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# Exploring the Macro-scale $CO_2$ Mitigation Potential of Photovoltaics and Wind Energy in Europe's Energy Transition

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**Abstract**

Replacing traditional technologies by renewables can lead to an increase of emissions during early diffusion stages if the emissions avoided during the use phase are exceeded by those associated with the deployment of new units. Based on historical developments and on counterfactual scenarios in which we assume that selected renewable technologies did not diffuse, we conclude that onshore and offshore wind energy have had a positive contribution to climate change mitigation since the beginning of their diffusion in EU27. In contrast, photovoltaic panels did not pay off from an environmental standpoint until very recently, since the benefits expected at the individual plant level were offset until 2013 by the $CO_2$ emissions related to the construction and deployment of the next generation of panels. Considering the varied energy mixes and penetration rates of renewable energies in different areas, several countries can experience similar time gaps between the installation of the first renewable power plants and the moment in which the emissions from their infrastructure are offset.

The analysis demonstrates that the time-profile of renewable energy emissions can be relevant for target-setting and detailed policy design, particularly when renewable energy strategies are pursued in concert with carbon pricing through cap-and-trade systems.

**Keywords**

Climate change mitigation, carbon payback time, renewable energy, technological innovation, $CO_2$ emissions

## 1. Introduction

In December 2015, 195 countries met in Paris and adopted the first-ever universal, legally binding global climate deal with the aim to keep the rise in global average temperature below 2°C compared to pre-industrial levels. This represents a turning point in international climate change policy.

There are already many examples of potential national-scale pathways to decarbonise the economy that could inform the development of future emission reduction strategies, such as the Deep Decarbonization Pathways Project (2015). A transition towards a low carbon energy system would be a common element of many – if not all – of them. The strategic planning of such transitions requires clear targets at the country level, yet it is the path taken towards targets, rather than the targets themselves, that will define a country's real contribution to meeting the Paris Agreement goals. After all, the mean peak temperature in 2100 will be a function of cumulative GHG emissions released over time (Friedlingstein et al., 2014) rather than emissions released in any single given target year.

This dynamic aspect to the energy and climate challenge is often overlooked in environmental policy assessment. When assessed from a whole life-cycle perspective, even renewable energy technologies result in the release of greenhouse gas (GHG) emissions during their manufacture and deployment due to the use of carbon intensive energies for production and transportation. We consider this explicitly in our paper, referring to the net cumulative mitigation benefit of different technologies over their whole life-cycle as their 'dynamic mitigation potential'. Due to the strong role likely to be played by renewable energy in future low carbon transitions (EC, 2013; IEA, 2014), a robust assessment of their dynamic mitigation potential is of relevance for planning and target-setting purposes.

Against this background, the work presented in this paper aims to explore:

i. To what extent have emissions savings from renewable energy generation been offset so far by indirect emissions associated with their deployment?
ii. What does a dynamic mitigation potential perspective on renewable energy technologies mean for future European energy policy and national scale emission reduction plans as part of energy transitions towards sustainability?

To this end, we provide insights on whether the emission mitigation potential of renewable energy has so far been neglected in European energy policy by carrying out an ex-post assessment of the $CO_2$ footprint related to the deployment and use of (onshore and offshore) wind turbines and photovoltaic panels (PV) in the period 1990-2013. The environmental footprint of each of these technologies is compared to that of their alternatives, which are defined using different counterfactual scenarios where these innovations are assumed not to diffuse into the energy system. We discuss the relevance of a dynamic mitigation perspective in the context of two central pillars of European energy policy (the promotion of renewable energy under the Renewable Energy Directive, and the pricing of carbon through the EU Emissions Trading Scheme (ETS)), and discuss the broader relevance of a dynamic mitigation perspective for analysis of how renewable energy subsidies and cap-and-trade policies can interact.

The paper is structured as follows. Section 2 contains background information. Section 3 describes the methodology and data sources used, while section 4 presents the results and a brief discussion. Last, section 5 formulates conclusions and highlights the main policy implications of the results.

## 2. Background

### 2.1. The cannibalisation effect

The life-cycle environmental benefits of renewable energy technologies at the micro-level have been largely documented and compared to those of other technologies (Hertwich et al., 2015; Masanet et al., 2013; Nugent and Sovacool, 2014). Nevertheless, these findings do not necessarily reflect the environmental performance of these technologies from a macro-level perspective, i.e. whether renewables as industries have generated net environmental savings and how large these savings have been. At this scale it can be challenging to identify the ex-post and ex-ante environmental consequences arising from the diffusion and uptake of technological innovations, because of a variety of indirect effects, including emissions hidden throughout the life-cycle, displaced in time or space, or induced via economic interactions such as rebound effects (McDowall et al., 2015).

When assessing the macro-level performance of renewable energies, the temporal dimension is of importance, since the associated environmental pressures are unevenly distributed over time. $CO_2$ emissions mainly take place during the construction phase of renewable energy technologies, which results in a delay of several years between the deployment of the technology and net environmental savings. During this period – commonly referred to as the 'carbon payback time' when addressing GHG emissions – the environmental pressure can be higher compared to a no-renewables alternative.

At the micro-level, the carbon payback time of a single renewable power station depends on its environmental performance, as well as on the technology it displaces. At the macro level, the penetration rate of the innovation also influences payback times, as any emission reductions arising from replacing a more emission-intensive power plant by a renewable power station might be cancelled out when building and installing additional renewable plants. Thus, a rapidly expanding renewable energy sector may generate more emissions (associated with manufacturing) than it avoids (from offset fossil fuel generation) for several years during the diffusion of the technology (Kenny et al., 2010, p. 1970). Under such circumstances the benefits of existing units are offset by the emissions related to the deployment of the next wave of units. This phenomenon is commonly referred to as the 'cannibalisation effect' (Pearce, 2009; 2012).

### 2.2. Relevance of dynamic mitigation for energy and climate policy

When planning a country-wide energy transition, having an understanding of the dynamic emission profiles of electricity-generating technologies – in other words, when the emissions take place – could be useful. Most obviously, this enables policymakers to understand when net emission reductions across the whole economy can be expected, which helps understanding expected macro-level mitigation outcomes from technology policies in the short- and mid-term.

The time-profile of renewable energy emissions can also be relevant for detailed policy design, particularly when renewable energy strategies are pursued in concert with carbon pricing, as in the case of Europe. In particular, it has sometimes been argued that subsidy support to renewables is inappropriate within an emissions trading scheme. The basic argument is that the abatement level is set by the cap, and that renewables subsides therefore do not result in additional carbon reductions, but rather distort abatement away from the optimum (for various views on this argument, see: Fankhauser et al. (2011); Lehmann and Gawel (2013); OECD (2003)). However, such arguments have typically been made on the basis of static emissions profiles of technologies, assuming that no emissions are associated with installation and deployment. A dynamic perspective changes the picture somewhat. We use PV as an illustrative example. Assuming that PV is produced domestically, policies to deploy PV will result in upward pressure on carbon prices in the near term (because of extra industrial activity associated with the manufacture of PV panels), and only result in downward pressure in later years (resulting from offset carbon-based power generation). If this effect is non-negligible, it has implications for how carbon trading interacts with renewables, and in particular with the design of 'when-flexibility' design features, such as banking, borrowing and commitment periods (Fankhauser and Hepburn, 2010).

### 2.3. Previous studies on dynamic mitigation potential

Emmott et al. (2014) have identified previous studies that have dealt with the issue of the time-profiles of energy and emissions from renewable energy deployment (see Table 1). These studies show diverging views on whether the diffusion rates of renewable energies should be limited, although most of them argue that the long-term benefits of a transition to a low carbon energy system justify having a brief period in which annual emissions increase (Emmott et al., 2014).

Table 1: Overview of studies addressing the time-profiles of energy and emissions from renewable energy deployment

| Study | Topic | Technologies |
|---|---|---|
| Bojić et al. (2011) | Dynamic energy balance | PV |
| Dale and Benson (2013) | Dynamic energy balance | PV |
| Gonçalves da Silva (2010a) | Dynamic energy balance | PV |
| Gonçalves da Silva (2010b) | Dynamic energy balance | PV |
| Görig and Breyer (2012) | Dynamic energy balance | PV |
| Gutowski et al. (2010) | Dynamic energy balance | PV |
| Kessides and Wade (2011) | Dynamic energy balance | Oil, natural gas, nuclear, hydro, wind, PV |
| Lloyd and Forest (2010) | Dynamic energy balance | PV |
| Mathur et al. (2004) | Dynamic energy balance | Coal, natural gas, hydro, wind, PV |
| Pearce (2012) | Dynamic energy balance | Nuclear |
| Arvesen and Hertwich (2011) | Dynamic carbon mitigation potential | Wind |
| Bojić et al. (2011) | Dynamic carbon mitigation potential | PV |
| Drury et al. (2009) | Dynamic carbon mitigation potential | PV |
| Emmott et al. (2014) | Dynamic carbon mitigation potential | PV |
| Kenny et al. (2010) | Dynamic carbon mitigation potential | Coal, natural gas, oil, biomass hydro, wind, PV, CSP, geothermal |
| Reich et al. (2011) | Dynamic carbon mitigation potential | PV |
| Wiebe (2016) | Dynamic carbon mitigation potential | Wind, PV |

Note: CSP: Concentrated Solar Power

As for the methods used in the studies in Table 1, the majority of them approach the subject from a life-cycle assessment (LCA) perspective, i.e. they are based on data from process-based life-cycle inventory (LCI) databases. LCI databases provide a very detailed picture of the physical inputs in the most important life-cycle stages of specific technologies. Nonetheless, LCI databases suffer from the so-called 'truncation error' – i.e. incomplete system boundaries –, which has been identified as one of the main shortcomings of these tools (Lenzen, 2000; Nielsen and Weidema, 2001).[1] Alternatively, environmentally extended input-output (EEIO) analysis is characterised by having complete system boundaries at the expense of losing sectoral detail. For these reasons, Arvesen and Hertwich (2011) adopted a hybrid approach to overcome the limitations of both methods. Here we also use our own hybrid method that offers benefits over EEIO analysis and LCA separately by combining the strengths of both. Compared to LCA, the use of hybrid methods ensures that system boundaries are complete. Further, in the case of our hybrid LCA/EEIO method (see Section3), we are able to generate the year-specific results required to represent the time profile of the emissions related to renewable energy deployment. This is an advantage compared to LCA, which usually omits the time dimension by providing a snapshot where all pressures and impacts are accumulated in single point in time (Reap et al., 2008).

## 3. Methodology and data sources

### 3.1. Overview of methodology

In this paper we carry out a scenario-based analysis of the environmental performance of individual technological innovations – namely PV panels, onshore and offshore wind turbines – and of their potential alternatives. To this end, we develop a historical scenario – also referred to as baseline scenario throughout the text – that captures technology-specific past developments in electricity production and the installation of new power plants. For each of the technologies above, we then define alternative counterfactual scenarios that suggest what could have happened if that technology had not diffused into the European energy system. By comparing the emissions in the historical and counterfactual scenarios, we assess the extent to which each of these innovations have so far contributed to reducing the $CO_2$ footprint of the EU27. Here we define footprint as the cradle to gate emissions attributable to electricity production and to the deployment of the required infrastructure.

Emission accounting in both cases uses data from annual high-resolution EEIO tables that depict the most important life-cycle stages of 18 technologies used to produce electricity (see Table 2, the full resolution of the EEIO table is given in the supplementary material). To generate these tables, we have reconciled technology-specific LCI data (ecoinvent Centre, 2010, 2013) and the 2000-2007 Eurostat EEIO tables for EU27 (Eurostat, 2011). Thus, we have selectively disaggregated the original Eurostat EEIO tables, which have a resolution of 59 product groups and represent electricity, gas, steam and hot water supply in a single category, into 125 product groups – also referred to as sectors or industries for readability purposes.

The disaggregated tables capture key past developments in electricity production such as changes in the electricity mix and the diffusion patterns for each technology. Following the selective disaggregation of the 2000-2007 EEIO tables, we use input-output based hybrid analysis (IOHA) – as defined by Suh et al. (2004) – to estimate separately the $CO_2$ footprint per unit output associated with the domestic energy produced with each technology (kt $CO_2$ per TJ) and its infrastructure (kt $CO_2$ per MW). Given that the tables only cover the period 2000-2007, we use this data as the basis for estimating the equivalent footprint intensities in the periods 1990-1999 and 2008-2013. To determine the environmental pressures with and without each of the technologies above, we multiply the $CO_2$ footprint intensities by the corresponding data in the historical and counterfactual scenarios.

Table 2: Technologies for electricity production and manufacturing of power plants/components represented in the disaggregated EEIO tables

| **Code** | **Description** |
|---|---|
| 31_rest | Rest - Electrical machinery and apparatus n.e.c. |
| 31.e1_f | Wind power plant onshore - fixed parts |
| 31.e1_m | Wind power plant onshore - moving parts |
| 31.e2_f | Wind power plant offshore - fixed parts |
| 31.e2_m | Wind power plant offshore - moving parts |
| 31.h | Inverter |
| 32_rest | Rest - Radio, television and communication equipment and apparatus |
| 32.h1 | Multi-Si PV panel |
| 32.h2 | Multi-Si PV cell |
| 32.h3 | Multi-Si PV wafer |
| 40.11.a1 | Electricity by coal with FGD - CHP |
| 40.11.a2 | Electricity by coal with FGD – only electricity |
| 40.11.a3 | Electricity by coal without FGD - CHP |
| 40.11.a4 | Electricity by coal without FGD - only electricity |
| 40.11.b1 | Electricity by gas - CCGT - CHP |
| 40.11.b2 | Electricity by gas - CCGT - only electricity |
| 40.11.b3 | Electricity by gas – conventional - CHP |
| 40.11.b4 | Electricity by gas – conventional - only electricity |

| | |
|---|---|
| 40.11.c | Electricity by nuclear |
| 40.11.d | Electricity by hydro |
| 40.11.e1 | Electricity by wind onshore |
| 40.11.e2 | Electricity by wind offshore |
| 40.11.f1 | Electricity by petroleum and other oil derivatives - CHP |
| 40.11.f2 | Electricity by petroleum and other oil derivatives - only electricity |
| 40.11.g1 | Electricity by biomass and waste - CHP |
| 40.11.g2 | Electricity by biomass and waste - only electricity |
| 40.11.h | Electricity by solar photovoltaic |
| 40.11.i | Others (solar thermal / tide, wave and ocean / geothermal / n.e.c.) |
| 40.12 | Transmission of electricity |
| 40.13 | Distribution of electricity |
| 40.2 | Manufactured gas and distribution services of gaseous fuels through mains |
| 40.3 | Steam and hot water supply services |
| 45_rest | Rest - Construction work |
| 45.a1 | Hard coal power plant - FGD - CHP |
| 45.a2 | Hard coal power plant - FGD - no CHP |
| 45.a3 | Hard coal power plant - no FGD - CHP |
| 45.a4 | Hard coal power plant - no FGD - no CHP |
| 45.b1 | Combined cycle gas power plant - CHP |
| 45.b2 | Combined cycle gas power plant - no CHP |
| 45.b3 | Conventional gas power plant - CHP |
| 45.b4 | Conventional gas power plant - no CHP |
| 45.c1 | PWR nuclear power plant |
| 45.d | Run-of-river hydropower plant |
| 45.f1 | Oil power plant - CHP |
| 45.f2 | Oil power plant - no CHP |
| 45.g1 | Municipal waste incineration plant - CHP |
| 45.g2 | Municipal waste incineration plant - no CHP |
| 45.h1 | 3kWp slanted-roof installation, multi-Si, panel, mounted, on roof |
| 45.h2 | electric installation, photovoltaic plant, at plant |
| 45.h3 | slanted-roof construction, mounted, on roof |

Note: FGD: Flue Gas Desulphurisation; CCGT: Combined Cycle Gas Turbine; CHP: Combined Heat & Power; Multi-Si: Multicrystalline Silicon, n.e.c.: Not Elsewhere Classified

Each counterfactual scenario assumes that a specific innovation being assessed (in this case, various renewable energy technologies) did not diffuse into Europe's energy system. Thus, the energy produced and the installed infrastructure of the innovation under assessment is replaced by that of other technologies (Table 3).

Table 3: Descriptions of used scenarios

| Case study | Scenario | Description |
|---|---|---|
| Wind onshore | Baseline | Historical development |
| | Counterfactual | Onshore wind energy does not develop in the EU27. The shortfall in generation is covered by all other technologies (including offshore wind and PV) based on their relative weight each year. The stock model determines the additional capacity required to satisfy the shortfall (see section 3.2). |
| Wind offshore | Baseline | Historical development |
| | Counterfactual | Offshore wind energy does not develop in the EU27. The shortfall in generation is covered by all other technologies (including onshore wind and PV) based on their relative weight each year. The stock model determines the additional capacity required to satisfy the shortfall (see section 3.2). |
| PV | Baseline | Historical development |
| | Counterfactual | PV energy does not develop in the EU27. The shortfall in generation is covered by all other technologies (including onshore and offshore wind) based on their relative weight each year. The stock model determines the additional capacity required to satisfy the shortfall (see section 3.2). |

For each innovation, the results of the baseline scenario are compared to those of the counterfactual scenario. If the cumulative $CO_2$ footprint in the historical scenario ($m_H$) is lower than that of the counterfactual scenario ($m_C$) (i.e. $m_H < m_C$), then the innovation has brought net environmental benefits. Conversely, if the historical pressures are higher than those of the counterfactual scenario (i.e. $m_H > m_C$), then it can be concluded that the rapid diffusion rate of the innovation has negated so far the technology's ability to mitigate climate change, thereby cannibalising its benefits.

The next sections describe the methodology and the main data sources used in more detail.

### 3.2. Developing baseline and counterfactual scenarios

The data for the amount of electricity produced (TJ) and the existing capacity in the baseline scenario (by technology) has been retrieved mainly from Eurostat (2016a, b). Additional sources have been used to split wind energy into onshore and offshore, electricity produced by gas into CCGT and open cycle, and electricity by fossil fuels into CHP and electricity only (see the supplementary material). Electricity consumption (TJ) is calculated by multiplying production (TJ) by the electricity consumption-to-production ratio (mio. €) available in the IO tables. The split between industries and households uses data from the International Energy Agency (IEA, 2013a, b) to account for the different prices paid by each type of consumer.

In order to quantify the $CO_2$ footprint of the infrastructure, this exercise requires data on the capacity of plants installed during the 1990-2013 period rather than on the existing installed capacity each year, for the total emissions in a given timeframe are a function of annual additions to the stock. In other words, we require information on how many new PV panels, wind turbines, coal power plants, etc. are installed each year, instead of the cumulative capacity. To do so, we have built a simple technology-specific stock model. The opening stock ($S_{1950}$) of technology $i$ is based on own estimates of the existing capacity in 1950 (see the supplementary material for more details). With the aid of average lifetime factors for the different plants taken from Ecoinvent (ecoinvent Centre, 2010), the annual stock changes in terms of installed ($S_{IN}$) and decommissioned ($S_{OUT}$) capacity have been estimated. The mathematical formulation of the model reads as follows:

$$S_{i,t} = S_{i,1950} + \sum_{t_0=1950}^{t} S_{i,IN} - \sum_{t_0=1950}^{t} S_{i,OUT} \qquad (1)$$

The counterfactual scenarios assume the same total electricity supply and demand as in the baseline scenario, but with a different generation mix, since either PV, onshore wind or offshore wind energy are removed and substituted with alternatives. For each innovation, a counterfactual scenario has been developed in which we assume that the shortfall in electricity generation comes from all other technologies based on their relative weight in the mix. We then calculate the capacity that would be required to generate the level of electricity supply found in the counterfactual.

The annual stock in each counterfactual is estimated as follows:

1) First, we calculate the maximum amount of electricity that could be produced with the existing stock using availability factors – i.e. maximum capacity factors – for traditional technologies (from Anandarajah et al. (2011)) and capacity factors for renewables (except hydro) (from the data in the baseline scenario). In doing so, we assume renewables to be exploited to their maximum capacity in the baseline.
2) Second, we check whether the increase in electricity generation attributed to the different technologies – as a result of a given innovation not diffusing – can be produced with the capacity in the baseline. This is only possible when power plants are not exploited to their maximum capacity, e.g. when overcapacity of fossil fuel-based power plants exists.
3) Third, we determine if the generation stock needs to change in the counterfactual or not. If the additional electricity can be produced with the existing capacity for technology *i*, we keep the current stock. Conversely, if additional capacity is required to meet the increased electricity demand of technology *i*, we add this to the stock in the baseline taking into account the different capacity factors. Based on the resulting capacity, we calculate the amount of new power plants installed each year with the stock model described above.

### 3.3. Selective disaggregation of the monetary input-output tables and the $CO_2$ emission accounts

In order to investigate to which extent the $CO_2$ emissions savings from renewable energy technologies have been offset by the emissions associated with their deployment, we use a variant of EEIO analysis, namely IOHA. As explained by Suh and colleagues (Suh and Huppes, 2005; Suh et al., 2004), this method consists of a selective disaggregation of one or more industries / product groups in an EEIO table and the consequent application of EEIO analysis.

All in all, we have disaggregated Eurostat's 2000-2007 symmetric IO tables from 59 to 125 product groups (see supplementary material), where all the flows are represented in monetary terms, except the rows that represent electricity use, which is given in TJ. The disaggregation process combines physical input coefficients of the representative technology taken from the Ecoinvent LCI database (ecoinvent Centre, 2010, 2013), prices (Gaulier and Zignago, 2010) and monetary input coefficients the EXIOBASE v2 database (Wood et al., 2015) with their corresponding outputs, which are either calculated in the previous step or obtained from alternative sources such as Eurostat's Structural Business Statistics (Eurostat, 2014b, c, d). It should be noted that the input coefficients from Ecoinvent are corrected to represent the average European generation efficiencies every year based on data of the International Energy Agency (IEA, 2013a, b) and that the inputs of the CHP plants are allocated to electricity and heat generation using the so-called 'efficiency method' (WRI and WBCSD, 2006). The industry-specific $CO_2$ emission data from Eurostat (2014a) has also been disaggregated based on the emission intensities obtained from Ecoinvent and EXIOBASE. More details about the disaggregation of the IO tables and the environmental extension are given in the supplementary material.

### 3.4. Input-output based hybrid analysis

Once the disaggregated EEIO tables are available, we apply a slightly modified version of EEIO analysis. The formulation reads as follows:

$m = B\,(I - A)^{-1}\,(x_E + y_I)$ (2)

*where:*

*m* denotes the $CO_2$ footprint of the domestic electricity production ($x_E$) plus that of the investments on energy infrastructure ($y_I$), *B* represents the $CO_2$-emission intensities of each product, and $(I\text{-}A)^{-1}$ is the Leontief inverse of the disaggregated *A* matrix. Given the scope of this exercise, it is important to note that the subject of the analysis is the total domestic production of electricity. This equals the intermediate demand of electricity produced in the EU27 ($z_E$) minus the 'auto-consumption' by the electricity sector when producing electricity ($z_{OWN\_E}$)[2] plus the final demand of electricity produced in EU27 ($y_E$). The 'auto-consumption' by the electricity sector refers to the amount of electricity that is required in the value chain prior to the electricity production process (e.g. in the extraction or processing of raw materials that are then burnt in power plants). In the mathematical formulation $z_{OWN\_E}$ is excluded from the reference product $x_E$ in order to avoid double counting. The emissions associated with the 'auto-consumption' are captured when multiplying $x_E$ by the Leontief inverse, which shows both the direct and indirect inputs required to produce one unit of each product represented in the IO table (including electricity required to produce electricity).

$$x_E = z_E - z_{OWN_E} + y_E \quad (3)$$

In practice, this means that instead of allocating the intermediate use of electricity to the product that will be purchased by final consumers (e.g. food, services, etc.), we account for its upstream emissions – i.e. the value chain prior to electricity generation – and ignore its downstream emissions – i.e. taking place after the transmission and distribution of electricity. This has the effect of isolating the direct and indirect environmental pressure of electricity from that of other products. In other words, we account for the all the cradle-to-gate emissions of domestic electricity generation independently from the sectors that consumes it. The logic applied to the formulation above is more commonly used in LCA exercises, where the reference product is not necessarily used by final consumers.

The emissions of the counterfactual scenario are calculated in the same way, but using the corresponding electricity production vector. Thus, the same emission intensities are assumed in those scenarios for each technology.

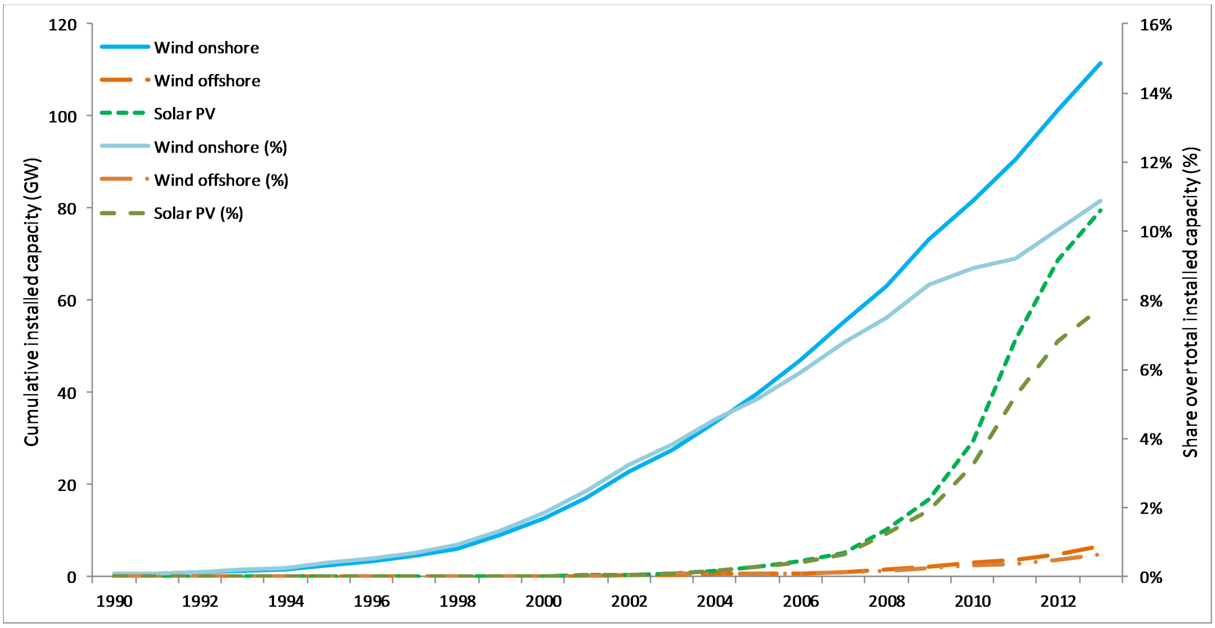
## 4. Results and discussion

### 4.1. Diffusion of innovations in the baseline scenario

This article addresses the environmental performance of onshore and offshore wind turbines and solar PV panels in the period 1990-2013 in the EU27. In order to contextualise the results provided in the next sections, Figure 1 shows the diffusion of these innovations in this period both in absolute and relative terms.

Onshore wind began its diffusion in the early 1990s and since then its relevance has increased considerably. By 2013 onshore wind turbines amounted to 111 GW, which represented more than 11% of the total installed capacity in the EU27. Germany and Spain accounted for more than 40% of the total of the existing capacity in 2013 (EWEA, 2015b).

Figure 1: Diffusion of the innovations in absolute and relative terms



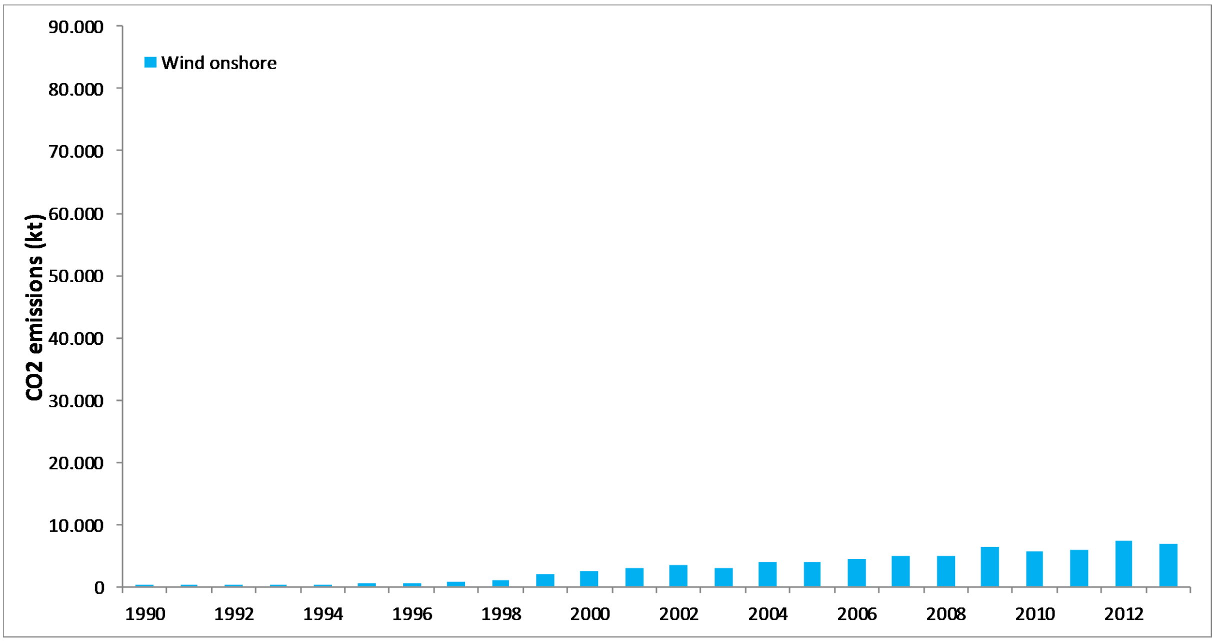

Offshore wind turbines, on the other hand, are in the very beginning of their diffusion curve. Until 2013, they only covered 1% of the existing capacity. In contrast to onshore wind power, the United Kingdom (56%) and Denmark (16%) were the frontrunners in 2013 (EWEA, 2015a).

As for solar PV panels, around 80 GW were installed in the EU27 in the period 1990-2013. In 2013, Germany and Italy accounted for 46% and 23% of these 80 GW respectively (Eurostat, 2016a). Annual growth rates in installed capacity oscillated between 51-98% in the EU27 between 2005 and 2011, yet they slowed down afterwards.

### 4.2. Onshore wind

Figure 2a shows the yearly evolution of the $CO_2$ footprint attributable to onshore wind electricity and its infrastructure based on historical data. Since the turbines do not result in direct $CO_2$ emissions during the electricity generation process, the footprint of the use phase is almost negligible compared to that of the construction phase. In 2013 the $CO_2$ emissions amounted to 6,987 kt (or 0.6% of the total emissions of the sector[3] that year – i.e. including all other technologies). Figure 2b shows the emissions from the counterfactual scenario in which onshore wind is assumed not to diffuse. In this case, the environmental pressure associated with replacing onshore wind energy infrastructure is lower compared to the baseline, but the annual emissions from producing electricity with alternative sources are much higher due to the partial substitution of wind energy by fossil fuel-based electricity.

**a**



**b**

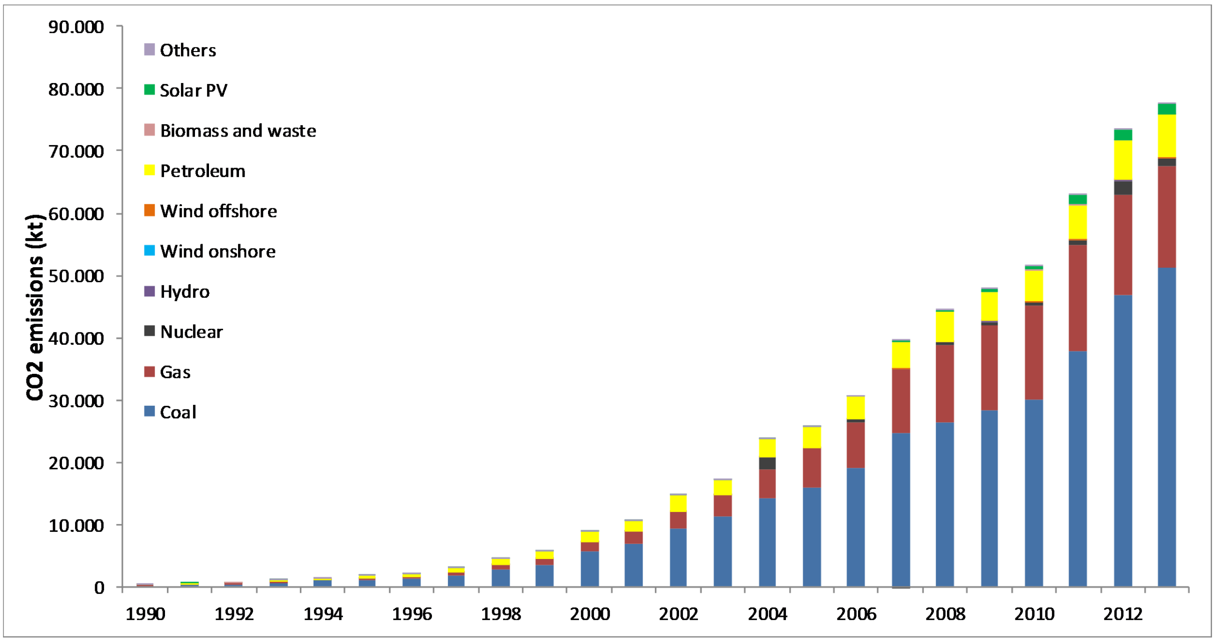
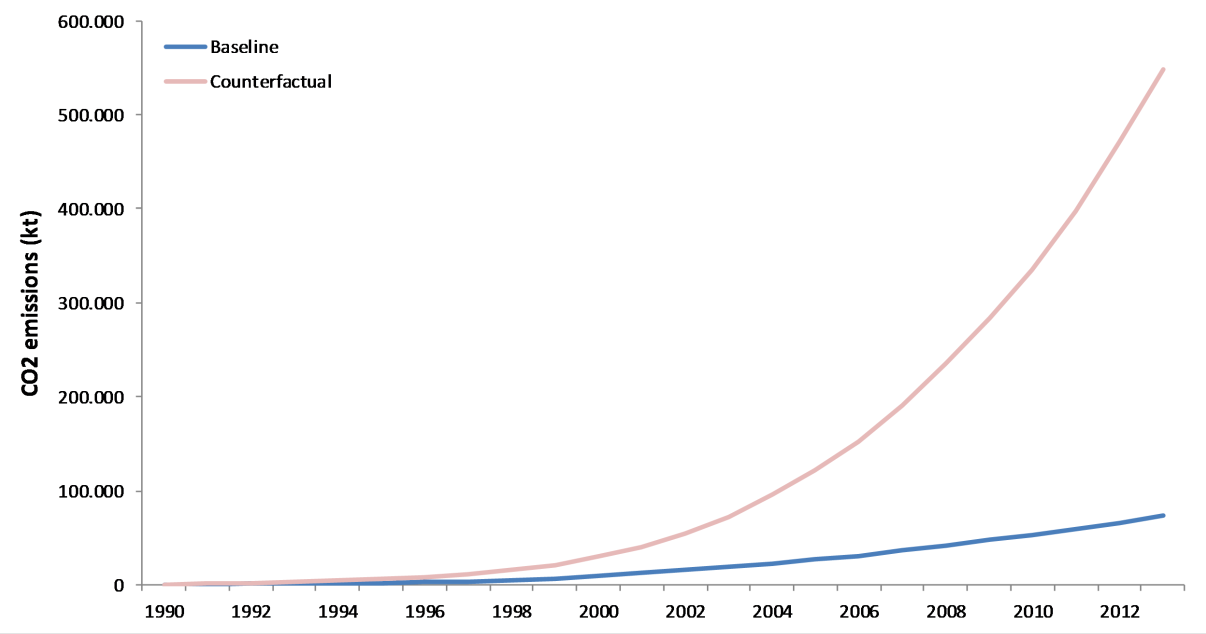



Figure 2: Annual $CO_2$ emissions of onshore wind turbines in the baseline scenario (a), and of its alternatives in the counterfactual (b)

Figure 3 depicts the cumulative emissions of the baseline and counterfactual in the period under assessment. Compared to the alternative scenario, onshore wind had a net contribution to emissions reduction already in 1990. Since the beginning of the time series there is a clear decoupling of the pressures exerted and those that would have taken place had onshore wind energy not diffused. Hence, the effects of 'energy cannibalisation' are not visible in this period.

Ex-ante projections suggest that onshore wind capacity will increase from 111 GW in 2013 to 146-189 GW in 2020 (EWEA, 2014). During this period onshore wind is expected to deliver additional environmental benefits.

Figure 3: Cumulative $CO_2$ emissions of onshore wind turbines in the baseline scenario, and of its alternatives in the counterfactual

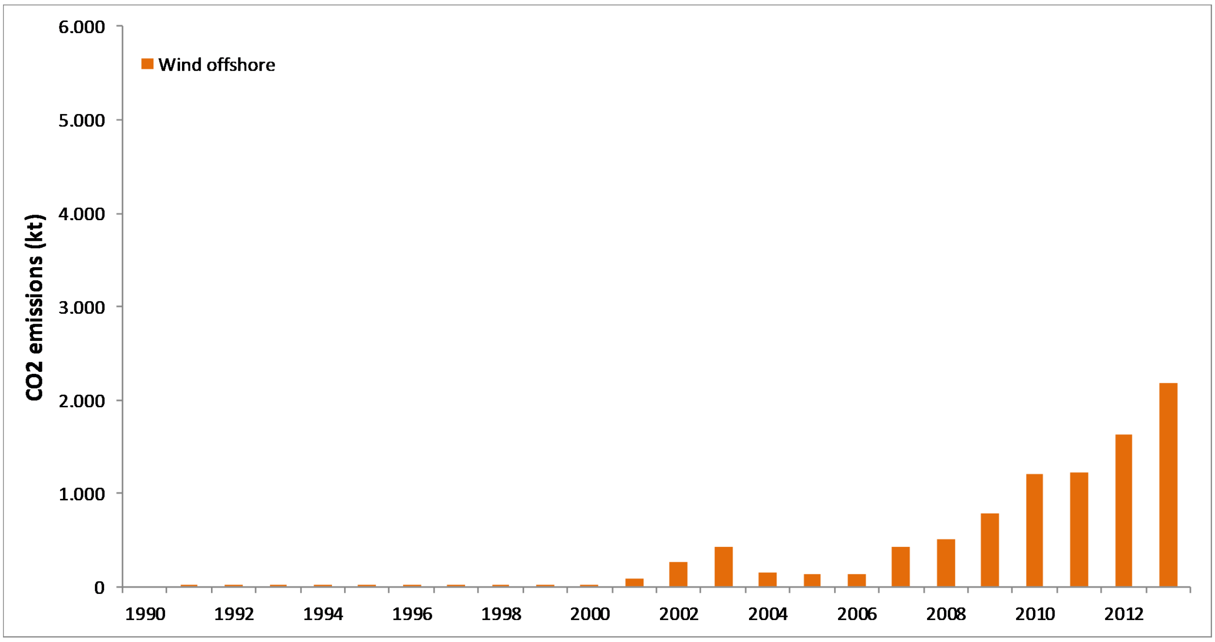



### 4.3. Offshore wind

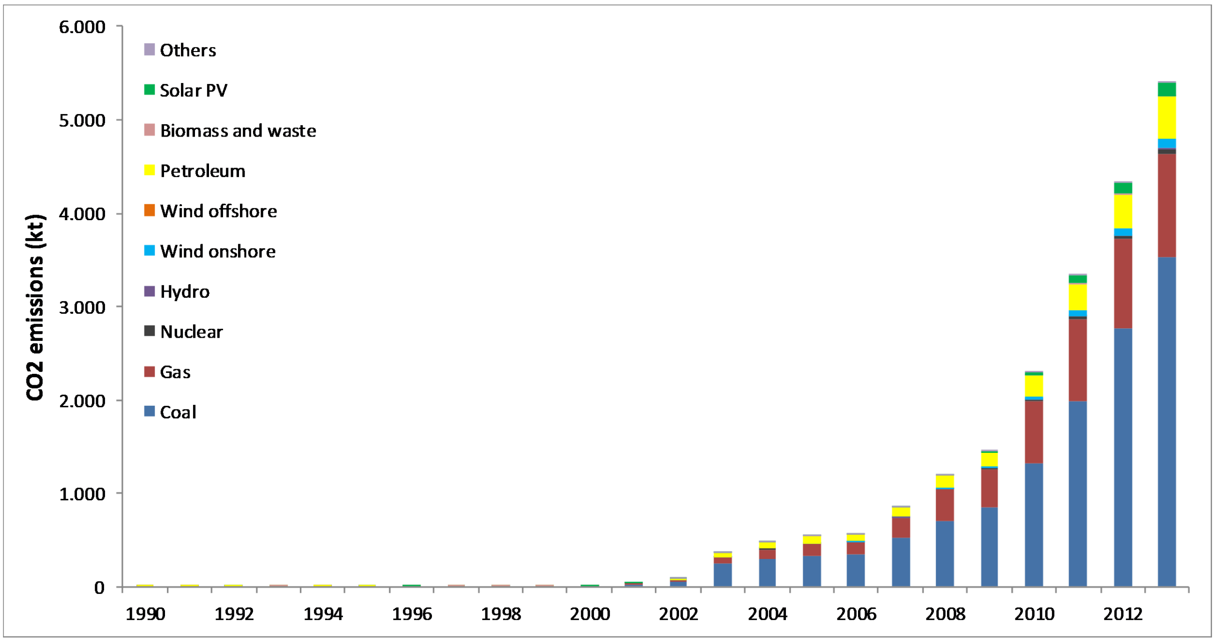
The emissions resulting from the construction of offshore wind farms have mainly taken place between the years 2000 and 2013 (Figure 4a). As in the case of onshore wind, the vast majority of upstream emissions are linked to the supply chain of the different parts comprising the offshore wind turbine and the platform, although their magnitude is relatively low due to its limited penetration in the energy market. In 2013, the related emissions were 2,184 kt $CO_2$ or 0.2% of the total sectoral emissions that year. The counterfactual scenario starts showing consistently lower emissions after 2004 (Figure 4b). After 2004, the emissions from electricity production in fossil fuel power plants outweigh considerably those of the infrastructure in the baseline scenario.

Figure 4: Yearly $CO_2$ emissions of offshore wind turbines in the baseline scenario (a), and of its alternatives in the counterfactual (b)

**a**



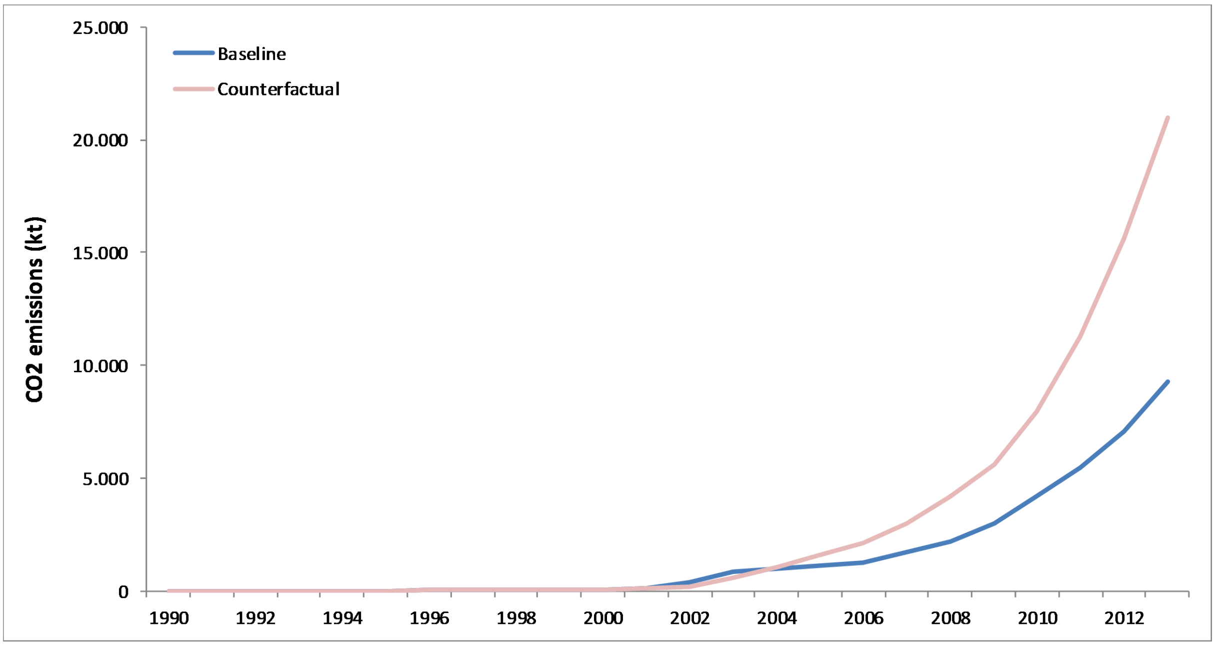

**b**




When looking at cumulative emissions (Figure 5), one can see that the $CO_2$ emissions related to the deployment of offshore wind turbines were not fully compensated until 2004 in the counterfactual scenario. Until then the environmental benefits of the first units installed were offset by the deployment of new turbines. The fast diffusion in the period 2007-2013 (yearly increase of 30-42%) has not reversed the trend since 2004 and thus offshore wind energy is still yielding net environmental benefits. This is mainly due to the amount of fossil fuel-based electricity it has replaced.

Against this background, ex-ante scenarios from the European Wind Energy Association (EWEA, 2014) project that the future capacity of offshore wind will range between 20-28 GW by 2020, compared against an installed capacity of 7 GW in 2013. The same projections estimate that the amount of electricity produced by offshore wind turbines will increase from 16 TWh in 2013 to 72-102 TWh in 2020. Thus, given that the rise in electricity production is expected to be higher than the expansion of existing capacity, it seems likely that the emission profiles shown below will continue to decouple until 2020, thereby increasing the net environmental benefits attributable to offshore wind turbines.

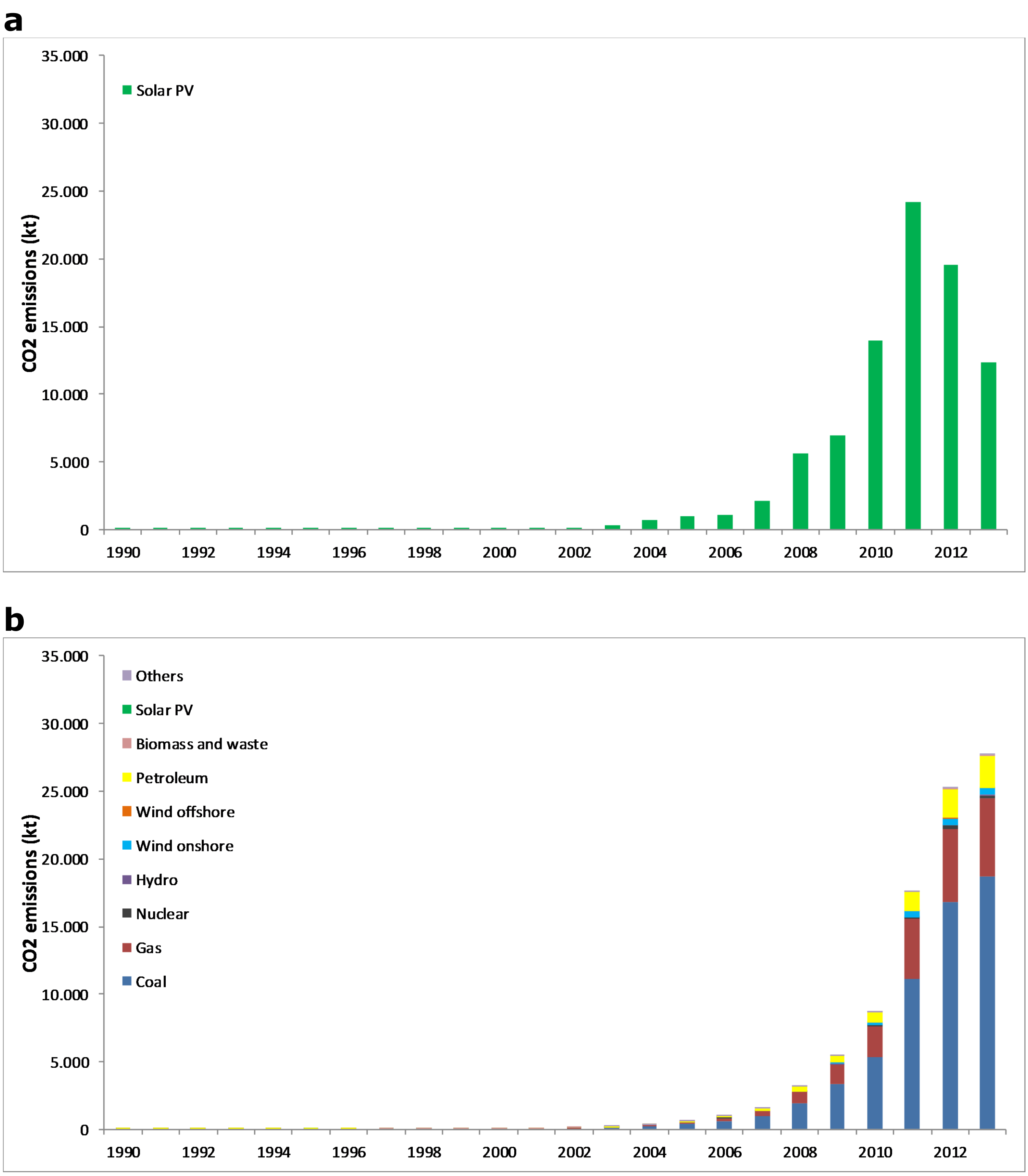
Figure 5: Cumulative $CO_2$ emissions of offshore wind turbines in the baseline scenario, and of its alternatives in the counterfactual




## 4.4. PV panels

For the assessment involving PV panels, the annual emissions found in the counterfactual scenario were generally higher than those of the baseline until 2002 (with a few exceptions). This suggests that PV panels were yielding small environmental benefits in the form of $CO_2$ emission reductions on an annual basis. Nonetheless, the diffusion of PV panels has rocketed in absolute terms in the last decade, and so has the related environmental footprint (Figure 6a). As a result of this rapid deployment, the trends were reversed and the annual emissions in the counterfactual were considerably lower than those of the baseline between 2007 and 2011 (Figure 6b). From 2012 on, the trends were reversed again.

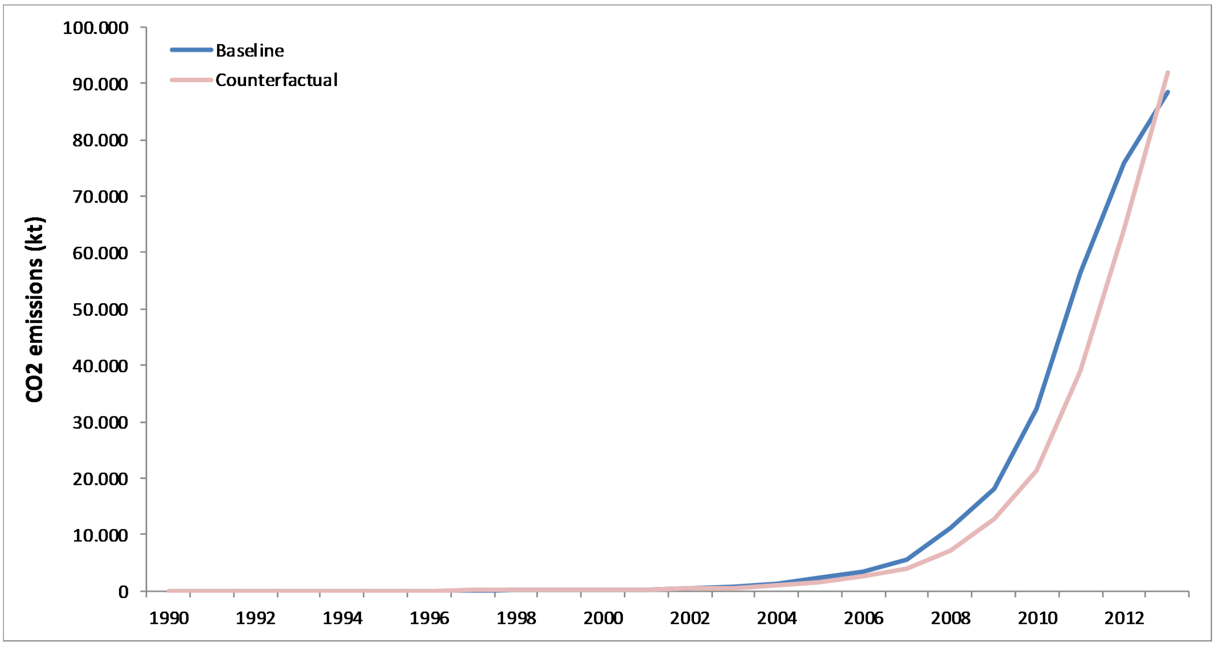
Figure 6: Yearly $CO_2$ emissions of solar PV panels in the baseline scenario (a), and of its alternatives in the counterfactual (b)



The cumulative emission data shown in Figure 7 suggests that it was not until very recently that energy production from PV panels offset the environmental pressures related to their physical construction. This points towards the cannibalisation of the expected environmental benefits from the PV panels installed during most of the period studied as a result of the fast deployment rate in the last years of the 2000s. The trend is only clearly reversed in 2013. Our results point in the same direction as those of Dale and Benson (2013) who found that in 2010 the world PV industry was still a net electricity consumer, but predicted that this trend would soon be reversed.

Regarding future developments, according to data from the European Photovoltaic Industry Association (EPIA, 2014), the yearly installation of new PV panels peaked in 2011, but new installations will continue to be significant until 2018. Its share in the European electricity mix is also expected to increase considerably by 2020 (EC, 2013). These trends suggest that the decoupling of emission profiles will likely continue in the coming years.

Figure 7: Cumulative $CO_2$ emissions of solar PV panels in the baseline scenario, and of its alternatives in the counterfactual



### 4.5. Discussion

The ex-post assessment of the selected renewable energy technologies describes a different case for each innovation. The contribution of onshore wind energy to $CO_2$ emission reduction is visible since almost the beginning of its diffusion process. Since the early 1990s our assessment shows that there has been clear decoupling between the pressures found in the baseline and counterfactual scenario. This indicates the extent to which $CO_2$ emissions have been reduced due to this innovation.

In contrast to onshore wind, offshore wind turbines only reached a net positive environmental balance around the year 2004. In previous years, the pressures related to the production and installation of new units outweighed the expected micro-level benefits of the individual units deployed. Since 2004, the decoupling between the emission profiles of the baseline and counterfactual scenario has increased significantly, giving some indication of the mitigation potential of this technology.

The assessment of PV panels, on the other hand, suggests that between 1990-2012 no net environmental benefits could be claimed by this technology. The environmental benefits from the first units deployed have actually been negated by the environmental pressures exerted during the installation of additional panels. It is only in since 2013 that PV panels have started contributing to the net decrease in environmental burden as a result of substituting for fossil-based electricity generation.

According to existing ex-ante scenarios, the capacity of onshore wind, offshore wind and PV energy will increase considerably until 2020. Our assessment suggests that the three technologies will continue having a net contribution to $CO_2$ emissions reduction in the coming years.

The results presented in this paper should be interpreted carefully, paying due attention to the inherent limitations of IOHA – particularly when using a single-region model that assumes the domestic technological level for imported goods – as well as to the assumptions made in the methodology. The assumptions made to produce the counterfactual scenarios are of particular importance here, since this determines whether the cannibalisation effect takes place or not. In this context, the counterfactual scenarios should not be interpreted as alternatives for the past, but as a set of assumptions to get a background for the present situation. When developing them, we have adopted what we considered to be the most neutral assumption, i.e. that the shortfall of electricity in absence of a given technology is generated with the average mix. Further, changes in the electricity mix in the counterfactual scenario would result in different electricity prices. Consequently, this would activate a range of price-based feedback mechanisms that could either increase or decrease consumption and production, and ultimately also affect emissions. Such effects are not considered here.

It also bears noting that carbon payback times of renewable technologies largely depend on site-specific factors that influence their performance. For this reason, assumption on where renewable power plants are installed influence the size of the cannibalisation effect. In this paper, we cover a single region that comprises 27 countries, which differ substantially from one another in factors such as solar irradiance (Šúri et al., 2007) or wind patterns (EEA, 2009). When generating the counterfactual scenarios, we have assumed that electricity is produced in average EU27 conditions. This could overestimate the emissions in the counterfactual compared to a counterfactual in which we instead assume higher capacity factors for renewables, e.g. as a result of installing the additional onshore wind turbines in agricultural and industrial areas in north-western Europe or offshore wind stations in low depth areas in the North Sea, the Baltic Seas and the Atlantic Ocean when PV does not diffuse. This could also be the case if we assume that in absence of wind energy, the additional PV power plants required are installed in Mediterranean countries, which receive much more solar irradiance than northern countries. Lower emissions in the counterfactual would delay the time at which the assessed renewables start bringing net environmental benefits. Nonetheless, irrespective of the concrete carbon payback time of each of the technologies assessed, our results show that the cannibalisation effect has taken place in EU27 as a whole.

The results also provide useful insights for users of energy system optimisation models that commonly only attribute the emissions from the use phase to energy supply technologies, i.e. they do not model the emissions from energy infrastructure explicitly, but as part of a generic industrial activity. In this vein, McDowall et al. (2014) found that modelling the indirect $CO_2$ emissions related to infrastructure deployment as a function of electricity production changes the optimal energy mix in the European TIMES model (Solano Rodriguez and Pye, 2015). In a related exercise, Daly et al. (2015) concluded that when allocating the upstream emissions of infrastructure to electricity-generating technologies, the cost optimal pathway to reduce domestic pressures leads to substantial carbon leakage.

## 5. Conclusions and policy implications

Meeting the expectations created after the signing of the Paris Agreement requires countries to plan a major transition towards a low carbon energy system, with significant roles for renewable energy. Although these technologies are near-zero emitters during the use phase, through the lens of a planner they should be seen as an environmental investment rather than as an immediate solution. Their deployment is more accurately represented as an upfront investment that locks in $CO_2$ emissions in the short-run to potentially yield a future environmental benefit. As our analysis shows, above a certain diffusion rate, renewable energy deployment can cannibalise the environmental benefits of previous units during early diffusion stages. In this period, renewables do not contribute to net climate change mitigation. Until 2012, this was the case of PV panels in the EU27. Offshore wind turbines experienced a similar situation until 2004.

When interpreting our results, one should note that individual countries will probably show very different pictures to the EU-wide pattern that we have described. This is as a result of different penetration rates at the national level and other site-specific factors that influence the environmental performance of renewable energies (e.g. solar irradiance, wind energy potential, etc.). In some European countries some of these technologies are certainly leading to net emission reductions, while in others they are not yet at this stage. Likewise, countries with limited low-carbon energy capacity could expect to experience the cannibalisation effect in periods with fast deployment of renewable technologies.

Here we argue that improved dynamic assessment of the short- and long-term mitigation potential of low carbon technologies can help better plan the energy transition and assist in the process of setting intermediate emission reduction targets to monitor progress towards the end goal. We note two specific policy implications:

1. Acknowledgement of dynamic emissions profiles suggests that cumulative carbon budgets are more appropriate than single-year emissions targets, as the latter can be met by strategies with different long-term emissions implications.
2. When cap-and-trade systems are combined with renewable energy subsidies, as in the EU, the 'when-flexibility' measures (Fankhauser and Hepburn, 2010) in the design of the trading system should consider dynamic, rather than static, emissions implications of renewables. If built domestically, rapid deployment of renewables may exert upward pressure on carbon prices, by stimulating industrial activity associated with the manufacture and installation phase; and yet the same renewable support policy can undermine longer-term carbon prices. The analysis in this paper suggests that arguments about renewable energy subsidies undermining the economic efficiency of cap-and-trade systems may need to be revisited in a dynamic framework: the analysis showed that during the first EU ETS trading period, emissions associated with PV manufacture and deployment outweighed those saved via PV-based generation. Optimal cap setting,

commitment periods and banking and borrowing may be influenced by such effects, though detailed analysis of this is beyond the scope of this paper.

In this vein, although micro-level static LCAs have proven useful to guide certain energy policies, our results support the need to complement these assessments with more dynamic tools that can better represent emission trajectories and their implications. Many policy decisions are taken in a much more complex system than the one depicted by some analytical tools. While we acknowledge the need to simplify complex systems to find a balance between the resources invested and the robustness of the results yielded, we should better define the needs arising from policy for an efficient policy-science interface.

In the case studied, this could be done, for instance, by adding dynamism to LCAs, using alternative tools such as EEIO analysis, hybridising these two methods or adding the indirect environmental effects of electricity supply technologies to energy system models. Such practices would better represent the temporal dimension of climate change mitigation potential of technological innovations and thus provide the necessary information for improving energy and eco-innovation policies, as well as for understanding their cross-sectoral implications. Likewise, these tools can also prove useful for more realistic target setting by pointing out when the investment made in the form of early life-cycle GHG emissions associated with low-carbon technologies will be paid off, and when these technologies will start to deliver net environmental benefits.

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[1] Although IOHA ensures complete system boundaries at economy level, the attribution of the pressures to a product differs from that of LCA. For instance, LCA attributes pressures from the construction of the infrastructure and upstream pressures from waste management practices to the product under assessment based on the cradle to grave approach, while IOHA allocates the pressures from infrastructure to capital formation, while waste management is commonly represented as a separate industry. Thus, when carrying IOHA at meso level as in this case, it is a modellers choice which pressures to attribute to the research subject.

[2] Here we use the term 'auto-consumption' to refer to the electricity consumption induced by electricity production itself, i.e. the amount of electricity that is required in the value chain prior to the electricity production process (e.g. in the extraction or processing of raw materials that are then burnt in power plants). Although this indicates an 'own use', this item should not be confused by 'Energy Industry Own Use' as defined by the International Energy Agency, which represents direct energy inputs (irrespective of the product) required in the transformation industries for heating, pumping, traction, and lighting purposes.

[3] We use the term sector to refer to domestic production of electricity and the required infrastructure.