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GENERAL & APPLIED ECONOMICS | RESEARCH ARTICLE

The benefits of investing into improved carbon flux monitoring

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Abstract: Operationalizing a Global Carbon Observing and Analysis System (www.geo-carbon.net) would provide a sound basis for monitoring actual carbon fluxes and thus getting quantities right when pricing carbon – be it in a cap-and-trade scheme or under a tax regime. However, such monitoring systems are expensive and—especially in times of economic weakness—budgets for science and environmental policy are under particular scrutiny. In this study, we attempt to demonstrate the magnitude of benefits of improved information about actual carbon fluxes. Such information enables better-informed policy-making and thus paves the way for a more secure investment environment when decarbonizing the energy sector. The numerical results provide a robust indication of a positive social value of improving carbon monitoring systems when compared to their cost, especially for the more ambitious climate policies.

Subjects: Climate Change; Environmental Economics; Environmental Studies & Management

Keywords: carbon flux monitoring; carbon pricing; uncertainty; investment; decarbonization

1. Introduction

The current knowledge about climate change is plagued by uncertainties. There are major uncertainties about climate sensitivity and about the thermal lag of the climate system (Caldeira, Jain, & Hoffert, 2003; Fasullo & Trenberth, 2012; Forest, Stone, Sokolov, Allen, & Webster, 2002; Hansen,

ABOUT THE AUTHORS

The authors (JS, SF, TK, MS, MG, MT, MH) are from different institutes (International Institute for Systems Aanlysis, Mercator Research Institute on Global Commons and Climate Change, The Inversion Lab, Lund University, Fondazione Eni Enrico Mattei, Comenius University, Lviv Polytechnic National University, Euro-Mediterranean Center on Climate Change (CMCC Foundation) and Max-Planck-Institute for Biogeochemistry) and represent a variety of disciplines (economics, mathematics, remote sensing, forestry, physics, biogeochemistry and integrated assessment of climate change and climate change mitigation). Under the EU-funded GEOCARBON project (www.geocarbon.net), they collaborated to evaluate the economic benefits of an improved carbon monitoring system.

PUBLIC INTEREST STATEMENT

With the Paris Agreement, the remaining emissions quota that can still be emitted to the atmosphere before substantially reducing chances to keep the degree of global warming below levels deemed to be "dangerous" by the UNFCCC, has been further decreased. Moving to implementation of these ambitious goals will require the penalization of fossil fuels and the support of clean technologies. However, pricing carbon is subject to uncertainty, i.a. because revisions in carbon measurements will be associated with revisions of caps. Frequent revisions of policy, however, will deter socially desirable investments and imply extra costs, which could be kept minimal if better observations of carbon fluxes were available. In times of tight public resources, an evaluation of the potential cost savings is essential for decision-makers investing in better observing systems. We find a positive social value of improving monitoring systems (compared to their cost), especially for ambitious climate policies.

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Russell, Lacis, Fung, & Rind, 1985; Hansen et al., 2005; Sherwood, Bony, & Dufresne, 2014; Skeie, Berntsen, Aldrin, Holden, & Myhre, 2014; Roe & Baker, 2007). Further down in the causal chain there are perhaps even larger uncertainties about impacts both from low probability threshold events (O'Neill & Oppenheimer, 2002) and from gradual changes in the climate. Thus, the climate policies based on this spread of evidence must be invariably vague and volatile as well. Climate change mitigation policy mainly consists in the reduction of greenhouse gas (primarily CO_2) emissions. But the difficulty in precisely quantifying current CO_2 fluxes and predicting future emissions makes it hard to set caps in e.g. emission trading schemes (Carbon Trust, 2009) posing a major challenge against the background of emerging trading schemes around the world (California, China, etc.). There is an urgent need for implementing a policy-relevant carbon observing system as recently highlighted by a report from the European Commission (Ciais et al., 2015). According to Ciais et al. (2014), even in developed nations where the uncertainty about annual fossil CO_2 emissions is around 5%, the total uncertainty associated with those estimates over a sequence of years tends to exceed the magnitude of the trends defined as the target of emission reduction policies. Uncertain emissions targets will have an impact on corresponding CO_2 prices (Durand-Lasserve, Pierru, & Smeers, 2010). Frequent adjustments of the cap will furthermore raise issues of policy credibility and can thus dampen investment incentives even more (Fuss, Johansson, Szolgayova, & Obersteiner, 2009; Koch, Grosjean, Fuss, & Edenhofer, 2016). Moreover, monitoring is a key element of discussion in international climate policy. Therefore, it appears that the economic value of improving the existing monitoring system to provide more precise measurements resulting in a better allocation and a more stable CO_2 price could easily exceed the cost of doing so.

In this study we focus on the question of how the investment decisions into carbon-neutral technologies are affected by future CO_2 price uncertainty and to which extent a decrease in CO_2 price volatility affects the resulting investment cost and behavior and thus the success of the policy to decarbonize the energy sector. This serves to quantify the economic value from having a better monitoring system, i.e. we can use these estimates to derive the benefits (or the maximum investment cost that can be justified) of an observing system as well. Obviously, this only covers one aspect of the potential benefits that such a system can offer—in as far as it influences investments—and many other benefits remain unvalued, e.g. the intrinsic scientific value or a larger societal value and co-benefits for society that the resulting emission reduction strategies can bring (e.g. reduction in air pollution with positive impacts on human and ecosystems health).

Methodologically, we first model the problem from the point-of-view of industry and formulate a stylized real options model (Dixit & Pindyck, 1994) to find the optimal timing and the resulting cost of a shift to a carbon-neutral technology in the presence of a stochastic carbon price. We model the price as a Geometric Brownian Motion (GBM), which, with additional assumptions (e.g. constant emissions intensity of the incumbent producers, more carbon-intensive technology), will enable us to derive the solution analytically as a function of the underlying parameters (price process parameters, technology cost, etc.). The assumption of increasing carbon prices is in line with price trajectories underlying 450, 480 and 520 ppm stabilization targets analyzed by Integrated Assessment Models (Riahi et al., 2011; IPCC AR5 Database, 2014).

In a second step, we take the point-of-view of a social planner. We use the results from the real options model to assess if (and to what extent) it is optimal for society to invest into improved monitoring of carbon quantities. Following the approach outlined in Kryazhimskiy, Obersteiner, and Smirnov (2008) and Chladná, Moltchanova, and Obersteiner (2006), we introduce the possibility to invest an arbitrary amount into an improved monitoring system at the beginning of the planning horizon, which will result in a decrease in the resulting carbon price volatility (as frequent adjustments will not be necessary anymore). Using the solution of the stylized model we will be able to derive the amount, which results in the lowest cost to society. The solution will enable us to further analyze the impact of changes in the underlying parameters and assumptions on its qualitative properties and identify its robust elements. This will give us an answer to the question of what would be optimal for society as a whole and not only for regulated firms (a more detailed formulation is given in Section 3).

Our contribution to the literature lies firstly in formulating a framework, which covers both the investment decision into monitoring equipment, which will reduce uncertainty and thus influence investment behavior in the energy sector. On the other hand, we also want to demonstrate the magnitudes for the analytical results in order to derive tangible policy conclusions regarding the financing of such equipment in reality. Using data from quantitative network design (QND) (see the following section for more detailed information) gives us a quantitative assessment of the potential of monitoring systems to reduce uncertainty.

The rest of the paper is organized as follows. Section 2 explains in more detail what QND is and how it can be used to assess the uncertainty reduction potential in carbon flux management. Section 3 gives a detailed description of the model, while the data used for the analysis is presented in Section 4. Results are discussed in Section 5. We close with conclusions in Section 6, which also contains recommendations for policy-makers.

2. Quantitative network design

QND is a technique that allows to evaluate potential observational networks (for an introduction see Kaminski & Rayner, 2008) providing measurements of a given system. It exploits the capability of modern data assimilation systems to propagate uncertainties from observations to the system's control variables and then forward to target quantities of interest (see Scholze, Kaminski, Rayner, Knorr, & Giering, 2007). It is worth noting that this technique only requires the sampling times and locations, an estimate of the combined uncertainty reflecting observational and model errors, and the sensitivity of the simulated observation with respect to the model's control variables. It does not require actual observations and is thus suitable to evaluate potential networks.
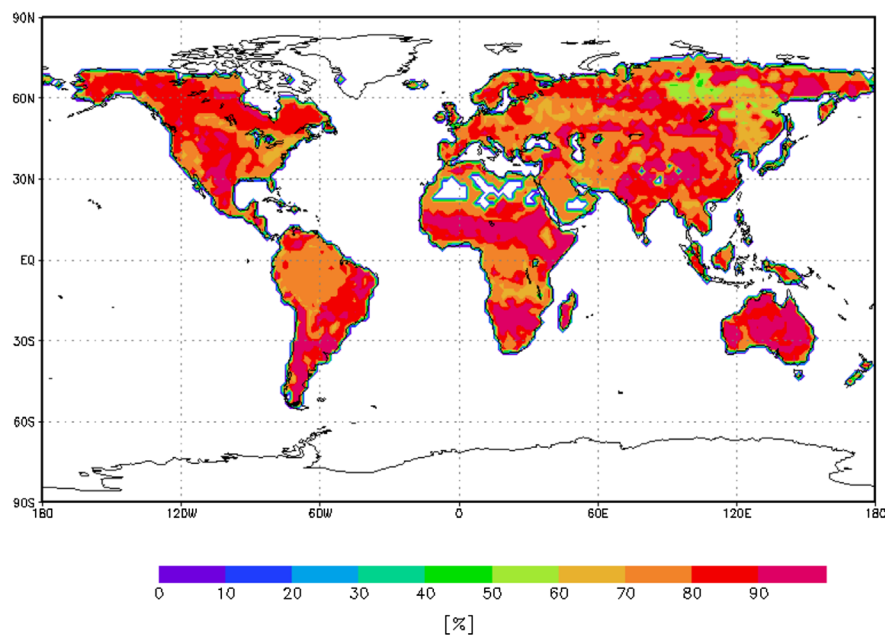
In the present study, we apply a QND framework (Kaminski, Rayner, Voßbeck, Scholze, & Koffi, 2012) that is built around the Carbon Cycle Data Assimilation System (Kaminski et al., 2013; Rayner et al., 2005; Scholze et al., 2016) and is suitable to evaluate networks observing the atmospheric and terrestrial carbon cycle. The CCDAS is set up in a configuration with 57 control variables, which are parameters in the process description of the terrestrial biosphere model BETHY (Knorr, 2000), and an initial value of the atmospheric CO_2 concentration. BETHY composes the global vegetation of 13 Plant Functional Types (PFTs). As the target quantity, we use the 20-year average of the annual mean Net Ecosystem Production (NEP) simulated on the model's 2 by 2 degree global grid.

2.1. Evaluation of a network example

As an example, we define an observational network that consists of 41 sites collecting monthly samples of the atmospheric CO_2 concentration and 10 sites providing direct flux measurements on an hourly time resolution, covering all PFTs that are available to BETHY over Europe. Both component networks are described by Kaminski et al. (2012), where they are, respectively, denoted as "flask" and "flux". Their combined network is sampling over a period of 20 years. In contrast to that study, in the simulation of the target quantity, we use here a model error of 5% of the simulated annual mean net primary production (NPP). The uncertainty reduction achieved by the network relative to the prior uncertainty, i.e. a nil network without any measurements, is displayed in Figure 1.

The uncertainty for a nil network is calculated by mapping our prior information on the BETHY process parameters to the target quantity. There is a debate about the number of PFTs required in a model to allow a realistic assessment. Kaminski et al. (2012) have tested configurations with higher numbers of PFTs. For quadrupling their number of PFTs from 13 to 52, for example, they found only a moderately weaker performance of the network "flask" and for a flux network sampling four times the number of PFTs as the original network "flux" they found almost the same performance as the network "flux" has in the original 13 PFT configuration.

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Figure 1. Reduction of uncertainty in 20-year average annual mean NEP relative to prior uncertainty.

Table 1. Reduction of uncertainty in 20-year average annual mean NPP relative to prior uncertainty

Region	Europe	Russia	Brazil
Uncertainty reduction (%)	0.81	0.71	0.93

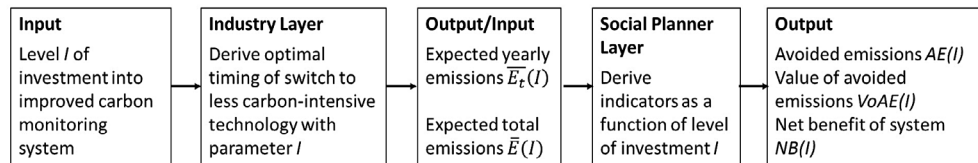Note: These estimates are based on the tool described in Kaminski et al. (2012).

Table 1 summarizes the uncertainty reduction in the 20-year average annual mean NPP relative to prior uncertainty. While we focus on Europe for the analysis of this study, we also display the reduction number for the regions denoted by Russia and Brazil here, where in the latter case potential uncertainty reduction is even higher and thus benefits are larger as well. We focus on NPP, which is used in the models to determine the absorption potential by plants, while the Net Ecosystem Productivity (NEP) mapped out in Figure 1 represents the net carbon exchange between the ecosystem and the atmosphere.

The uncertainty reduction from Table 1 is subsequently used to determine the decrease in carbon price volatility (cf. Section 4).

2.2. Cost of an observational network

The observational network evaluated above is composed of two types of measurements, atmospheric flask samples and direct flux measurements. The respective costs can be divided into installation costs and operating costs. The installation of an analysis laboratory for atmospheric flask samples (with a lifetime of 10 years) is estimated to cost about 2.5 million EUR and its operation is estimated to cost about 1.5 Million Euro per year (ICOS Stakeholder Handbook, 2012). The annual costs for the operation of a flask sampling site can be estimated to amount to 10 thousand EUR on average. For the ecosystem network, on average per site, installation costs are estimated to amount to 48 thousand EUR (for a lifetime of 7 years), and the operation about another 30 thousand EUR per year (A. Lindroth, personal communication). For the analysis, we calculate the total expected cost for both networks with the discount rate used in the model. For the base case (discount rate of 10%), the total cost is just below 30 million EUR.[1]

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Figure 2. Model structure.

Input	Industry Layer	Output/Input	Social Planner Layer	Output
Level *I* of investment into improved carbon monitoring system	Derive optimal timing of switch to less carbon-intensive technology with parameter *I*	Expected yearly emissions $\overline{E_t}(I)$ Expected total emissions $\overline{E}(I)$	Derive indicators as a function of level of investment *I*	Avoided emissions *AE(I)* Value of avoided emissions *VoAE(I)* Net benefit of system *NB(I)*

3. The impact of improved carbon flux monitoring on investment into carbon-free energy technology

The model analyzing the benefit side consists of two layers. The goal of the model as a whole is to assess if, and to which extent, an improved carbon monitoring system leads to benefits related to investments and production in the power sector. The first layer takes the point-of-view of the industry and derives the optimal timing of a switch to a less carbon-intensive (or actually carbon-saving) technology. The level of investment into an improved carbon monitoring system is assumed to be an external parameter to the first layer and the output of the first layer is parameterized by it. The second layer analyzes the social planner's point-of-view, using the industry's response derived in the first layer.

The overall scheme of the model (with main indicators and output) is shown in Figure 2.

3.1. Industry layer

3.1.1. Problem formulation

As has already been described, the first layer should assess the optimal timing of a switch to a carbon-neutral (or a less carbon-intensive) technology from the point-of-view of the industry (i.e. the power sector). We will assume that the decision-maker is facing a stochastic carbon price, modeled as a GBM[2]

$$dP_t = \mu P_t dt + \sigma(I)P_t dW, \tag{1}$$

with μ and $\sigma(I)$ representing its trend and volatility, respectively, and dW denoting the increment of a Wiener process. We assume that $\sigma(I)$ is a function of investment into an improved carbon monitoring system and that the level of I and thus also $\sigma(I)$ is an external parameter for the decision-maker in this layer. We will denote the original price by P^0. We assume an infinite planning horizon, where the decision-maker can choose only the timing of the switch to the new technology. We assume a constant emission intensity of both the incumbent (more carbon-intensive) and new (less carbon-intensive) technology and denote the difference between them as Q. Thus, the switch to the lower carbon technology is connected to capital (and unit operational) costs[3] of investment C,[4] but will at the same time result in yearly savings QP_t of carbon payments.[5] We denote by r the discount rate. We assume that the decision-maker is risk-neutral and seeks to minimize the underlying present value of costs of both decisions.[6] Since we are interested in the timing of the decision and assume the decision-maker is risk-neutral, our focus is on costs. Any changes in the electricity price would affect each kWh sold symmetrically and the electricity price is thus assumed external for the sake of simplifying the analysis and having clear results on the costs.

The described problem of the power plant investor can thus be formulated as an optimal control problem

$$rr \min_{\tau} \quad E\left[\int_0^{\tau} e^{-rt}QP_t dt + Ce^{-r\tau} + \int_{\tau}^{\infty} e^{-rt}Qc\,dt\right]$$
$$dP_t = \mu P_t dt + \sigma(I)P_t dW, \tag{2}$$

where τ is a stopping time and I is an external parameter.

3.1.2. Real options problem solution

The formulated problem for the investor can be transformed (for details see the Appendix 1) into a standard real options problem

$$rF(P^0) = \max_{\tau} \quad E[e^{-r\tau}\left(Q\frac{P_\tau}{r-\mu} - C - Q\frac{c}{r}\right)]$$

(3)

$$dP_t = \mu P_t dt + \sigma(I)P_t dW$$

where $F(P^0)$ is denoting the value of the option to switch to the low carbon technology if the present carbon price is P^0 and the investment is carried out optimally. Following Dixit and Pindyck (1994), we see that the solution is to switch to the carbon-neutral technology as soon as the carbon price hits the following threshold:

$$P^*(I) = \frac{\beta}{\beta-1}(r-\mu)\left(\frac{C}{Q} + \frac{c}{r}\right),$$

(4)

where β is the positive root of the quadratic equation

$$\frac{1}{2}\sigma^2(I)\beta(\beta-1) + \mu\beta - r = 0,$$

and thus

$$\beta = \frac{1}{2} - \frac{\mu}{\sigma^2(I)} + \sqrt{\left(\frac{\mu}{\sigma^2(I)} - \frac{1}{2}\right)^2 + 2\frac{r}{\sigma^2(I)}} > 1.$$

The option value can be further expressed as

$$F(P^0) = \left[Q\frac{P^*(I)}{r-\mu} - C - Q\frac{c}{r}\right]\left(\frac{P^0}{P^*(I)}\right)^\beta$$

3.1.3. Output simulation

Even though the derived optimal strategy (i.e. to invest as soon as the threshold price $P^*(I)$ is reached) is a very important indicator of the industry's response, it does not give us the properties the realized decisions have. For such an analysis, we use forward Monte Carlo simulations. We simulate N CO_2 price paths $\{P_t^k\}_{k=1}^N$ (assuming they follow (1)) and extract the corresponding realized decisions using the derived strategy (4). This gives us the realized timings $\{t_k^*(I)\}_{k=1}^N$

$$t_k^*(I) = \min\{t|P_t^k \geq P^*(I)\}$$

and the average timing $\overline{t^*}(I)$ of the switch to the new technology

$$\overline{t^*}(I) = \frac{1}{N}\sum_{K=1}^{N} t_k^*.$$

Similarly, we derive the total cost of the decision-maker for each simulation $TC_k(I)$ as

$$TC_k(I) = Ce^{-rt_k^*} + \sum_{t=0}^{t_k^*-1} e^{-rt}QP_t^k + \sum_{t_k^*}^{\infty} e^{-rt}Qc.$$

Both the timing and the total cost give an indication as to what impact a carbon policy has on the industry's response. As an input for the next layer, we derive also the expected yearly emissions $\overline{E}_t(I)$ in year t

$$\overline{E}_t(I) = \frac{Q}{N}\sum_{k=1}^{N}[t < t_k^*]$$

and also the total expected emissions $\bar{E}(I)$

$$\bar{E}(I) = \sum_{t=0}^{\infty} \overline{E}_t(I) = Q\overline{t^*}(I),$$

where $[\cdot]$ denotes the characteristic function.

3.2. Social planner layer

In the second layer, we take the point-of-view of the social planner, who has to decide on the optimal level of investment I into an improved carbon monitoring system. As already motivated in the introduction, we assume that investing in a carbon monitoring system will lead to a decrease in the volatility of CO_2 permit price, i.e. we assume that $\sigma(I)$ is decreasing in I.

It should be noted here, that the goal of the analysis is not to analyze all the benefits of such a monitoring system. We will concentrate only on impacts associated with the first layer, i.e. we will look at both social and economic benefits of reducing large-scale fossil fuel usage for electricity generation.

We will use the output of the first layer to derive three indicators measuring those benefits. All are defined by the deviation from the base case, which is the case where no improved monitoring system exists, i.e. $I = 0$. The first indicator is the amount of avoided emissions AE(I)

$$AE(I) = \bar{E}(0) - \bar{E}(I),$$

which for each level of investment into the improved carbon monitoring system gives the difference in the amount of emissions when compared to the base case. This gives the social planner an idea about the social benefit of the monitoring system. The second indicator attaches a monetary value to it, measuring the value of the avoided emissions

$$VoAE(I) = \sum_{t=0}^{\infty} e^{-rt}(\overline{E}_t(0) - \overline{E}_t(I))\overline{P}_t = \sum_{t=0}^{\infty} e^{(\mu-r)t}(\overline{E}_t(0) - \overline{E}_t(I))P^0,$$

where P_t denotes the expected CO_2 price at time t. None of the previous indicators, however, accounts for the cost of such a system. Therefore we look also at the third indicator giving the net benefit

$$NB(I) = VoAE(I) - I.$$

All indicators are in fact functions of the level of investment I and the natural next step is to ask what is the optimal level of investment. This, of course, depends also on a variety of factors not accounted for in this analysis and we do not try to give an absolute, numerically precise answer. Rather, we are aiming to get an impression of the magnitude that such benefits can have in order to evaluate the cost effectiveness of installing the monitoring system. It would therefore not be completely correct to look only at the level of investment, for which the net benefit is maximized. That would assume that the social planner has to bear all the cost associated with the system and that no additional benefits can be expected, while in reality there are other benefits such as an improved understanding of the carbon cycle and the associated gain in knowledge. Moreover, it would mean the social planner ignores the social benefit connected to avoided costs, large parts of which are not directly measurable in monetary terms such as health improvements caused by more successful climate policy. Therefore, it is important to take also the other indicators into account and to consider them more as guidelines rather than as predictions.

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4. Data

To avoid the severe consequences of climate change, there is an increasing need to mitigate greenhouse gas emissions. Generation of electricity and heat was by far the largest producer of CO_2 emissions and was responsible for 41% of world CO_2 emissions in 2010 (International Energy Agency, 2012). Over 40% of the electricity within the EU is currently produced by coal and gas (International Energy Agency, 2008a) and a phase-out of coal-fired electricity is unlikely following the sudden phase-out of nuclear in e.g. Germany, the position of coal-rich countries like Poland and other European countries suffering from economic weakness.[7]

Furthermore, the only technology available to mitigate GHG emissions from large-scale fossil fuel usage in power generation is CO_2 capture and storage (CCS) (International Energy Agency, 2008a). The role of CCS in achieving substantial GHG reductions has been assessed using scenario analysis (International Energy Agency, 2008b). A core result of the scenario analysis is that CCS in power generation is one of the important mitigation measures needed to achieve the CO_2 reductions envisaged in the scenarios. The importance of CCS is supported also by the European Strategic Energy Technology Plan (SET Plan) that includes enabling of commercial use of technologies for CO_2 capture, transport and storage at industrial scale among its key technological challenges. Therefore, for our analysis, we concentrate on the EU 27 region and the coal and gas sector of the power industry, with the CCS retrofit being the low-carbon technology available to the investor.[8]

4.1. CO_2 permit prices

Since we are interested in long-term prices, we use shadow price projections based on SRES B1 assumptions (Nakicenovic, Kolp, Riahi, Kainuma, & Hanaoka, 2006). Compared to the new scenarios produced for the IPCC AR5, the underlying assumptions lean more toward sustainability and thus the climate targets are more easily achieved (Riahi et al., 2011). We consider this as a conservative choice, as picking a more challenging scenario would further increase the benefit. We assume that the CO_2 price follows a GBM, which is also consistent with results in the literature (Fuss et al., 2009; Yang et al., 2007). Based on the B1 shadow price development, we assume a trend of 0.0488 with a starting price depending on the strictness of the stabilization target (see Table 2 for details).

4.2. CO_2 price variance function

Several approaches have been used in the literature for the calibration of carbon prices (e.g. Fuss et al., 2009; Kettunen, Bunn, & Blyth, 2011; Roques, Newbery, & Nuttall, 2008), where the estimates for the volatility range mostly between 20 and 30%. For example, a volatility of 25% has been used in Roques et al. (2008), Fuss et al. (2009) consider a range up to 30%. According to Celebi and Graves (2009), the price projection studies imply a CO_2 price volatility of as high as 50% per year. We keep our carbon price volatility in line with those used in such studies.
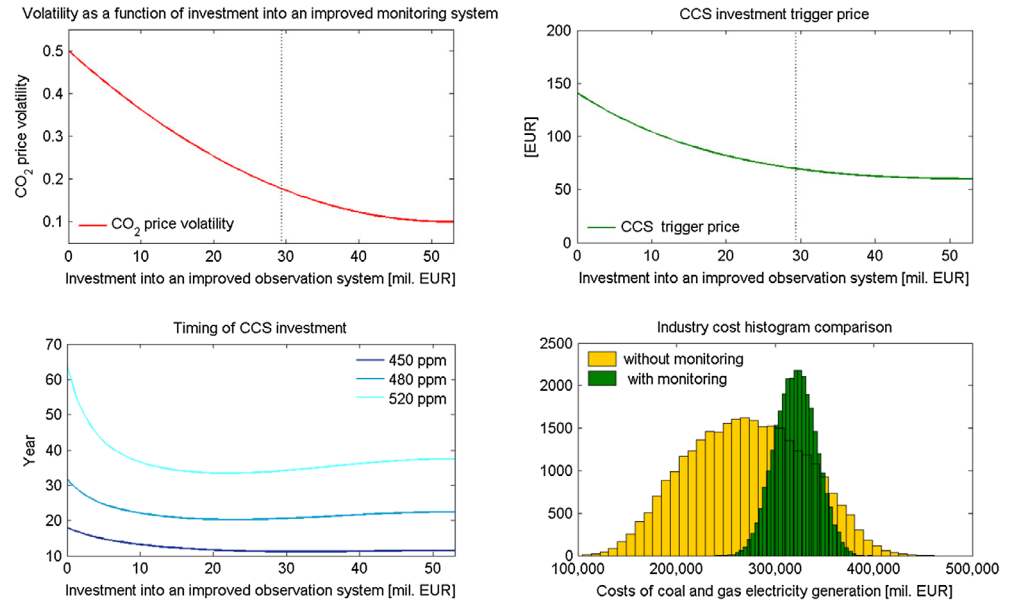
Following the previous section, we assume the CO_2 price volatility is a decreasing function of the investment into the carbon monitoring system. In particular, we use a quadratic decrease,[9] which enables us to capture the fact that the impact of incrementally improving the monitoring system will be diminishing.[10] To calibrate the curve we use following assumptions:

(1) Without any observing system the volatility is 50% (as estimated by Celebi and Graves (2009))

(2) There is a "market" part of volatility that cannot be reduced by any monitoring system, which we set at 10%. The remaining part of the volatility can be attributed to policy uncertainty and as discussed is a decreasing function of the level of investment into the monitoring system.

Table 2. CO_2 prices			
Stabilization target (ppm)	450	480	520
Starting price in 2015 (EUR/tCO_2)	28.51	14.36	5.85
Trend (yearly growth rate)	0.0488	0.0488	0.0488

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Figure 3. Impacts of investment into an improved carbon observing system for energy producers.

(3) The monitoring system as presented above results in an uncertainty reduction of 81% (cf. Table 1).

These assumptions imply a single quadratic curve, which is depicted in Figure 3 (in the top left panel the dotted line shows the level of investment presented in Section 2 and used for calibration). Note that the results are robust to changes in these assumptions (cf. Note 10), as long as improved information enables a less volatile price signal, which we consider a fair assumption given the literature reviewed above.

4.3. Discount rate

The International Energy Agency (2010) recommends that lower discount rates (5%) should be considered as the rate available to an investor with a low risk of default in a fairly stable environment, whereas higher discount rates (10%) are more appropriate for investors facing substantially greater financial, technological and price risks. Similarly, Roques, Nuttall, Newbery, Neufville, and Connors (2006) report discount rates in power plant investment between 5–12.5%. Since we analyze a long-term investment into a new risky technology, a 10% discount rate has been considered as a baseline. To test the qualitative robustness of the results, we further perform sensitivity analyses for a range of 6–10%.

4.4. Technology and CCS

Table 3 lists technological parameters and costs for both coal- and gas-fired power plants.[11] The emission intensity of the technologies is taken from the technical report on CO_2 emissions from fuel combustion of the International Energy Agency (2012), whereas the region-specific data (technology share, energy supply) comes from the IEA Energy Policies Review for the European Union (International Energy Agency, 2008a). The power plant parameters and costs are derived from the "Projected Costs of Generating Electricity—2010" report (International Energy Agency, 2010). They provide expected technical and economic characteristics for both coal and gas capture plants, together with their reference plants without CCS. This enables us to derive the cost of a CCS retrofit used as an input to the model.

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Table 3. Technological parameters and CCS cost data (International Energy Agency [IEA], 2008b, 2010, 2012)		
Technology	**Coal**	**Gas**
Emission intensity (tCO$_2$/GWh)	920	351
Technology share (%)	21	20
Energy supply (GWh)	696,234	663,080
Levelized cost of electricity without CCS (EUR/MWh)	51.59	61.6
Levelized cost of electricity with CCS (EUR/MWh)	85.47	82.01
Capture rate (%)	85	85

Notes: Fuel prices in the IEA's "Projected Cost of Generating Electricity" (2010) are at US\$ 3.60 per GJ for hard coal (OECD), US\$ 9.76 per GJ for natural gas (OECD Europe) and US\$ 11.09 per GJ for natural gas (OECD Europe). For brown coal, national assumptions have been used, as it is not traded. Also, large gas and coal producers (e.g. Australia) can deviate from the price assumptions, in which cases domestic price assumptions have been used. The majority of respondents foresee an escalation of coal and gas prices for the duration of their plant's lifetime.

5. Results

The results have been organized in three separate sections. We start with the impact that the improvement in carbon monitoring will have on industry, which is quite different from the social planner perspective taken in the modeling and presented in the second subsection. While industry itself has been asking for a more stable carbon price signal in order to avoid stranded assets and to enable optimization of investment plans, firms can also benefit from fluctuations in carbon prices by exploiting deviations in their favor. It is therefore important to make a difference between the impact on industry and the impact in terms of the actual policy objective, emissions reductions. Still, it is essential to also discuss the impacts on those that at least partially have to bear the cost, as this is important information when it comes to political feasibility and potential distributional considerations.

5.1. Industry

As explained above, the different players have different objectives and thus experience different benefits and costs under a climate change mitigation regime when better information leads to more price stability. Starting with the industry, a representative energy company actually benefits to a certain extent from fluctuations in the CO$_2$ price, as it can exploit them to increase its profits. In Figure 3, we see that with an expansion of monitoring equipment, the CO$_2$ price variance decreases (upper left panel) and so does the price triggering the lower carbon technology (carbon capture and storage, upper right panel). Note that both are independent of the stabilization level we are investigating, while this does matter for the timing of investment into CCS (lower left panel). For each stabilization path tested (450, 480, 520 ppm), the investment timing first falls as we install more monitoring equipment and thus erode the plant owner's capacity to exploit carbon price fluctuations making later investment unattractive. In real options terms, the value of keeping the CCS option open decreases, as the uncertainty around the carbon price is reduced. Eventually, the CCS investment timing stabilizes for an improved observing system exceeding 10 million EUR. CCS is furthermore installed earlier, the more stringent the CO$_2$ reductions, i.e. the more ambitious the stabilization path chosen, with 450 ppm requiring investment as early as year 18 and 520 ppm shifting the investment out to year 60. The final panel (lower right) of Figure 3 summarizes the argument by displaying the cost distributions of gas- and coal-fired power plant owners, where the one with improved carbon monitoring does not only have a more narrow spread, but also exhibits a much higher expected value (i.e. the cost distribution shifts to the right).

In summary, the industry is not necessarily better off by improvements in monitoring leading to a more stable price signal. Even though larger shifts in the carbon price (e.g. due to a change in policy, cf. Fuss et al., 2009) have been perceived as disincentive for investors to commit large sums of

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money to installing less carbon-intensive or even carbon-saving technology, the fluctuations that we are analyzing here are less drastic and actually enable the firm to exploit them in its favor.
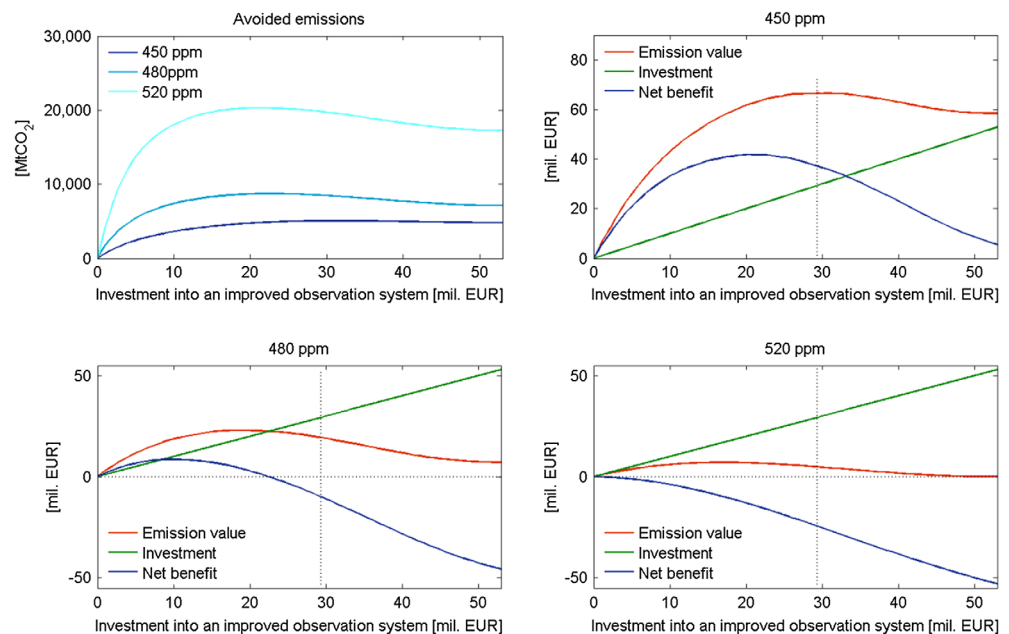
Having said that, it is clear that climate policy is not targeted at making fossil-fuel-fired power generation more attractive and thus we need to shift our focus to the government (or society) in order to estimate the actual benefit of improved carbon monitoring in terms of the emissions we can avoid by doing so.

5.2. Social planner perspective

The government, which aims at reducing total emissions, is confronted with the problem that energy emissions are relatively easy to measure, since these are coming from point sources, whereas the emissions of other sectors, e.g. agriculture and forestry, are less easily inferred in many cases. This can be due to activities that are not accounted for (e.g. illegal logging, non-compliance with sustainable practices) or because processes and interactions between them are not well understood and thus estimates of emissions flawed or at least biased. An improved carbon monitoring system that can measure the actual fluxes can thus help to reduce this uncertainty and therefore have a positive impact on price formation, which will then be subject to fewer adjustments and can thus deliver a more stable signal to industry and other sectors. But whether the expense for the improved observing system is justified needs to be weighed against a benefit that is even more difficult to estimate. In this study, we have decided to focus on the benefit directly associated with the policy objective; that is emissions reductions. We do acknowledge, however, that there are many co-benefits, which we do not incorporate into our benefit estimate and which could lead to much higher values of the total net benefit. This includes an inherent value society might place on decarbonization, but also a contribution to science such as e.g. an improvement in scientific understanding of the carbon cycle.

Figure 4 illustrates that—as could be expected from the results concerning the investment timing presented in Section 5.1—avoided emissions increase both with better carbon monitoring and with more relaxed climate goals (upper left panel), as the total amount of emissions that can be avoided is much higher than under 450 or 480 ppm. In the case of stricter targets, CCS is installed relatively earlier, so even with higher carbon price volatility the timing is not affected substantially. In the case of a less ambitious emission reduction target, however, investment is triggered late and—in

Figure 4. Benefits of investment into an improved carbon observing system.

instances of high carbon price volatility—sometimes not at all. Therefore, the avoided emissions are much higher in the 520 ppm scenario. In general, the reduction of the level of price volatility will be higher in more stringent scenarios, as the CO_2 price needed to achieve the more ambitious target will be higher to begin with.

The other three panels show the value of the avoided emissions (monetized by multiplying with the corresponding GHG shadow prices consistent with the 450 ppm (upper right panel), 480 ppm (lower let panel) and 520 ppm (lower right panel) pathways) as a red curve. The green curve corresponds to the investment level and the blue line finally represents the net benefit measured in million EUR. We see that the emission value is highest when the climate goal is most ambitious, as this pathway has the highest carbon prices, and that it first increases with improved carbon monitoring, but this effect diminishes, as carbon monitoring achieves larger scales. The net benefit is always positive when try-ing to reach 450 ppm, which is consistent with limiting global warming to 2°C above pre-industrial levels. For 480 ppm the net benefit soon turns negative and for 520 ppm---not surprisingly, as carbon prices are very low---better carbon monitoring makes only a little difference and the net benefit is negative, even though emissions are avoided also in this case. A more comprehensive valuation, how-ever, could lead to a positive net benefit, even in the absence of stringent emission reduction goals.
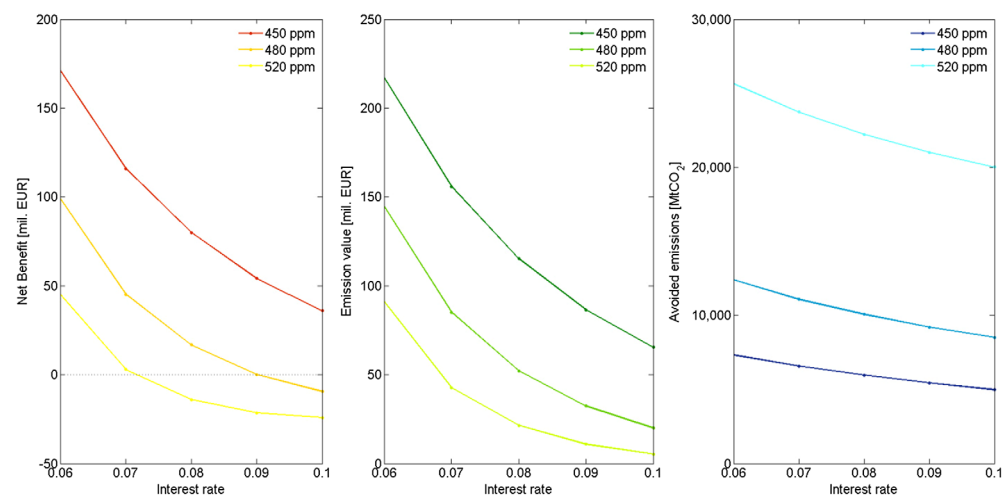
5.3. Sensitivity analysis

Obviously, the results are dependent on the parameterization and assumptions, cf. Sections 3 and 4 on data and methodology. However, having been on the conservative side for the assumptions, we do believe our results to be valid and maybe even more pronounced if some of the parameters were chosen in a less conservative manner. A number of sensitivity analyses have been conducted to back this up and the highest sensitivity has been found when varying the discount rate, which is why the results of this are presented in Figure 5 below.

Figure 5 shows that even if the discount rate is as high as 10%, there is a positive net benefit for the 450 ppm pathway, while discounting by a rate exceeding 9% turns the net benefit negative for 480 ppm. For the 520 ppm pathway, the net benefit is only positive when discounted at less than 8% (left panel). The less we discount the future, the higher this benefit becomes, reaching up to 170 mil-lion EUR for the 450 ppm path and 6% discount rate.

In addition, this sensitivity analysis also illustrates nicely again the restrictions of this benefit as-sessment, as avoided emissions under 520 ppm are very high already under 10% discounting and even higher under 7% discounting (almost 25 Gt CO_2). Monetizing this at the GHG shadow price con-sistent with 520 ppm drives down the emission value, but this does not include other co-benefits and the social benefits might be undervalued in this way (cf. discussion above).

Figure 5. Discount rate sensitivity analysis.

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6. Conclusion

In this study we have investigated one aspect of the benefit provided by improving carbon flux monitoring. In particular, we have examined the impact of investment when there is less uncertainty about the emissions reductions needed for stabilization at concentrations of 450, 480 and 520 ppm, respectively, which enables policy-makers to send a more stable price signal to investors and producers in the electricity sector. Our findings show that the relatively small fluctuations in carbon price trends that slight adjustments of the emissions cap imply are actually not entirely of disadvantage to investors. In fact, they can exploit these fluctuations economically and achieve extra profits. However, especially with a less stringent target, investment into decarbonization technology tends to be postponed under carbon price uncertainty, which is a typical real options result, and this means that the aim of the policy is jeopardized. So from the social planner's point-of-view, the benefit of having a better observing system should be measured in terms of the successfulness of reducing emissions, which we value at the corresponding CO_2 shadow prices before subtracting the cost of installing the monitoring equipment. For discount rates of up to 7% we find positive net benefits for all three concentration targets reaching up to 170 million EUR for the 450 ppm path and at a 6% discount rate. Taking into account that this concerns just one aspect of the benefit and many co-benefits of mitigation (e.g. in terms of reduced air pollution and improved health) or observation per se (e.g. in terms of supporting scientific research and an improved understanding of the carbon cycle) have not been considered, this is a sufficiently large value to justify investment into a better observing system.

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Notes

1. The total expected cost for operating the whole network are determined by summing the cost for each year and discounting back to the first period until infinity, as we are looking at the long run.
2. This is in accordance with rising shadow prices for carbon under any stabilization target. Carbon prices rise exponentially over time if emission reductions are allocated optimally over time, or if banking and borrowing of emission permits is allowed. These assumptions are standard in first best analysis of climate stabilization policies.
3. We assume both the investment and operational cost to be constant. This simplification is important for the model complexity, since it will enable us to derive the results analytically thus to provide the results necessary for the second layer.
4. There is no learning-by-doing, which could in this setup only be integrated in the form of special learning functions and would be beyond the scope of our analysis.
5. For example in an EU ETS type of scheme or in the form of taxation.
6. The assumption of risk neutrality is standard in economic analysis of such investment problems and incorporating risk aversion in this specific setup is mathematically intricate and beyond the scope of our analysis. Intuitively, the impact on the results should depend on how the risk aversion would be modeled, but should not reduce the benefits from improved monitoring, as volatility would be valued negatively by investors.
7. See Knopf et al. (2013) for a model comparison focusing on five countries from the EU-27, in particular Germany.
8. Note that in some countries CCS is not an option currently due to legal barriers (Austria) and low public acceptance (Germany, see Von Hirschhausen, Herold, & Oei, 2012), which would need to be overcome for full realization of the potentials calculated here. However, we are presenting only one possible pathway of

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transformation of the energy system and others which are conceivable and comparable in cost structure would similarly benefit from a more stable pricing signal, which is independent of the technology chosen for the analysis.

9. An exponential decrease has been tested as well. The results remain qualitatively the same; the difference in quantitative results is only minor.

10. This is a simplifying assumption. In order to determine the actual decrease more precisely, we would need to evaluate further (smaller) networks and their efficiency would depend very much on the specific sites excluded, the baseline network for monitoring, the timing of improving the baseline network. However, we think it is fair to assume that beyond a certain level of observation, marginal additions will not lead to major improvements in carbon price stability when it has already been stabilized substantially.

11. All $ values are converted into EUR values at an exchange rate of 1.3 US$/EUR.

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Appendix 1

The expected value in the objective of the original formulation (1) can be reformulated by following steps

$$E\left[\int_0^\tau e^{-rt}QP_t\,dt + Ce^{-r\tau} + \int_\tau^\infty e^{-rt}Qc\,dt\right] = E\left[\int_0^\infty e^{-rt}QP_t\,dt + Ce^{-r\tau} + \int_\tau^\infty e^{-rt}Q(c-P_t)\,dt\right]$$

$$= Q\frac{P^0}{r-\mu} + E\left[Ce^{-r\tau} + e^{-r\tau}\int_0^\infty e^{-rs}Qc\,ds - \frac{P_\tau}{P^0}\int_0^\infty e^{(\mu-r)s}QP^0\,ds\right]$$

$$= Q\frac{P^0}{r-\mu} + E\left[Ce^{-r\tau} + e^{-r\tau}Q\left(\frac{c}{r} - \frac{P_\tau}{r-\mu}\right)\right].$$

Thus Equation (1) is equivalent to $\min\limits_{\tau} Q\frac{P^0}{r-\mu} + E\left[Ce^{-r\tau} + e^{-r\tau}Q\left(\frac{c}{r} - \frac{P_\tau}{r-\mu}\right)\right].$

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