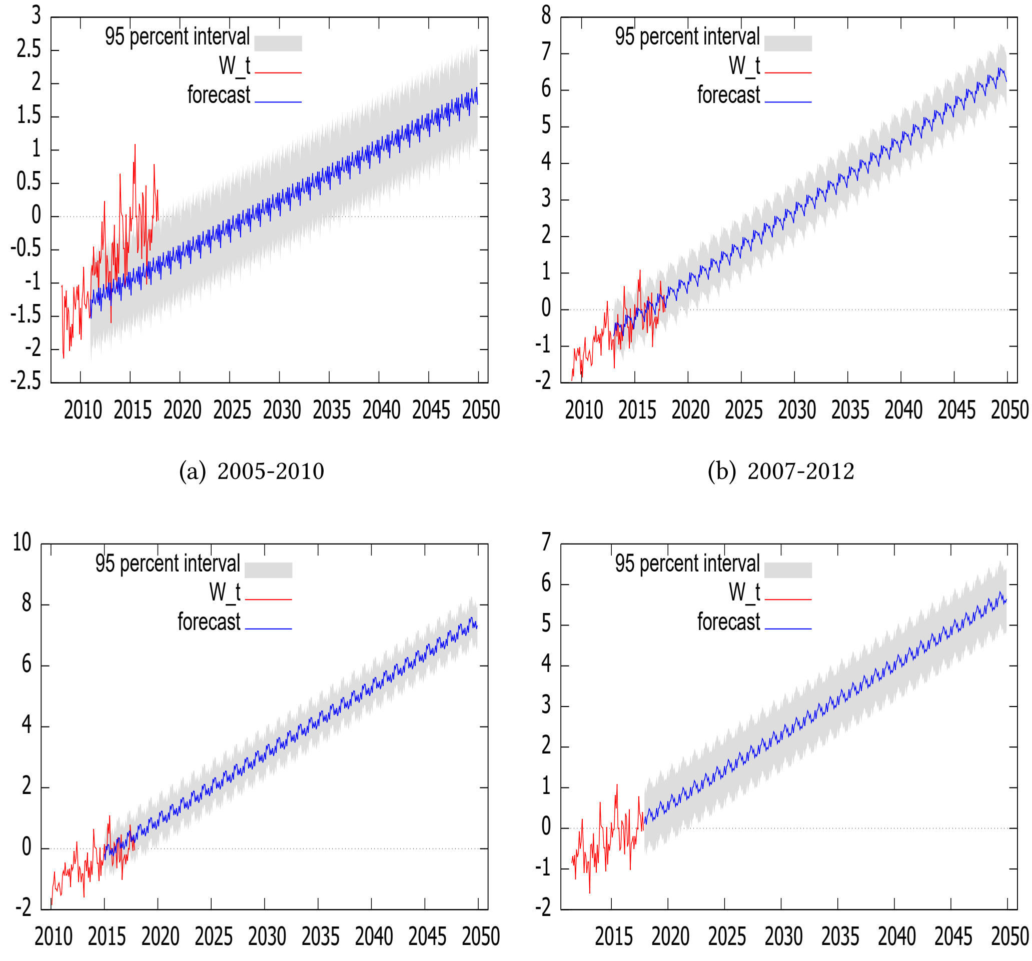
Figure 5: Impulse-response functions from VAR(2) model. In gray the bootstrapped 90% confidence bands.

perform a repeated forecasting analysis, with out-of-sample forecasts computed on the basis of four different in-sample periods. In this way, we try to assess the potential consequences for the long run of such trend breaks.

Focusing first on the 2050 goal, Figure 6 reports the multiple forecasts of W_t obtained from the VAR(2) model based on the different in-sample estimation periods, namely, 2005-2010 in Panel (a), 2007-2012 in Panel (b), 2009-2014 in Panel (c), and the full sample, 2005-2017, in Panel (d). In addition, the full sample itself is shown in each panel, along with the forecasts. Not surprisingly, the confidence bands around the predicted values of W_t are very narrow in all cases. Indeed, the deterministic terms, i.e., trend and seasonal terms, are responsible for most of the observed variability of W_t, while the stochastic component of the model, i.e., $\varepsilon_{w,t}$, is associated with a small variance and not accumulated over time.

In all four cases, the predicted slope is positive. It becomes steeper when moving from Panel (a) to (b) and (c) (note that axes differ), corresponding to later in-sample periods. In Panel (a) (in-sample estimation period 2005-2010), comparing forecasts and actual data over the 2011-2017 period, the red line (i.e., actual observations) is above the confidence band in most cases, thus indicating a difference in slope between the estimation period 2005-2010 and the rest of the sample, 2011-2017. From Panels (b) and (c), the forecasts based on estimation periods 2007-2012 and 2009-2014 are coherent with the remaining part of the sample, 2013-2017 and 2015-2017, respectively, as the ex-post realizations to a large extent are contained within the confidence band of the prediction. This evidence signals a change in the growth rate of W_t around 2005, which might be due to the increased attention to green energy by the Danish government, defining its strategy towards 2050 at the time, following the Kyoto protocol and the EU ETS, and possibly to technological innovation, as well (cf. Section 4.1).

The linear trend in W_t is a associated with a monotonic and non-linear trend in w_t, the share



(a) 2005-2010

(b) 2007-2012

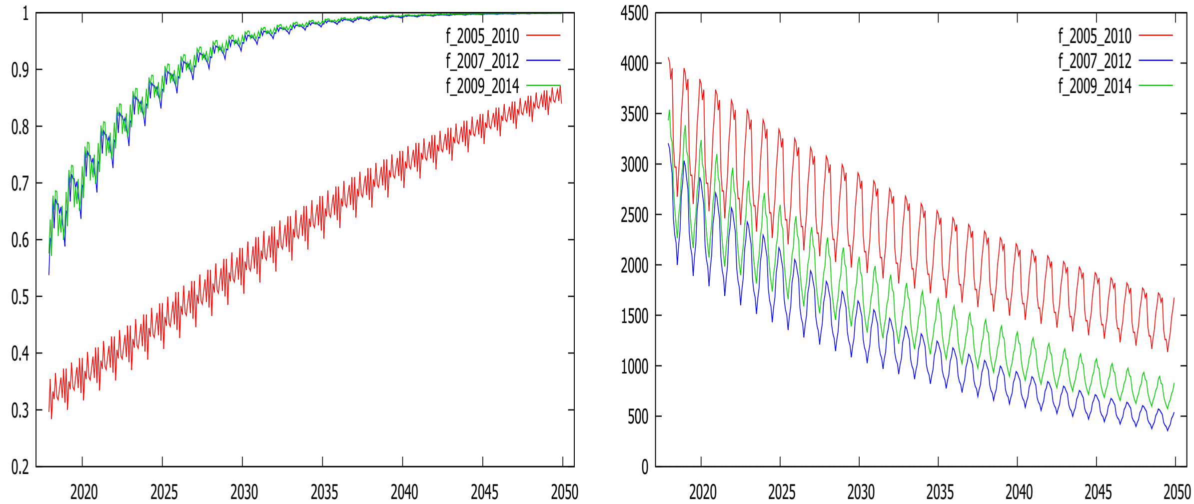
(c) 2009-2014

(d) 2005-2017

Figure 6: Long-run forecasts of W_t based on a VAR(2) plus linear-trend specification and alternative in-sample estimation periods. The gray region is the confidence band. In red the last portion of the observed W_t series.

of wind in total energy production, obtained using the logistic (inverse logit) transformation, see Figure 7, Panel (a). Based on the in-sample estimation period from 2005 to 2010, the projected growth would lead to a wind share of 85% by 2050. Instead, projecting the trends based on the later estimation sub-periods in data into the future leads to a match by 2050 with the goal of 100% wind energy production. Forecasts based on the 2007-2012 and 2009-2014 in-sample estimation periods are very similar, essentially indistinguishable in the figure, and should be more reliable than those based on the 2005-2010 in-sample period. The policy implication is that Denmark appears to have been on track to meet its 2050 fossil-free energy goal after the change in trends around 2005, but not before.

In Panel (b) of Figure 7, we repeat the analysis for CO_2 emissions. The projected reduction in CO_2 emissions by 2050 compared to 2017 (without correction for Jensen's inequality) is 58%, based on the in-sample estimation period from 2005 to 2010, and 87%, based on the 2007-2012 in-sample period.



(a) Multiple forecasts of wind share

(b) Multiple forecasts of CO_2

Figure 7: Long-run forecasts. Panel (a) reports long-run forecasts of wind share w_t, based on the VAR(2) plus linear-trend specification, different in-sample estimation periods (2005-2010; 2007-2012; 2009-2014), and the logistic (inverse logit) transformation $w_t = \frac{\exp(W_t)}{1+\exp(W_t)}$. Panel (b) reports long-run forecasts of CO_2 emissions, based on the same VAR(2) plus linear-trend specification and in-sample estimation periods, and the transform $CO_{2,t} = \exp(E_t)$.

In addition to the goal of fossil-free energy by 2050, the government has in June, 2019, set a goal of reducing GHG emissions by 70% by 2030, relative to the level in the United Nations base year, 1990. From our annual data, the reduction in CO_2 emissions between 1990 and 2016 is already 31%. From the emissions forecasts from the VAR(2) model (monthly data), shown in Figure 7, Panel (b), the predicted further reduction by 2030 is 27% and 59% for the 2005-2010 and 2007-2012 in-sample estimation periods, respectively. This corresponds to total reductions from 1990 to 2030 of 50% and 72% in the two cases, i.e., on either side of the government's policy goal. Again, the prediction based on the 2007-2012 estimation period (72%) should be the most reliable of the two, given the presence of the trend break.

Overall, it appears that the structural break around 2005 shifted the trend sufficiently that the country since then appears to have been on track to meet both its 70% emission reduction target by 2030, at least in terms of CO_2 emissions from energy production, and its 100% green energy target by 2050, although it was not before.

5.2 Long-run equilibrium

While the VAR analysis of Section 5.1 allows impulse-response analysis and forecasting, we now investigate the possibility that the emissions and wind energy series follow paths that are tied together in the long run.

In particular, this possibility arises in case the series are (fractionally) cointegrated, i.e., move together in an equilibrium relation. It is natural to examine this by means of the fractional vector error-correction model (FVECM) of Granger (1986),

$$\Delta^d Y_t = c + \alpha\beta' L_b \Delta^{d-b} Y_t + \sum_{j=1}^{k} \Gamma_j \Delta^d Y_{t-j} + \varepsilon_t \,, \tag{10}$$

in which $Y_t = (E_t^*, W_t^*)'$ contains the seasonally adjusted series of E_t and W_t, c is a 2×1 vector of unrestricted constant terms, and $\varepsilon_t \sim N(0, \Sigma)$. In (10), Δ^d is the fractional difference operator,

$$\Delta^d := (1-L)^d = \sum_{j=0}^{\infty} (-1)^j \binom{d}{j} L^j \,,$$

with L the (ordinary) lag operator, i.e., $LY_t = Y_{t-1}$, and $L_b := 1 - \Delta^b$ the *fractional lag operator* of Johansen (2008). The long-run dynamics in (10) are governed by the $2\times r$ matrices α and β. Here, the columns of β are the equilibrium or cointegration vectors, α the speeds of error correction or adjustment to equilibrium, and $r \in \{0,1,2\}$ the cointegration rank. Short-run dynamics are governed by the 2×2 matrices Γ_j, $j = 1,\ldots,k$, and $\Sigma > 0$ is the positive definite covariance matrix of the FVECM error terms ε_t. The coefficient d determines the order (degree) of long memory or fractional integration of the series Y_t, and $b \geq 0$ the *cointegration gap*, i.e., while Y_t is integrated of order d, or $I(d)$, the departure from equilibrium or error-correction term $\beta' Y_t$ is $I(d-b)$. If $d > 0$, the original series Y_t exhibit long memory, with autocorrelation functions decaying hyperbolically, as opposed to geometrically, as in the stationary ARMA case (in which $d = 0$). If, in addition, $b > 0$, then the long memory series move together in the long run, in that a linear combination of them, given by the error-correction term, exhibits shorter memory than the original series. The classic cointegrated VECM model studied in Johansen (1991, 1995) corresponds to the special case $d = b = 1$.

Model (10) is slightly different from that proposed by Johansen (2008), as it does not involve the fractional lag operator L_b in the short-run component. To avoid identification problems stemming from an over-specified lag structure, as outlined in Carlini and Santucci de Magistris (2019a), we adopt the FVECM specification introduced by Granger (1986) and subsequently studied by Davidson (2002) and Carlini and Santucci de Magistris (2019b). The estimation of the FVECM model is carried out in MATLAB, adapting the routine of Nielsen and Popiel (2018) to the FVECM.

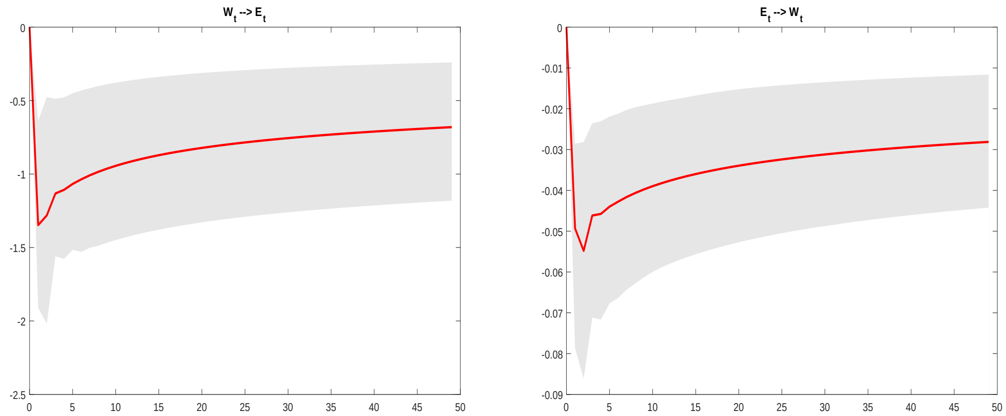
Estimation results are reported in Table 5. The Johansen and Nielsen (2012) test indicates that fractional cointegration exists, with rank $r = 1$, i.e., one cointegrating relation. This justifies the regression analysis of Section 4, i.e., regressions are not spurious. The results in Table 5 are based on $r = 1$ and $k = 1$, one lagged short-run dynamic term. The estimate of d is .782 and significantly different from both .5 and 1.0 at conventional levels, indicating that the series E_t and W_t exhibit long memory and are not covariance stationary, as $d > .5$, but do display mean-reverting behavior, $d < 1$. Thus, the effect of a shock persists for a long period of time, reflecting the long memory behavior, and the series do move together in the long run, as indicated by the cointegration rank. On the other hand, there is no unit root, which would be the case $d = 1$, so the long run equilibrium is more appropriately studied in the FVECM than in the classic cointegrated VECM. Further, the Ljung-Box and Doornik and Hansen (2008) tests (bottom of table) show no sign of misspecification.

	E_t				W_t			
	Est.	Std.Err.	t-stat	p-val	Est.	Std.Err.	t-stat	p-val
Estimates								
c	-0.004	0.006	-0.667	0.505	0.017	0.032	0.531	0.595
d	0.782	0.109	7.174	0.000	0.782	0.109	7.174	0.000
b	0.782	0.194	4.030	0.000	0.782	0.194	4.030	0.000
α	-0.362	0.167	-1.958	0.050	-2.145	0.884	-2.427	0.015
E_{t-1}	-0.160	0.160	-1.000	0.317	0.798	0.828	0.969	0.332
W_{t-1}	0.039	0.033	1.181	0.237	-0.030	0.182	-0.166	0.868
Misspecification tests								
LB(5)	3.547	–	–	0.616	4.172	–	–	0.525
LB(10)	7.851	–	–	0.643	7.539	–	–	0.674
Normality	2.977	–	–	0.226				

Table 5: FVECM results. The table reports the parameter estimates of the FVECM using the monthly (seasonally adjusted) emission and wind energy series E_t^* and W_t^* over the period January, 2005, through November, 2017. The Johansen and Nielsen (2012) test of fractional cointegration takes the value 34.268 (p-value = 0.000) for $r = 0$ and 0.005 (p-value = 0.895) for $r = 1$. AIC selects $k = 1$. The estimated cointegration vector for $r = 1$ is $\hat{\beta} = (1, 0.246)'$. The bottom lines report Ljung-Box (LB) tests for five and ten periods, the associated p-values, and the Doornik and Hansen (2008) test of multivariate normality. The value of the log-likelihood function is 137.42.

From Table 5, the estimate of b is likewise 0.782, so that, as in classic cointegration, d and b coincide, although in the present case not at unity. This result shows that the paths of emissions and wind energy are closely tied, i.e., the error-correction term $\beta' Y_t$ is a weakly dependent process, and departures from equilibrium short-lived. The estimated parameter β_2 is 0.246, confirming once more the negative contemporaneous relation between CO_2 emissions and wind energy production, cf. Section 4.3. When W_t increases, CO_2 emissions must decrease in order to maintain the stable equilibrium relation given by $\beta' Y_t = E_t + \beta_2 W_t = \psi$, with ψ the long-run equilibrium value of $\beta' Y_t$, i.e., $E_t = \psi - \beta_2 W_t$, with $\beta_2 > 0$. The parameters governing the adjustment to this equilibrium, α, are both significantly negative (p-values of 5.0% and 1.5%), so that if either variable is too large (equilibrium errors $\beta' Y_t > \psi$), both will be subsequently reduced, with W_t moving faster towards the equilibrium than E_t. The parameters in Γ_1 (rows labeled E_{t-1} and W_{t-1} in Table 5) are individually insignificant, but AIC selects one lag (Wald and LR tests confirm their joint significance), and the point estimates are consistent with stationarity of the short run components.

Figure 8 reports the IRFs from the FVECM, obtained following the recursive algorithm presented in Carlini and Santucci de Magistris (2019b). The IRF of each variable displays a negative



(a) Response of CO_2 emissions to wind energy (b) Response of wind energy to CO_2 emissions

Figure 8: Impulse-response functions from FVECM model. In gray the bootstrapped 90% confidence bands.

reaction to a shock in the other variable. The long-memory property of both series is reflected in the very slow decay rate of the IRFs, both of which remain significant more than four years after the shock. Comparing to Figure 5, it is clear that the possibility of simultaneity and long-run co-movement of the series strongly impacts the predicted policy effect of wind adoption on emissions, as well as the response of the policy to emissions. From the FVECM results, a one percentage point increase in the share of wind in total energy production is estimated to generate a reduction in CO_2 emissions of 0.04% within the first month, and a cumulated impact over 24 months of -0.49%, corresponding to a MEA at .686, based on the IRF (cf. footnote 18). These cumulated impacts are larger than those calculated off the IRF of the basic VAR model in Figure 5, at -0.27% and 0.375, because of the long memory and long-run equilibrium among the series in the FVECM. From the empirical results, this long-run equilibrium likely prevails.

As a final robustness check, we also consider the special case of standard $I(0)$-$I(1)$ cointegration, in the sense of Engle and Granger (1987). Here, the individual series in Y_t are $I(1)$ or unit root processes, and departures from equilibrium $I(0)$ or stationary short-memory processes. This classic case may be analyzed by means of the cointegrated VAR studied by Johansen (1991, 1995), or, equivalently, the (non-fractional) VECM obtained by imposing the restrictions $d = b = 1$ on the FVECM in (10). Results from estimation of the restricted VECM appear in Table 6. As in the FVECM case, the Johansen and Nielsen (2012) test points to one cointegrating relation, and the classic trace test of Johansen (1988) (unreported) indicates the same. Estimates of equilibrium adjustments α and short run coefficients Γ_1 are in line to those from the FVECM. However, the log-likelihood value for the VECM is only 134.16, against 137.42 for the FVECM in Table 5. Following Johansen and Nielsen (2018), the validity of the restrictions imposed by the VECM in the FVECM framework, that is, $d = b = 1$, can be tested by means of a likelihood-ratio (LR) test, with an asymptotic χ^2-distribution on two degrees of freedom under the null.

	E_t				W_t			
	Est.	Std.Err.	t-stat	p-val	Est.	Std.Err.	t-stat	p-val
Estimates								
c	-0.002	0.005	-0.436	0.662	0.009	0.032	0.2703	0.787
α	-0.375	0.147	-2.548	0.011	-2.567	0.866	-2.965	0.003
E_{t-1}	-0.294	0.092	-3.214	0.001	0.957	0.679	1.462	0.144
W_{t-1}	0.037	0.025	1.410	0.159	-0.142	0.092	-1.548	0.122
Misspecification tests								
LB(5)	8.083	–	–	0.152	4.591	–	–	0.468
LB(10)	13.989	–	–	0.174	8.086	–	–	0.621
Normality	1.602	–	–	0.449				

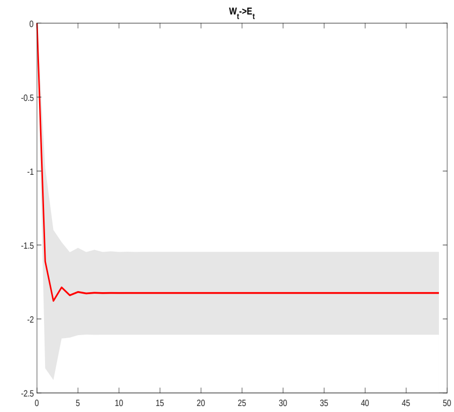
Table 6: VECM results. The table reports the parameter estimates of the FVECM using the monthly (seasonally adjusted) emission and wind energy series E_t^* and W_t^* over the period January, 2005, through November, 2017. The Johansen and Nielsen (2012) cointegration test takes the value 65.724 (p-value = 0.000) for $r = 0$ and 2.219 (p-value = 0.136) for $r = 1$. The estimated cointegration vector for $r = 1$ is $\hat{\beta} = (1, 0.2401)'$. The bottom lines report Ljung-Box (LB) tests for five and ten periods, the associated p-values, and the Doornik and Hansen (2008) test of multivariate normality. The value of the log-likelihood function is 134.16.

The LR statistic takes the value 6.51, for a p-value of 0.039. Hence, at level 5%, we reject the restrictions imposed by the VECM in favor of a fractional order of integration, $d = b = 0.782$, for E_t and W_t. This is consistent with the evidence against the unit root case in Table 5.

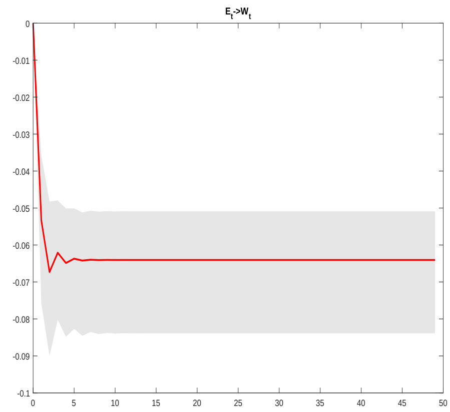
Figure 9 exhibits the IRFs associated with the estimated VECM from Table 6. They are on the same scale as of those for the FVECM in Figure 8, with a one percentage point increase in the share of wind associated with a reduction in emissions of 0.05% within a month. However, the VECM implies that a shock to one variable has a permanent effect on the other, due to the lack of mean-reversion under the restriction $d = 1$. Hence, the IRFs converge to a non-zero constant. In contrast, in the FVECM case, the impact of a shock is partially absorbed after 50 periods due to the mean-reverting, albeit persistent, behavior of the series for $d < 1$.

6 Conclusion

It is important for policy purposes to determine whether the decline in CO_2 emissions observed in many countries can be causally tied to the adoption of renewable energy. In this paper, we have considered the evolution of CO_2 emissions and the share of wind in energy production, as well as the relation between the two variables, in Denmark. This country is in a unique position to substitute wind for other energy sources, and data are available over a sufficiently long time span to allow a relatively precise estimation of an upper bound on the potential impact of the adoption of wind on the reduction in emissions. We separate causal impacts from endogenous effects in regressions using instrumental variables, and from spurious effects in dynamic sys-



(a) Response of CO_2 emissions to wind energy



(b) Response of wind energy to CO_2 emissions

Figure 9: Impulse-response functions from VECM model. In gray the bootstrapped 90% confidence bands.

tems using impulse-response analysis and cointegration techniques. From our empirical results, adoption of clean energy is an important contributor to the observed decline in CO_2 emissions, even after controlling for rising temperatures and increasing electricity import from neighboring countries. A regression analysis shows that wind energy production is endogenous with respect to emissions, consistent with the policy nature of the production decision, i.e., instrumentation matters, in contrast to the result of Novan (2015). Accounting for this endogeneity, the causal effect of a one percentage point increase in wind share in energy production is a 0.3% reduction in emissions. Long-term dynamic system effects, accommodating feedback between emissions and wind energy, are obtained in a vector autoregressive model. Estimated impulse-response functions are consistent with a causal and dynamic effect of wind energy production on CO_2 emission reduction.

In addition, we construct multiple long term forecasts based on different estimation periods. Our findings suggest that a structural break in 2005, following the introduction of the Kyoto Protocol and the EU ETS, and possibly related to technological innovation, as well, led to a change in trends in subsequent years. The country appears to have been on track towards meeting its policy goals by 2030 and 2050 in terms of abatement of CO_2 emissions from energy production and wind adoption, respectively, after this change, but not before, thus suggestive of the importance of the international agreements. Further, a long-run (fractional cointegration) equilibrium among the variables likely prevails, implying long-lasting impulse-responses, with significant reductions in emissions more than four years after investments in wind energy technology. In this case, a one percentage point increase in wind share is predicted to lead to a reduction in emissions of 0.5% after 24 months, after allowing the cumulative effects to take place. This corresponds to an estimated displacement emissions factor of .69, in tonnes of CO_2 emissions avoided on the margin, per additional MWh of wind energy produced. In an international context, this estimate is in the high end, relative to values reported in both the simulation and statistical literature. The magnitude of the estimate, even at the relatively high wind penetration in Denmark, averaging 31% over our monthly data period, is consistent with the notion that the Danish case allows an estimation of the upper bound on potential emissions abatement by wind adoption.

In principle, a shift to 100% wind should eliminate emissions from energy production. This is neither reflected in the estimated emission reduction of 0.5% per percentage point increase in wind, nor in the long-run forecasts presented, predicting 100% wind energy share by 2050, but only an emission reduction of about 90%, relative to 1990 levels. Estimated coefficients represent local effects, not based on any engineering relation, but instead on one country's actual experience. In some cases, wind energy produced may be wasted due to limitations in storage technology, or shortcomings and delayed expansion of the power grid. The multiple long term forecasts reported are to be understood differently, i.e., not as predicting the impact of a given policy change. Instead, they show the consequences of continuing according to current trends, and, in particular, the predicted long term consequences of the change in trends that took place around 2005, according to our findings.

Summing up, on the methodological and data analytic side, the main contributions of the paper are (i) the introduction of the detailed dynamic system analysis, including fractional cointegration, to the area of emissions abatement by renewable energy adoption, (ii) the separation of the resulting causal impact from spurious effects, showing the former exists in Denmark, (iii) the estimation of the upper bound on this impact, presumably applicable to other regions, as well, and (iv) the documentation of the structural break around 2005, and the importance for the long term of the associated technological and policy changes. On the substantive side, our results suggest that a shift towards investment in wind energy can be a significant policy tool for CO_2 abatement in Denmark, and by implication in other countries sufficiently near the upper bound.

Some caveats apply, relating in particular to carbon leakage. Reduction in emissions in one country can lead to increases in other countries, due to the export of dirty technology overseas. Coal, oil, and natural gas not used in Denmark can be sold to other countries. Further, the more wind that is used in Denmark, the more hydropower is needed from Norway and Sweden for off-times, and generating hydropower increases CO_2 emissions, too, although to a lesser extent than using fossil fuels. Future research could consider a larger area, e.g., the Nordic countries, or in other ways attempt to adjust for carbon leakage effects, as well as investigate, in addition, emissions of other GHGs and from other sources than the combustion of coal, oil, and natural gas for energy production. Other sources include transportation, agriculture, and the burning of biomass and non-biodegradable waste. Our methods could be used to assess the impact on emissions from these sources of the adoption of electric vehicles, changes in fodder, replanting of vegetation, recycling of waste, and other supposedly GHG emissions reducing policies.

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