CECILIA 2050

OPTIMAL EU CLIMATE POLICY

Choosing Efficient Combinations of Policy Instruments for Low-carbon development and Innovation to Achieve Europe's 2050 climate targets

Dealing with uncertainty in the European climate policy

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LIST OF ABBREVIATIONS

FIP	Feed-In-Premium
FIT	Feed-In-Tariff
GHG	Greenhouse Gas
RPS	Renewable Portfolio Standard
TRQ	Tradable Renewable Quota
PV	Photovoltaic

1 Executive summary

While European climate policy has been the target of a large number of economic analyses, both from academics and from the European Commission services, almost all modelling exercises have been deterministic, allowing at best for testing a few scenarios. Stochastic economic models of environmental policies have been developed but in most cases without numerical application to climate policies. In the few exceptions, the climate policy only consists in CO_2 pricing, implemented either through a tax, an ETS or a rate-based policy (e.g. an intensity target) – without including more realistic policy packages.

Yet the history of climate policy is full of surprises, including the swings in EU ETS allowance price and the unexpected surge in photovoltaic investment in Germany. This deliverable first provides a survey of economic analyses devoted to uncertainty in climate policy-making (section 3). This allows us to identify gaps in the literature, which because of these gaps cannot shed light on the existing European policy package. Thus we try to fill this gap by developing a simple stochastic model of the European energy sector featuring the most important uncertainty sources in this context, i.e. economic activity in CO_2-intensive sectors and the cost of key technologies, as well as the interaction between climate policy and renewable energy subsidies (section 4).

It turns out that uncertainty changes the (ex ante) optimal policy choice. In particular, most analysts conclude that if CO_2 emissions from the power sector are covered by an ETS, climate change mitigation does not justify subsidies to renewable energy or electricity savings; cf. e.g. Böhringer and Rosendahl (2010). Yet, if uncertainty is high enough, emissions may fall below the ETS cap in some states of the world, leading to a nil allowance price. Hence, we show that such subsidies at a proper level are justified as a kind of insurance that at least some abatement will happen in these states of the world, which is welcome since the marginal benefit of CO_2 abatement is positive in these states of the world also.

Moreover, we show that the design of renewable energy subsidies should take into account uncertainty. In particular, a feed-in-tariff, a feed-in-premium and a renewable quota all respond in a specific way to a change in renewable energy cost, in fossil fuels price or in electricity demand. We analyse the ranking of renewable subsidy instruments in terms of expected welfare when they are implemented together with an ETS, as is currently the case in the EU. Compared to the premium, the feed-in-tariff provides a subsidy which decreases with the electricity price, itself positively correlated to the CO_2 price. Hence it helps to stabilise the marginal abatement cost, which is welcome for a stock pollutant like CO_2 whose marginal benefit curve is flat. On the opposite, a renewable quota generates a higher marginal abatement cost when it is less needed, so it appears as the worst policy instrument in this context.

Given the difficulties faced to reform the ETS, and the sharp criticisms addressed to the Market Stability Reserve proposal, it seems reasonable to consider that, at the time of writing, we do not know whether the EU ETS cap will bind or not in the following years. Such a context calls for the following recommendations:

- Try to fix the EU ETS in order to stabilise the CO_2 price, if possible by setting a price floor, or by implementing a reform package with as similar an outcome as possible.
- Maintain incentives to renewable energies and energy savings, even in the electricity sector, in spite of the fact that its emissions are covered by the ETS: we cannot take for granted that the ETS will work in the near future. Incidentally, the rationale for renewable support presented here applies for electricity savings instruments (labels, standards, subsidies, white certificates…), while more analysis is required to compare these instruments in terms of efficiency under uncertainty.

When choosing instruments to foster renewables and energy savings, take into account uncertainty and interaction with other policy instruments, including of course the EU ETS. In this regard, it is unfortunate that the recent guidelines of the European Commission (2014) invite Member States to refrain from using feed-in-tariffs, while our analysis indicate that in the present context, it may well be the preferred renewable support instrument..

2 Introduction

While European climate policy has been the target of a large number of economic analyses, both from academics and from the European Commission services, almost all modelling exercises have been deterministic, allowing at best for testing a few scenarios. Stochastic economic models of environmental policies have been developed but in most cases without numerical application to climate policies. In the few exceptions, the climate policy only consists in CO_2 pricing, implemented either through a tax, an ETS or a rate-based policy (e.g. an intensity target) – without including more realistic policy packages.

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3 Uncertainty in climate policy-making: key insights from economic studies

The limited literature devoted to the choice of a climate policy under uncertainty can be split in two parts: the first one (3.1) deals with a hypothetical global climate policy, the main uncertainty being scientific: in most cases the climate sensitivity (i.e. the equilibrium global average temperature increase entailed by a doubling in CO_2 atmospheric concentration) and sometimes other parameters. The second one (3.2) is about policy-making at a domestic or EU level and is more diverse about the uncertainties analysed.

3.1 Global analyses

It is widely recognised that climate change involves a 'cascade of uncertainty': the above-mentioned climate sensitivity, the carbon cycle, the regional features of global change (rainfall, extreme events), the biophysical impacts (e.g. on crop yield), the socio-economic costs or benefits of these impacts, the socio-economic costs of adaptation and of mitigation are all very uncertain. Obviously, including all these sources of uncertainty in a model at the same time would be extremely difficult, so the first articles have focused on a single one, in most cases a damage parameter, climate sensitivity or the target GHG-concentration, i.e. the concentration above which ''dangerous interference with the climate system'' (the avoidance of which being the official aim of the UNFCCC) would occur.

Ha-Duong et al. (1997) focus on the latter, using a compact inter-temporal optimization model, DIAM, featuring inertia in capital, unlike the well-known DICE model (Nordhaus, 1994), which includes inertia only in its climate module. This is a key point because without inertia in capital, the transition costs for switching from one emission path to another would be nil, and uncertainty would be less critical. DIAM determines the least-cost CO_2-emission pathway consistent with staying below a given or stochastic atmospheric CO_2 concentration ceiling. While analyses based on early integrated assessment models of climate change without technical inertia (such as the influential work of Wiley et al., 1996) concluded that the optimal trajectory involves very little abatement in the short run, Ha-Duong et al. show that the optimal trajectory with uncertainty requires abatement even in the short run, and a sequential decision strategy which allows to adapt the trajectory when information about the best target CO_2 concentration becomes available. Since then, many other studies, reviewed by Parson and Karwat (2011), have applied this kind of sequential decision-making.

More recently, the most influential work on this topic was a series of articles initiated by Weitzman (a good introduction to which being Weitzman, 2014), showing that even with a very small probability and moderate risk-aversion, the possibility that climate change may have a catastrophic impact has the potential to increase the social cost of carbon significantly – or even to make it infinite. Admittedly the result of an infinite social cost of carbon is clearly a *reductio ad absurdum*, but it highlights the importance of considering unlikely but potentially very severe climate change-induced catastrophes in economic analyses.

While the works mentioned up to now determine the optimal emission *trajectory*, they do not deal with the *policies* to implement them, so we do not present these debates in more details, and now turn to analyses of climate *policies* under uncertainty – first at the global level, policy-making at the domestic level being dealt with in section 3.2 below.

In this respect, a key point is the inertia in policy-making, which is unavoidable for at least two reasons: policies take time to negotiate (this is perhaps especially true for climate policies), and too frequent changes in public policies increase risk for investors in long-lasting capital, thus they limit investment, including those aiming at abating emission. Hence there is a trade-off between *predictability* of policies and *frequent optimisation* of them in view of new information. It may take a decade or more before a policy is adapted to this new information, and in the meantime different policies will lead to different outcomes, following the same change in, say, abatement costs. For instance, if abatement costs drop, a price instrument will lead to less emissions but a quantity instrument will leave emissions unchanged (as long as the cap is binding) while the CO_2 price will drop.

The majority of the studies which deal with the choice of climate policy instruments at the global level build on the theoretical papers by Weitzman (1974) and Roberts and Spence (1976) on the choice between price instruments, quantity instruments and hybrid instruments in case of uncertainty on the abatement cost. Pizer (1999), perhaps the first researcher to apply this framework to climate policies, shows that a price instrument (a global carbon tax) performs much better than a quantity instrument (a global cap-and-trade system) because the marginal damage curve is flatter than the marginal cost curve, which itself is because CO_2 is a stock pollutant. Interestingly, this conclusion is robust to the possibility of a climate catastrophe, implemented as a threshold in the damage function, if the location of the threshold is unknown (which is the case in reality), as shown by Pizer (2003). Since a global carbon tax may be more difficult to implement than a global cap-and-trade system (whose implementation is itself far from easy), some of these papers have assessed hybrid instruments *à la* Roberts and Spence (1976) and concluded that a global cap-and-trade system with a price cap and a price floor (if set at the ex ante-optimal levels) would bring only a slightly higher expected welfare than a tax, but a much higher expected welfare than a pure quantity instrument (Philibert, 2009).

3.2 Policy-making at the domestic level

3.2.1 Carbon pricing

At the domestic level, the marginal benefit curve is even flatter than at the global one, since a single country cannot change CO_2 concentration by a large amount over the time period relevant for analysis, i.e. before the policy is amended in view of new information. Hence, if the benefit from GHG abatement for a country is assumed to be climate change mitigation, a price instrument has an obvious advantage over a quantity one. Hence, analyses at the domestic level have taken a different route.

First, several papers have compared a quantity instrument, not (or not only) to a price instrument but also to an intensity target, i.e. a target function of current GDP. The rationale for this instrument, proposed in the late 1990s, is that if GDP is higher than expected, so will unabated emissions. Hence, with a fixed target, the required abatement will also be higher than expected, while if the target is proportional to GDP, the required abatement will be less affected by the surge in GDP. More generally, if unabated emissions were perfectly proportional to GDP, the required abatement with an intensity target would be unaffected by variations in GDP; since costs are convex, this implies that the expected welfare is higher than with an uncertain, fixed, target. Unfortunately, this proportionality is not perfect, so indexing the target on GDP creates some noise which reduces the expected welfare of intensity targets. For this reason, intensity targets bring a lower (respectively higher) expected welfare than fixed targets in countries which feature a rather low (respectively high) correlation between GDP and emissions (e.g. Jotzo and Pezzey, 2007; Newell and Pizer, 2008; Ellerman and Sue Wing, 2003; Branger and Quirion, 2014). It is also possible to design more complex instruments with a higher expected welfare, like partial indexation of the target on GDP, or dual targets, one of which is fixed and the other indexed on GDP, but this comes at the cost of more complexity. To sum up, while uncertainty influences the choice between fixed and indexed targets, economic analysis does not provide a clear ranking yet.

In the above-mentioned analyses, the benefit from CO_2 abatement consists in climate change mitigation. Yet, for a country party to the Kyoto Protocol or a similar treaty which fixes a cap on aggregate emissions, less emissions from one party allows more emissions from the others, since the former can sell (or buy less) emissions allowances. This context is analysed by Quirion (2010), who quantifies uncertainty based on a multi-model ensemble. Even with a completely flat marginal benefit curve, this paper concludes that the quantity instrument dominates the price instrument in some regions (the US and Japan) and brings a similar expected welfare for Europe. This result contradicts the basic version of the Weitzman's (1974) model, which states that a price instrument is to be preferred if the marginal cost curve is steeper than the marginal benefit curve. However, it is consistent with a more elaborated version of Weitzman's model, which accounts for the correlation between costs and benefits. This correlation is positive in this case because if e.g. the cost of abatement technologies is lower than expected then this will typically happen in many parts of the world, so the international price of GHG allowances (the marginal benefit in this framework) will also drop. As explained by Stavins (1996), a positive correlation between marginal costs and benefits raises the expected welfare of a quantity instrument compared to a price instrument. Yet, the political relevance of this analysis is limited in the current context since the climate regime does not evolve towards a global cap-and-trade system with a global carbon price, but towards a more bottom-up architecture.

3.2.2 Renewable energy support

While virtually all developed and emerging countries support renewable energy, these subsidies take various forms, the most common being Feed-In-Tariffs (FIT), Feed-In-Premiums (FIP) and Tradable Renewable Quotas (TRQ), also called Renewable Portfolio Standards (RPS) or Tradable Green Certificate systems. Under a FIT, a fixed price (above the expected electricity market price) is guaranteed to producers of renewable electricity for a period of typically ten to twenty years. The FIP is a per-unit subsidy for electricity from renewables, added to the electricity price. Finally, the RPS requires producers of fossil-generated electricity to acquire a certain number of 'green certificates' for each unit of output. These certificates are generated by the producers of renewable electricity, who receive one certificate for each unit of output. Of course, reality is more complex than this simple segmentation between FIT, FIP and RPS: the concrete implementation of these instruments differs across jurisdictions, other instruments exist (such as investment subsidies or tenders) and several support systems are often combined (del Río and Mir-Artigues, 2014). Yet, this segmentation is essential to understand how renewable support policies react to uncertainty. Indeed, in a first-best setting with full information, it is obvious that with each instrument the social optimum can be implemented, i.e. the share of renewables can be increased up to the desired level. However, in reality many of the parameters that would be needed to optimally set the level of the policy instrument (i.e. how high the FIT, or the FIP, or the amount of required green certificates should be) are not perfectly known. For example, the exact production costs for renewable electricity and also for fossil-generated electricity might be private information of the producers. In addition, the regulator's *ex ante* knowledge about future electricity demand, which can be expected to significantly influence the impact of any renewable policy, is surely less than perfect.

In the presence of such uncertainty, the overall impact of any of the three instruments will also be uncertain. This is well illustrated by the case of photovoltaic electricity (solar PV) in Germany, where "reality has overtaken model projections" (Schmid et al. 2013), i.e. the capacity expansion induced by the FIT paid to solar PV exceeded all previous scenario projections (Ibid.,Fig.(8)). The reason for this surprising surge is that costs for solar panels went down much faster than expected (Bazilian et al. 2013). The resulting large solar PV capacity in Germany is now often criticized by economists as an unwarranted overshoot and taken as evidence that in hindsight the FIT for solar PV was set excessively high (Frondel et al. 2012), but an alternative conclusion – that this higher than expected PV expansion is justified by the cost decrease – cannot be ruled out *a priori*. Hence, even though this expansion would have not occurred with a RPS (and less so with a FIP), a model is needed to assess which support system would have brought the best outcome.

A few papers have compared FIT, FIP and RPS (or just FIT and RPS) according to the way they react to uncertainty. Menanteau et al. (2003), in a qualitative analysis without formal model, illustrate and compare the different mechanics of FIT and RPS, also under uncertainty, and use a multi-criteria analysis to derive their conclusion that the efficiency of the former is superior. Butler and Neuhoff (2008) corroborate this finding in a comparative case study on onshore wind-energy in Germany and the UK, citing as one of the main reasons the lower risk to developers the FIT offers.

The effect of risk-aversion on the side of investors is also investigated by Fagiani et al. (2013), who use a system-dynamic numerical model to compare the performance of FIT and RPS.

They find that while in theory FIT again offers a superior performance, the RPS might be more robust and still offer acceptable cost-efficiency as long as risk-aversion is moderate, and actually become the preferred instrument in the presence of additional constraints, like excessive time-discounting by investors. Similarly, in an *ex post* analysis of wind power deployment in Denmark, Gavard (2015) concludes that due to investors' risk-aversion a higher subsidy is required if it takes the form of a FIP instead of a FIT. More precisely, on average a 21 €/MWh support on top of the laisser-faire electricity price is necessary to observe monthly connections of new turbines to the grid with a probability of 0.5, while under a FIP this probability is reached for a support policy of 27 €/MWh.

The more formal study by Rivers and Jaccard (2006) also develops a model of the electricity market (which is then simulated numerically), but focusses on the regulatory choice between command-and-control or market-based instruments. Tamás et al. (2010) study the difference between FIT and RPS under imperfect competition in a theoretical model, but in a purely static setting without learning effects and also without uncertainty. The review of Fischer and Preonas (2010) addresses the interaction of different policy goals and instruments. They use a formal model, but mainly to illustrate the mechanics of the various policy instruments, and do not allow for uncertainty. Noteworthy, they report an increasing preference for RPS as the instrument of choice for stimulating the deployment of renewables.

Marschinski and Quirion (2014) compare FIT, FIP and RPS in terms of expected welfare under three sources of uncertainty: on electricity demand, on the cost of fossil-based electricity and on the cost of renewable electricity. In their model, the justification for supporting renewables is that they induce technical progress, a part of which is an external benefit, through learning-by-doing. More precisely, the cost of renewables in the second period is lower, the higher the investment in renewables in the first period. The ranking of support systems depends on the uncertainty sources and on parameters, but as a general rule, FIP and FIT perform better than RPS because they allow the investment in renewables to surge if the relative cost of renewables compared to fossils is lower than expected, and vice-versa. A numerical application on the US confirms this result: the instrument which provides the highest expected benefit is the FIT if uncertainty concerns the cost of renewables, the FIP if it concerns the cost of fossils and the RPS if it concerns electricity demand, but in the latter case, the superiority of RPS is quantitatively negligible (less than 100 million USD/year), while the RPS entails a large extra cost over the other support system in case of cost uncertainty (up to 4 billion USD/year).

3.2.3 Combination between carbon pricing and renewable energy support

In the articles presented in the last section, renewables support policies are assumed to be implemented in isolation, while in the EU, as in some US States or Chinese provinces, or in Korea, they coexist with a cap-and-trade system covering CO_2 emissions from electricity generation. If the emission cap binds in all states of nature, the paradox labelled "green promotes the dirtiest" by Böhringer and Rosendahl (2010) arises: CO_2 abatement induced by renewables decrease the CO_2 price, favouring coal vs. gas and leaving CO_2 emissions unchanged since they are fixed by the cap. Incidentally, this substitution rises local pollutant emissions hence “promotes the dirtiest”[1].

Yet Lecuyer and Quirion (2013) show that if in some states of nature the emission cap does not bind, then it is better (ex ante) to implement a subsidy to renewable energy in addition to the ETS, even though in the model CO_2 abatement is the only rationale for renewable energy support. This is not only a theoretical result: as evidenced by the authors, in most ETS worldwide, the cap has been non-binding during a part of their history. Concerning the EU ETS, we do not know now whether its cap will become binding in the forthcoming years, because of the importance of the surplus (more than one year of emissions; Sandbag, 2014) and of the political difficulty to adopt an ambitious reform. The debate about renewable energy targets and policies often takes the form of a dialogue of the deaf, because some experts and stakeholders assume that the EU ETS cap will bind (implying the “green promotes the dirtiest” paradox) while others assume that it will not, which implies that supporting renewables will cut CO_2 emission. Explicitly introducing uncertainty in the analysis has the potential to allow a balanced view and a more inform dialogue between stakeholders with opposite views.

The main limitations of Lecuyer and Quirion’s (2013) analysis are, first, that only a FIP is modelled, while FIP, FIT and RPS interact differently with an ETS and, second, that the electricity sector modelling is rather crude. Thus the model presented in the next section attempts to overcome these two limitations.

4 Uncertainty and interaction of climate and energy policies in the European context

4.1 Motivation and scenarios

Many surprises occurred in the last decade in the climate-energy landscape. Fossil fuel prices have followed ups and downs, the cost of renewable-based electricity has declined much faster than expected, and economic activity in some CO_2-intensive sectors (especially in building materials) has crashed in many European countries. All these surprises have impacted CO_2 emissions in various ways, the most striking being the two crashes of the EU ETS allowance price at the end of phase I in 2006-2007 and following the economic crisis in 2008-2009. In many other ETS around the world, the allowance price has been driven down to zero or to the floor price (the US SO_2 ETS, RGGI…) and there is no reason to think that no surprise will occur in the next decades as well, also impacting CO_2 emissions. While it is well-known that uncertainty impacts the relative expected cost of policy instruments (e.g.

[1] On the other hand, as mentioned by Philibert (2014), this substitution may improve Europe’s energy security by cutting imports of Russian gas. In addition investment in renewables generates irreversibility and learning which is not the case for coal-gas substitution (Philibert, 2011).

Weitzman, 1974), how precisely it changes the ordering of which instrument requires a specific modelling, taking into account the features of the considered policy landscape.

To investigate the effect of uncertainty on the optimal policy choice for mitigation in the European electricity sector, we develop a two-stage model with uncertainty. Several renewable energy support instruments being implemented in various member states, we compare three different policy instruments.

- A feed-in tariff (FIT), denoted ρ, consisting in a guaranteed output price. This is the most widely instrument currently in place: it exists in at least 18 countries in Europe, 80 to 90 worldwide, plus some states and provinces in India, Australia, the US and Canada (REN21, 2014). However the European Commission's (2014) recent guidelines on State aid for environmental protection and energy suggest limiting FIT to small installations (less than 3 MW for wind, less than 0.5 MW for solar).
- A production subsidy (or feed-in premium, FIP), denoted Θ, added to the market price. This instrument has recently replaced the FIT for most market segments in Germany, and France is currently implementing a similar change (MEDDE, 2014) following the above-mentioned European Commission's recent guidelines.
- A renewable portfolio standard (RPS), also called Tradable Renewable Quota or Tradable Green Certificate system, sets a minimum share of renewables, denoted α, in electricity production or consumption. Such a system was employed, e.g. in the UK and is currently in place in many states of the US, Sweden, South Korea and Flanders (REN21, 2014). In some of these systems but not all, electricity providers may comply with their obligation by buying 'green certificates' sold by providers who over-comply.

For tractability reasons and for a better comparison between instruments, we do not consider the earmarked electricity consumption tax that often accompanies the FIT and FIP in European countries (but not the RPS).

As the European Commission restated in numerous occasions the central role of the EU-ETS, we consider that the renewable support instrument is always combined to an emission cap, which may, or not, bind. As explained above, whether or not the cap binds drastically change the usefulness of renewable support policies. Taking into account this uncertainty renews the analysis of the interaction between climate and renewable energy policies. Moreover, as we will show, in such a context the type of renewable energy policy matters in a way that has not been analysed so far. More precisely, results qualitatively vary with the level of uncertainty: at a relatively low level, the optimal policy mix does not qualitatively change compared to a situation without uncertainty, while at a relatively high level, the optimal policy mix is qualitatively different.

The next sections (4.2 and 4.3) will present the model setting with an uncertainty on the level of the future demand, in the form of a possible shock on the baseline demand level. Section 4.4 will discuss the differences when the uncertainty affects the cost of renewable technologies or gas production. Section 4.5 presents a numerical implementation of the model, quantified for the EU electricity market and section 5 concludes.

4.2 A simple model: uncertainty on electricity demand and a single fossil-fuel technology

We base our theoretical analysis on an extension of the work by Lecuyer and Quirion (2013). We model a stylised European electricity market with an uncertain demand. There is a possibility of a shock on fossil electricity production, hence on CO_2 emissions (absent climate policy), resulting in an uncertain abatement effort for any given emission cap. In this section the shock is on electricity demand and may be due to the business cycle or to other unexpected variations in electricity demand.

The model is a two-stage framework, with three types of agents: a social planner, representative electricity producers and representative consumers. In the first stage, the social planner chooses the level of various policy instrument settings, facing an uncertainty about the level of future electricity demand. In the second stage, uncertainty is resolved and electricity producers maximise their profit given the policy instrument levels.

The model is solved backwards. We first present the profit maximisation programs of the representative producers, and their reaction functions for the various policy settings considered. We then present the social planner's expected welfare maximisation problem, taking into account the reaction of producers to the various policy settings.

4.2.1 The producer's profit maximisation problem

We consider two types of electricity generation technologies: fossil fuels (f) and renewables (r), producing a perfectly substitutable product that is sold at a price p on the electricity wholesale market. The representative producer faces an aggregate emission cap Ω, with an allowance market producing a carbon price ϕ, equal to the shadow value of the emission cap constraint. The representative producer also benefits from a renewable promotion scheme. The producer maximises its profit Π, as shown in the equations below. The four instrument settings yield three different profit maximisation programs:

- the FIT is represented in program (1),
- the FIP is in program (2),
- the RPS is in program (3),

The RPS is associated with a shadow cost of the renewable quota constraint π. It is also the price of green certificates if the latter are exchanged on a specific market associated to the RPS. The programs are:

$$\max_{f,r} \Pi[p,f,r,\phi,\rho] = p\,f + \rho\,r - C_f[f] - C_r[r] - \phi\,\tau\,f \tag{1}$$

$$\max_{f,r} \Pi[p,f,r,\phi,\rho] = p\,f + (p+\theta)\,r - C_f[f] - C_r[r] - \phi\,\tau\,f \tag{2}$$

$$\max_{f,r} \Pi[p,f,r,\phi,\rho] = p\,f + (p+\pi)\,r - C_f[f] - C_r[r] - \phi\,\tau\,f \tag{3}$$

where $C_f(f)$ and $C_r(r)$ are the production costs from fossil fuel and renewable respectively. ρ is the level of the FIT and θ is the level of the FIP. We assume decreasing returns for renewables and constant returns for fossil-based power plants ($C_f'(f)>0$; $C_r'(r)>0$; $C_f''(f)=0$ and $C_r''(r)>0$). τ is the unabated carbon intensity of fossil fuel-based electricity production. The cost functions have a classical linear-quadratic form:

$$C_f[f] = \iota_f \cdot f$$

$$C_r[r] = \iota_r \cdot r + \frac{r^2}{2\sigma_r}$$

with ι_f and ι_r as the intercepts (iota like intercept) of the fossil fuel and the renewable marginal supply function respectively and σ_r is the slope (sigma like slope) of the renewable marginal supply function. We define a linear downward sloping electricity demand function d(p) (with d'(p)<0) whose intercept depends on the state of the world. We consider two different states s occurring with a probability P_s, one with a high demand ($d_+(p)$) and one with a low demand ($d_-(p)$). The demand function is defined as:

$$d[p] = (\iota_d \pm \Delta) - \sigma_d p$$

with the intercept being $\iota_d+\Delta$ in the high-demand state of the world and $\iota_d-\Delta$ in the low-demand state. The equilibrium conditions on the markets for electricity, CO_2 allowances, and green certificates (under the RPS scenario) thus depend on the state of the world.

If uncertainty is low enough so that the cap is binding in all states of demand, the market clearing conditions on the electricity, the CO_2 allowance market and the green certificate market are given by the following three equations:

$$f + r = d(p) \tag{4}$$

$$\tau f = \Omega \tag{5}$$

$$\begin{cases} r = \alpha(r+f) \\ \pi > 0 \end{cases} \text{or} \begin{cases} r > \alpha(r+f) \\ \pi = 0 \end{cases} \tag{6}$$

Equation (4) states that in each state of the world, the electricity supply has to meet the demand on the electricity market. Equation (5) states that emissions equal the emission cap, while equation (6) states that if a RPS is implemented two cases can occur. If the RPS target is binding (left part of the equation), the price of the green certificates π is positive and the share of renewables is α. If the RPS target does not bind, $\pi = 0$ and renewable production is higher than the RPS target.

We also consider the case where uncertainty can be so high that even for the optimal level of the emission cap, the carbon price can be driven down to zero in the low-demand state of the world (see Lecuyer and Quirion (2013) for a discussion of this possibility and a graphical illustration).

$$\begin{cases} \tau \cdot f^- < \Omega \\ \phi^- = 0 \end{cases} \text{or} \begin{cases} \tau \cdot f^+ = \Omega \\ \phi^+ > 0 \end{cases} \tag{9}$$

The set of (in)equalities (9) expresses the joint constraint on emissions and carbon price. In the high-demand state of the world, total emissions equal the cap Ω and the carbon price is therefore strictly positive. In the low-demand state, we assume that the emission cap constraint is non-binding, hence the carbon price is nil.

The first order conditions of the producer maximisation problem are the following:

$$p = \tau \cdot \phi + \iota_f \tag{10}$$

$$\rho = \iota_r + \frac{r}{\sigma_r} \tag{11}$$

$$p + \theta = \iota_r + \frac{r}{\sigma_r} \tag{12}$$

$$p + \pi = \iota_r + \frac{r}{\sigma_r} \tag{13}$$

Equation (10) states that fossil fuel producers will equalise marginal production costs with the wholesale market price, net from the price of emissions.

Renewable producers will equalise marginal production costs with the wholesale market price, net from the policy instrument or their shadow cost: in (11) the FIT, in (12) the FIP plus the market price, in (13) the market price plus the shadow cost of the RPS.

The first order equations and market clearing conditions are used to compute the reaction functions of the representative producer in the four policy settings considered. The following equations are considered:

- (4), (5) or (9), (10), (11) in the case of a FIT;
- (4), (5) or (9), (10), (12) in the case of a FIP;
- (4), (5) or (9), (6), (10), (13) in the case of a RPS.

4.2.2 The social planner's expected welfare maximisation problem

All agents are assumed risk-neutral. As in Lecuyer and Quirion (2013), the social planner maximises the expected welfare by choosing the level of two policy instruments: the emission cap and a renewable promotion instrument, taking the reaction functions of producers as given. P_s is the probability of the state of the world s: $P_+=\lambda$ and $P_-=(1-\lambda)$, $\lambda \in [0,1]$. CS(p) is the consumer surplus and dam(f) is the environmental damage function from GHG emissions. The last two terms of the expected welfare are the impact of the ETS auctions and renewable subsidies on government budget: they equal, with the opposite sign, transfers to/from producers included in the profit functions. Depending on the policy mix, the program is:

$$\max_{\Omega,\rho} \sum\nolimits_{s \in \text{states}} P_s[CS(p) + \Pi[p, f, r, \phi, \rho] - dam(f) - (\rho - p)r + \phi\, \tau\, f] \tag{14}$$

$$\max_{\Omega,\rho} \sum\nolimits_{s \in \text{states}} P_s[CS(p) + \Pi[p, f, r, \phi, \rho] - dam(f) - \theta\, r + \phi\, \tau\, f] \tag{15}$$

$$\max_{\Omega,\rho} \sum\nolimits_{s \in \text{states}} P_s[CS(p) + \Pi[p, f, r, \phi, \rho] - dam(f) - \pi\, r + \phi\, \tau\, f] \tag{16}$$

Equation (14) is the program for a combination ETS-FIT; equation (15), the program for a combination ETS-FIP for renewable; equation (16), the program for a combination ETS-RPS.

The consumer surplus is:

$$CS(p) = \int_0^{d(p)} d^{-1}(q)\, dq - p\, d(p)$$

The damage function is flat, reflecting the fact that emissions from the European electricity sector over one phase of the EU ETS do not change the CO_2 atmospheric concentration by a large amount: hence, in the range of uncertainty and for the policy mixes considered, the marginal benefit from abating emissions is similar.

$$\mathrm{dam}[f] = \delta\, \tau\, f$$

With δ the constant environmental damage coefficient (Newell and Pizer, 2003). After having substituted the market variables in the expected welfare functions (14)-(16) with the reaction functions coming from the producer problems, we maximise the expected welfare. The first-order conditions give the optimal levels of the policy instruments across all states. Re-injecting the optimal policy levels in the reaction functions of producers give the optimal level of prices and quantities in the two states of the world, as well as the expected welfare level.

4.3 Results of the simple model

4.3.1 Optimal policy levels when uncertainty is low

There is a threshold in the level of the shock, where the optimal policy mix changes qualitatively. Below this threshold, it is optimal to define an emission cap such that the expected abatement cost is equal to the marginal damage from their emissions. The carbon price is higher than the marginal damage in the high demand state, because it is more expensive to comply with any given level of the cap, but it is lower in the low demand state. Below this threshold, it is never optimal to support renewables.

The optimal relative levels of the support in the high and low demand states depend on the details of the support mechanism. It seems reasonable to assume that renewables can never be taxed, even implicitly. This is equivalent to say that renewable producers can choose between benefitting from the FIT or receiving the market price once the uncertainty is resolved, or that the RPS is only binding in one direction, that is it does not prevent renewable producers from overachieving the target.

In all settings, the optimal emission cap is:

$$\Omega^* = \tau(\iota_d + \iota_r\sigma_r - \Delta(1-2\lambda) - (\sigma_d + \sigma_r)(\delta\tau + \iota_f))$$

and the optimal instruments are:

$$\rho^* = \frac{(\delta\tau + \iota_f)(\sigma_d + \sigma_r) - 2\,\Delta\,\lambda}{\sigma_d + \sigma_r}$$

$$\theta^* = 0$$

$$\alpha^* = \frac{\sigma_r(-2\Delta(\lambda - 1) + (\delta\tau + \iota_f - \iota_r)(\sigma_d + \sigma_r))}{(\iota_d - (\delta\tau + \iota_f)\sigma_d)(\sigma_d + \sigma_r) + \Delta((2\lambda - 1)\sigma_d + \sigma_r)}$$

We see immediately that the FIP is set at zero. As discussed above, the FIT and the RPS are non-binding in the high-demand state of the world, because in this case, the high electricity price makes the market alternative more attractive for renewable producers. Moreover each one of them is set so as to give a zero additional incentive for renewables in the low demand state, i.e. the optimal FIT corresponds to the optimal low demand state price while the optimal RPS corresponds to the optimal low demand renewable market share – in other word, they have no impact. Even though in the low state an additional incentive would be welcome (since the CO_2 price is below the marginal damage), such an additional incentive cannot come from renewable support because it would further reduce the CO_2 price. This is the same mechanism as the one modelled e.g. by Böhringer and Rosendahl (2010) without uncertainty. To sum up, whatever the renewable support instrument, when uncertainty is low it is better not to use them – of course this result would not hold if the other justifications for renewable support were included in the model.

4.3.2 Optimal policy levels when uncertainty is high

The higher the uncertainty, i.e. the higher the difference between the activity levels in the high and low states, the more the optimal carbon prices diverge, getting higher in the high state and lower in the low state. Above a certain uncertainty threshold given by the expression below, the optimal carbon price is driven to zero in the low state when the social planner sets the emission cap by equalising the expected marginal cost to the marginal benefit:

$$\tilde{\Delta} = \frac{\delta\ \tau(\sigma_d + \sigma_r)}{2\ \lambda}$$

The threshold value $\tilde{\Delta}$ is increasing with the marginal damage δ times the emission intensity τ, the slopes of renewable supply and electricity demand, and is decreasing with the probability of the high demand state λ. The intuition is the following: a higher externality per kWh ($\delta\ \tau$) leads the social planner to set a more stringent cap, reducing the possibility that a negative shock on electricity demand leads to a nil carbon price. Moreover, there are two channels of emission reductions: electricity savings and deployment of renewables. The higher σ_d and σ_r, the more efficient these channels and the more elastic the allowance demand, again reducing the possibility of a nil carbon price. Finally, the higher the probability of a high demand state, the less the social planner takes into account the outcome in the low demand state, so he or she lets the CO_2 price fall to zero for a lower uncertainty.

When the negative shock on the baseline demand level is above the threshold value, the carbon price is driven down to zero. As it cannot become negative, the welfare maximisation problem undergoes a qualitative change: in the low state, renewable support does not reduce the CO_2 price anymore. Thus it becomes optimal to ensure that some abatement takes place by the means of renewable production even in the low state, where the nil carbon price does not incentivise any abatement. This is true even though renewable support is an imperfect instrument since it *increases* electricity consumption, while *reducing* consumption is part of the first-best solution. Improving the expected outcome is possible with the FIP and with the FIT but not with the RPS because the latter generates more abatement in the high state (when it is not required) than in the low state (when it is required), so it is optimal not to implement an RPS (or to set a non-binding RPS, which is the same).

With high uncertainty, the optimal level of the emission cap becomes less stringent because it optimises emissions in the high state only, as it is non-binding in the low state anyway:

$$\Omega^* = \tau(\Delta + \iota_d + \iota_r\sigma_r - (\sigma_d + \sigma_r)(\iota_f + \delta\,\tau))$$

while the optimal FIT and FIP levels are higher than in the low-uncertainty situation:

$$\rho^* = \iota_f + \delta\,\tau$$

$$\theta^* = (\delta\,\tau)\frac{(1-\lambda)(\sigma_d + \sigma_r)}{\sigma_d + (1-\lambda)\sigma_r}$$

The FIT level simply equals the electricity price in the low state (equal to ι_f since the CO_2 price is nil in this state) plus the externality per kWh ($\delta\,\tau$). Thus the implicit support from the FIT equals the externality per kWh. The FIP equals the externality per kWh times a factor between zero and one so its implicit support is lower than the FIT. This is because in the high state of demand, the FIP reduces the CO_2 price so it replaces (partly) an instrument, the CO_2 price, which uses both channels of abatement, electricity demand reduction and renewables, by another one, the FIP, which uses only the latter channel and is thus less efficient (in this state of demand).

4.3.3 Ordering renewable support instruments with uncertainty when combined to an emission cap

When a choice is given to electricity producers between selling at the market price or benefitting from the support scheme (which seems reasonable), all three policy settings are strictly identical in terms of expected welfare if the uncertainty is below the threshold. The entirety of the abatement is realised by the means of the emission cap, and renewable promotion schemes should not distort the carbon and the electricity prices. Details in the policy design may change this outcome, but always in the sense of a divergence from the optimum. If e.g. the RPS comes as a hard constraint, it will act as an implicit tax on renewables in the high state, because the optimal level of renewables will always be above the average quantity in all states.

Above the uncertainty threshold however, significant changes occur. Instruments are no longer equivalent, because they give different incentives in both states. Instruments are then ordered as follows:

$$E(W)_{FIT} > E(W)_{FIP} > E(W)_{RPS}$$

When the risk that the carbon price drops to zero cannot be excluded, the FIT performs best, and the FIP is in between the FIT and the RPS.

Compared to the premium and the RPS, the feed-in-tariff provides a subsidy that decreases with the electricity price, itself positively correlated to the CO_2 price. Hence it helps to stabilise the marginal abatement cost. This is welcome for a stock pollutant like GHG gases, whose marginal benefit curve is flat. The RPS has the opposite effect of increasing the subsidy level with the electricity price, at least in the realistic case where the marginal cost of renewables increases faster than the marginal cost of fossil production. Having a constant subsidy level, the FIP is in-between.

4.4 Alternative model settings: uncertainty in the cost of renewable technologies and multiple fossil technologies

As we have seen in section 3.2.2, in the framework of Marschinski and Quirion (2014), policy instruments react differently according to the origin of the uncertainty. When considered in isolation and when learning-by-doing is the justification for renewable support, a RPS reacts better to demand uncertainty, a FIT reacts better to uncertainty on the cost of renewable production, and a FIP reacts better to uncertainty on the cost of fossil production (all these results being for a numerical application to the US). The intuition is that the RPS lets the renewable production level change with the demand level, whereas the FIT and the FIP let it change with new information on the cost of renewables, and the FIP also with new information on the cost of fossil fuels.

When combined to a cap on emissions, and without learning-by-doing, the mechanisms are however different. In the framework of the present study, the justification for renewable support is to mitigate emissions from fossil fuel electricity production when the carbon price is deficient. As such, the main driver for the cost-effectiveness of a policy combination is the way the support level reacts to changes in the CO_2 price. As discussed previously, the implicit support level provided by the optimal instruments will vary with the cost of production and the demand, but the ordering will stay the same.

A direct consequence is that uncertainties on the cost of renewables or fossil energy will only change the probability of a zero carbon price in the low state. Once the carbon price reaches zero however, the ordering of policy instruments in terms of expected welfare will remain the same:

$$E(W)_{FIT} > E(W)_{FIP} > E(W)_{RPS}$$

The question of the effect of uncertainty on the occurrence of nil carbon prices remains however open. To investigate this, we develop three extensions of our analytical framework. In a first one, we test the consequence of a shock on the production costs of renewables. In another extension, we introduce a second fossil technology, e.g. coal vs. gas, to test whether an uncertain future level of demand yields the same results. This version also allows to test the impact of a shock of the cost of one fossil technology, e.g. the shale gas revolution in the US.

4.4.1 Uncertainty in the cost of renewable technologies

We model a shock on the renewable cost function, by considering that there are two possible states in the second stage of our previously described framework: one where renewables have the same reference cost function, and one where the cost of renewables is decreased by a factor β. The demand function and the renewable cost function are modified as follows:

$$d[p] = \iota_d - p\,\sigma_d$$

$$(C_r)^+[r] = r\iota_r + \frac{r^2}{2\sigma_r}$$

$$(C_r)^-[r] = \left(r\iota_r + \frac{r^2}{2\sigma_r}\right)/\beta$$

where β is a shock parameter between 0 and 1. The model being linear, results would be fully symmetric with a positive shock (β >1).

Compared to the uncertainty on the demand level, uncertainty on the cost of renewables will have two distinct effects on the MAC curve, which can be summarised in the boundary condition for a zero carbon price in the low state $\tilde{\beta}$:

$$\tilde{\beta} = 1 + \frac{\delta\,\tau(\sigma_d + \sigma_r)}{\lambda\,\iota_f\sigma_r}$$

The determinants of $\tilde{\beta}$ are roughly the same as those of $\tilde{\Delta}$: $\tilde{\beta}$ is increasing with the marginal damage δ times the emission intensity τ, the slope of renewable supply σ_r and is decreasing with the probability of the high demand state λ. However it is decreasing with the electricity demand slope σ_d and with the marginal cost of fossils ι_f.

4.4.2 Multiple fossil technologies, uncertain future demand

The model is modified by adding a fossil technology (e.g. coal) to the existing one (e.g. gas). The second fossil technology has a quadratic cost function and contributes to emissions, with a higher emission rate ($\tau_c > \tau_g$). The constant returns assumption is kept for the first fossil technology, gas (g) for tractability reasons and because combined cycle gas turbines are more homogenous than power stations based on solid fuels.

The influence of adding a second fossil technology on the occurrence of nil carbon prices can be again analysed by looking at the threshold expression:

$$\tilde{\Delta} = \frac{\delta(\tau_g{}^2(\sigma_d + \sigma_r) + \sigma_c(-\tau_g + \tau_c)^2)}{2\,\lambda\,\tau_g}$$

Two effects can be characterised. As before, the demand shock indirectly affects the demand for allowances by shifting the baseline market equilibrium as the market price (set by the constant returns technology g) changes the equilibrium quantity of renewables produced (term $\delta\ (\sigma_r+\sigma_d)\ \tau_g^2$). The demand for allowances is also affected by the substitutions between the two fossil technologies, depending on the elasticity of coal supply and the difference in the emission rates (term $\delta\ \sigma_c\,(\tau_g - \tau_c)^2$).

4.5 Numerical application to the European electricity market for 2030

4.5.1 Model setting

We base our numerical application on the calibration made by Flues et al. (2014) for the European electricity sector. They use data from the reference scenario of the “EU energy trends for 2030” (Capros et al., 2009). The numerical version of the model features five different electricity production technologies: two fossil-based (coal and gas), two renewables (wind and solar) and nuclear energy. The other technologies present in the European market (petroleum, hydro, biomass) are included but at a fixed level. As for the analytical model, It is assumed that aggregated production costs per technology are quadratic in output, but with three parameters:

$$C_i[q_i] = q_i \iota_i + \frac{\sigma_i}{2}(q_i - q_{i0})^2$$

where q_{i0} is the baseline (no policy) output for technology i, ι_i is the (constant) marginal cost in the baseline scenario — i.e. the reference price P_0 – and σ_i is the slope parameter, derived from Capros et al. (2009) (see Flues et al. (2014) for a full description).

The other equations are similar to the analytical model. Demand is calibrated so that at the reference demand level (3675 TWh) and the reference price of electricity, the price-elasticity is equal to 0.1.

Table 1: Parameter values used for calibration in the numerical application

Parameter	Description	Value
P_0	Price of electricity (EUR/MWh)	95
σ_n	Slope supply curve nuclear (EUR/ MWh2)	$2.9644\ 10^{-7}$
σ_c	Slope supply curve coal (EUR/MWh2)	$5.4724\ 10^{-8}$
σ_g	Slope supply curve gas (EUR/MWh2)	$2.5630\ 10^{-7}$
σ_w	Slope supply curve wind (EUR/MWh2)	$3.3420\ 10^{-7}$
σ_s	Slope supply curve solar (EUR/MWh2)	$1.1743\ 10^{-6}$
τ_c	CO_2 intensity coal-fired (tCO2/MWh)	0.9150
τ_g	CO_2 intensity gas-fired (tCO2/MWh)	0.3647
λ	Probability of the high state	0.5

4.5.2 Ordering instruments with demand uncertainty

The results are well in line with the theory. As predicted, all instruments perform identically when uncertainty on demand is low so that the carbon price gives a correct incentive for mitigating emissions, and the FIT dominates the FIP, which itself dominates the RPS. The latter target is not binding, so in all the figures below, the RPS scenario is equivalent to an ETS in isolation.

Figure 1 shows the welfare losses occurred when the various renewable support schemes are combined to an emission cap, as a function of uncertainty (represented as a shock on the baseline demand level). The losses are calculated as the welfare difference with a first-best setting, i.e. a carbon tax at the marginal environmental damage. The graph has two parts. On the left hand side, all instruments yield the same welfare difference compared to the 1st best (a CO_2 tax set at the marginal benefit, i.e. 30 €/t CO_2), a difference increasing with uncertainty. In other words, alternative settings are less and less cost-effective when compared to the 1st best scenario. Moreover renewable support instruments do not improve the situation compared to the ETS in isolation. When the shock reaches a threshold, a qualitative change happens: the cost-effectiveness of the policy settings do not vary with the variance anymore and instruments are not equivalent. Note that this threshold value is only 5% of electricity demand while Marschinski and Quirion (2014) estimate that the 2009 recession lowered electricity demand in the US by around 9%. The ranking of instruments is consistent with the analytical model presented above and the FIT brings an expected welfare of around 300 million €/yr. compared to the ETS in isolation (or to the RPS).

Figure 1: Expected welfare losses (in bn. €/yr.) compared to a 1st best carbon tax as a function of demand uncertainty. In the left part, the three instruments are ineffective hence they all bring the same welfare as an ETS in isolation. The RPS is never binding so brings the same outcome as the ETS in isolation also in the right part.

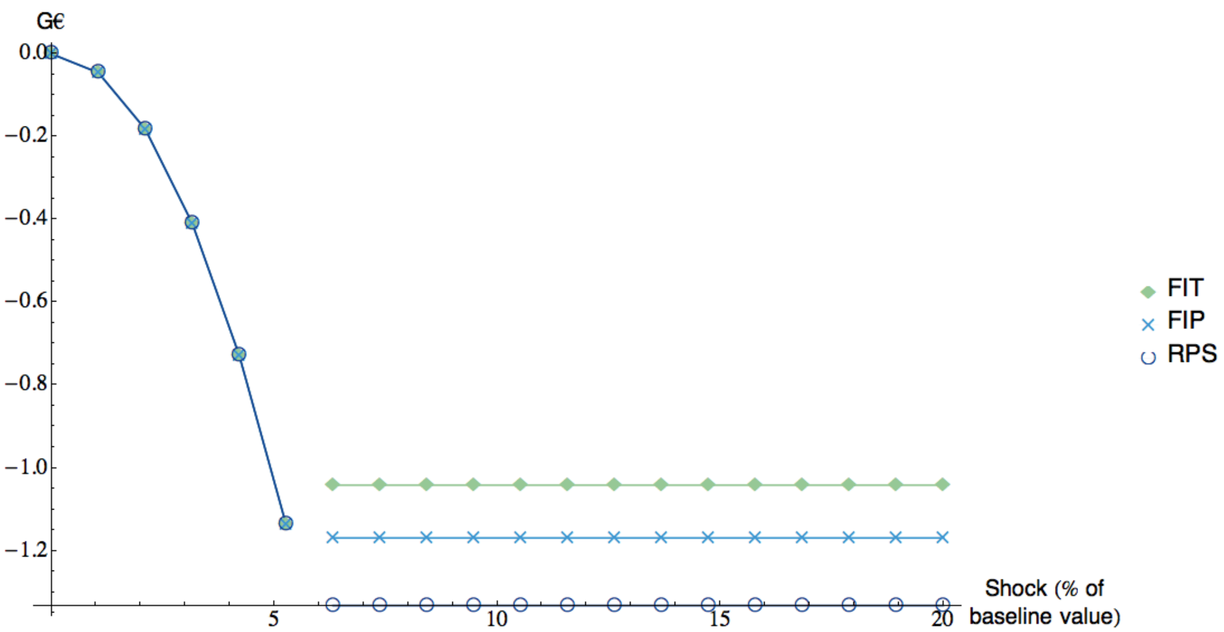


Figure 2 shows the level of the carbon price for the various policy settings in the high (continuous line) and the low (dotted line) states of demand. At the extreme left side of the Figure, the carbon price starts at the marginal damage (30 €/t). Then it diverges symmetrically in the low and high states when uncertainty increases. The zero CO_2 price in the low demand state above the threshold is also clearly visible.

In the high state of demand, the carbon price is always equal to the marginal damage for the FIT and the RPS (and thus also for the ETS in isolation), and a bit less for the FIP. The latter result comes from the fact that when both the renewable support scheme and the emission cap contribute to abatement, it is the average expected mitigation effort that should be equal to the marginal damage (see Lecuyer & Quirion (2013) for a discussion). The FIT can be designed to give an incentive only in the low state, and the RPS does not give any incentive in either state. The FIP however always adds an additional incentive in both states, so that the carbon price has to be lower also in the high state.

Figure 2: CO_2 price as a function of demand uncertainty. Dotted lines denote the low-demand state, solid lines the high-demand state. The RPS is not binding and brings the same outcome as the ETS in isolation.

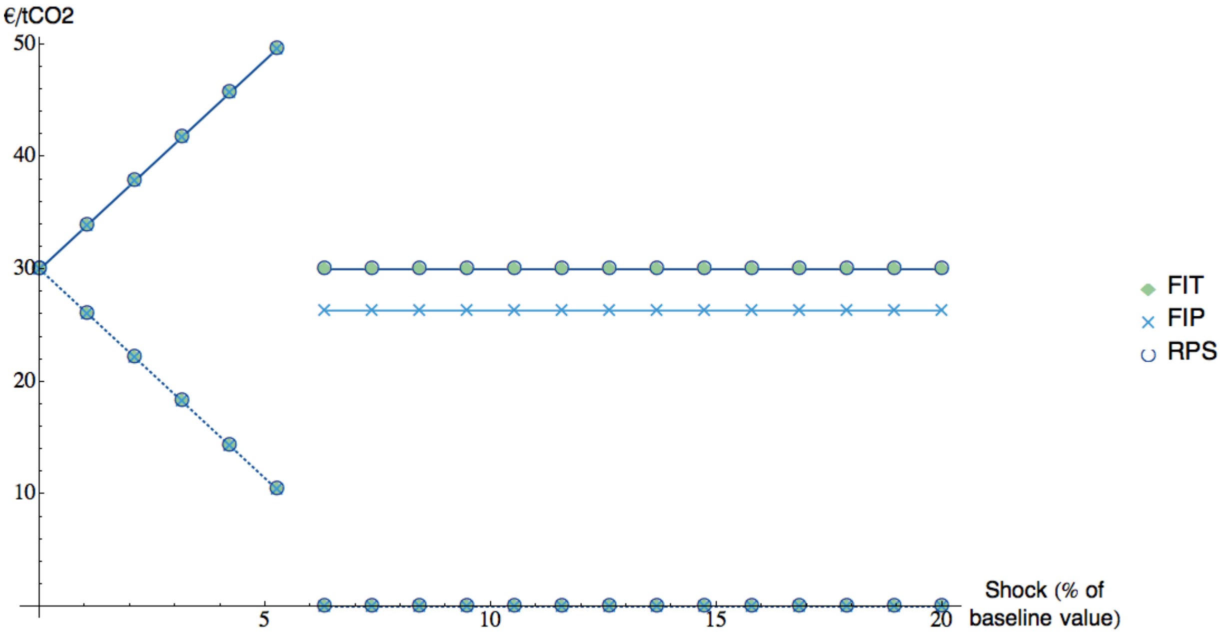


Figure 3 shows the implicit support level to renewable production for the various instruments in the high and low states, as a function of uncertainty. As long as the carbon price is positive in both states, the implicit support has to stay equal to zero. For zero carbon prices however, the optimum requires to support renewables as the only other option to mitigate emissions in place of the deficient carbon price. This is done differently by the various policy instruments considered. The optimal FIP gives the same positive support level in both cases (around 10.4 €/MWh), while the optimal FIT gives a positive implicit support only in the low demand case, but at a higher level (around 18 €/MWh)[2]. In fact, the optimal FIT is exactly

[2] The current FIT in Germany is in the range of 60-90 €/MWh for onshore wind and 90 € for large PV installations, so the support level for these renewable technologies is between 20 and 50 €, at the current wholesale electricity price of around 40 €/MWh. So in our model indicates that GHG abatement alone justifies the lower range of German FITs, while other rationales such as learning-by-doing, not accounted for in our model, might justify also the higher range.

equal to the electricity market price in the high demand state in this setting, so that its implicit support to renewable production is zero in this state. This makes it more cost-effective than the FIP, because the additional support is needed in the low state only. It also explains why the RPS is even less cost-effective. As discussed earlier, when the marginal cost of renewable production increases faster than that of fossil production (a reasonable assumption as long as renewables do not reach grid parity), the baseline share of renewables (i.e. without policy) decreases with the total demand (and hence with the electricity price and the carbon price). As a result, for a given RPS target, the support level has to be higher for higher carbon prices, and the optimal RPS is necessarily non-binding for the low state, where the carbon price is nil. The consequence is that it is not possible to have an incentive to mitigate emissions through renewables in the low state without prohibitive costs in the high state, thus the implicit support level is zero in both states. As such, in our simplified model setting the RPS is equivalent to an emission cap alone.

Figure 3: Renewable support as a function of demand uncertainty. Dotted lines denote the low-demand state, solid lines the high-demand state. The RPS is not binding and brings the same outcome as the ETS in isolation. The FIP brings the same outcome in both states.

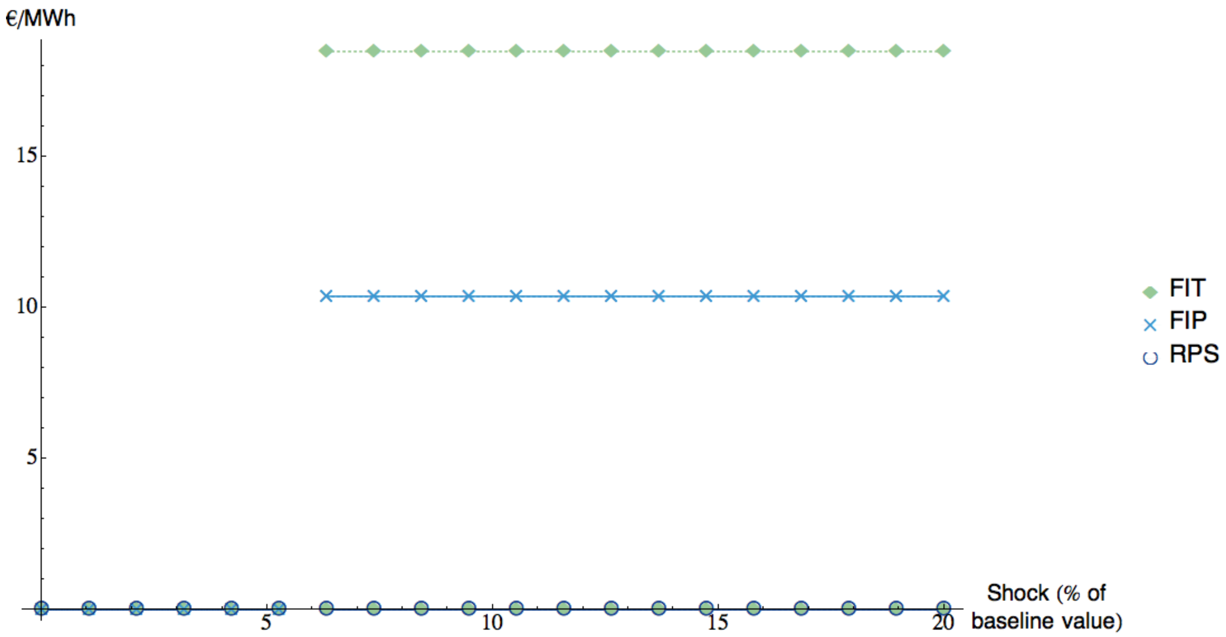


Figure 4 shows the effect on renewable production. On the left side, when the carbon price is always positive in the two states, the production is diverging but it is the same for all instruments. When the carbon price drops to zero in the low state, the results differ across instruments. In the high state (continuous line), the FIP leads to a higher renewable production level than the FIT and RPS, while in the low state, the FIT leads to the highest renewable production, the FIP to an intermediary level and the RPS to the lowest level. These results directly come from the level of renewable support displayed in Figure 3.

Figure 4: Renewable electricity production as a function of demand uncertainty.

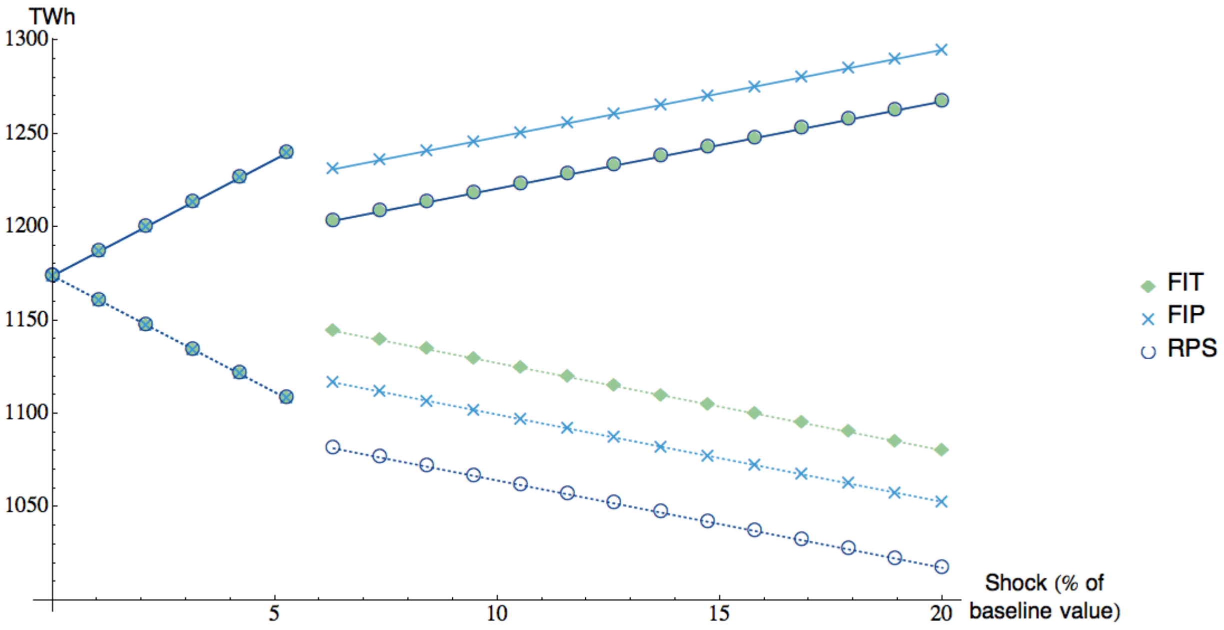
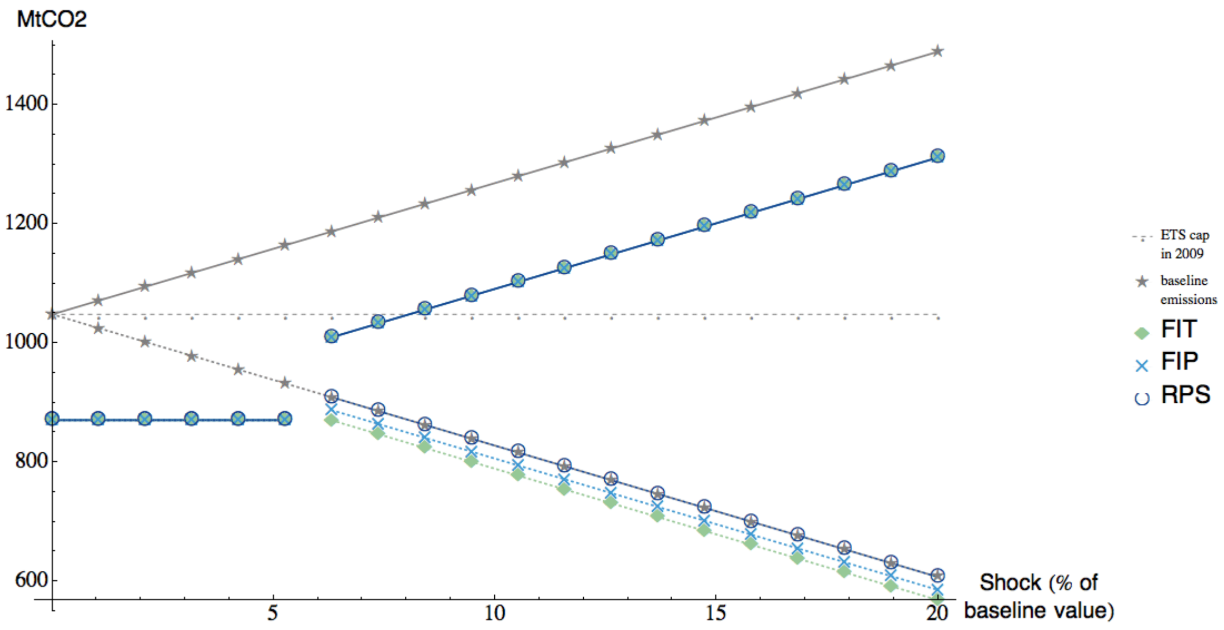


Figure 5 shows the emission level in the various policy settings, in the high (continuous line) and low (dotted line) states, as well as the baseline (no policy) emission level, and the emission cap of the EU-ETS in 2009. In the high state, the emission cap is binding, so that all instruments give the same level of emission, whereas in the low state, when the carbon price is equal to zero, the emission level varies according to the incentive given by the instrument supporting renewables. Remind that the optimal cap is equal to the high state emissions when the carbon price is nil in the low state. In the low state, the RPS brings no additional incentive and the emissions are the same as in the baseline scenario.

Figure 5: CO_2 emission level as a function of demand uncertainty.



It is noteworthy that the optimal emission cap for a marginal damage at 30€/tCO_2 (for a low uncertainty level) is much lower than the actual EU-ETS cap in 2009 (the dotted horizontal line in Figure 5). The total EU-ETS emission allowance is in fact closer to the optimal emission cap for a 10% shock on demand. An interpretation could be that policymakers who defined the EU-ETS cap were optimistic as regards the business cycle, and neglected the possibility of a lower electricity demand. Another explanation (in line with our model) could be that they took this possibility into account but did not want to take the risk of too high a CO_2 price in the event of a high demand, so they accepted the risk of a zero CO_2 price in the event of a low demand. Of course, one cannot rule out other explanations (e.g. the model is far from the those used by policymakers, or the latter did not value the marginal damage at 30€/tCO_2) but this simple model highlights a mechanism by which even benevolent policymakers can set a much more lenient cap than the one which would maximise welfare absent uncertainty.

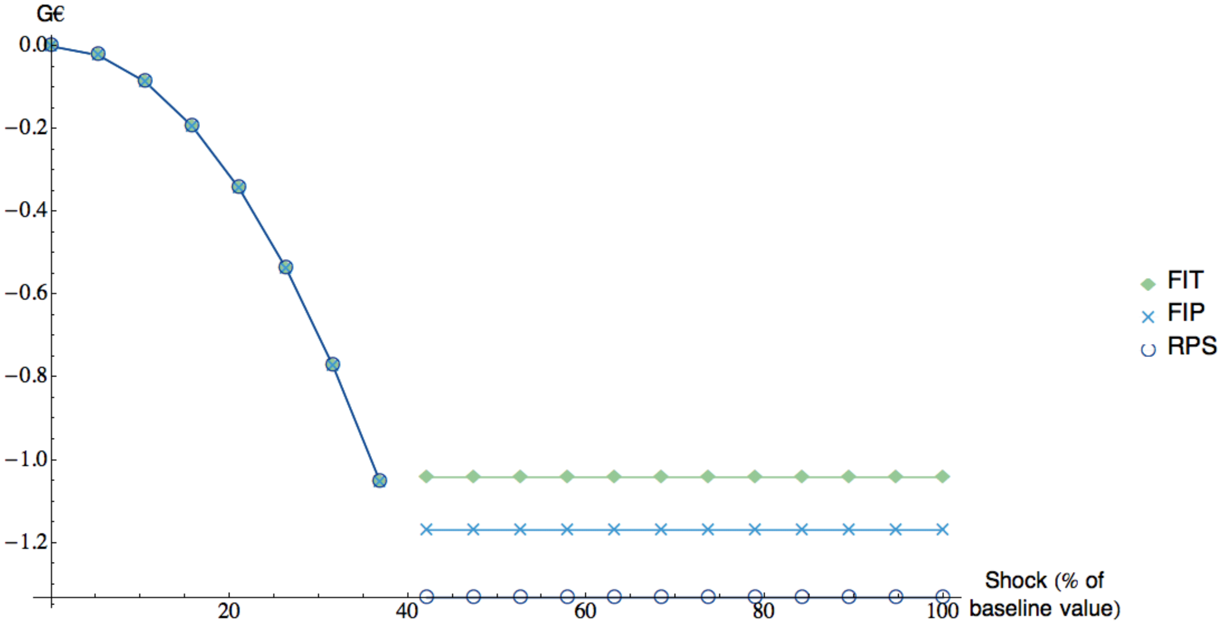
4.5.3 Technology uncertainty

The analytical section shows that the ordering of the FIT, the FIP and the RPS does not depend on the source of the uncertainty, when they are combined to an emission cap and when the only justification for intervention is the emission externality. The origin of uncertainty will however influence the threshold level at which a zero carbon price occurs.

To investigate this, we consider two alternative formulations of the numerical model, where a shock on the demand level is combined with a shock on the cost function of renewable technologies or gas production. The shocks on the cost functions apply to the baseline production parameter q_{i0} to allow for a comparison with the shock on the total baseline demand. A shock on the baseline production parameter implies a shift of the baseline equilibrium: for a given level of price, the cost goes down such that the baseline quantity of renewables or gas is increased by a given amount.

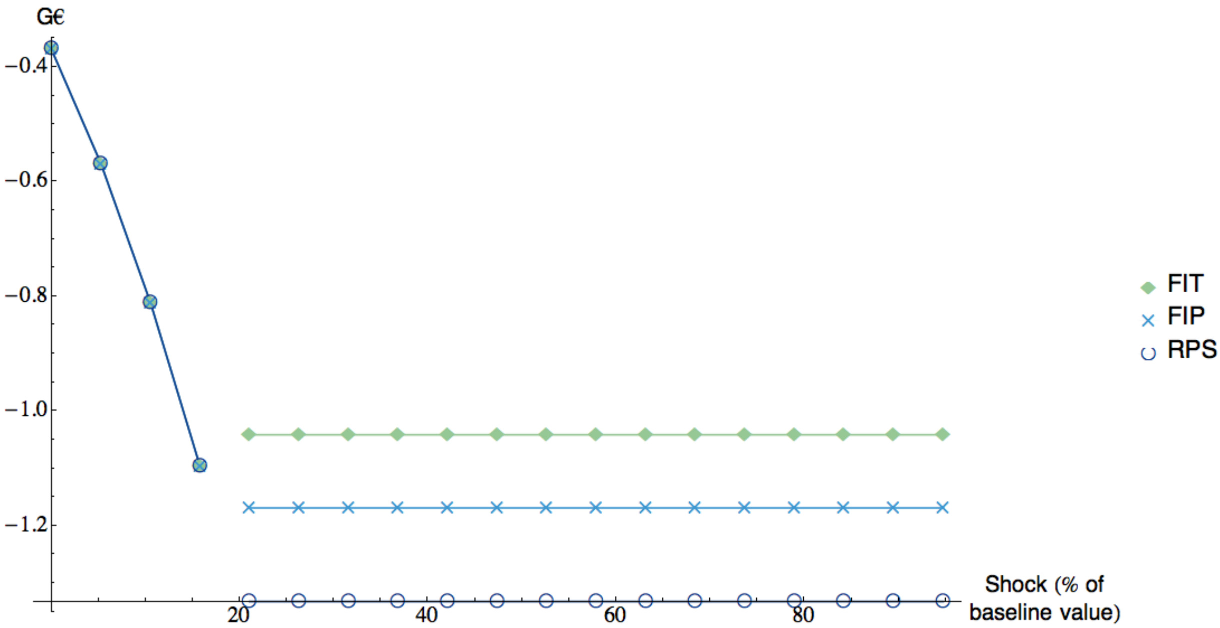
Figure 6 displays the welfare losses as in Figure 1, but with uncertainty in the cost of renewables instead of demand on the x-axis. We see that the cost decrease has to entail a 40% surge in renewables (wind+PV) deployment for the CO_2 price to become non-binding, and for renewable support instruments to become justified. This may seem unrealistic, but given the simplified nature of the model, we should devote more attention to the qualitative insight, which is that a lower-than expected renewables cost actually provides a justification for the FIT, contrary to many commentaries which have criticised the FIT for generating an excessive PV deployment, following the drop in investment cost (e.g. Frondel et al., 2012).

Figure 6: Expected welfare losses (in bn. €/yr.) compared to a 1st best carbon tax as a function of uncertainty in the cost of renewables. In the left part, the three instruments are ineffective hence they all bring the same welfare as an ETS in isolation. The RPS is not binding so brings the same outcome as the ETS in isolation also in the right part.



Up to now, we have considered uncertainties on electricity demand and renewables cost independently, while they may happen simultaneously (and they actually did in 2008-2009). Figure 7 displays the welfare losses as a function of uncertainty in renewables cost, but assuming in addition a -3% shock in electricity demand (arguably in the low range of the outcome of the 2009 economic crisis). We see that a drop in renewables cost generating a 20% increase in renewables (wind+PV) deployment is now enough to generate a nil carbon price in the low state, and to justify a FIP or (better) a FIT.

Figure 7: Same as Figure 6 but assuming a -3% shock in electricity demand in addition to the shock on renewable energy cost.



5 Conclusions

Although uncertainty is widely recognised as a key issue in the climate change issue, most economic models used to assess the GHG abatement policy mix are deterministic. Yet including uncertainty in the analysis does not only change the optimal abatement trajectory (which has been discussed since the late 1990s) but also the optimal policy mix. Building on the seminal Weitzman's (1974) 'prices vs. quantities' analysis, several authors have started to analyse this issue. A tentative general conclusion from this literature is that pure quantity instruments are too rigid and should be avoided: for CO_2 emissions, a carbon tax or a hybrid system with price floor and price cap should be preferred to pure cap-and-trade system, while for renewable energy deployment, a feed-in-tariff or a feed-in-premium should be preferred to a tradable renewable quota (also called a Renewable Portfolio Standard).

Yet the detailed conclusions depend on the particular context. In Europe, a key uncertain outcome is whether the EU ETS cap will become binding again in the next years, which cannot be taken for granted (Sandbag, 2014). The excessive supply of allowances is not a singular event: based on other examples mentioned in Lecuyer and Quirion (2013), it could even be argued that the emission cap has become non-binding during a part of the history of most ETS worldwide. Given the difficulties faced to reform the ETS, and the sharp criticisms addressed to the Market Stability Reserve proposal, it seems reasonable to consider that, at the time of writing, we do not know whether the EU ETS cap will bind or not in the following years. Such a context calls for the following recommendations:

- Try to fix the EU ETS in order to stabilise the CO_2 price, if possible by setting a price floor, or by implementing a reform package with as similar an outcome as possible.
- Maintain incentives to renewable energies and energy savings, even in the electricity sector, in spite of the fact that its emissions are covered by the ETS: we cannot take for granted that the ETS will work in the near future. Incidentally, the rationale for renewable support presented here applies for electricity savings instruments (labels, standards, subsidies, white certificates…), while more analysis is required to compare these instruments in terms of efficiency under uncertainty.
- When choosing instruments to foster renewables and energy savings, take into account uncertainty and interaction with other policy instruments, including of course the EU ETS. In this regard, it is unfortunate that the recent guidelines of the European Commission (2014) invite Member States to refrain from using feed-in-tariffs, while our analysis indicate that in the present context, it may well be the preferred renewable support instrument.

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