# Can renewable energies with learning-by-doing compete with forest sequestration to cost-effectively meet the EU carbon target for 2050?

*Miriam Münnich Vass*

Swedish University of Agricultural Sciences (SLU)
Department of Economics / Institutionen för ekonomi

Working Paper Series 2015:04
Uppsala 2015

ISSN 1401-4068
ISRN SLU-EKON-WPS-15/04-SE

## Abstract

Renewable energies have great potential to contribute to $CO_2$ emission reductions by substituting for fossil fuels. This study examines whether renewable energies with learning-by-doing technical change can compete with forest sequestration to cost-effectively achieve the EU carbon target for 2050. Cost-effective abatement solutions are obtained from a dynamic, partial equilibrium model that accounts for three kinds of mitigation options: renewable energies and abatement in the forest and fossil fuel sectors. The results show a net present cost of reaching the target of approximately 286 billion Euros and a carbon price of 364 Euro/ton $CO_2$ in 2050. Furthermore, the stock of renewables in 2050 can deliver twice as much as the current electricity production from renewables, which implies a contribution of 8.7% to meeting the emissions target. However, the cost per unit emissions reduction is at least fifteen-fold higher for renewables than for forest sequestration. Hence, the results indicate that renewables are unable to compete with forest sequestration unless they receive continued government support.

*Key words: cost-effective, EU climate policy, forest sequestration, learning-by-doing, renewable energies.*

# 1. Introduction

Renewable energies except bioenergy are carbon-free. Hence, they have great potential to contribute to $CO_2$ emissions reductions by substituting for fossil fuels and reducing Europe's dependence on imported energy sources, which may cause political tensions. However, renewable energies are relatively costly, and accordingly, their share in European energy and electricity consumption is comparatively low, 14.1% and 23.5%, respectively (Eurostat 2014). The largest contribution derives from hydro power, followed by wind power, bioenergy and solar photovoltaic (PV) energy (Eurostat 2012). The cost of renewables is expected to fall in the future due to technological developments, which are driven in particular by government policy to reduce emissions and factors affecting the accumulation of knowledge and experience (e.g. IEA 2008; Hoefnagels et al. 2011).

In view of the cost reductions possible with technological development, renewable energies could potentially be part of a cost-effective strategy to combat climate change. The European Commission (2011) has proposed a roadmap to achieve a competitive low carbon economy by 2050. The objective is to reduce $CO_2$ emissions cost-effectively by 80-95% compared with the level in 1990. Consequently, low cost abatement methods such as forest sequestration (Murray et al. 2009; Sohngen 2009; Gren et al. 2012; Munnich Vass and Elofsson 2013) need to be recognised.

The aim of this study is to examine the potential contribution from renewable energies, with learning-by-doing (LBD) technical change, to cost-effectively achieve the EU emissions target for 2050 with forest sequestration as an alternative abatement method. The analysis only considers additional sequestration, defined as the amount of sequestration achieved when forest harvesting is reduced compared with the current level. Here, LBD can contribute to continuous reductions in both the investment cost and running costs of renewables, depending on previous experience in using the technology and its maturity. LBD means that the optimal allocation of abatement across technologies is determined not only by the marginal effect of current abatement on current cost, but also on the effect of current abatement on all future costs. This has implications for optimal carbon policy design.

A dynamic partial equilibrium model is developed in which abatement costs are minimised subject to the 2050 $CO_2$ emissions target. Dynamic cost functions are estimated for this purpose for solar PV, wind and hydro power in each EU member state. Building a dynamic model that covers several decades is particularly useful in that it provides the possibility to analyse the consequences of technological change on the cost of renewables.

Endogenous technological change can be modelled in several ways and includes LBD, learning-by-researching and learning-by-using (Kahouli-Brahmi 2008). The motive for focusing on LBD in this study is specifically its inherent nature, implying that developments occur naturally with experience in using the technology. With respect to renewables, with varying maturity, it is interesting to quantify the implications of LBD on costs. Lately, LBD has been introduced in energy-environment-economy models (see Kahouli-Brahmi (2008) for a review). However, the way it is introduced into models differs. Goulder and Mathai (2000) introduced it in the abatement cost function to address the significance of policy-induced technological change for the design of cost-efficient abatement policies. Their theory has since been advanced by e.g. Rosendahl 2004; Bramoullé and Olson 2005. In a recent application by Lindqvist and Gren (2013), this approach was used for assessing the cost-efficiency of different marine abatement options. In the present study, LBD is introduced as suggested in the theoretical work of Bramoullé and Olson (2005). It also extends the work by Lindqvist and Gren (2013) by having the learning rate differentiated between technologies and using an alternative cost function combined with a dynamic renewable energy function. This study thus develops previous research in quantifying the effect of LBD on the cost-effectiveness of different renewables.

The contribution of this paper to the literature is threefold: *1)* It introduces LBD into the cost function to empirically assess its impact on the cost-effective level of investment in renewables energy in the EU; *2)* it determines the cost-effectiveness between renewable energies and forest sequestration; and *3)* it helps understand the implications on technological development of introducing low-cost (forest sequestration) abatement options in EU climate policy.

The paper starts with a theoretical background in section 2, followed by a description of the dynamic programming model in section 3. Empirical functions and associated data are presented in section 4. Section 5 presents the empirical results, which are discussed and conclusions are drawn in section 6.

## 2. Theoretical background

The modelling approach in this paper is related to previous work in the field of cost-effective abatement strategies to reduce greenhouse gas emissions in both the energy sector, with technical change over time, and the forest sector (Sohngen and Mendelsohn 2003; Rokityanskiy et al. 2007; Tavoni et al. 2007; Hedenus and Azar 2009). The main differences between these models relate in particular to the type of modelling used; top-down versus bottom-up. Top-down models, such as that employed here, are used to evaluate the cost competitiveness of mitigation options and the implications across markets, sectors and regions over time (e.g. Sohngen and Mendelsohn 2003). Bottom-up models are based on detailed technological engineering, process and cost data for individual technologies applied at specific locations (e.g. Rokityanskiy et al. 2007; Hedenus and Azar 2009). Consequently, bottom-up models generally assess how much mitigation is available at a given carbon price, while top-down models estimate how much mitigation is used to achieve the given target at the lowest cost (Rose et al. 2012). Tavoni et al. (2007) uses a hybrid modelling approach, involving a mix of top-down and bottom-up.

Moreover, models differ between studies and, in comparison with the present study, with respect to forest sequestration modelling [1] and three main energy sector aspects: *1)* Determination of the level of energy demand; *2)* calculation of energy costs; and *3)* inclusion of technological development. In our model the energy demand is determined endogenously, which is similar to the approach in Sohngen and Mendelsohn (2003) and Tavoni et al. (2007). However, energy costs are given exogenously in the model, following the approach of Rokityanskiy et al. (2007) and Hedenus and Azar (2009). Technological development is included endogenously, using LBD. This is similar to the approach in Tavoni et al. (2007). A central difference in the present model compared with previous models is the focus on renewables in European countries.

The model presented in this paper (see below) builds on that described by Munnich Vass and Elofsson (2013), with two fundamental extensions: *1)* Inclusion of dynamic stock functions for three kinds of renewable energies; and *2)* inclusion of dynamic cost functions for renewables, where the dynamics are based on LBD.

[1] For differences in modelling approaches with regard to sequestration in previous studies, see Munnich Vass and Elofsson (2013).

## 3. Model

This section develops a dynamic, partial equilibrium model to obtain cost-effective solutions to reach the EU 2050 carbon emissions target. The abatement strategies available are: (i) Renewable energies, (ii) additional sequestration in forests, (iii) additional storage in forest products and (iv) reductions in fossil fuel and forest bioenergy consumption. Bioenergy is modelled differently from other renewable energies because of the emissions associated with harvesting, transporting, processing and combusting wood in the short run. In addition, there is an inherent connection between different abatement strategies in the forest sector, with a trade-off between forest sequestration, on the one hand, and harvesting for the production of bioenergy and forest products on the other. This makes it necessary to separate bioenergy from the other renewable energies in terms of modelling.

The level of electricity production from renewable energies in any year is determined by the invested stock and the flow of new investments. In the model, the stock of renewable energies at time $t$ is denoted $R_t^{ig}$, with $t=1\ldots T$ in country $i$, with $i=1\ldots.z$, and technology $g$, with $g=1\ldots.q$. The yearly rate of depreciation of renewable energies is denoted $\vartheta$, and is assumed to be constant throughout the policy period. This assumption is appropriate considering how costs are calculated and follows previous work by e.g. Bosetti and Maffezzoli (2013). The annual depreciation rate is determined by the payback time required by the investor, which in turn is determined by the life expectancy of the technology. Hence, in period $t+1$ the stock of renewables is equal to the remaining stock from historical investments, at the beginning of period $t$, and new investments, denoted $N_t^{ig}$, carried out during year $t$. This is calculated as follows:

$$R_{t+1}^{ig} = (1-\vartheta)R_t^{ig} + N_t^{ig}$$

$$R_0^{ig} = \overline{R}^{ig} = 0, t = 0 \ldots T-1 \qquad (1)^2$$

[2] In the model it is assumed that the cost-effective stock of renewables is zero at the start of the policy period. However, the investments made during the policy period are additional to the current real stock (Eurostat 2014), which has received government support. By the end of the policy period, the current real stock should be completely depreciated.

Renewable energies are measured in Mega Watt hours (MWh). Renewable energies, such as solar PV, wind and hydro power, have no direct impact on $CO_2$ emissions, since they are carbon-neutral. However, there is an indirect effect when renewable energies replace fossil fuels in the electricity production sector. This carbon offset is captured in the parameter $\varsigma$, which reflects the carbon content of the business-as-usual (BAU) mix of fossil fuels. The BAU mix is the combination of fossil fuel consumption in the first model year, where each fuel has a specific share in the total. Net reductions in emissions by use of renewable energies are hence calculated as:

$$W_t^i = \varsigma \sum_g R_t^{ig} \tag{2}$$

The amount of carbon dioxide that can be sequestered in forests each year is determined by the volume of standing biomass, $V_t^i$. The biomass volume in period *t+1* is determined by the volume in period *t*, the annual growth in standing biomass, $G^i(V_t^i)$, and the annual harvest, $H_t^i$, which takes place at the end of the year as follows:

$$V_{t+1}^i = V_t^i + G^i(V_t^i) - H_t^i \tag{3}$$

$$V_0^i = \overline{V^i}$$

where $\overline{V^i}$ is the actual volume in each country during the initial year and $G^i(V_t^i)$ is a continuous function, quasi-concave in $V_t^i$. The variables, $V_t^i$, $G^i(V_t^i)$ and $H_t^i$ are all measured in cubic metres. Furthermore, it is assumed that the area of forest land in each country remains constant over the entire policy period, which means that land currently used for other purposes cannot be converted to forest land. This assumption is made to avoid interference with other sectors such as agriculture, which is not part of the model.

Harvested biomass can either be used for bioenergy, $B_t^i$, or forest products, $F_t^i$, which includes all products made of wood such as timber, pulp and paper. Thus, the amounts of bioenergy and forest products are determined endogenously by the yield level as follows:

$$H_t^i = B_t^i + F_t^i \tag{4}$$

Forest bioenergy and forest products are both measured in cubic metres. It is assumed in the model that the levels of bioenergy and forest products are constant at the BAU level when there is no emissions reduction target. The BAU level is the unregulated quantity produced and consumed during the first model year.

Emissions from bioenergy are determined by three factors: *1)* The carbon content of wood released to the atmosphere during combustion, $\eta^i$; *2)* emissions from harvesting, transporting and processing bioenergy, denoted $\varphi$; and *3)* the carbon offset, which is due to the replacement of fossil fuels, denoted $\gamma$. These emissions and offsets are assumed to take place in the same period as the biomass is harvested. Net emissions from bioenergy are then calculated as:

$$L_t^i = (\eta^i + \varphi - \gamma)B_t^i \tag{5}$$

Net storage of carbon in forest products is determined by two factors: *1)* The carbon content of wood, $\eta^i$ and *2)* emissions associated with harvesting, transporting and processing forest products, $\varphi$, which are equivalent to the amount released from bioenergy. The net amount of carbon stored in forest products is hence calculated as:

$$M_t^i = (\eta^i - \varphi)F_t^i \tag{6}$$

Net annual forest sequestration, $S_t^i$, is calculated as the difference in biomass volume between years. This volume is multiplied by the carbon content of wood, $\eta^i$, which turns volume into metric tonnes (ton) of $CO_2$ emissions removed from the atmosphere. Forest sequestration is calculated as follows:

$$S_t^i = \eta^i (V_{t+1}^i - V_t^i) \tag{7}$$

Emissions to the atmosphere from combustion of fossil fuels are determined by the quantity of fossil fuels consumed, $X_t^{ij}$, by fossil fuel type, $j$, with $j=1\ldots q$. This quantity is measured in ton oil equivalents (toe) and is converted to $CO_2$ emissions by the parameter $\alpha^j$ for each fossil fuel:

$$Q_t^i = \sum_j \alpha^j X_t^{ij} \tag{8}$$

The overall level of energy consumption is determined endogenously by the model, which means that an increase in renewable energy or a decrease in bioenergy does not affect the level of fossil fuel consumption and vice versa. This assumption differs from the exogenous approach in some energy sector models such as that presented by Hedenus and Azar (2009), where the consumption level is determined by results from another model. The main reason for assuming endogenous energy demand is in order to focus on abatement potential among different technologies, rather than building a fully-fletched energy sector model where energy technologies substitute for each other. The latter has been done by a number of others (e.g. Capros and Mantzos 2000; Azar et al. 2003; Kitous et al. 2010).

Net emissions to the atmosphere are then calculated as follows:

$$E_t = \sum_i (Q_t^i + L_t^i - M_t^i - W_t^i - S_t^i) \quad (9)$$

Net emissions must be lower or equal to the emissions target, $E_T^{MAX}$ , in the final year, *T*. This target is determined by EU climate policy to be achieved by 2050 and stated in terms of a maximum amount of $CO_2$ in the atmosphere:

$$E_T \leq E_T^{MAX} \quad (10)$$

Technological change in renewable energies is modelled so that it affects their cost over time. The specification stems from Bramoullé and Olsson (2005) and is calculated as follows:

$$Z_t^{ig} = Z_0^{ig} + \sum_{\tau=0}^{t-1} N_\tau^{ig} \quad (11)$$

where $Z_t^{ig}$ is the stock of knowledge or the level of experience in using a certain technology in a country, at time *t*. This stock is determined by the initial level of experience, $Z_0^{ig}$ , and the sum of experience gained from all previous investments in this technology, $N_\tau^{ig}$ , where $\tau$ refers to previous time periods. The cumulative level of abatement by a technology in a country is thus regarded as a measure of experience. In this formulation there is no spillover in experience between countries in using a technology. This assumption is similar to that in Watanabe (1995) and Lindqvist and Gren (2013).

The cost function for renewable energies is assumed to have constant elasticity. This function is increasing and convex in renewable energies and decreasing and convex in experience. The learning implies that the cost of renewable energies is reduced, at a decreasing rate, and that the benefit of experience is higher for infant technologies than for mature technologies. The cost function is expressed as follows:

$$C_t^{iR}(R_t^{ig}, Z_t^{ig}) = (\psi^{ig} R_t^{ig} + \theta^{ig} R_t^{ig^{\beta}}) Z_t^{ig^{-\varpi^g}} \tag{12}$$

where $\psi^{ig} > 0$, $\theta^{ig} > 0$, $\beta > 1$, $\varpi^g > 0$ and $\beta > \varpi^g + 1$. Given a certain $Z_t^{ig}$, the parameters $\psi^{ig}$ and $\theta^{ig}$ determines the slope of the cost function ; $\beta$ is the exponent that determines the curvature and $\varpi^g$ is the learning rate, which differs between technologies. The constant elasticity cost function has the standard learning curve properties, meaning that each doubling of experience leads to a reduction in costs by a fixed factor, $2^{-\varpi}$.

Forest sequestration above the BAU level is achieved through costly reductions in bioenergy or forest products. The BAU sequestration is the amount that would occur if the level of bioenergy and forest products remained at the constant BAU level throughout the policy period. The costs incurred by forest owners for reducing the provision of bioenergy and forest products are denoted $C_t^{iB}(\widehat{B} - B_t^i)$ and $C_t^{iF}(\widehat{F} - F_t^i)$, where $\widehat{B}$ and $\widehat{F}$ are the constant BAU levels, respectively. The cost of reducing fossil fuels is calculated similarly and denoted $C_t^{iX}(\widehat{X} - X_t^i)$, where $\widehat{X}$ is the BAU level of fossil fuel consumption, i.e. the consumption in the first year. These cost functions are all assumed to be continuous, decreasing and convex in $B_t^i, F_t^i, X_t^i$.

The decision problem of the policy maker under the EU 2050 scenario is then formulated as the minimisation of total abatement costs in present value terms:

$$\underset{N_t^{ig}, B_t^i, F_t^i, X_t^{ij}}{Min} \quad TC = \sum_t \sum_i \rho^t \begin{pmatrix} \sum_g C_t^{iR}(R_t^{ig}, Z_t^{ig}) + C_t^{iB}(\widehat{B}^i - B_t^i) + \\ C_t^{iF}(\widehat{F}^i - F_t^i) + \sum_j C_t^{iX}(\widehat{X}^{ij} - X_t^{ij}) \end{pmatrix} \tag{13}$$

subject to (1)-(12) and to the following restrictions:

$0 \leq N_t^{ig}$ $\forall i, g, t$

$0 \leq B_t^i \leq \widehat{B}^i$ $\forall i, t$

$0 \leq F_t^i \leq \widehat{F}^i$ $\forall i, t$

$0 \leq X_t^{ij} \leq \widehat{X}^{ij}$ $\forall i, j, t$

where $\rho = \frac{1}{(1+\delta)}$ is the discount factor and, $\delta$ , is the discount rate.

The decision problem (13) is solved using the dynamic Lagrangian for discrete time. The focus is on an interior solution and the resource Equations (1) and (2) enter as binding constraints.

$$L = \sum_t \sum_i \rho^t \begin{bmatrix} \sum_g ((\psi^{ig} R_t^{ig} + \theta^{ig} R_t^{ig\,\beta})(Z_0^{ig} + \sum_{\tau=0}^{t-1} N_\tau^{ig})^{-\varpi^g}) + C_t^{iB}(\widehat{B}^i - B_t^i) + \\ C_t^{iF}(\widehat{F}^i - F_t^i) + \sum_j C_t^{iX}(\widehat{X}^{ij} - X_t^{ij}) - \\ \sum_g \rho \chi_{t+1}^{ig}((1-\vartheta) R_t^{ig} + N_t^{ig} - R_{t+1}^{ig}) - \\ \rho \mu_{t+1}^i (V_t^i + G^i(V_t^i) - (B_t^i + F_t^i) - V_{t+1}^i) - \end{bmatrix}$$
$$\rho^T \lambda_T (\sum_i (-\sum_j \alpha^j X_T^{ij} - (\eta^i + \varphi - \gamma) B_T^i + \varsigma \sum_g ((1-\vartheta) R_{T-1}^{ig} + N_{T-1}^{ig}) +$$
$$(\eta^i - \varphi) F_T^i + \eta^i (V_T^i - V_{T-1}^i)) + E_T^{MAX}) \qquad (14)$$

where, $\chi_t^{ig}$ , $\mu_t^i$ and $\lambda_T$ are the Lagrangian multipliers. Note that the first and the third multipliers are positive, while the second can be either positive or negative. These multipliers are the shadow costs for the stock of renewable energies, standing biomass volume and the emissions target in the final year, respectively. The shadow cost for the emissions target illustrates the cost-efficient level of a carbon tax or, equivalently, the allowance price under an emissions trading system.

Equations (1)-(12) define a convex optimisation problem and hence the cost-effective allocation of emissions reductions can be determined from the solution to (13). The necessary first order conditions for cost minimisation, assuming an interior solution, which gives the optimal allocation of $N_t^{ig}, B_t^i$, $F_t^i$ and $X_t^{ij}$ can then be derived. Appendix A shows how the derivative of the cost function for renewable energies is determined. The first order conditions for the Lagrange multipliers, $\chi_t^{ig}, \mu_t^i$ and $\lambda_T$ , return the same equations as in (1), (3) and (9) and are hence not shown here.

$$\frac{\partial L}{\partial N_t^{ig}} = \rho^t \begin{bmatrix} (\psi + \beta\theta^{ig} N_t^{ig^{\beta-1}})(Z_0^{ig} + \sum_{\tau=0}^{t-1} N_\tau^{ig})^{-\omega^g} - \\ \omega^g \sum_{\tau=t+1}^{T} \rho^\tau (\psi^{ig} R_\tau^{ig} + \theta^{ig} R_\tau^{ig^\beta})(Z_0^{ig} + \sum_{\tau=0}^{\tau-1} N_\tau^{ig})^{-\omega^g-1} - \\ \rho\chi_{t+1}^{ig} - \rho^{T-t}\lambda_T\varsigma \end{bmatrix} = 0 \tag{15}$$

$$\frac{\partial L}{\partial R_t^{ig}} = \rho^t \begin{bmatrix} (\psi + \beta\theta^{ig} R_t^{ig^{\beta-1}})(Z_0^{ig} + \sum_{\tau=0}^{t-1} N_\tau^{ig})^{-\omega^g} - \\ \omega^g \sum_{\tau=t+1}^{T} \rho^\tau (\psi^{ig} R_\tau^{ig} + \theta^{ig} R_\tau^{ig^\beta})(Z_0^{ig} + \sum_{\tau=0}^{\tau-1} N_\tau^{ig})^{-\omega^g-1} - \\ \rho\chi_{t+1}^{ig}(1-\vartheta) + \chi_t^{ig} - \rho^{T-t}\lambda_T\varsigma(1-\vartheta) \end{bmatrix} = 0 \tag{16}$$

$$\frac{\partial L}{\partial B_t^i} = \rho^t \left[ \frac{\partial C_t^{iB}(\hat{B}^i - B_t^i)}{\partial B_t^i} + \rho\mu_{t+1}^i + \rho^{T-t}\lambda_T(\eta^i + \varphi - \gamma) \right] = 0 \tag{17}$$

$$\frac{\partial L}{\partial F_t^i} = \rho^t \left[ \frac{\partial C_t^{iF}(\hat{F}^i - F_t^i)}{\partial F_t^i} + \rho\mu_{t+1}^i - \rho^{T-t}\lambda_T(\eta^i - \varphi) \right] = 0 \tag{18}$$

$$\frac{\partial L}{\partial V_t^i} = \rho^t \left[ \mu_t^i - \rho\mu_{t+1}^i(1 + \frac{\partial G^i}{\partial V_t^i}) - \rho^{T-t}\lambda_T\eta^i \right] = 0 \tag{19}$$

$$\frac{\partial L}{\partial X_t^{ij}} = \rho^t \left[ \frac{\partial C_t^{ij}(\hat{X}^{ij} - X_t^{ij})}{\partial X_t^{ij}} + \rho^{T-t}\lambda_T\alpha^j \right] = 0 \tag{20}$$

### 3.1 Marginal cost of renewables

Equation (15) can be rewritten in order to show the effect of LBD on the abatement cost over time:

$$
\begin{aligned}
&(\psi + \beta\theta^{ig} R_t^{ig^{\beta-1}})(Z_0^{ig} + \sum_{\tau=0}^{t-1} N_\tau^{ig})^{-\omega^g} = \\
&\omega^g \sum_{\tau=t+1}^{T} \rho^\tau (\psi^{ig} R_\tau^{ig} + \theta^{ig} R_\tau^{ig^\beta})(Z_0^{ig} + \sum_{\tau=0}^{\tau-1} N_\tau^{ig})^{-\omega^g-1} + \rho\chi_{t+1}^{ig} + \rho^{T-t}\lambda_T \varsigma
\end{aligned}
\tag{21}
$$

The left-hand side of (21) shows that the marginal cost of abatement in renewables at time *t* has been decreased by the cumulative learning effect from abatement by renewables in all previous periods. The right-hand side consists of three factors. The first shows the effect on future abatement cost of investing in renewables in period *t*. The second shows the discounted marginal value of investments in renewables, which reflects the impact on the stock of renewables in period *t+1* of investing in an additional unit in period *t.* The third factor shows the discounted shadow cost of the emission target, multiplied by the impact on emissions of one unit abatement by renewables. The optimal level of abatement in period *t* requires the marginal cost of abatement by renewables to equate to the impacts on emissions in the final period, *T,* when $\lambda_T$ is different from zero and when the cost has been adjusted for the cumulative marginal saving that current abatement has on future cost and the marginal value of investments in renewables.

### 3.2 Marginal cost of bioenergy, forest products and fossil fuels

Equation (17), (18) and (20) can be rewritten in terms of the marginal cost of an additional unit of reduction in bioenergy, forest products and fossil fuels in period *t:*

$$
\frac{\partial C_t^{iB}(\hat{B}^i - B_t^i)}{\partial B_t^i} = -\rho^{T-t}\lambda_T(\eta^i + \varphi - \gamma) - \rho\mu_{t+1}^i
\tag{22}
$$

$$\frac{\partial C_t^{iF}(\hat{F}^i - F_t^i)}{\partial F_t^i} = \rho^{T-t}\lambda_T(\eta^i - \varphi) - \rho\mu_{t+1}^i \tag{23}$$

$$\frac{\partial C_t^{ij}(\hat{X}^{ij} - X_t^{ij})}{\partial X_t^{ij}} = -\rho^{T-t}\lambda_T\alpha^j \tag{24}$$

The marginal cost of reducing bioenergy, forest products and fossil fuels is determined by the discounted shadow costs of the emissions target, $\lambda_T$ , multiplied by their respective impacts on net emissions. The effect of reductions in bioenergy and fossil fuels means that net emissions to the atmosphere are reduced, while the reduction in forest products means that fewer carbon emissions are stored in products. The marginal cost of reducing bioenergy and forest products in (22) and (23) is also determined by the discounted shadow cost of the stock of biomass, $\rho\mu_{t+1}^i$. This cost is the marginal user cost of harvesting an additional unit in period *t*, due to the impact it has on the forest stock, accompanying stock growth and hence sequestration in the next period. The marginal user cost is either positive or negative and is determined by the shape of the forest growth function.

### *3.3 The dynamics of abatement*

The model set-up has implications on the dynamics of abatement. First, the introduction of a discount factor mean that the abatement cost for all abatement options is falling over time in present value terms, implying a postponement of abatement. Second, the effect of LBD on the timing of abatement by renewable energies is ambiguous, since there are two counteracting forces. On the one hand, the learning component of the cost curve reduces future abatement costs, which implies a postponement of abatement. On the other hand, early abatement leads to the accumulation of experience, which in turn reduces future costs. Analytically it is unclear which of these effects will dominate the timing of abatement, as pointed out by Goulder and Mathai (2000), Rasmussen (2001), Manne and Richels (2004) and Bramoullé and Olson (2005). Third, the shadow value of investments in renewables, $\chi_t^{ig}$, is increasing over time as can be seen in equation (16), which means that the marginal cost of abatement by renewables is increasing, implying that abatement is brought forward. Fourth, abatement is decreasing when the shadow cost of the emission target is increasing. A positive Lagrangian multiplier, $\lambda_T$, therefore implies that abatement is brought forward. Fifth, the user cost of harvesting an additional unit today, $\mu_t^i$, in equation (19) can either increase or decrease over time depending in particular on the size of forest growth in relation to the discount rate. The implication of an increasing (decreasing) $\mu_t^i$ is that the marginal cost of reducing bioenergy and forest products in favour of sequestration is increased (reduced) over time. This means that sequestration is brought forward (postponed). Due to these counteracting forces, an empirical analysis is needed to understand the different driving forces. Hence, the empirical functions and accompanying data are described next.

# 4. Empirical functions and data

In the present application, the empirical model is divided into yearly time periods and run until 2060[3] with the same emissions constraint every year after 2050 to achieve realistic terminal conditions. All costs are discounted with a 3% annual discount rate for all 27 EU countries. This rate is in between the rates given in Stern (2007) and Nordhaus (2007), who have different views on the appropriate discount rate in models that analyse the cost-effective allocation of carbon abatement over time. The empirical model is set up in GAMS, using the CONOPT3 solver for all calculations (Brooke et al. 1998).

## *4.1 The stock of renewable energies*

The stock of renewable energies available each year in the 27 EU countries is determined by previous investments, yearly depreciation and current investments. The rate of depreciation of the different technologies – solar PV, wind and hydro power - is calculated from the payback time required by investors in the technologies. The depreciation rate is assumed to be 35% per year, since the payback time is 15 years for all technologies and countries in Faber et al., (2009)[4], which is the source of the cost data used. These data are taken from the Green-X

[3] Results are only shown for the policy period 2010-2050. The analytical model in section 3 is written with a single emission restriction in 2050 for simplicity.
[4] The data on the CD-ROM is updated from a previous version, but the methodology behind the cost-resource curves is the same as in the first version and is described in detail in Ragwitz et al. (2003)

database and have been used in a number of studies (e.g. Resch et al. 2006, 2008; Hoefnagels et al. 2011). The depreciation rate is important for the overall results and therefore a sensitivity analysis on the assumption is performed (see section 5.1).

The amount of emissions avoided by replacing fossil fuels with renewables is calculated similarly to Sims et al. (2003) and van Vuuren et al. (2007), where it is assumed that renewables will replace in particular coal- and gas-fired power plants. The net reductions in emissions by renewables in the present model are based on the replacement of a combination of fossil fuels, where each fuel has its own emissions coefficient. The combination is based on the weighted average emissions factor for coal, oil and gas, where the weights are the initial 2010 levels of these fuels. The calculated carbon offset factor for renewables is given in Appendix B.

### *4.2 The cost of renewable energies*

The shape of the dynamic cost functions for renewable energies is determined from static marginal cost functions, for which data is available from the Green-X database. This data has been compiled by a consortium of researchers in Europe (Faber et al. 2009). The marginal cost functions in the database increase step-wise reflecting cost and resource potentials at band level. Each band has the same economic, technical, social and geographical conditions. The methodology used for calculating these marginal cost functions is the same for each technology and EU country and is described in detail in Appendix C.

Renewable energies are characterised by having a comparatively high investment cost and a relatively low running cost. In order to verify the accuracy of the marginal cost data used, they are compared against other sources. The cost range of wind power used is 45-115 Euro/MWh, with the lowest cost found in Germany and the highest in Austria. This range is in line with estimates from the European Wind Energy Association (2009) of 50-110 Euro/MWh. Similarly, the cost range for hydro power used here is 25-190 Euro/MWh, with the lower figure found in Estonia and the higher in Belgium and the Netherlands. This can be compared against the figure of 20-80 Euro/MWh in Ecofys (2008), which is said to increase. For solar PV, the range used is 300-1250 Euro/MWh with the lowest in Spain and the highest in the Baltic States. The global cost range is estimated to be 190-570 Euro/MWh (IEA 2010), with the highest cost found in Europe.

From the step-wise marginal cost-resource curves, it is possible to econometrically fit static marginal cost functions for each technology and country using the statistical software Minitab. Static marginal cost functions are thus fitted for solar PV, small-scale hydro power and onshore wind power. These marginal cost functions are assumed to be quadratic and have the following form:

$$C^{ig} = a^{ig} + b^{ig}(R^{ig})^2 + \varepsilon^{ig} \tag{25}$$

where $a^{ig}$ is the intercept and $b^{ig}$ is the coefficient, representing the fixed investment cost and the slope of the marginal cost curve, respectively. The estimated intercepts and coefficients are presented in Appendix D (Table D1-D3) together with the econometric results from fitting these functions to the data. Appendix D (Figure 10 and 11) shows the fit of the curve to the data for France, which is a large investor in renewable energies. The fit is good for most countries and technologies, based on the standard error estimate and the summary statistics.

To form the dynamic cost functions in equation (12), the marginal cost function is integrated and the parameter $\psi^{ig}$ in (12) is replaced by the estimated intercept $a^{ig}$ and the coefficient $\theta^{ig}$ is replaced by the estimated coefficient, $\frac{b^{ig}}{3}$. In addition, the exponent $\beta$ in (12) is replaced by the number 3, which stem from the integration of the quadratic marginal cost function. The dynamics is then introduced in (12) as a cost reduction, based on the increases in experience in a technology $Z_t^{ig}$ .

The learning rate, $\varpi^g$, in the dynamic cost functions influences the cost of abatement by renewable energies. For each doubling of experience, the cost of renewable energies is reduced by a fixed amount, $2^{-\varpi^g}$ . Estimation of learning rates in the field of renewable energies has a fairly long history and the literature is vast. In general, learning rates vary depending on the specific technology, geographical location and period referred to. A study by Neij (2008) gives different learning rates for solar PV, ranging from 10-47%, with an average of 20%. De Noord et al. (2004) and McDonald and Schrattenholzer (2001) report the same average learning rate of 20%, while the IEA (2010) technology roadmap for solar PV quotes an average of 18%. Hydropower is viewed as a mature technology that is already cost-competitive on the market (IRENA 2012c). However, McDonald and Schrattenholzer (2001) quote a learning rate of 1.4% and Kahouli-Brahmi (2008) report 0.40-1.96%. The learning rate for onshore wind power varies between studies. Junginger et al. (2004) report 15-19% and Hoefnagel et al. (2010) report a range from previous literature of 0-19%. Others (McDonald and Schrattenholzer 2001; Neij 2008) report lower learning rates, in the range 6-8%. In the present study, it is assumed that the learning rate for solar PV is 20%, hydro power 1% and wind power 15%. These rates are varied in the sensitivity analysis due to their importance for the model. It is also assumed that renewables only can triple in size each year, in each country, which implies that investments will be brought forward in time compared with a case without this restriction.

### *4.3 Abatement in the forest sector*

Forest sequestration is modelled at aggregate level in each country. Biomass in standing forest is based on a representative stand of one hectare comprising a constant mix of tree species of average age, in each country. The volume on this stand is multiplied by the forest area, which is then converted to $CO_2$ emissions by the carbon content of wood $\eta^i$ (see Appendix B). The calculation of biomass volume in Equation (3) is based on an exponential function, which is described in Appendix E.

The harvested biomass is assumed to be used for either bioenergy or forest products, where bioenergy produces electricity and/or heating and hence replaces fossil fuels. The amount of emissions avoided by the replacement is calculated similarly as for renewable energies. This carbon offset parameter, $\gamma$, can be found in Appendix B together with emissions related to harvesting, transporting and processing biomass, $\varphi$.

### *4.4 Cost functions for reducing bioenergy, forest products and fossil fuels*

The cost of reducing bioenergy and forest products, for the benefit of increased forest sequestration, is defined as reductions in producer and consumer surpluses. This approach follows Adams et al. (1996, 1999), Alig et al. (1997), Gren et al. (2012) and Munnich Vass and Elofsson (2013). Reductions in producer surplus are foregone producer profits and reductions in consumer surplus are foregone consumption value of the same products.

The costs of fossil fuel reductions are calculated similarly to the cost of reducing bioenergy and forest products, except that it only includes reductions in consumer surplus for three main classes of fossil fuel products; oil, coal and natural gas. It is assumed that the EU is a price taker on the world market of fossil fuels, implying a perfectly elastic supply function and hence no producer surplus (Gren et al. 2012; Munnich Vass and Elofsson 2013).

Restrictions are imposed on bioenergy, forest products and fossil fuels by an upper quantity bound, constant over time and equal to the BAU level of production/consumption, and a lower bound equal to zero. The reduction in these three product categories can only be 20% per year, which means that reductions will be carried out earlier in the policy period compared with a case without this restriction. Quantities, prices and elasticities for the products used to calculate the cost functions, are taken from Munnich Vass and Elofsson (2013).

### *4.5 Emissions target*

Total emissions according to the model from fossil fuel and bioenergy in Europe are approximately 4.1 billion ton $CO_2$ in 2010, based on the amounts consumed and their emissions factors. The amount of emissions in 2010 reported by Eurostat (2013) is 3.8 billion ton $CO_2$ from the energy and transport sectors. The difference is likely to be due to emissions related to bioenergy, which is treated as carbon-neutral in EU climate policy. The calculation of the emissions target set for the year 2050 is based on an 80% reduction in reported emissions in 1990 of 4.3 billion ton $CO_2$ (Eurostat 2013), adjusted for the difference between model emissions and reported emissions. This means that emissions in 2050 must be below or equal to 930 million ton $CO_2$. In the results section, only the additional amount of sequestration in forests and forest products is presented, meaning that the BAU sequestration is deducted in all calculations. Similarly, the results only consider reductions in emissions from reduced bioenergy use, where the amount is reduced from the BAU level.

## 5. Results of cost-effective solutions

The cost-effective abatement path to 2050 in the EU is described below. The development of the stock of renewable energies is shown in Figure 1[5]. There is no stock of solar PV at any time up to 2050. This is mainly explained by its relatively high initial cost, but also by low learning and depreciation rates in relation to cost. Hence, solar PV is not a cost-effective abatement option during the policy period. However, wind power and hydro power increased at a growing rate. There are two factors that explain the dramatic increases towards the end of the policy period, when the target date is approaching: *1)* The discount rate[6], which makes it cheaper to invest the longer the policy period has progressed; and *2)* the learning rate, meaning that the cost falls with increased experience in a technology. Hence, the results point towards a delay in abatement by renewable energies, despite the fact that learning-by-doing means that early abatement reduces future costs.

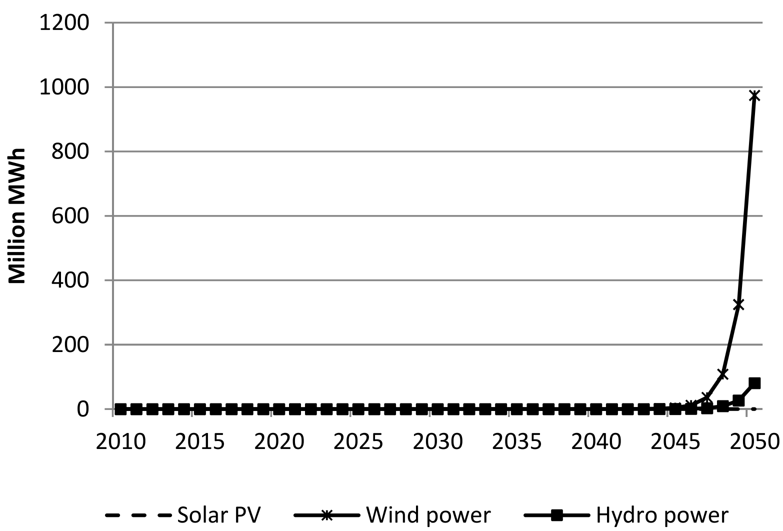



***Fig. 1*** *Changes in the stock of renewable energies in all 27 EU countries to 2050*

[5] This is the cost-effective stock, which is in addition to the real stock in 2010 of 539 million MWh (Eurostat 2014)

[6] When varying the discount rate from 3 to 1%, the implication for the stock of renewables is that there is a slightly lower level of investment throughout the period, implying that the learning rate has a smaller effect. In 2050 the stock delivers 1032 million MWh instead of 1055 million MWh.

The stock of renewable energies in 2050 can deliver 1055 million MWh electricity, with 974 million MWh from wind power and the rest from hydro power. This means a reduction of 274 million ton $CO_2$ based on fossil fuel substitution. This amount can contribute to approximately 8.7% of the emissions reduction required by 2050, when the reduction is from the BAU level, i.e. the same amount of emissions as in 2010. The reported electricity production in 2010 from solar PV, wind and hydro power amounted to 539 million MWh (Eurostat 2014), where the majority is derived from hydro power. The changes in the stock of renewable energy can be compared against results from other models. In Knopf et al. (2013) 13 different models are used to analyse the technology pathway to achieve the 2050 emission reduction target for the EU. As in the present study, they found that wind power will experience the largest increase during the policy period. Hydro power will remain more or less constant and solar PV will increase moderately. The different models estimated that wind power will increase on average seven-fold between 2010 and 2050 and that wind power together with solar PV will contribute on average 27% to the emissions reduction target in 2050. This share is higher than the estimate in the present study. The discrepancy can be due to a number of factors apart from model construction, including differences in initial costs of renewable energies, learning and depreciation rates.

The amount of annual investment in renewable energies varies considerably between EU countries due to cost differences. Figure 2 shows how total investments over the entire policy period in wind power are distributed among the 27 EU countries. The diagram shows that large emitting countries, such as Germany, France, Italy and the UK, generally also invested the most. However, the proportion of investment relative to the BAU emissions level varies. For example, in France the proportion of investments to emissions is 19%, when measured in the same units, which is five times as much as in Germany.

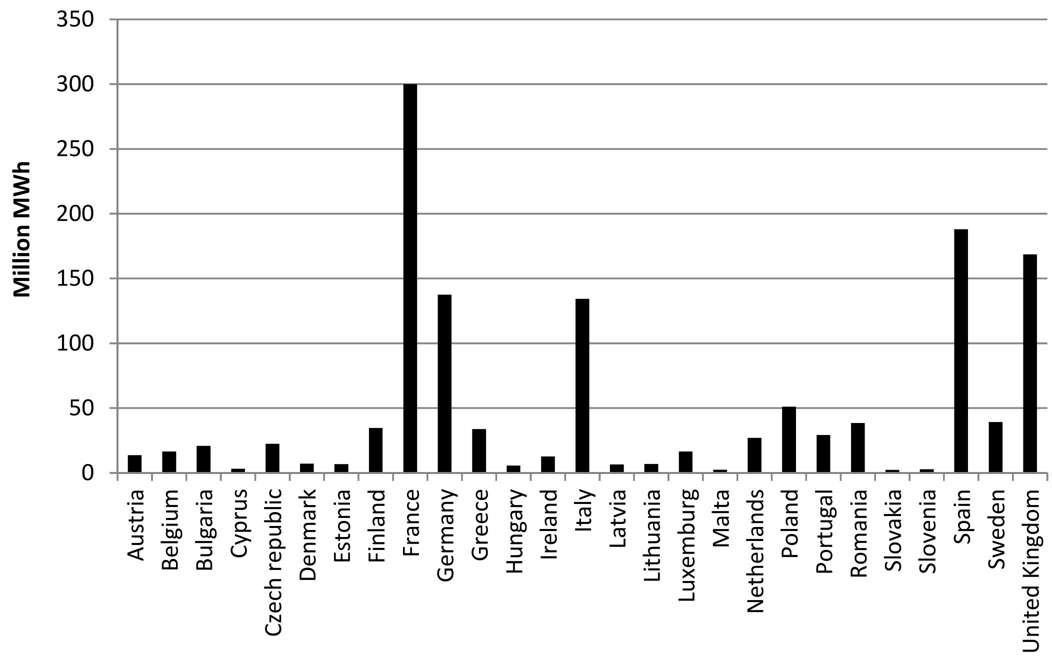



***Fig. 2*** *Total annual investments in wind power to 2050 in the 27 European countries*

The total amount of sequestration in forests and carbon storage in forest products is shown in Figure 3 as optimal sequestration. This is plotted against the BAU sequestration, which is the amount achieved when bioenergy and forest product production is assumed to be constant throughout the policy period at the 2010 level. The difference between the two lines is the additional sequestration, which can be considered to be abatement. Both lines are increasing over time and follow each other closely until 2037, when optimal sequestration starts increasing at a higher rate. The large increase during the final 13 years is achieved at the expense of both bioenergy and forest products and can be explained by the fact that abatement becomes cheaper in present value terms the longer it is postponed. The difference between the two lines is 103 million ton $CO_2$ in 2050, which corresponds to 3.2% of the emissions reduction required in that year.

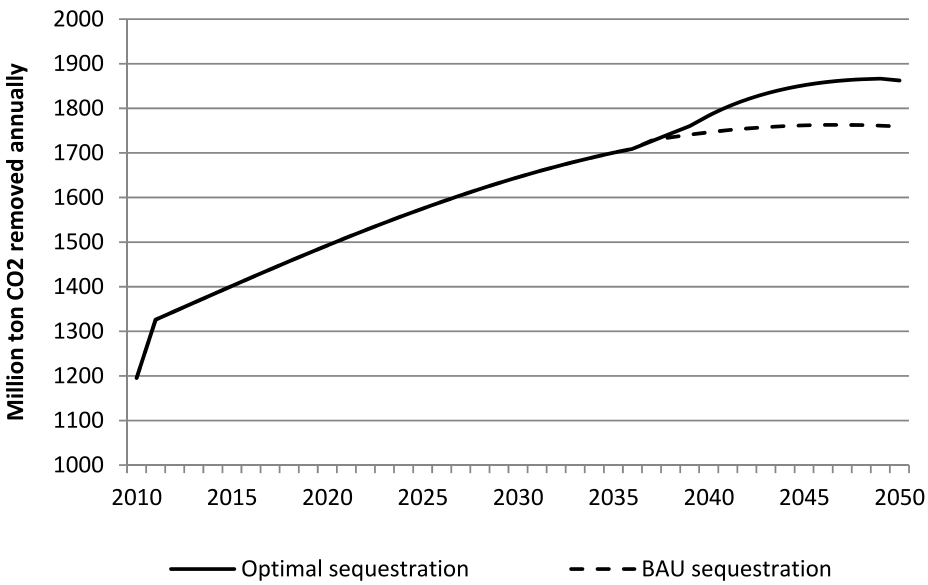



***Fig. 3*** *Annual optimal and business-as-usual (BAU) sequestration in European forests and forest products to 2050*

This is lower than the renewable energy contribution of 8.7%. The contribution is small compared with the values reported in Sohngen and Mendelsohn (2003) and Tavoni et al. (2007) who both estimated that global forest sequestration could contribute approximately 33% to carbon targets in 2100. However, the target ambitions are difficult to compare due to differences in the units used. The main explanation for the comparatively small contribution in the present study is the focus on additional sequestration on existing forest land in Europe, i.e. conversion of e.g. agricultural land to forestry is not considered an option.

The amount of sequestration mainly increases at the expense of bioenergy, which declines slowly from 2036 and is more or less phased out in 2050 (see Figure 4). This is explained by the positive net emissions associated with bioenergy and the comparatively low cost of reducing these. The phase-out of bioenergy indicates that the amount of additional sequestration has more or less reached its limit. The only possibility to increase it further would be to reduce forest products, but that is costly compared with the gain in reduced atmospheric emissions. The reduction in bioenergy, and also in forest products, means that European forests became older earlier and that higher future growth, and hence sequestration, is brought forward in time compared with the BAU case.

The change in fossil fuel consumption is also shown in Figure 4. The trend is similar for the different fossil fuels, with the level staying constant during the first decades and then being substantially reduced. The reduction starts in different years for each fuel, reflecting their respective carbon content and cost of reduction. Hence, coal, with the highest carbon content and lowest cost, is reduced earlier than oil and gas.

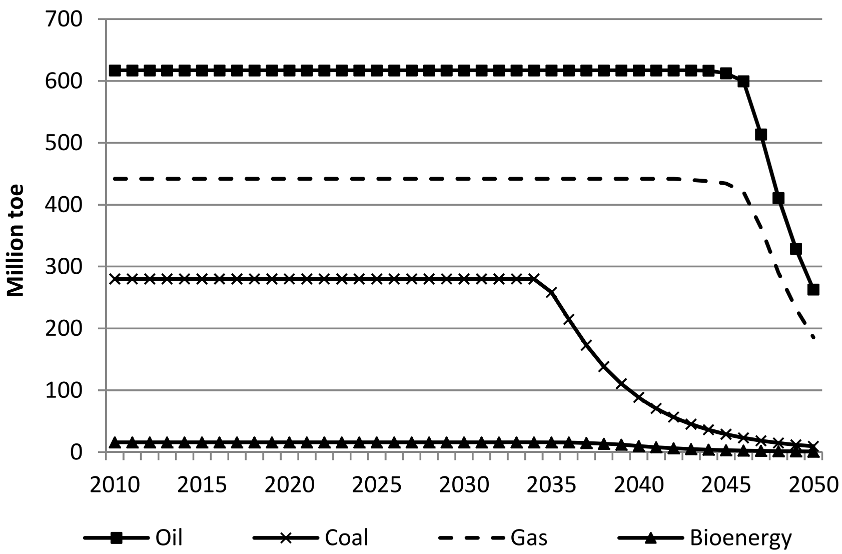



***Fig. 4*** *Change in fossil fuel and bioenergy consumption to 2050*

The changes illustrated in Figures 1-4 resulted in an overall abatement cost, in present value terms, of 286 billion Euros for reducing emissions in the EU by 80% by 2050. The majority of this cost is incurred during the last five years. If renewable energies are excluded as abatement options, the net present cost of achieving the target would increase to 374 billion Euros. Hence, there is a cost saving of approximately 31% with renewables. The carbon price in 2050, which is equivalent to the marginal cost of abatement, is estimated to be 364 Euro/t$CO_2$. These cost estimates can be compared against estimates in previous studies. In a model comparison study consisting of 13 models, the carbon price was estimated to be between 240-1127 Euro/t$CO_2$ in 2050, with a median of 521 Euro/t$CO_2$ (Knopf et al. 2013). The carbon price reported in Capros et al. (2012) varied between 147-370 Euro/t$CO_2$, depending on the scenario. These estimates are quite close to that obtained here.

In terms of the overall cost of reaching the 2050 target, Capros et al. (2012) found an average annual cost in 2011-2050 of 2659-3090 billion Euro, depending on the scenario analysed. In that study an energy system model was used, which did not recognise land use sequestration of any kind. The key reason for the higher costs found by Capros et al. (2012), apart from not including forest sector abatement, was the modelling of energy demand. Their demand was determined by the market equilibrium, which meant that it could increase during the study period. The model used in the present study is constructed with an upper BAU limit on energy demand. Furthermore, renewable energies do not need to substitute for reductions in fossil fuels. Both of these aspects contribute to a lower overall cost of achieving the target.

The cost per unit in Euro/MWh for wind power is shown in Figure 5 for two scenarios: with and without the learning rate (LR).

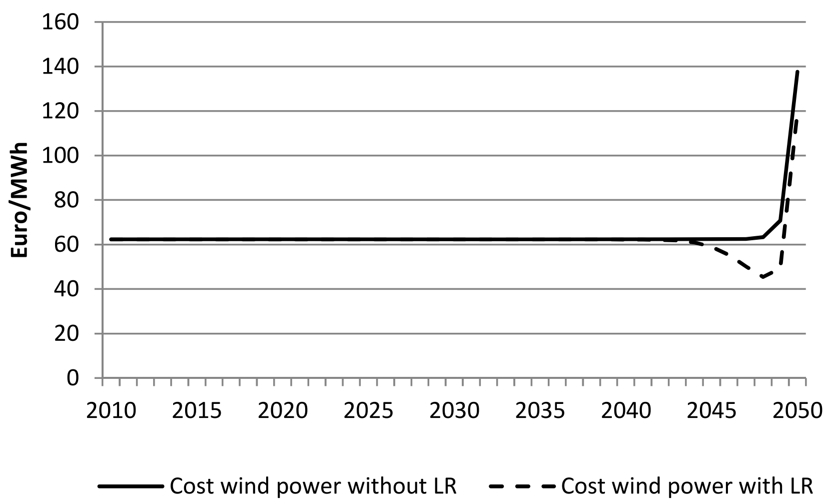



***Fig. 5*** *Cost per unit (Euro/MWh) of wind power with/without the learning rate (LR) to 2050*

The difference between the two lines is due to the LR, which indicates that the cost is reduced when experience increases. The cost is the same until 2043 and after that it is always lower with LR. This shows that the benefit of learning starts paying off after 2043. The general shape of the two curves is determined by a combination of four factors: 1) The curvature of the quadratic cost function; 2) the learning implications (in the scenario with LR); 3) the depreciation rate; and 4) the discount factor. The cost is constant in both scenarios until 2043 when there is hardly any investment. When investments start increasing, the cost with learning is reduced. In both scenarios the cost increases during the last two years and this is explained by the increasing stock, which involves a move upwards on the quadratic cost function.

Figure 6 compares the unit cost of wind power, hydro power and additional sequestration in Euro/ton $CO_2$. As the curves show, both wind power and hydro power are more costly than additional sequestration throughout the policy period. During this period, the cost of renewables is at least fifteen times higher than that of additional sequestration. This means that none of the renewable energy technologies can compete with additional forest sequestration. Hydro power is also more expensive than wind power during the last years when most of the investments take place. The reason for the lower cost for wind power during the last years is most likely explained by the curvature of the cost function and that learning starts paying-off.

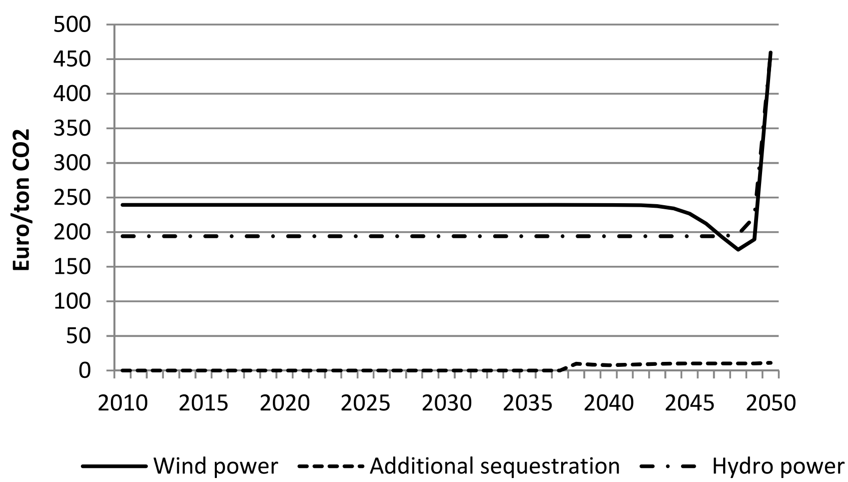



***Fig. 6*** *Unit cost (Euro/ton $CO_2$) of wind power, hydro power and additional sequestration to 2050*

The total costs of reductions in fossil fuels, bioenergy and forest products and of increases in renewable energies in all 27 EU countries are shown in Figure 7. The majority of the costs originate from reductions in fossil fuels. The high cost share of fossil fuels reflects a comparatively high per unit cost and large deployment of this abatement method, which in turn is explained by the comparatively high cost of renewable energies and the limited scope of additional sequestration. The variation that emerges between countries with regard to the cost of renewable energy investments is explained by differences in the cost per unit emissions reduction. Similarly, variations in the cost of additional sequestration is explained by differences in per unit cost and in forest age, which in turn involves differences in growth potential and hence sequestration.

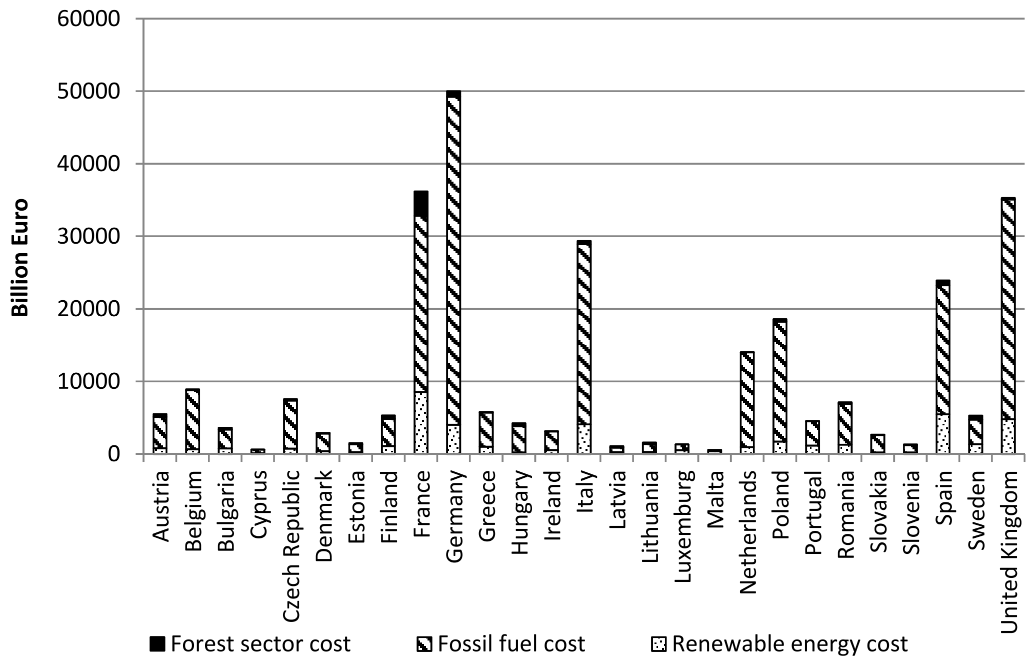



***Fig. 7*** *Total discounted costs per country in the EU-27 countries, divided into cost relating to reductions in fossil fuels, bioenergy and forest products and to increases in renewable energies*

At aggregate level, the total costs in each EU country largely reflect its need to abate in order to meet the overall emission target. This means that countries with high BAU emissions pay the most. The five countries with the highest costs – Germany, France, UK, Spain and Italy – together pay 62% of the total costs and contribute 62% to total BAU emissions.

### *5.1 Sensitivity analysis*

The rate of technological development cannot be predicted and hence here we have to rely on historical estimates for the learning rates and assume that these will continue. However, historical estimates vary between studies, due in particular to differences between countries and between study periods. In this respect, the learning rates used above may have been over- or underestimated. Hence, a sensitivity analysis is carried out on the learning rate (LR) to determine its effect in terms of overall cost and investments in renewable energies. Figure 8 shows the effect of changing the LR of wind power, which is the main contributor to the overall stock of renewables. It shows that the stock of wind power in 2050 increases when the LR increases. The sensitivity to change is greatest under low LR values.

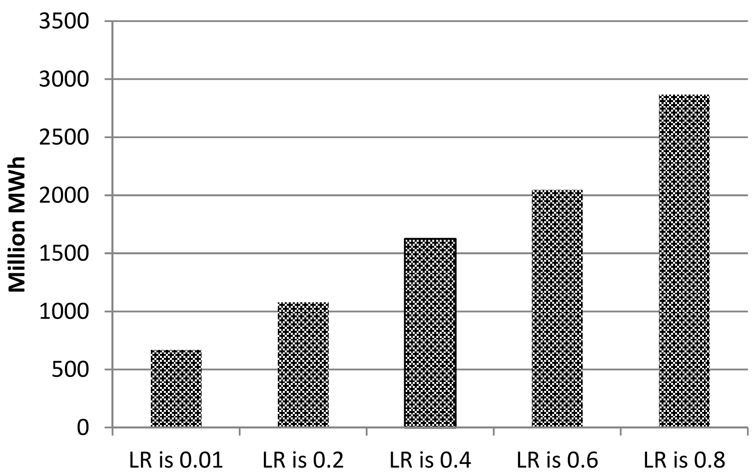



***Fig. 8*** *Stock of wind power in 2050 under different learning rates (LR)*

Figure 9 shows the total abatement cost on varying the LR for wind power. The cost is reduced with higher LR values and the reduction is substantial, with 44% when the LR changes from 0.01 to 0.8, reflecting the comparatively high cost of renewables initially.

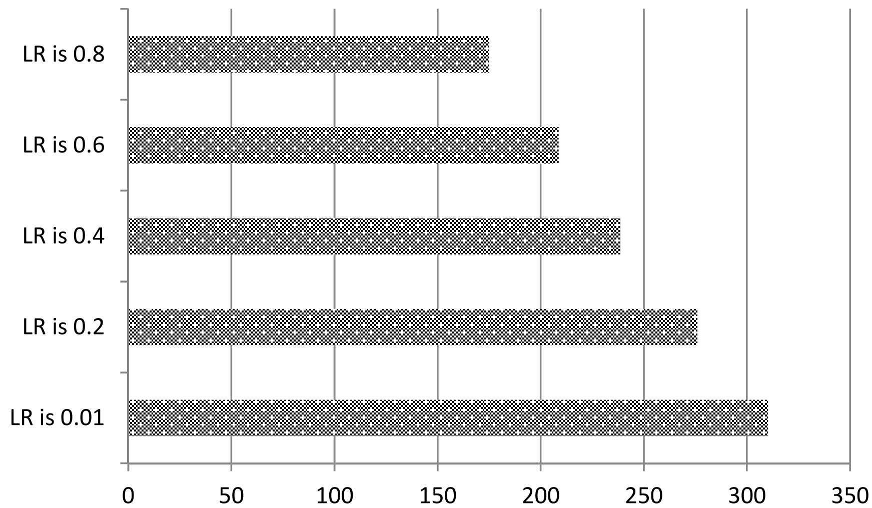



***Fig. 9*** *Total abatement cost in 2050 under different learning rates (LR) for wind power*

The effect of changing the LR for hydro power is much lower than for wind power, due to a low LR for this mature technology. On adjusting the LR of hydro power from 0.01 to 0.05, the change in total cost is negligible and the stock only increases from 81 to 86 million MWh. Despite an increase in the LR of solar PV to 1, the stock is still zero.

The rate of depreciation of renewable energy technologies is an important factor that determines the overall cost results, since it determines how long it is necessary to pay for an investment. Early investments are comparatively expensive and part of these investments will remain in operation for approximately 15 years, in the base case in section 5. A high depreciation rate implies a shorter lifetime and vice versa. On changing the depreciation rate of all technologies from 35% to 50%, meaning that the technologies would be more or less completely depreciated after 10 years, the cost reduction is approximately 0.1%, and the total stock of renewable energies can deliver 3% more electricity from wind and hydro power than the figures quoted in the base case. When increasing the depreciation rate for one technology at a time, the magnitude of the cost reduction and the increases in stock are still comparatively low for both wind and hydro power. These results suggest that changes in the depreciation rate have smaller implications for the cost and investment in renewables than changes in the learning rate.

A reduction in the initial 2010 cost of renewables is also tested in order to see whether that can deliver a stock of solar PV. Table 1 shows the results of reducing the cost of all renewables by a certain percentage. The results show that a reduction in cost of 80% would return a comparatively large stock of solar PV. The stock of wind and hydro power would increase at the same time, with approximately 66% and 89%, respectively, compared to the amount resulting from the model in section 5.

*Table 1. Change in the stock of renewables in 2050 and total abatement cost to 2050 on reducing the cost of renewable energies by a certain percentage*

| Reduced cost | Stock wind *Million MWh* | Stock hydro *Million MWh* | Stock solar PV *Million MWh* | Total cost *Billion Euro* |
|---|---|---|---|---|
| -20% | 1069 | 91 | 0 | 275 |
| -40% | 1202 | 106 | 0 | 261 |
| -60% | 1410 | 128 | 0 | 241 |
| -80% | 1614 | 153 | 690 | 189 |

## 6. Discussion and conclusions

The aim of this study was to analyse whether renewable energies with learning-by-doing (LBD) technical change can compete with forest sequestration in a cost-effective EU climate policy up to 2050. This is an unexplored area of research and the results contribute to the understanding of how renewable energies, with endogenous technical change, react to the inclusion of a low-cost abatement method like forest sequestration in terms of investments and technological development.

The cost-effective solutions based on a dynamic programming model reveal that the amount of investments in wind and hydro power over the policy period generate a stock of renewable energies in 2050 that can deliver approximately 1055 million MWh. This is twice as much as the current production from these renewable sources (Eurostat 2014). This stock of renewables can contribute roughly 8.7% to the emissions reduction target in 2050, which is higher than the 3.2% share from the forest sector. Hence, most of the reductions stem from the fossil fuels sector. The main reason for a comparatively low contribution from renewables is their relatively high cost per unit emissions reduction. The explanation for the low contribution from forest sequestration is the limited scope of this option in the analysis, which is due to the focus on additional sequestration and the land use change constraint in the model.

Additional sequestration is the amount achieved when bioenergy and forest products are reduced compared with their current levels of production.

Throughout the policy period, the cost per unit emissions reduction is at least fifteen-fold higher for renewable energies than for forest sequestration. Hence, renewable energies with LBD are unable to compete with forest sequestration. This result has important policy implications, since it indicates that there is a need for continued financial support for the three renewable energy technologies if they are to deliver most of the emissions reduction required in 2050. However, any government support scheme should ideally be phased out slowly and should be directly related to the reduction in cost that stems from increased learning in a technology. The phase-out should hence be initiated when the learning starts kicking-in, which happens in 2043 for wind power according to the present analysis. An alternative or additional approach would be to direct political support to forest sequestration, by recognising this abatement option, which has large potential and low cost. That could also be a beneficial approach in terms of increasing ecosystem services. Furthermore, the availability of cheaper abatement options means that technological development in renewable energies will halt, which has previously been pointed out by e.g. Tavoni et al. (2007). This slowdown can potentially be avoided if political measures are taken to directly incentivise technological change. Identifying the kinds of measures that best support continuous developments in renewables, which are accompanied by cost uncertainties, is a separate area of research that is not discussed here.

The results also show that the cost of achieving the 2050 emissions target would be approximately 286 billion Euros when recognising renewable energy potential – solar PV, wind and hydro power – and abatement in the forest and fossil fuel sectors. The cost of carbon is estimated here to be 364 Euros/t$CO_2$ in 2050. These cost figures can be compared against results from other models to get a benchmark for the present results and explain any differences. Capros et al. (2012) estimated the overall cost to be 2659-3090 billion Euros. The large discrepancy compared with the present study is most likely due to model structures and assumptions, in particular with regard to energy demand. In the same study, the estimated carbon price is 147-370 Euro/t$CO_2$, which is close to that obtained here.

Future research to improve the understanding of different abatement methods could include e.g. an analysis of the contribution from agricultural abatement. Furthermore, climate change impacts on forestry, which could amend the forest growth function and lead to changes in land allocation, would be another interesting research topic.

## References


Adams, D.M., Alig, R.J., Callaway, J.M., McCarl, B.A., Winnett, S.M. (1996). The Forest and Agricultural Sector Optimization Model (FASOM): Model structure and policy applications. United States Department of Agriculture Forest Service Research Paper PNW-RP-495. Pacific Northwest Research Station, Portland, OR.

Adams, D.M., Alig, R.J., McCarl, B.A., Callaway, J.M., Winnett, S.M. (1999). Minimum cost strategies for sequestering carbon in forests. *Land Economics*, 75, 360-374.

Alig, R.J., Adams, D.M., McCarl, B.A., Callaway, J.M., Winnett, S.M. (1997). Assessing effects of mitigation strategies for global climate change with an intertemporal model of the U.S. forest and agriculture sectors. *Environmental Resource Economics*, 9, 259-274.

Azar, C., Lindgren, K., Andersson, B. (2003). Global energy scenarios meeting stringent CO2 constraints – Cost effective fuel choices in the transportation sector. *Energy Policy*, 31, 961–976.

Bosetti, V., Maffezzoli, M. (2013). Taxing carbon under market incompleteness. Fondazione Eni EnricoMattei Working Papers. Paper 831. http://services.bepress.com/feem/paper831 Accessed 12 November 2014.

Bramoullé, Y., Olson, L.J. (2005). Allocation of pollution abatement under learning by doing. *Journal of Public Economics*, 89, 1935-1960.

Brooke, A., Kendrick, D., Meeraus, A. (1998). Gams – a user's guide. The Scientific Press, San Francisco.

Capros, P., Mantzos, L. (2000). Endogenous learning in European post-Kyoto scenarios: results from applying the market equilibrium model PRIMES. *International Journal of Global Energy Issues*, 14, 249-261.

Capros, P., Tasios, N., De Vita, A., Mantzos, L., Paroussos, L. (2012). Model-based analysis of decarbonising the EU economy in the time horizon to 2050. *Energy Strategy Reviews*, 1, 76-84.

De Noord, M., Beurskens, L.W.M., de Vries, H.J. (2004). Potentials and costs for renewable electricity generation. A data overview. ECN report. http://www.ecn.nl/docs/library/report/2003/c03006.pdf Accessed 14 September 2014.

Ecofys (2008). Global potential of renewable energy sources: a literature assessment. http://www.ecofys.com/files/files/report_global_potential_of_renewable_energy_sources_a_literature_assessment.pdf Accessed 5 September 2014.

European Commission (2011). A Roadmap for moving to a competitive low carbon economy in 2050. COM(2011)112 final.

European Wind Energy Association (2009). The Economics of Wind Energy. http://www.ewea.org/fileadmin/ewea_documents/documents/00_POLICY_document/Economics_of_Wind_Energy__March_2009_.pdf Accessed 7 October 2014.

Eurostat (2012). Statistics in focus: renewable energies. Issue, 44/2012.

http://epp.eurostat.ec.europa.eu/portal/page/portal/product_details/publication?p_product_code=KS-SF-12-044 Accessed 6 October 2014.

Eurostat (2013). Energy, transport and environment indicators. Eurostat pocketbooks. http://epp.eurostat.ec.europa.eu/portal/page/portal/product_details/publication?p_product_code=KS-DK-13-001 Accessed 6 October 2014.

Eurostat (2014). Energy statistics quantity database: renewable energies. http://epp.eurostat.ec.europa.eu/portal/page/portal/energy/data/database Accessed 23 September 2014.

Faber, T., Huber, C., Resch, G. (2009). Green-X database on CD-ROM. Energy Economics Group, Vienna University of Technology. http://www.green-x.at/download%20(re).htm

Goulder, L.H., Mathai, K. (2000). Optimal $CO_2$ abatement in the presence of induced technological change. *Journal of Environmental Economics and Management*, 39, 1-38.

Gren, I-M., Elofsson, K., Carlsson, M., Munnich, M. (2012). Stochastic carbon sinks for combating carbon dioxide emissions in the EU. *Energy Economics*, 34, 1523–1531.

Hedenus, F., Azar, C. (2009). Bioenergy plantations or long-term carbon sinks? –A model based analysis. *Biomass and bioenergy*, 33, 1693-1702.

Hoefnagels, R., Junginger, M., Panzer, R., Resch, G., Held, A. (2011). Long Term Potentials and Costs of RES. Part I: Potentials, Diffusion and Technological learning. http://www.reshaping-res-policy.eu/downloads/Long-term%20potentials%20and%20cost%20of%20RES%20-%20part%20I%20(Re-Shaping%20report,%202011).pdf Accessed 20 August 2014.

IEA (2008). Renewables information 2008 edition, International Energy Agency, OECD Publishing, Paris.

IEA (2010). Technology Roadmap Solar photovoltaic energy. International Energy Agency, Paris. http://www.iea.org/publications/freepublications/publication/pv_roadmap.pdf Accessed 25 May 2014.

IRENA (2012a). Renewable energy technologies: Cost analysis series: Wind power. www.irena.org Accessed 7 October 2014.

IRENA (2012b). Renewable energy technologies: Cost analysis series: Solar photovoltaics. www.irena.org Accessed 7 October 2014.

IRENA (2012c). Renewable energy technologies: Cost analysis series: Hydro power. www.irena.org Accessed 7 October 2014.

Junginger, M., Faaij, A., Turkenburg, W.C. (2004). Global experience curves for wind farms. *Energy Policy*, 33, 133–150.

Kahouli-Brahmi, S. (2008). Technological learning in energy–environment–economy modelling: A survey. *Energy Policy*, 36, 138-162.

Kitous, A., Criqui, P., Bellevrat, E., Chateau, B. (2010). Transformation Patterns of the Worldwide Energy System – Scenarios for the Century with the POLES Model. *The Energy Journal*, 31, 49-82.

Knopf, B., Chen, Y-H., De Cian, E., Förster, H., Kanudia, A., Karkatsouli, I., Keppo, I., Koljonen, T., Schumacher, K., Van Vuuren, D.P. (2013). Beyond 2020 — Strategies and costs for transforming the European Energy System. *Climate Change Economics*, DOI: 10.1142/S2010007813400010

Lindqvist, M., Gren, I-M. (2013). Cost effective nutrient abatement for the Baltic Sea under learning-by-doing induced technical change. Swedish University of Agricultural Sciences, Department of Economics Working Paper Series; 2013:01.

Manne, A.S., Richels, R.G., (2004). The impact of learning-by-doing on the timing and costs of $CO_2$ abatement. *Energy Economics*, 26, 603-619.

McDonald, A., Schrattenholzer, L. (2001). Learning rates for energy technologies. *Energy Policy*, 29, 255-261.

Munnich Vass, M., Elofsson, K. (2013). Is forest sequestration at the expense of bioenergy and forest products cost-effective in EU climate policy to 2050? Swedish University of Agricultural Sciences, Department of Economics Working Paper Series; 2013:11.

Murray, B., Lubowski, R., Sohngen, B. (2009). Including international forest carbon incentives in climate policy: understanding the economics. Nicholas Institute for Environmental Policy Solutions. Duke University.

Neij, L. (2008). Cost development of future technologies for power generation - A study based on experience curves and complementary bottom-up assessments. *Energy Policy*, 36, 2200-2211.

Nordhaus, W. (2007). A Review of the Stern Review on the Economics of Climate Change. *Journal of Economic Literature*, 45, 686–702.

Rasmussen, T.N. (2001). $CO_2$ abatement policy with learning-by-doing in renewable energy. *Resource and Energy Economics*, 23, 297-325.

Ragwitz, M., Huber, C., Resch, G., White, S., (2003). Dynamic cost-resource curves. Work package 1, within the 5th framework programme of the European Commission supported by DG Research. http://www.green-x.at Accesses 5 June 2014.

Resch, G., Faber, T., Haas, R., Ragwitz, M., Held, A., Konstantinaviciute, I. (2006). Potentials and cost for renewable electricity in Europe - The Green-X database on dynamic cost-resource curves; Report of the project OPTRES as conducted by a consortium lead by Fraunhofer ISI for the European Commission, DGTREN, Intelligent Energy for Europe.

Resch, G., Faber, T., Ragwitz, M., Held, A., Panzer, C., Haas, R. (2008). 20% RES by 2020– a balanced scenario to meet Europe's renewable energy target. A report within the futures-e project funded by the European Commission. http://www.futures-e.org . Accessed 4 May 2014.

Rokityanskiy, D., Benitez, P.C., Kraxner, F., McCullum, I., Obersteiner, M., Rametsteiner, E., Yamagata, Y. (2007). Geographically explicit global modeling of land-use change, carbon sequestration, and biomass supply. *Technological Forecasting Social Change*, 74, 1057-1082.

Rose, S.K., Ahammad, H., Eickhout, B., Fisher, B., Kurosawa, A., Rao, S., Riahi, K., van Vuuren, D.P. (2012). Land-based mitigation in climate stabilization. *Energy Economics*, 34, 365–380.

Rosendahl, K.E. (2004). Cost-effective environmental policy: implications of induced technological change. *Journal of Environmental Economics and Management*, 48, 1099-1121.

Sims, R.E.H., Rogner, H-H., Gregoryc, K. (2003). Carbon emission and mitigation cost comparisons between fossil fuel, nuclear and renewable energy resources for electricity generation. *Energy policy*, 31, 1315–1326.

Sohngen, B., Mendelsohn, R. (2003). An optimal control model of forest carbon sequestration. *American Journal of Agricultural Economics*, 85, 448-457.

Sohngen, B. (2009). An analysis of forestry carbon sequestration as a response to climate change. Copenhagen Consensus on Climate. Copenhagen Consensus Center. Denmark.

Stern, N. (2008). The economics of climate change. *The American Economic Review*, 98, 1-37.

Tavoni, M., Bosetti, V., Sohngen, B. (2007). Forestry and the carbon market response to stabilize climate. Fondazione Eni Enrico Mattei. Italy.

van Vuuren, D.P., den Elzen, M.G.J., Lucas, P.L., Eickhout, B., Strengers, B.J., van Ruijven, B., Wonink, S., van Houdt, R. (2007). Stabilizing greenhouse gas concentrations at low levels: an assessment of reduction strategies and costs. *Climatic Change*, 81, 119–159.

Watanabe, C. (1995). Identification of the role of renewable energy. *Renewable Energy*, 6, 237-274.

## Appendix A. Calculation of the derivative of the cost function for renewable energies

In order to solve the model, the time derivative of the cost function for renewables, equation (11), is solved. The problem is set up for five periods, where the superscripts, *i* and *g*, are omitted to facilitate reading and $Z_0$ is set to 1 for convenience.

$$C = \sum_{t=0}^{T=4} \rho^t (\psi R_t + \theta R_t^{\beta})(1 + \sum_{\tau<t} N_\tau)^{-\varpi}$$

$$\Leftrightarrow C = \rho^0(\psi R_0 + \theta R_0^{\beta}) + \rho^1(\psi R_1 + \theta R_1^{\beta})(1 + N_0)^{-\varpi} + \rho^2(\psi R_2 + \theta R_2^{\beta})(1 + N_0 + N_1)^{-\varpi}$$
$$+ \rho^3(\psi R_3 + \theta R_3^{\beta})(1 + N_0 + N_1 + N_2)^{-\varpi} + \rho^4(\psi R_4 + \theta R_4^{\beta})(1 + N_0 + N_1 + N_2 + N_3)^{-\varpi}$$

$$\frac{\partial C}{\partial N_0} = \rho^0(\psi + \beta\theta R_0^{\beta-1}) - \varpi\rho^1(\psi R_1 + \theta R_1^{\beta})(1 + N_0)^{-\varpi-1} - \varpi\rho^2(\psi R_2 + \theta R_2^{\beta})(1 + N_0 + N_1)^{-\varpi-1} -$$
$$\varpi\rho^3(\psi R_3 + \theta R_3^{\beta})(1 + N_0 + N_1 + N_2)^{-\varpi-1} - \varpi\rho^4(\psi R_4 + \theta R_4^{\beta})(1 + N_0 + N_1 + N_2 + N_3)^{-\varpi-1}$$

$$\frac{\partial C}{\partial N_1} = \rho^1(\psi + \beta\theta R_1^{\beta-1})(1 + N_0)^{-\varpi} - \varpi\rho^2(\psi R_2 + \theta R_2^{\beta})(1 + N_0 + N_1)^{-\varpi-1} -$$
$$\varpi\rho^3(\psi R_3 + \theta R_3^{\beta})(1 + N_0 + N_1 + N_2)^{-\varpi-1} - \varpi\rho^4(\psi R_4 + \theta R_4^{\beta})(1 + N_0 + N_1 + N_2 + N_3)^{-\varpi-1}$$

$$\frac{\partial C}{\partial R_2} = \rho^2 \beta\theta R_2^{\beta-1}(1 + N_0 + N_1)^{-\varpi} - \varpi\rho^3(\psi + \theta R_3^{\beta})(1 + N_0 + N_1 + N_2)^{-\varpi-1} -$$
$$\varpi\rho^4(\psi + \theta R_4^{\beta})(1 + N_0 + N_1 + N_2 + N_3)^{-\varpi-1}$$

$$\frac{\partial C}{\partial N_3} = \rho^3(\psi + \beta\theta R_3^{\beta-1})(1 + N_0 + N_1 + N_2)^{-\varpi} - \varpi\rho^4(\psi R_4 + \theta R_4^{\beta})(1 + N_0 + N_1 + N_2 + N_3)^{-\varpi-1} -$$

$$\frac{\partial C}{\partial N_4} = \rho^4(\psi + \beta\theta R_4^{\beta-1})(1 + N_0 + N_1 + N_2 + N_3)^{-\varpi}$$

These derivatives show a pattern that can be used to derive the general time derivative of the renewable cost function as follows:

$$\frac{\partial C}{\partial N_t} = \rho^t(\psi + \beta\theta R_t^{\beta-1})(Z_0 + \sum_{\tau=0}^{t-1} N_\tau)^{-\varpi} - \varpi \sum_{\tau=t+1}^{T} \rho^\tau (\psi R_\tau + \theta R_\tau^{\beta})(Z_0 + \sum_{\tau=0}^{\tau-1} N_\tau)^{-\varpi-1}$$

## Appendix B. Conversion parameters

*Table B1. Conversion parameters used in the model*

| Parameter | | Value |
|---|---|---|
| $\eta^i$ | carbon content of wood (ton $CO_2/m^3$) | 1.459/0.912[a] |
| $\varphi$ | harvesting, transporting and processing emissions (ton $CO_2/m^3$) | 0.024 |
| $\gamma$ | carbon offset from bioenergy (ton $CO_2/m^3$) | 0.544 |
| $\varsigma$ | **carbon offset from renewables (ton $CO_2$/MWh)** | 0.260 |
| $\alpha^{oil}$ | emissions from oil (ton $CO_2$/toe) | 3.019 |
| $\alpha^{coal}$ | emissions from coal (ton $CO_2$/toe) | 4.100 |
| $\alpha^{gas}$ | emissions from gas (ton $CO_2$/toe) | 2.349 |

[a] The first number refers to all countries with temperate forest and the second to countries with boreal forest

All the values apart from the carbon offset from renewables stem from Munnich-Vass and Elofsson (2013)

The carbon offset from renewables is calculated based on the conversion factor translating toe into MWh of 0.086 (Onlineconversion 2014) as well as the weighted average of the three fossil fuels 3.024, where the weights are calculated based on the BAU levels of these fuels in 2010

## Appendix C. Calculation of step-wise cost-resource potential curve

Annual costs, quoted on the y-axis of the step-wise curve, cover investment costs and operation and maintenance costs (Ragwitz et al. 2003) and are calculated as follows:

$$K^{ig} = \frac{I^{ig} * CRF}{H^{ig}} + \frac{C^{ig}_{O\&M}}{H^{ig}} \qquad \text{(C1)}$$

where $K^{ig}$ is the power generation cost in each country, *i*, for each renewable energy technology, *g*, measured in Euro/MWh; $I^{ig}$ is the fixed investment cost in Euro/MW; $C^{ig}_{O\&M}$ is the operation and maintenance costs per energy unit in Euro/MW per year; $H^{ig}$ is the full-load hours per year; and $CRF$ is the capital recovery factor, which is calculated as follows:

$$CRF = \frac{r(1+r)^P}{\left[(1+r)^P - 1\right]} \qquad \text{(C2)}$$

where *r* is the interest rate and *P* is the payback time required by investors. The $CRF$ converts the total investment cost into an annual cost in present value terms, i.e. an annuity, which is recurring for a pre-specified number of years. The payback time and interest rate are the same for all technologies and countries and are 15 years and 6.5%, respectively. No taxes are included in the various cost components in equation (C1).

The renewable energy potentials, which are quoted on the x-axis of the step-wise cost-resource curves, provide additional potential for electricity generation. The potential is determined by taking into account the technical feasibility, social acceptance, planning aspects, growth rate of industry and market distortions. The cost and potentials in the database refer to the year 2006 (Resch et al. 2008). These costs remained more or less constant between 2006 and 2010 (IRENA 2012a; IRENA 2012b; IRENA 2012c), and hence there is no need to adjust the data to fit the model.

## Appendix D. Input data in model regarding renewable energies

*Table D1. Statistical results of fitting a static, quadratic, constant elasticity function to the data on costs and resource potentials for wind power. The intercept and the coefficient are used in equation (28) for renewable energies*

| ***Country*** | ***Intercept***[a] | ***SE Estimate*** | ***Coefficient***[a] | ***SE Estimate*** | ***No of obs.*** | ***SSE***[b] |
|---|---|---|---|---|---|---|
| Austria | 69 | 1.48 | 4.14 | 0.31 | 20 | 475.717 |
| Belgium | 70 | 0.97 | 2.89 | 0.15 | 24 | 252.529 |
| Bulgaria | 76 | 2.14 | 1.86 | 0.33 | 22 | 1554.23 |
| Cyprus | 69 | 0.74 | 57.54 | 4.11 | 16 | 52.1538 |
| Czech Republic | 67 | 1.51 | 1.69 | 0.14 | 22 | 440.392 |
| Denmark | 57 | 0.91 | 13.98 | 0.56 | 32 | 404.647 |
| Estonia | 61 | 0.67 | 15.29 | 0.90 | 21 | 77.3810 |
| Finland | 64 | 0.90 | 0.78 | 0.03 | 24 | 232.644 |
| France | 60 | 0.96 | 0.02 | 0.00 | 30 | 345.984 |
| Germany | 61 | 2.22 | 0.06 | 0.01 | 20 | 1235.00 |
| Greece | 65 | 0.93 | 0.81 | 0.03 | 24 | 257.949 |
| Hungary | 70 | 0.99 | 20.76 | 1.69 | 18 | 142.193 |
| Ireland | 52 | 0.59 | 5.08 | 0.39 | 19 | 50.2131 |
| Italy | 70 | 0.84 | 0.06 | 0.01 | 22 | 141.157 |
| Latvia | 67 | 0.79 | 16.11 | 1.00 | 21 | 119.521 |
| Lithuania | 68 | 0.85 | 14.05 | 1.18 | 18 | 100.541 |
| Luxembourg[c] | 70 | 0.97 | 2.89 | 0.15 | 24 | 252.529 |
| Malta[d] | 69 | 0.74 | 57.54 | 4.11 | 16 | 52.1538 |
| Netherlands | 63 | 1.09 | 1.23 | 0.06 | 28 | 400.330 |
| Poland | 65 | 1.19 | 0.38 | 0.03 | 22 | 268.832 |
| Portugal | 62 | 1.24 | 1.07 | 0.08 | 28 | 632.922 |
| Romania | 64 | 1.15 | 0.64 | 0.05 | 22 | 249.123 |
| Slovakia | 74 | 1.25 | 99.90 | 8.30 | 18 | 223.177 |
| Slovenia | 70 | 0.93 | 68.77 | 5.01 | 18 | 122.918 |
| Spain | 57 | 0.96 | 0.04 | 0.01 | 32 | 490.958 |
| Sweden | 63 | 0.91 | 0.62 | 0.03 | 26 | 246.789 |
| United Kingdom | 54 | 0.99 | 0.04 | 0.01 | 32 | 419.252 |

[a] *Intercept and coefficient in static cost function in equation (31)*

[b] *Sum of Squared Error/Residuals*

[c] *Luxemburg has the same estimates as Belgium*

[d] *Malta has the same estimates as Cyprus*

*Table D2. Statistical results of fitting a static, quadratic, constant elasticity function to the data on costs and resource potentials for solar PV. The intercept and the coefficient are used in equation (28) for renewable energies*

| ***Country*** | ***Intercept[a]*** | ***SE Estimate*** | ***Coefficient[a]*** | ***SE Estimate*** | ***No of obs.*** | ***SSE[b]*** |
|---|---|---|---|---|---|---|
| Austria | 455 | 31.0071 | 5.25 | 0.7855 | 12 | 64814.6 |
| Belgium | 565 | 32.5374 | 18.44 | 2.4163 | 12 | 73072.4 |
| Bulgaria | 400 | 26.7243 | 7.16 | 1.0087 | 12 | 41533.5 |
| Cyprus[c] | 431 | 28.0321 | 0.33 | 0.0493 | 12 | 52926.8 |
| Czech Republic | 436 | 28.2938 | 3.96 | 0.5943 | 12 | 51956.5 |
| Denmark | 582 | 36.3392 | 23.13 | 3.5493 | 12 | 86579.2 |
| Estonia[e] | 652 | 35.8836 | 16.59 | 2.3767 | 12 | 87944.5 |
| Finland | 652 | 35.8836 | 16.59 | 2.3767 | 12 | 87944.5 |
| France | 449 | 30.2411 | 0.14 | 0.0206 | 10 | 59822.7 |
| Germany | 436 | 28.4833 | 0.16 | 0.0251 | 12 | 55903.0 |
| Greece | 373 | 26.0841 | 3.94 | 0.6197 | 12 | 45151.5 |
| Hungary | 453 | 32.2701 | 14.77 | 2.2737 | 12 | 63502.2 |
| Ireland[f] | 552 | 36.0377 | 0.33 | 0.0469 | 12 | 88444.4 |
| Italy | 431 | 28.0321 | 0.33 | 0.0493 | 12 | 52926.8 |
| Latvia[e] | 652 | 35.8836 | 16.59 | 2.3767 | 12 | 87944.5 |
| Lithuania[e] | 652 | 35.8836 | 16.59 | 2.3767 | 12 | 87944.5 |
| Luxembourg[d] | 565 | 32.5374 | 18.44 | 2.4163 | 12 | 73072.4 |
| Malta[c] | 431 | 28.0321 | 0.33 | 0.0493 | 12 | 52926.8 |
| Netherlands | 556 | 47.8047 | 4.45 | 0.7834 | 10 | 89456.1 |
| Poland | 643 | 34.5772 | 0.98 | 0.1400 | 12 | 76933.8 |
| Portugal | 327 | 21.1583 | 3.63 | 0.5573 | 12 | 29330.5 |
| Romania | 420 | 27.2665 | 2.33 | 0.3400 | 12 | 45748.2 |
| Slovakia | 544 | 33.9365 | 26.48 | 3.9264 | 12 | 73873.6 |
| Slovenia | 600 | 34.7407 | 207.45 | 30.377 | 12 | 80189.0 |
| Spain | 339 | 23.6548 | 0.14 | 0.0212 | 12 | 34648.0 |
| Sweden | 653 | 34.9342 | 3.49 | 0.5215 | 12 | 83341.5 |
| United Kingdom | 552 | 36.0377 | 0.33 | 0.0469 | 12 | 88444.4 |

[a] *Intercept and coefficient in static cost function, equation (31)*
[b] *Sum of Squared Error/Residuals*
[c] *Malta and Cyprus have the same estimates as Italy*
[d] *Luxembourg has the same estimates as Belgium*
[e] *Estonia, Latvia, Lithuania have the same estimates as Finland*
[f] *Ireland has the same estimates as UK*

*Table D3. Statistical results of fitting a static, quadratic, constant elasticity function to the data on costs and resource potentials for hydro power. The intercept and the coefficient are used in equation (28) for renewable energies*

| ***Country*** | ***Intercept***[a] | ***SE Estimate*** | ***Coefficient***[a] | ***SE Estimate*** | ***No of obs.*** | ***SSE***[b] |
|---|---|---|---|---|---|---|
| Austria | 54 | 1.53048 | 3.59410 | 0.15012 | 24 | 636.509 |
| Belgium[c] | 74 | 8.64991 | 23.4689 | 7.58467 | 11 | 2146.59 |
| Bulgaria | 61 | 1.30448 | 64.6103 | 5.21795 | 24 | 499.656 |
| Cyprus | NA | NA | NA | NA | NA | NA |
| Czech Republic | 45 | 2.5193 | 158.588 | 11.8985 | 20 | 1096.60 |
| Denmark | NA | NA | NA | NA | NA | NA |
| Estonia[d] | 68 | 0.77186 | 117.005 | 8.35075 | 18 | 78.1050 |
| Finland | 68 | 0.77186 | 117.005 | 8.35075 | 18 | 78.1050 |
| France | 42 | 1.32308 | 3.38210 | 0.14531 | 24 | 418.563 |
| Germany | 74 | 8.64991 | 23.4689 | 7.58467 | 11 | 2146.59 |
| Greece[e] | 45 | 1.14325 | 20.5762 | 0.82722 | 24 | 285.063 |
| Hungary[f] | 45 | 2.51930 | 158.588 | 11.8985 | 20 | 1096.60 |
| Ireland[g] | 46 | 0.82810 | 13.6972 | 0.58546 | 22 | 137.969 |
| Italy | 45 | 1.14325 | 20.5762 | 0.82722 | 24 | 285.063 |
| Latvia[d] | 68 | 0.77186 | 117.005 | 8.35075 | 18 | 78.1050 |
| Lithuania[d] | 68 | 0.77186 | 117.005 | 8.35075 | 18 | 78.1050 |
| Luxembourg | NA | NA | NA | NA | NA | NA |
| Malta | NA | NA | NA | NA | NA | NA |
| Netherlands[c] | 74 | 8.64991 | 23.4689 | 7.58467 | 11 | 2146.59 |
| Poland | 33 | 0.83646 | 8.92540 | 0.92257 | 18 | 92.9149 |
| Portugal[h] | 48 | 1.12397 | 4.77170 | 0.43116 | 22 | 250.477 |
| Romania | 77 | 2.60500 | 23.9016 | 2.55690 | 20 | 1226.70 |
| Slovakia | 32 | 0.56072 | 17.8631 | 1.08962 | 24 | 84.7816 |
| Slovenia[e] | 45 | 1.14325 | 20.5762 | 0.82722 | 24 | 285.063 |
| Spain | 48 | 1.12397 | 4.77170 | 0.43116 | 22 | 250.477 |
| Sweden | 46 | 0.82810 | 13.6972 | 0.58546 | 22 | 137.969 |
| United Kingdom[g] | 46 | 0.82810 | 13.6972 | 0.58546 | 22 | 137.969 |

[a] *Intercept and coefficient in static cost function in equation (31)*

[b] *Sum of Squared Error/Residuals*

[c] *Same as Germany*

[d] *Same as Finland*

[e] *Same as Italy*

[f] *Same as Czech Republic*

[g] *Same as Sweden*

[h] *Same as Spain*

***Fig. 10*** *Fitted cost curve for wind power in France*

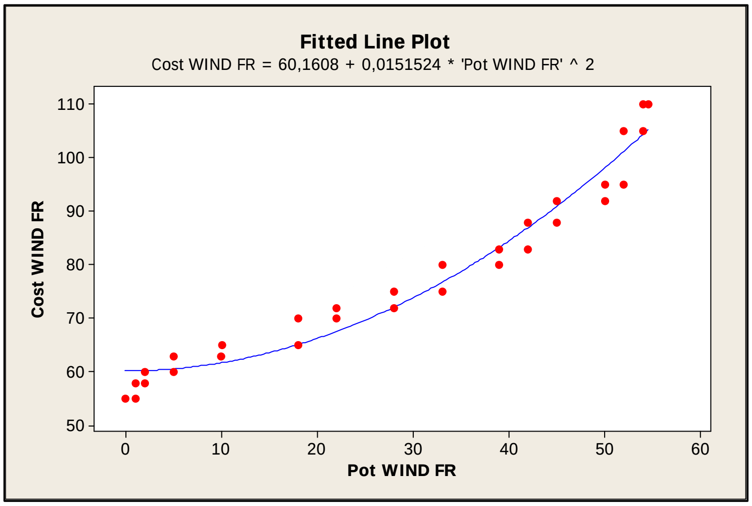
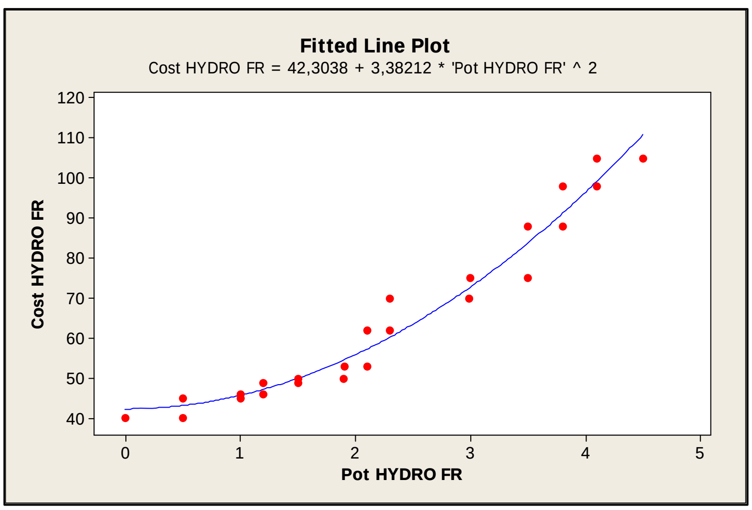



***Fig. 11*** *Fitted cost curve for hydro power in France*



## Appendix E. Abatement in the forest sector

The Chapman-Richard function measures cumulative standing biomass volume, $V_t^i$, in cubic metres over the area, $A^i$, and age, $y_t^i$, of the forest, as follows:

$$
\begin{aligned}
V_t^i(y_t^i) &= A^i k^i (y_t^i)^{m^i} e^{-n^i y_t^i} \\
V_0^i(y_0^i) &= \overline{V}(\overline{y^i})
\end{aligned}
\qquad \text{(E1)}
$$

where, $k^i$, $m^i$, and $n^i$, are positive country specific parameters. These were calibrated by Munnich Vass and Elofsson (2013) based on data for unmanaged forests. The growth, $G^i(V_t^i)$, in standing biomass volume is calculated by taking the derivative of the volume function (E1) with respect to age. The average age of the forest varies over time due to forest growth and harvestings. The forest is rejuvenated when the harvesting level is higher than the growth level in any one year, and depleted when it is not.

Sveriges lantbruksuniversitet
Institutionen för ekonomi
Box 7013
750 07 Uppsala
Tel +46 18 671000

Swedish University of Agricultural Sciences
Department of Economics
P.O. Box 7013
SE-750 07 Uppsala, Sweden
Fax + 46 18 673502