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Interaction between CO_2 emissions trading and renewable energy subsidies under uncertainty: feed-in tariffs as a safety net against over-allocation

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Abstract

We study the interactions between a CO_2 emissions trading system (ETS) and renewable energy subsidies under uncertainty over electricity demand and energy costs. We first provide evidence that uncertainty has generated over-allocation (defined as an emissions cap above business-as-usual emissions) during at least part of the history of most ETSs in the world. We then develop an analytical model and a numerical model applied to the European Union electricity market in which renewable energy subsidies are justified only by CO_2 abatement. We show that in this context, when uncertainty is small, renewable energy subsidies are not justified, but when it is big enough, these subsidies increase expected welfare because they provide CO_2 abatement even in the case of over-allocation.

The source of uncertainty is important when comparing the various types of renewable energy subsidies. Under uncertainty over electricity demand, renewable energy costs or gas prices, a feed-in tariff brings higher expected welfare than a feed-in premium because it provides a higher subsidy when it is actually needed i.e. when the electricity price is low. Under uncertainty over coal prices, the opposite result holds true. These results shed new light on the ongoing switch from feed-in tariffs to feed-in premiums in Europe.

Keywords

Emissions trading; ETS; renewable energy; feed-in tariff; feed-in premium; policy interaction; uncertainty

Introduction

Many economists (Branger et al., 2015) have long presented carbon pricing as an efficient tool for the reduction of CO_2 emissions. A growing number of jurisdictions worldwide accept this opinion and are implementing this tool, most often in the form of an Emissions Trading System (ETS) (World Bank, 2015). At the same time, electricity generation from renewable energies is subsidised in various ways, including, in most of the jurisdictions which limit CO_2 emissions from the power industry, by an ETS (REN21, 2015). Yet, as long as CO_2 emissions are determined by the ETS emissions cap, an increase in electricity generation from renewable energies cannot have an impact on CO_2 emissions: either they replace other fossil-free technologies like nuclear power, or, more likely, they increase the CO_2-intensity of fossil based electricity generation, typically by replacing gas with coal, a fuel switch dubbed “green promotes the dirtiest” by Böhringer and Rosendahl (2010). In this context, not only are renewable subsidies inefficient at reducing CO_2 emissions but they prevent the achievement of a cost-efficient electricity generation mix, thus reducing welfare.

Does this mean that subsidies to electricity generation from renewable energies should be scrapped in jurisdictions that limit CO_2 emissions from the power industry by an ETS? A first counter-argument is that there are other reasons to subsidise renewables, including the positive externality generated by unappropriated learning-by-doing (Fischer and Preonas, 2010; Fischer et al., 2014; Marschinski and Quirion, 2014). We do not develop this point further because it is straightforward.

This paper is devoted to the implications of a second counter-argument, first introduced by Lecuyer and Quirion (2013): if there is a possibility of over-allocation, i.e. that the emissions cap be actually higher than the emissions which would have occurred without the ETS, then subsidising renewables does reduce expected CO_2 emissions, so these subsidies can be justified even without accounting for other externalities.

The contribution of this paper is twofold. First, we provide evidence that over-allocation has occurred in most ETSs implemented worldwide. Most of the economic mechanisms that have generated this situation may well operate again in the future, so we argue that the possibility of over-allocation should be taken seriously in the analysis of climate policy mixes.

Second, we show that the debate about various types of subsidies to renewables is stimulated by taking into account uncertainty, the interaction between these subsidies and an ETS, as well as the possibility of over-allocation. More specifically, in our numerical model, if uncertainty over future electricity demand reaches 10% or more, then a feed-in tariff brings a higher expected welfare than a feed-in premium. Uncertainty over future renewable energy or fossil fuel costs alone is unlikely to generate over-allocation but can contribute to it, together with uncertainty over demand. In this case, uncertainty over renewables costs or gas prices favours feed-in tariffs over feed-in premiums, while the opposite is true for uncertainty over coal prices.

These results shed light on the restructuring of subsidies to renewable energies, currently taking place in Europe (Roach, 2016). The largest deployment of wind and photovoltaic energies has occurred in countries which implemented a feed-in tariff (FIT)[1]: Denmark since 1984, Germany since

[1] Under a FIT, a fixed price is guaranteed to producers of electricity generated by renewables for a period of typically 10 to 20 years.

2000 and China since 2005. A FIT is now implemented in 73 countries worldwide, plus 35 federal states and provinces in India, Australia, the US and Canada (REN21, 2015). Yet several European countries have switched, or are switching, from a feed-in tariff to a feed-in premium (FIP)[2], including Denmark, Germany and France. Moreover the European Commission (2014) guidelines on State aid for renewable energies invite EU Member States to limit FIT to the smallest projects. Our results cast some doubts on the usefulness of this development.

The rest of this paper is structured as follows. In the first section, we provide evidence that there has been over-allocation during at least part of the history of most existing ETSs worldwide, and that such over-allocation cannot be excluded for the next phases of the European Union Emissions Trading System (EU ETS). In section 2 we present an analytical model from which we derive our main results. In section 3 we develop a slightly more complex, numerical version of the model, which allows us to provide some quantitative results. Section 4 concludes.

1 Context

1.1 Evidence of over-allocation in existing ETSs

While many scientific articles have analysed emissions trading systems (ETSs), including a growing number of ex post studies (Cf. Martin et al., 2016 for ex post studies devoted to the EU ETS), one aspect has generated surprisingly little attention: whether the emissions cap adopted in existing ETSs has been binding, i.e. whether it has been set above the emissions level which would have occurred without these systems. If this is not the case, one can say that there was over-allocation or that the cap was not binding. The existence of over-allocation is not an easy question to address ex-post, since the counterfactual emissions scenario cannot be observed when the ETS has been implemented. Yet in several cases an answer can be inferred either because the difference between allocations and emissions is too big to be reasonably attributed to abatement, or because a convincing counterfactual scenario has been built by researchers, or because the proposed ETS has not been implemented (such as in the Waxman-Markey case).

More than a dozen ETSs have been implemented to date[3]. Addressing the question of over-allocation for all of them would deserve at least a full paper, so we provide in this section a brief synthesis of what can be learned from the existing literature on this issue. In order to obtain enough perspective, we limit ourselves to ETSs implemented at least five years ago (with the exception of the ETS proposed in the Waxman-Markey bill, which was not implemented), neglecting in particular the regional ETSs implemented in China[4], California and Quebec, and the Korean ETS. We end up with the following six cases, presented in chronological order.

[2] A FIP is a subsidy to electricity generated by renewables, which adds up to the market price at which electricity is sold. In this paper we consider a fixed FIP, i.e. independent of the electricity price. A floating FIP, under which a variable subsidy complements the market price to guarantee a fixed remuneration, would be equivalent to a FIT (Dressler, 2014).

[3] For a survey of ETSs covering greenhouse gases, see World Bank (2015 https://ieta.wildapricot.org/The-Worlds-Carbon-Markets or http://carbon-pulse.com/. In addition, some ETSs have been discontinued or deal with other pollutants, including those listed in this section or in Boemare and Quirion (2002).

[4] However, there is a growing evidence of over-allocation in most Chinese pilot ETS markets (Reklev, 2016).

The **Regional Clean Air Incentives Market (RECLAIM)** has covered nitrogen oxides and sulphur oxides in the Los Angeles basin since 1994. According to Fowlie et al. (2012) “it is clear that emissions permits were initially over-allocated”. The aggregate cap did not start to bind until 1999. Because permits could not be banked from one year to another, impacts of the initial over-allocation were, however, confined to the early stages of RECLAIM (Fowlie et al., 2012), and the cap seems to have been binding since then.

The **US SO_2 allowance trading system**, which started in 1995, is often presented as the first large-scale implementation of emissions trading. It is generally considered to be a success. While it did reduce emissions significantly in its first decade of its existence (they dropped by 36% between 1990 and 2004), the subsequent decrease in emissions (which halved between 2004 and 2010) was due to other regulations that imposed tighter restrictions so the emissions cap no longer binds. Moreover there is no prospect that it will bind in the future. Indeed, courts ruled that the Environmental Protection Agency (EPA) could not strengthen the emissions cap without a new piece of legislation from Congress, which was not adopted. “In response, state-level and source-level constraints were put in place that ultimately rendered the SO_2 cap-and-trade system itself nonbinding and effectively closed down the allowance market.” (Schmalensee and Stavins, 2013).

The **UK Greenhouse gas ETS** was in operation from 2002 to 2006. It soon appeared that emissions were much lower than allocations: in the first two years, a surplus of 7.5 Mt CO2e was created, amounting to around one third of yearly emissions and leading the government to consult stakeholders on the most appropriate way to address the surplus amount. In November 2004 the government reached a voluntary agreement with six participants among the main emitters to reduce allocations by 8.9 Mt CO2e over the remaining years of the scheme but “it became evident that despite the voluntary agreement, a considerable surplus still existed” (ENVIROS Consulting, 2006). As a consequence the allowance price, which reached 12 £/tCO2e in mid-2002, stayed below 4 £/tCO2e from early 2003 to the end of the scheme’s lifetime. To quote Smith and Swierzbinski (2007) “The UK experience indicates that excessive generosity in setting the baseline for individual firms can expose the system to—in effect—excessive allowance allocations, with an aggregate implied emissions cap that may require little additional abatement effort, and a consequently low permit value.”

In the **Regional Greenhouse Gas Initiative (RGGI)**, which has covered power plant CO_2 emissions from North-Eastern US states since 2008, phase one carbon emissions fell 33% below cap (Point carbon, 2012). As a consequence, the CO_2 price fell to the price floor, around 2 \$/tCO_2, and stayed at this level from mid-2010 to the beginning of phase 2, in January 2013. Murray and Maniloff (2015) identify the key factors behind this emissions drop: the economic recession, new natural gas discoveries, and complementary policies (renewable energy support and clean air policies, which increase the cost of coal-based generation). They conclude that RGGI reduced covered emissions by 19%, so emissions would have been lower than the cap even without this policy. Moreover RGGI features other incentives than the CO_2 price (in particular energy efficiency subsidies), incentives whose effect is included in the 19% abatement estimated by Murray and Maniloff. To address the disparity between the cap and actual emissions, RGGI states agreed in 2013 to reduce the existing cap by 45%, thus provoking an increase in the CO_2 price. The revised cap took effect in January 2014 (Ramseur, 2015) and the CO_2 price had increased up to 8 \$/tCO_2 by January 2016 (Szabo, 2016).

The **Waxman-Markey** proposal for a national greenhouse gas ETS in the US was passed by the House of Representatives in 2009 but not by the Senate, and thus did not come into force. This provides an opportunity to compare the emissions cap specified by this proposal with observed, unregulated, emissions. The Rhodium Group estimates that 2015 emissions in the US will be approximately 5557 Mt CO_2, i.e. 150 Mt below the cap specified by the Waxman-Markey act (Sierra Club 2015). Hence, this estimation implies that if it had been adopted, the Waxman-Markey bill would have set a non-binding cap, at least in 2015.

The first phase of the **EU ETS** (2005-2007) should be analysed separately from subsequent phases (since 2008), because phase 1 allowances could not be banked. In phase 1, emissions were below allocations by around 3% according to Ellerman and Buchner (2008) who conclude that a part of this surplus is due to abatement but that over-allocation did occur (i.e. the cap was higher that business-as-usual emissions[5]). As a consequence, the allowance price dropped to zero in 2007. In the second phase (2008-2012), the cap was tightened by the European Commission. Yet, because of the economic recession, emissions have dropped again below the emissions cap since 2009, generating a surplus equivalent to 2.1 billion tonnes (i.e. more than one year of emissions) at the end of 2014, without any prospect of a decrease before the end of the decade (European Environment Agency, 2015). Bel and Joseph (2015) performed an econometric analysis and concluded that even though the EU ETS did reduce emissions, "the biggest share of abatement was attributable to the effects of the economic crisis" and that business-as-usual emissions would have been well below the cap.

To sum up, there is convincing evidence that the cap has been above business-as-usual emissions during at least part of the history of these prominent ETSs. The reasons differ from one case to another, and include lack of information on historical emissions, unexpected falls in the production of polluting goods, unexpected decreases in the relative price of less-polluting fuels, as well as the impact of other regulations. While the first reason is arguably limited to a newly implemented ETS (since a well-functioning ETS normally provides reliable information on emissions), the others are not. In particular, all of them may occur again in the near future in Europe, and will determine whether the EU ETS cap will bind or not.

1.2 Will the EU ETS over-allocation problem be solved?

For several reasons, we do not know whether the EU ETS cap will bind in the near future. First, the revision proposed by the European Commission (2015) is currently being examined, and this process will not end before 2017. The Commission proposal is based on the already adopted target of a reduction of at least 40% in total domestic GHG emissions by 2030 compared to 1990, with a contribution from the ETS amounting to a 43% reduction compared to 2005, implying a yearly decrease of the emissions cap by 2.2% from 2021 onward.

Second, even if the Commission proposal is adopted in its current form, business-as-usual emissions may still be lower than forecast. Several factors that have a large impact on emissions are highly uncertain: the production level of polluting goods, mainly electricity and building materials; fuel prices, in particular the relative price of gas and coal, and the ambition of policies promoting non-fossil fuel power generation, especially renewables. Note that the cap under discussion covers the

[5] By business-as-usual emissions, we mean the emissions which would have occurred in the absence of the ETS.

period 2021-2030, so the EU is currently discussing the cap for a period whose mid-point is ten years into the future, sufficiently far away to hold many surprises.

The two main forecasts of EU emissions currently available are published by Sandbag (2014, 2015) and by the European Environment Agency (2015). Based on submissions by member states, the latter forecasts that EU ETS emissions will fall by an average of 0.8% a year from 2014 to 2020, while the former forecasts a drop of 3.8% a year on average. In the first case, the surplus would stabilize while in the second it would double, reaching around 4 billion tonnes. Note that Sandbag's forecasts can hardly be dismissed *prima facie* since they have proven more reliable so far than the official European Environment Agency forecasts. Moreover, for the period up to 2030, uncertainty is of course even greater.

Admittedly, the Commission reform proposal includes a Market Stability Reserve (MSR) in which some allowances would be placed if the surplus reaches a certain threshold. In the Commission proposal, this threshold is 833 Mt and beyond it 12% of allowances in circulation each year would be placed in the reserve. However, there is no agreement on whether the allowance placed in the reserve will be ultimately released onto the market or cancelled. In the former case, the MSR would postpone the over-allocation problem rather than solving it. A final argument that over-allocation may remain is provided by market participants themselves: the European Federation of Energy Traders (2016) has recently issued a position paper stating that "the EU ETS is drastically oversupplied" while the EU ETS CO_2 price has dropped below 5 €/t CO_2 at the time of writing this article (Garside, 2016).

2 Analytical model

2.1 Analytical framework and scenarios

The social planner maximizes an expected welfare function and chooses the optimal level of various instruments among a given set of policies in a context of uncertainty. We consider four different policy sets:

- TAX: a carbon tax at a fixed rate set at the marginal level of environmental damage, useful as a benchmark to which the other policy sets can be compared;
- CAP: a CO_2 emissions cap for the electricity industry, limiting the emissions from electricity production;
- FIT: a combination of a CO_2 emissions cap and a feed-in tariff, the latter allowing renewable electricity producers to sell electricity at a fixed price rather than on the electricity market, where the feed-in tariff ρ is higher than the market price;
- FIP: a combination of a CO_2 emissions cap and a feed-in premium, which allows renewable electricity producers to sell electricity on the power market and in addition to receive a subsidy θ for every unit of electricity produced.

We moreover consider three independent sources of uncertainty:

- DEM: a case of economic uncertainty, i.e. uncertain future level of electricity demand,

- REN: a case of technological uncertainty , i.e. uncertain future cost of renewables, and
- FOS: a case of fossil fuel market uncertainty, i.e. uncertain future cost of fossil-based electricity.

In each case, the uncertainty is represented as a random variable following a given distribution of probability $\mathcal{D}_{source}$, where $source$ stands for the source of uncertainty: DEM, REN or FOS.

The risk that the carbon price drops to zero in the case of low demand, low cost of renewables or high cost of fossil fuels is explicitly taken into account. The electricity market is assumed to be perfectly competitive, which implies a 100% pass-through of the emissions allowance cost. The model has a two-stage framework. In the first stage, the social planner chooses the level of the various policy instruments in the face of one of the above-mentioned sources of uncertainty. In the second stage, electricity producers maximize their profit given the policy instrument levels, with the uncertainty resolved. The model is solved backwards.

Step 1: the producer profit maximization problem

We consider two types of electricity generation: fossil fuels f and renewables r. p is the wholesale electricity price, which is also the marginal revenue from selling fossil-based electricity. Producers face an aggregate emissions cap Ω and benefit from a level of support for renewables through a FIP or a FIT. In both cases Θ is the marginal revenue from selling electricity from renewable energy. ω is the carbon price emerging from the allowance market, equal to the shadow value of the emissions cap constraint. The producer[6] maximizes its profit Π (Table 1 describes all the variables and parameters):

$$\max_{f,r} \Pi(p, f, r, \omega, \Theta, x, y) = p \cdot f + \Theta \cdot r - C_f(f) - C_r(r) - \omega \cdot \mu \cdot f$$

where $C_f(f)$ and $C_r(r)$ are the production costs from fossil fuel and renewables respectively, assumed to be both increasing and convex: $C_f^{'}(f) > 0$, $C_f^{''}(f) > 0$, $C_r^{'}(r) > 0$, $C_r^{''}(r) > 0$. The decreasing returns assumption is justified as the best production sites are used first and further development of production implies investing in less and less productive sites. This is obvious for renewables, since wind and sun vary greatly across Europe. Admittedly it is less obvious for fossils, but for them also the local availability of some resources, in particular lignite and the natural gas network, differ from one site to another. The cost functions have a classical linear-quadratic form:

$$C_f(f) = x \cdot f + \frac{f^2}{2\,\sigma_f}$$

$$C_r(r) = y \cdot r + \frac{r^2}{2\,\sigma_r}$$

with σ_f and σ_r the slopes (sigma-like slope) of the fossil and renewables marginal supply function respectively[7]. x and y are two random variables denoting the uncertainty over the future marginal

[6] Since we assume perfect competition it would make no difference to assume that some producers use fossils and other use renewables, rather than assuming a representative producer using both technologies.
[7] Adding linear terms to the cost function would make the resolution much more complicated without bringing more insight. Hence we add them only in the numerical model below.

cost of fossil and renewable production respectively. They follow the modified Bernoulli distributions $\mathcal{D}_{FOS}$ and $\mathcal{D}_{REN}$, where both random variables can take two opposite values $\{-\gamma, \gamma\}$ with equal probability. This results in the following moments: $\overline{\mathcal{D}}_{FOS} = \overline{\mathcal{D}}_{REN} = 0, V_{FOS} = V_{REN} = \gamma^2$, where the bar stands for mean and V for variance.

We define a linear downward sloping electricity demand function $d(*)$ (with $d^{'}(*) < 0$) whose intercept depends on a random variable z following a similar modified Bernoulli distribution centred on zero, taking two opposite values $\{-\Delta, \Delta\}$ with equal probability. Similarly, $\overline{\mathcal{D}}_{DEM} = 0, V_{DEM} = \Delta^2$. The demand function is defined as:

$$d(p, z) = i_d + z - \sigma_d \cdot p$$

with the expected intercept i_d. The electricity market equilibrium is:

$$f + r = d(p, z)$$

In each state of nature, electricity supply has to meet demand. The equilibrium depends on the constraint on emissions and on the related carbon price. More precisely it depends on whether or not it reaches a corner solution, namely a zero carbon price:

Case 1 (corner solution):

$$f < \Omega; \omega = 0$$

Case 2 (interior solution):

$$f = \Omega; \omega > 0$$

To obtain an interior solution, total emissions equal the cap Ω and the carbon price is therefore strictly positive. In states of nature where a corner solution is reached, the emissions cap constraint is non-binding, hence the carbon price is nil.

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

$$p = i_f + \frac{f}{\sigma_f} + \mu \cdot \omega$$

Fossil fuel producers equalize marginal production costs with the wholesale market price, net of the price of emissions.

$$\Theta = i_r + \frac{r}{\sigma_r}$$

Renewable producers equalize marginal production costs with their effective marginal revenue, which depends on the type of support policy put in place ($\Theta = p + \theta$ for a FIP and $\Theta = \rho$ for a FIT).

The values of the market variables (p, f, r, ω) as a function of policy instruments are found by solving the system of first-order conditions and market clearing conditions. They represent the reaction functions of the electricity producer. Note that these reaction functions depend on whether the solution is a corner or an interior solution.

Step 2: the social planner's expected welfare maximization problem

The social planner, assumed to be risk-neutral and giving the same weight to consumers and producers, faces uncertainty over the future level of demand, the future fossil-based electricity cost or renewable electricity cost. He uses the policy instruments at his disposal (i.e. an emissions cap and a renewables support policy) to maximize the expected welfare. We assume no excess burden of taxation, because otherwise we would have to distinguish several cases with and without auctioned CO_2 allowances. We therefore keep our welfare function as simple as possible:

$$\max_{\Omega,\Theta} E[W(\Omega,\Theta)] = E[CS(p) + \Pi(p,f,r,\omega) - Dam(f) - (\Theta - p)\cdot r + \omega\cdot\mu\cdot f]$$

where $E[\quad]$ is the expectation operator, depending on the random variable taken into account: x, y or z. When, for example, the uncertainty over future electricity demand is examined, only the random variable z is considered, and the two equally probable states of a positive demand shock ($z = \Delta$) and a negative one ($z = -\Delta$) are taken into account. $CS(p)$ is the consumer surplus and $Dam(f)$ is the environmental damage function from GHG emissions. The last two terms of the expected welfare equation cancel pure transfers between agents included in the profit functions. The consumer surplus and the damage function are taken to be as simple as possible for clarity. In particular, consumers are assumed to be risk-neutral:

$$CS(q) = \int_0^q d^{-1}(\alpha)\mathrm{d}\alpha - p\cdot d(p)$$

$$Dam(f) = \delta\cdot\mu\cdot f$$

With δ the marginal environmental damage coefficient, which is assumed constant because CO_2 is a stock pollutant (Newell and Pizer, 2003) and the emissions covered by the EU ETS (around 2 Gt CO_2/year) account for only around 5% of world emissions (around 46 Gt CO_2 in 2012, taking into account the 6 Kyoto gases and land-use-change, cf. WRI, 2016). Hence variations in EU ETS emissions over a few years cannot significantly change the marginal environmental damage.

The social planner anticipates producers' reactions. To solve the welfare maximization problem we first need to substitute the market variables in the expected welfare function with the reaction functions coming from the producer problem, depending on whether the equilibrium of each state is a corner or an interior solution. The first-order conditions then give the ex-ante optimal levels of the policy instruments across all states.

2.2 Social optimum with an interior solution

Proposition 1: In an interior solution, neither a FIP nor a FIT can improve welfare when combined with an ETS.

Proof: As detailed in Appendix A.2, the optimal subsidy level is always zero when there is a carbon price in all states of nature, for all sources of uncertainty. □

When there is already an incentive to reduce emissions in all states of nature, it is never desirable to subsidize renewables. The expected carbon price should be equal to the marginal damage from emissions, and any additional instrument would only distort incentives without affecting total emissions.

The optimal policy mix is, however, different when a corner solution is considered. The next section discusses the incidence of corner solutions and their impact on optimal policy levels and on welfare for the three separate sources of uncertainty: future electricity demand, the future cost of renewables and the future cost of fossil-based electricity.

2.3 Ordering policy mixes in a corner solution

When the variances of the shock distribution functions increase, lower demand levels, lower renewable costs and higher fossil prices lead to a decreasing carbon price, to the point where it reaches zero. Once the carbon price is at zero, the nature of the system changes and a corner solution is reached.

Proposition 2: When the variance of the shock on the future demand level or the future cost of renewables is above a certain threshold $\tilde{V}$ depending on the policy set,

a) the FIT setting (ETS plus feed-in tariff) brings a larger optimal expected welfare (EW^*) than the FIP setting (ETS plus feed-in premium), itself bringing a larger EW^* than the CAP setting (ETS alone):

$$EW_{DEM}^{*CAP} < EW_{DEM}^{*FIP} < EW_{DEM}^{*FIT}$$

$$EW_{REN}^{*CAP} < EW_{REN}^{*FIP} < EW_{REN}^{*FIT}$$

b) The optimal FIT then equals the electricity price which would have occurred had a cap been optimised on the low-state case.

c) The optimal FIP is equal to the electricity price which would have occurred had a cap been optimised on the low-state case, minus a factor reflecting the trade-off between producing enough renewable energy in the low state and not producing too much in the high state. The optimal carbon price in the high state equals the marginal damage minus the same factor.

d) The variance threshold above which a corner solution occurs is higher for the FIP than for the FIT setting; for both the FIP and the FIT, thresholds are below the CAP threshold, i.e. the variance level above which the carbon price drops to zero in the setting with an ETS alone:

$$\tilde{V}_{DEM}^{CAP} > \tilde{V}_{DEM}^{FIP} > \tilde{V}_{DEM}^{FIT}$$

$$\tilde{V}_{REN}^{CAP} > \tilde{V}_{REN}^{FIP} > \tilde{V}_{REN}^{FIT}$$

All thresholds increase with the marginal damage, faster in the FIP than in the FIT setting, but fastest in the CAP setting.

e) When the marginal damage increases, the difference of EW* between the CAP and FIT settings increases, as does the difference of EW* between the CAP and FIP settings, and between the FIT and FIP settings. Expressions are identical for a shock on demand and on renewables costs. The CAP-FIT difference increases at the fastest rate, followed by the CAP-FIP difference. The FIT-FIP difference increases at the slowest pace:

$$\frac{\partial(\Delta EW^*_{FIT-CAP})}{\partial\delta} > \frac{\partial(\Delta EW^*_{FIP-CAP})}{\partial\delta} > \frac{\partial(\Delta EW^*_{FIT-FIP})}{\partial\delta}$$

f) Compared to a first best carbon tax setting, the expected total production (ΔEQ) is too high and the expected electricity price (ΔEP) is too low in the CAP, FIP and FIT settings. The FIP setting leads to the biggest difference, followed by the FIT setting and the CAP setting:

$$\Delta EQ^*_{FIP} > \Delta EQ^*_{FIT} > \Delta EQ^*_{CAP}$$

$$\Delta EP^*_{FIP} < \Delta EP^*_{FIT} < \Delta EP^*_{CAP}$$

Proof: See Appendix A.3 for details. Proposition 2.a is directly shown by comparing the expressions for the optimal expected welfare, once functions for the reaction of producers and optimal policy instrument levels have been reinjected into the initial welfare expression. Propositions 2.b and 2.c are demonstrated by computing the optimal emissions cap for the low state only, and by comparing it with the optimal instrument levels. Proposition 2.d follows from the comparison from the limit shock values for which the expressions for the optimal expected welfare are equal with and without a corner solution. Finally, these threshold values and the difference of expected welfare expressions are derived with respect to the marginal damage to yield: propositions 2.e and 2.f.

The Intuition behind the proof is that when the variance of the shock distribution exceeds the threshold, it is preferable to implement a cap that only binds in the high state. The costs incurred by a tight cap in the high state exceed the costs incurred by a lack of mitigation in the low state, since the latter are bounded by the zero carbon price limit. As discussed in Lecuyer and Quirion (2013), this leaves room for improvement by an additional instrument that would mitigate emissions in the low state without incurring too much cost in the high state. Feed-in tariffs and premiums behave differently in this respect.

While it is possible to devise a tariff that binds only when the electricity price is low and the carbon price nil, a premium necessarily promotes renewable production in all states. A tariff can therefore restore the optimal renewable production level even if the carbon price is zero, and can do that without affecting the incentive from the ETS in the high state, whereas a premium faces the trade-off of promoting more renewables in the low state but not too many in the high state.

Another interesting result is that adding renewable subsidies to the ETS reduces the variance threshold above which the uncertainty drives the carbon price down to zero. This effect can be related to the merit-order effect discussed at length in the literature, or the “green promotes the dirtiest” effect discussed by Böhringer and Rosendahl (2010): when active, a subsidy to renewables reduces the price of electricity and eases any given emissions constraint, leading to zero carbon prices at lower shocks. Note, however, that in the current setting, this does not imply that policy instruments promoting renewables are undesirable, quite the reverse. Despite lower electricity and carbon prices (and hence too high a consumption of electricity compared to the first best), adding a tariff or premium (set at the right level) increases welfare when uncertainty is big. Results show that adding a FIP leads to higher electricity consumption than the FIT setting.

Results differ when the uncertainty leads to opposing effects on the carbon and the electricity price, as is the case with shocks on the cost of fossil fuels, e.g. following the volatility of fossil fuel markets.

Proposition 3: In a framework with one fossil fuel, when the shock is on the cost of fossil fuels, if the variance of the shock distribution is above a certain threshold $\tilde{V}_{FOS}^{FIP}$,

a) the FIP setting (ETS plus feed-in premium) brings a larger optimal expected welfare than the CAP setting (ETS alone):

$$EW_{FOS}^{*CAP} < EW_{FOS}^{*FIP}$$

b) The optimal FIP is equal to the electricity price which would have occurred had a cap been optimised on the high-state case, minus the factor mentioned in Proposition 2.

c) The FIP threshold is lower than the CAP threshold:

$$\tilde{V}_{FOS}^{CAP} > \tilde{V}_{FOS}^{FIP}$$

d) The FIT cannot improve expected welfare.

e) Both the FIP and the CAP thresholds increase with the marginal damage, but the CAP thresholds increase faster. The difference between expected welfare expressions also increases with the marginal damage.

f) Total expected electricity production is higher in the FIP setting than in the CAP setting (both higher than in a first best carbon tax setting), and the expected electricity price is lower in the FIP setting than in the CAP setting (both lower than in a first best carbon tax setting).

Proof: For the details see Appendix A.4. Results are obtained in the same way as for Proposition 2. □

With a shock on the price of fossil fuels, the carbon price drops to zero when the electricity price is high. The result is that a tariff is of no use, since it cannot be designed in a way to be active only when the carbon price is zero. The premium, however, can still bring some benefits, and its optimal level is given by the same rule: it should be equal to the carbon price had a cap been optimized on the high state only, minus the same factor as with the shock on demand or the cost of renewables.

3. Numerical application to the European electricity industry

The numerical model is calibrated on the large-scale Poles model in its last version, used for the EU Advance FP7 project (Criqui and Mima, 2016)[8]. Table 2 in the Appendix lists all the variables and parameters, and the model code is available as Supplementary material. The time horizon is 2025 and we use two runs from the model: a "no-policy" run and a "climate policy" one in which a CO_2 price is implemented. This provides us with two price-quantity pairs for the electricity market. The CO_2-intensity of fossil-based generation is also taken from Poles. We assume a price elasticity of electricity demand of 0.1, a value consistent with Lijesen's (2007) econometric study and literature review. Finally, we assume a marginal damage δ= 60 €/tCO_2, consistent with the official values used for policy appraisal in France (Quinet, 2009) and the UK (UK DECC, 2015).

[8] Previous versions of this model have been used many times by the European Commission and have generated a large number of academic papers, including Kitous et al. (2010) and Criqui et al. (2015).

3.1 Changes compared to the analytical model

We use the framework described in the analytical section, with the three following modifications.

- We consider four energy sources rather than two: subsidised renewables (which includes wind, solar and biomass), gas, coal, and a fossil-free energy which does not benefit from the FIT or FIP, including hydro-electric power[9] and nuclear power. Lignite and oil[10] are included with coal.
- As explained above, the cost functions are slightly more complex since they include a linear element, so the marginal cost curves include an intercept and a slope parameter σ_i:

$$Cost(q_i, x_i) = p^0 \cdot q_i^0 + p^0 \cdot \left(q_i - q_i^0\right) + x_i \cdot q_i + \sigma_i \cdot (q_i - q_i^0)^2$$

  Where $i \in \{r, n, c, g\}$ is the technology: renewables, non-subsidized non-fossil, coal or gas. p^0 and q_i^0 are the "no policy" electricity price and production; x_i is a random variable, representing a possible shock on the intercept of the cost function.

- We consider an endogenous tax on electricity consumption, calculated *ex post* to cover the renewables subsidy cost, as is done in most countries. For example, this tax is called EEG-Umlage in Germany and is a part of the *Contribution au service public de l'électricité* (CSPE) in France[11].

3.2 Quantification of shocks

As explained above, the fact as to whether uncertainty is big or small generates a qualitative change in the model's behaviour, since renewable subsidies can only increase welfare if uncertainty is big enough. Hence quantifying uncertainty is important, while obviously being very difficult. We rely on a simple approach: we compare observations with past predictions looking around 10 years ahead. This only provides a rough idea of the amount of uncertainty at stake but it is doubtful whether sophisticated methods would provide much more insight.

For gross electricity production, we compare the forecast made in 2005 by the European Commission (2006) for the year 2014 with the actual value. The forecast for the EU 25 was 3682 TWh and the observation was 3044 TWh i.e. 17% lower (Enerdata, 2016). Several factors may explain this gap, including the economic recession and the unanticipated effectiveness of energy saving policies. In the future, the same kind of uncertainty exists: the forecasts made for EU 28 electricity consumption in 2020 by the European Commission (2013) and by the NGO Sandbag (2014) differ by 10% (3400 TWh vs. 3050). We conclude that an uncertainty range of 10%-20% is not exaggerated regarding uncertainty over electricity consumption forecasts for ten years hence.

For the cost of generating electricity from renewable energy, we rely on Marschinski and Quirion (2014) who calculated that in 2010 the cost of photovoltaic electricity was 30% lower than forecast,

[9] Admittedly, small hydro-electric schemes are often subsidised but are not separated from large schemes in Poles and the potential for new capacity is limited in Europe so this is not of great importance.
[10] Lignite is not separated from coal in Poles and the percentage of oil used in electricity generation is so small (0.1% in 2025) that it is not worth keeping it as a separate technology.
[11] We also ran the model without this tax. The welfare gain from subsidising renewables is higher with the tax because the latter reduces electricity consumption which, as we have seen in the analytical section, is too high.

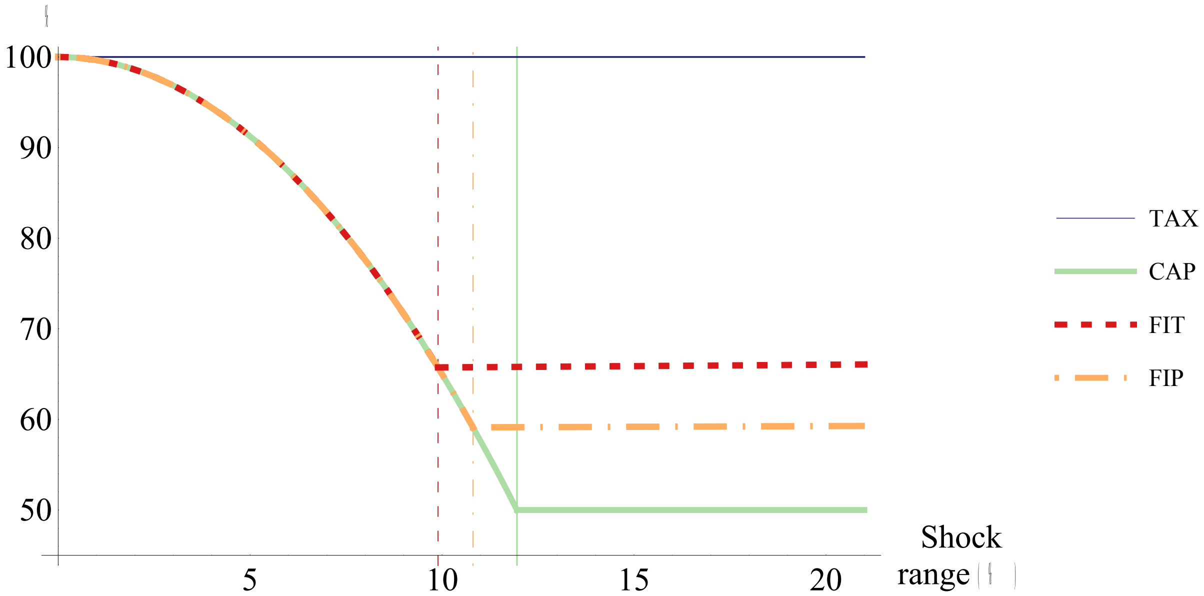
using data from Feldman et al. (2012, Fig.14). Since the forecast errors were lower for the other forms of renewable energy, here again a range of 10%-20% seems reasonable.

For the cost of fossil-based electricity, we use the past editions of the IEA (2006, 2011, 2015) *World Energy Outlook* (WEO), for the European natural gas import price and steam coal import price. The WEO 2006 underestimated the 2014 natural gas price by 24% and the coal price by 10%, while it underestimated the 2010 natural gas price by 15% and the coal price by 59%. Since fossil fuels account for roughly half of the electricity generation cost, a 10-30% forecast error seems reasonable.

3.3 Results with uncertain demand

Figure 1 shows the expected welfare gain generated by the different policy packages, compared to a no-policy scenario and normalised at 100% for the first-best policy (the CO_2 tax). The x-axis indicates the shock range, as a percentage of the expected value. Without uncertainty (at the extreme left of the x-axis), the TAX and the CAP policies achieve the same outcome, which is the first-best. So do FIT and FIP on the graph, but actually with these scenarios the subsidy to renewables is set at zero because the ETS is sufficient to achieve the optimal level of renewables, so they are identical to CAP, which is consistent with Proposition 1.

Figure 1. Expected welfare gain from policy packages when demand is uncertain



The x-axis presents the shock range as a percentage of electricity production under the no-policy scenario.
The y-axis presents the expected welfare gain compared to the no-policy scenario, as a percentage of the first-best policy.

When uncertainty increases, CAP becomes less interesting than TAX because the CO_2 price departs from the marginal environmental damage, as in Weitzman's (1974) seminal paper. However when the shock range reaches around 12% of demand, the relative disadvantage of CAP is bounded at 50% of the first-best welfare gain because past this threshold, the cap is optimised for the case of a positive shock (which occurs with a probability of 0.5) and does not bind in the case of a negative shock.

Consistently with Proposition 2a, when a subsidy to renewables is added to the ETS, the expected welfare gain under a big uncertainty is larger than with CAP alone, and more so with FIT than with

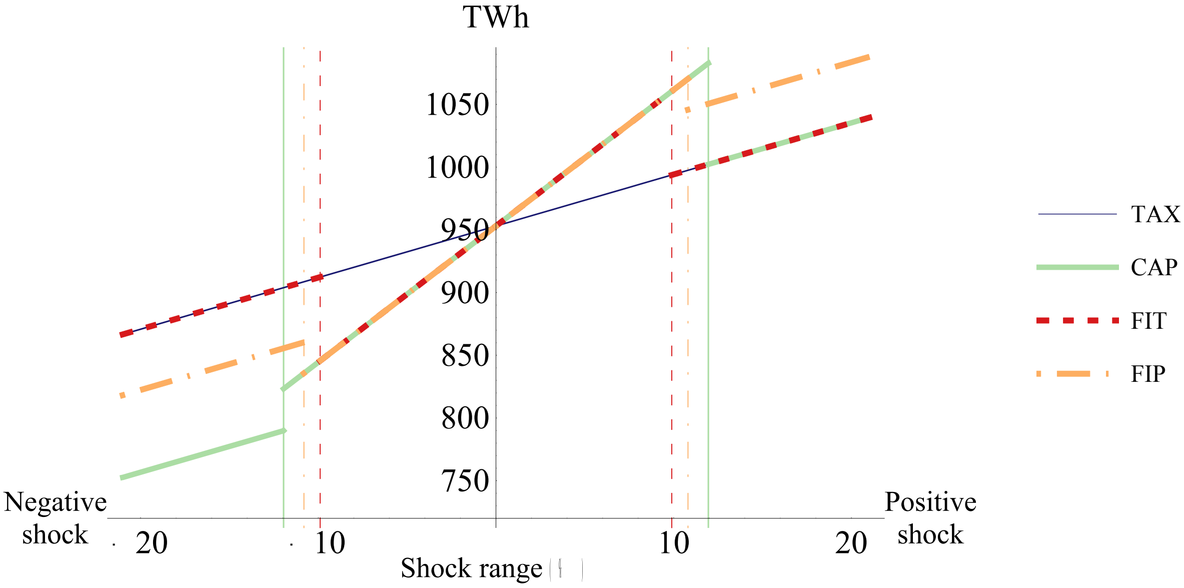
FIP: +16 percentage points (pp) with FIT and +9 pp with FIP. Since the welfare gain from the tax compared to the no-policy scenario amounts to 8.6 billion €/yr., FIT brings an expected welfare gain of 1.4 billion €/yr. compared to CAP, and FIP 0.8 billion €/yr. Figure 1 also confirms Proposition 2d, i.e. that the shock level beyond which the CO_2 price goes down to zero in the case of a negative shock is lower for FIT than for FIP, and lower for FIP than for CAP, although the difference is small (respectively, 9.9%, 10.8% and 11.9% of the electricity production in the no-policy scenario).

As demonstrated in section 2, the superiority of FIT over FIP is due to the fact that the former is effective only when it is needed i.e. under a negative demand shock. As a consequence the FIT support level can be optimised for this state of nature, thus, under FIT, production of renewable electricity equals the first-best level, i.e. that of the TAX scenario (Figure 2). With a big positive demand shock this production is also optimal since it is determined by the cap, itself set at the optimal level. On the contrary, since the renewables subsidy in the FIP scenario does not discriminate between the demand states, production of renewable electricity is too high in the case of a positive shock and too low in the case of a negative shock[12]. As a consequence, under a negative demand shock emissions are lower with FIT than with CAP, FIP being at an intermediary level (Figure 3).

Yet, as long as uncertainty is not too big, FIP improves expected welfare compared to CAP alone. The intuition for this result is that the marginal cost of departing from the first-best level of abatement increases with the distance from this first-best level. Under CAP, for a big negative shock, the gap between the CO_2 price and the marginal benefit from abatement is large: it equals δ = 60€/t CO_2. Hence a subsidy to renewables brings a relatively large benefit. On the contrary, for a big positive shock, under CAP the CO_2 price equals the marginal benefit from abatement (Figure 3), because the cap is optimised on this situation. Hence in this case a subsidy to renewables generates a relatively low additional cost.

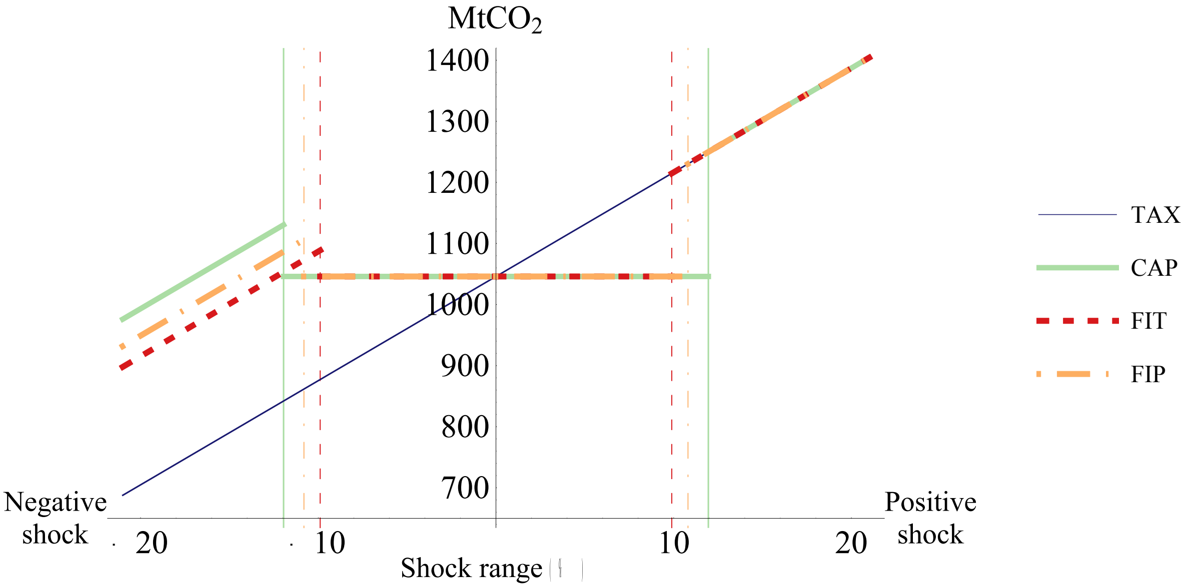
[12] The renewable support level in the case of a large negative demand shock is around 16 €/MWh for FIT vs. 9 €/MWh for FIP. These levels are in the low range of the renewables subsidies currently in place in Europe, which can be explained by two factors. First, these subsidies are also justified by other externalities not accounted for in our model (air quality, learning-by-doing…). Second, we model the situation in 2025 and renewable energy costs and subsidies will most likely decrease by this date.

Figure 2. Electricity production from renewables when demand is uncertain



The x-axis presents the shock range as a percentage of electricity production under the no-policy scenario.

Figure 3. CO_2 emissions when demand is uncertain



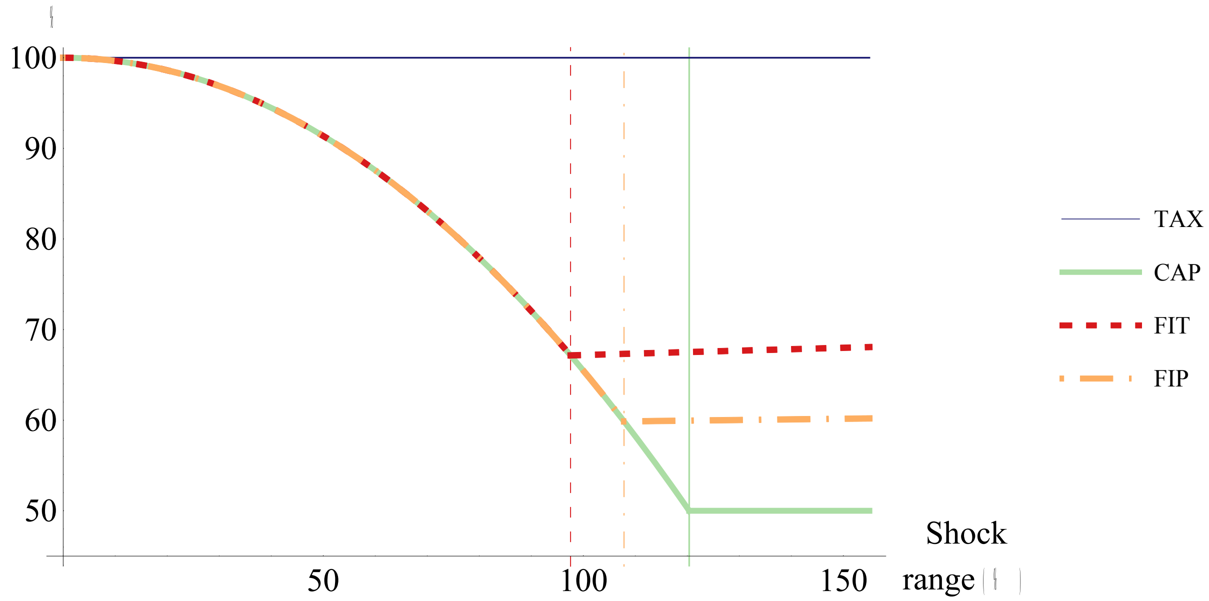
The x-axis presents the shock range as a percentage of electricity production under the no-policy scenario.

However even with a big shock FIT does not bring the first-best welfare level, for two reasons. First, because the CO_2 price is nil, there is too much coal and too little gas compared to the first-best solution. Second, as in the analytical model, electricity consumption is too high because the electricity price is too low. Notice that this latter drawback is mitigated by the electricity tax implemented to fund subsidies for renewables: this tax increases expected welfare by 5.7 percentage points for FIT and by 3.5 percentage points for FIP, compared to FIT and FIP policies optimised without this cap. The tax rate which covers the subsidy cost is around 5 €/MWh for FIP and 9 €/MWh for FIT.

3.4 Results with uncertain cost of renewables

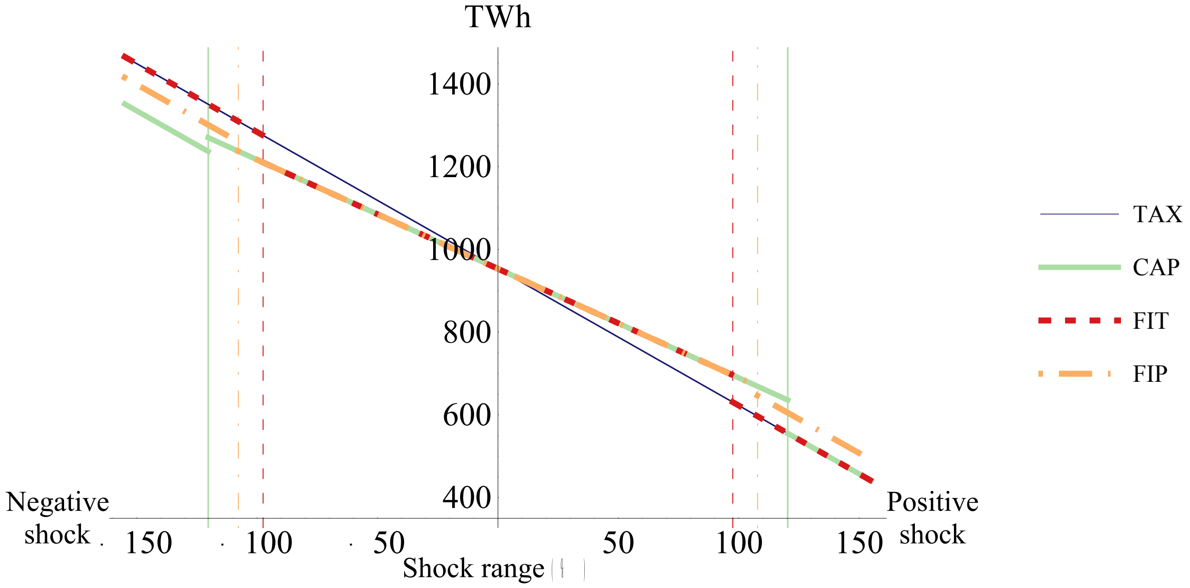
Figures 4 to 6 present the results with uncertainty over the cost of renewables rather than over electricity demand. The corner solution of a nil CO_2 price is reached for much higher levels of uncertainty: a shock of nearly 100% on the marginal cost of renewables for the FIT and even above for FIP and CAP, expressed as a percentage of the electricity price under the no-policy scenario. A shock above 100% reflects a negative intercept, but does not mean that all renewables have a negative marginal cost. This rather imperfectly approximates a very big shock in a linear model. This result nevertheless indicates that uncertainty over renewables alone is unlikely to generate corner solutions. However in combination with a drop in demand, a lower than expected renewables cost may contribute to generating a corner solution.

Figure 4. Expected welfare gain from policy packages when renewables cost is uncertain



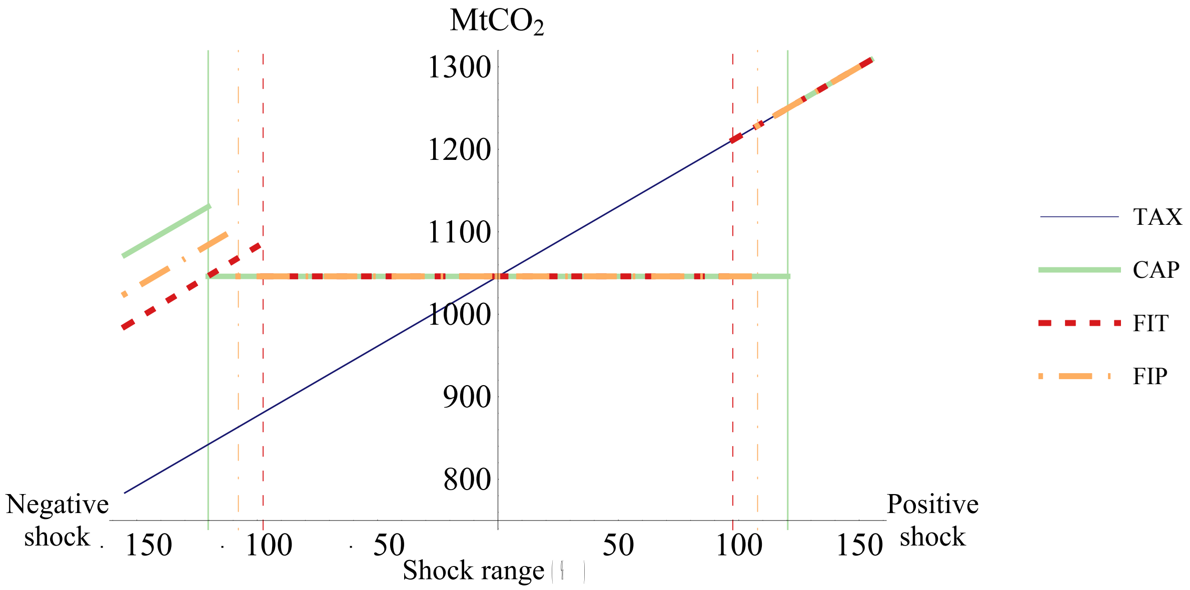
The x-axis presents the shock range as a percentage of the electricity price under the no-policy scenario.
The y-axis presents the expected welfare gain compared to the no-policy scenario, as a percentage of the first-best policy.

Figure 5. Electricity production from renewables when renewables cost is uncertain



The x-axis presents the shock range as a percentage of the electricity price under the no-policy scenario.

Figure 6. CO_2 emissions when renewables cost is uncertain



The x-axis presents the shock range as a percentage of the electricity price under the no-policy scenario.

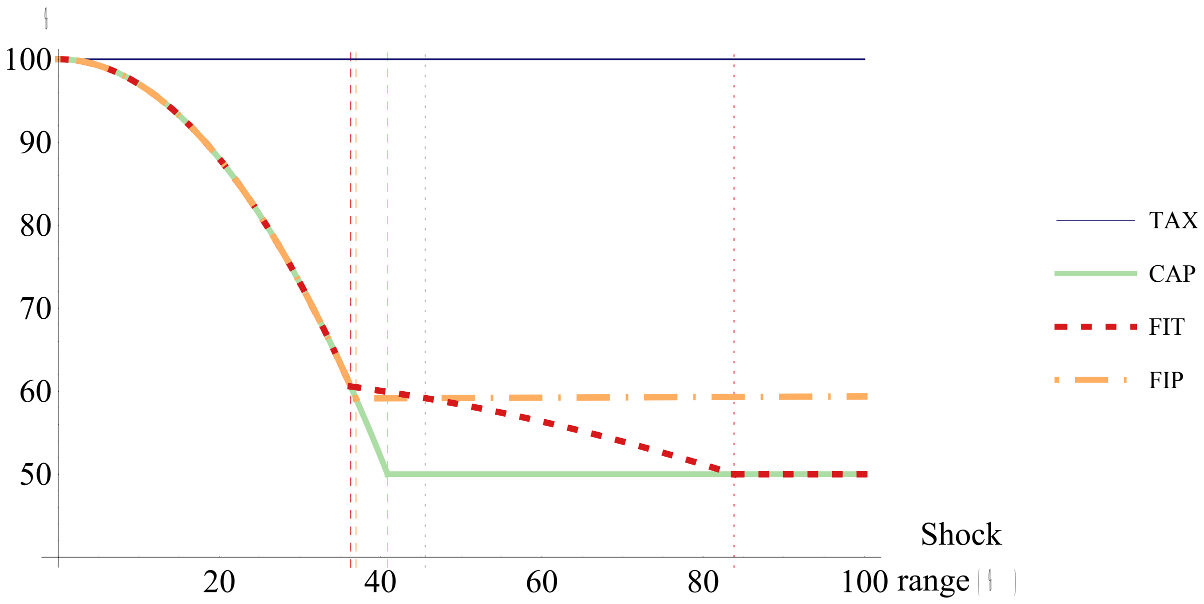
3.5 Results with uncertain cost of coal

When uncertainty concerns the cost of coal-based electricity generation, results are very different for the FIT scenario: a nil CO_2 price can only occur in the case of a higher than expected coal cost, which also generates a higher than expected electricity price. Hence it is impossible to have a feed-in tariff subsidising renewables only in the case of a nil CO_2 price, as in the previous cases.

Yet, as is apparent from Figure 7, FIT increases the expected welfare over CAP for an uncertainty between 35% and 85% of the no-policy electricity price. As shown in Figure 8, in the case of a positive shock on coal price in this range, FIT brings renewable production closer to its first-best level. The drawback is that in the case of a negative shock it increases this production beyond its first-best level – just like the FIP. As explained in section 3.3 above, in terms of expected welfare, at the margin the gain from adding renewables in the case of a nil CO_2 price is larger than the loss from adding renewables in the case of an optimal CO_2 price: this explains the superiority of FIP over CAP, whatever the uncertainty at stake, and that of FIT over CAP under uncertainty over coal price – for a limited uncertainty range.

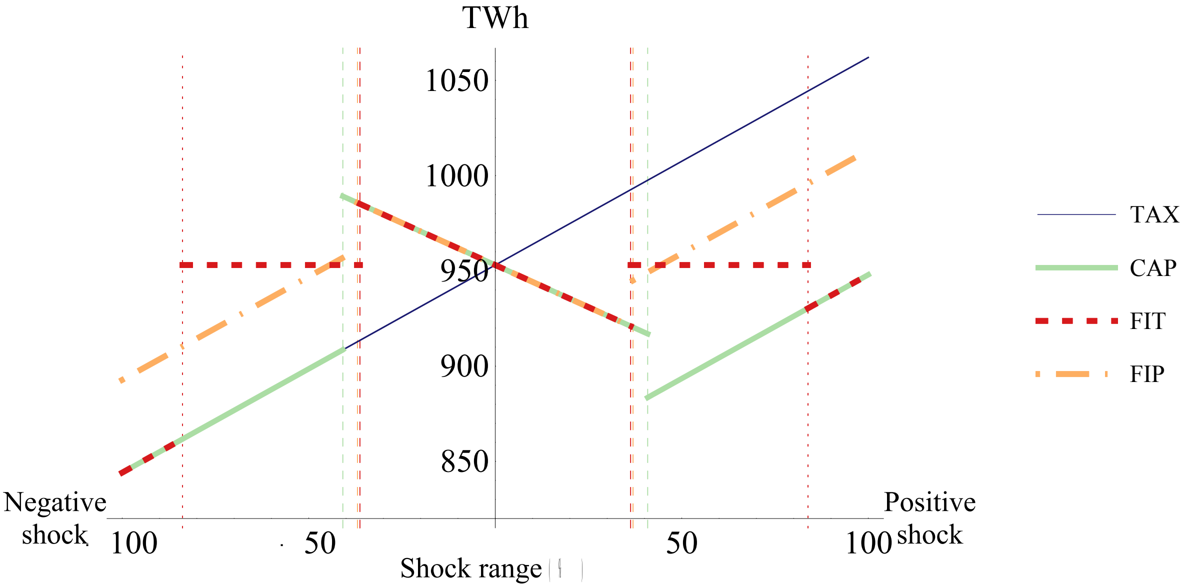
However if uncertainty is too big (>85%), FIT no longer improves the situation over CAP, because then having a FIT higher than the electricity price when it is needed (a very big positive shock on coal prices) implies that in the case of a very big negative shock on coal prices, the FIT would lead to a massive subsidy to renewables and hence it would be too costly. As Figure 10 makes clear, at the 85% threshold the implicit subsidy from FIT is only 6€/MWh in the case of a positive shock (when it is needed) but reaches 26€/MWh in the case of a negative shock (when it is detrimental).

Figure 7. Expected welfare gain from policy packages when coal cost is uncertain



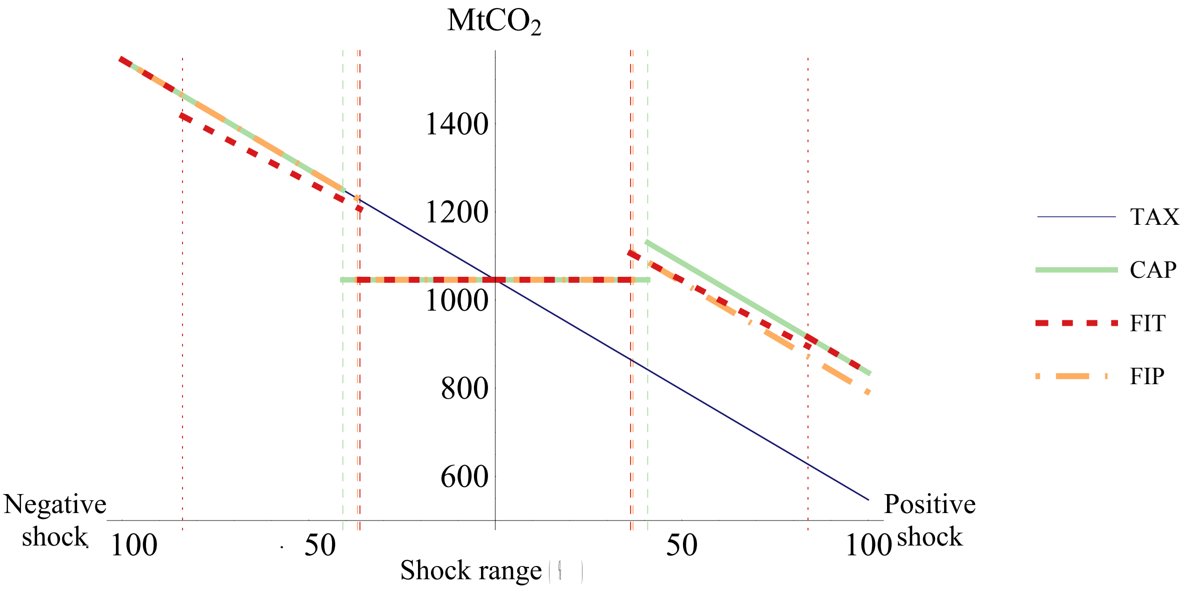
The x-axis presents the shock range as a percentage of the electricity price under the no-policy scenario.
The y-axis presents the expected welfare gain compared to the no-policy scenario, as a percentage of the first-best policy.

Figure 8. Electricity production by renewables when coal cost is uncertain



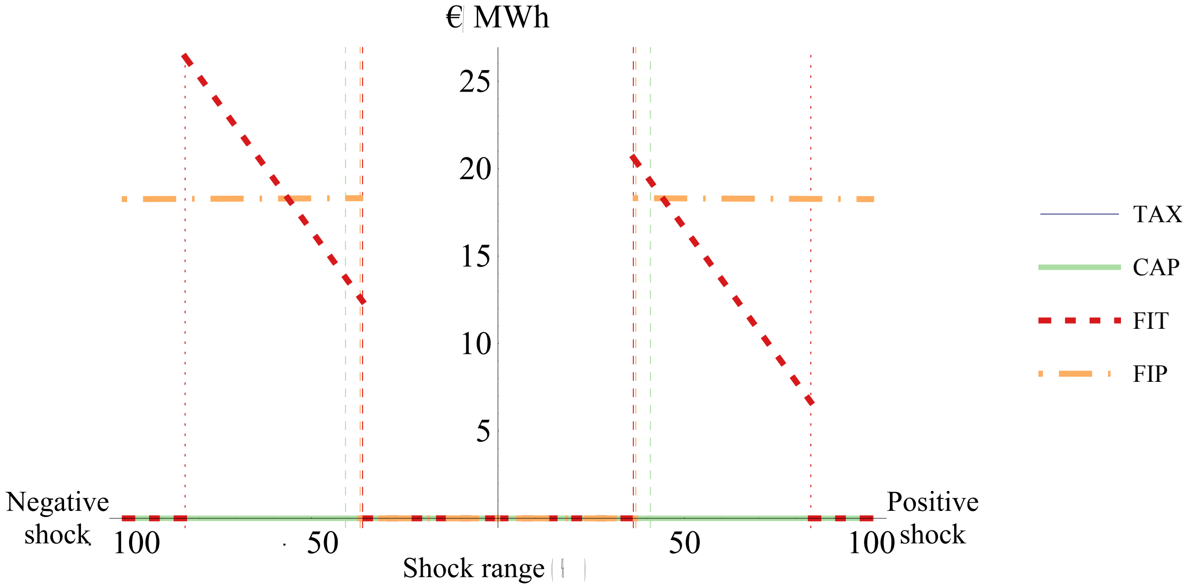
The x-axis presents the shock range as a percentage of the electricity price under the no-policy scenario.

Figure 9. CO_2 emissions when coal cost is uncertain



The x-axis presents the shock range as a percentage of the electricity price under the no-policy scenario.

Figure 10. Implicit renewables subsidy when coal cost is uncertain



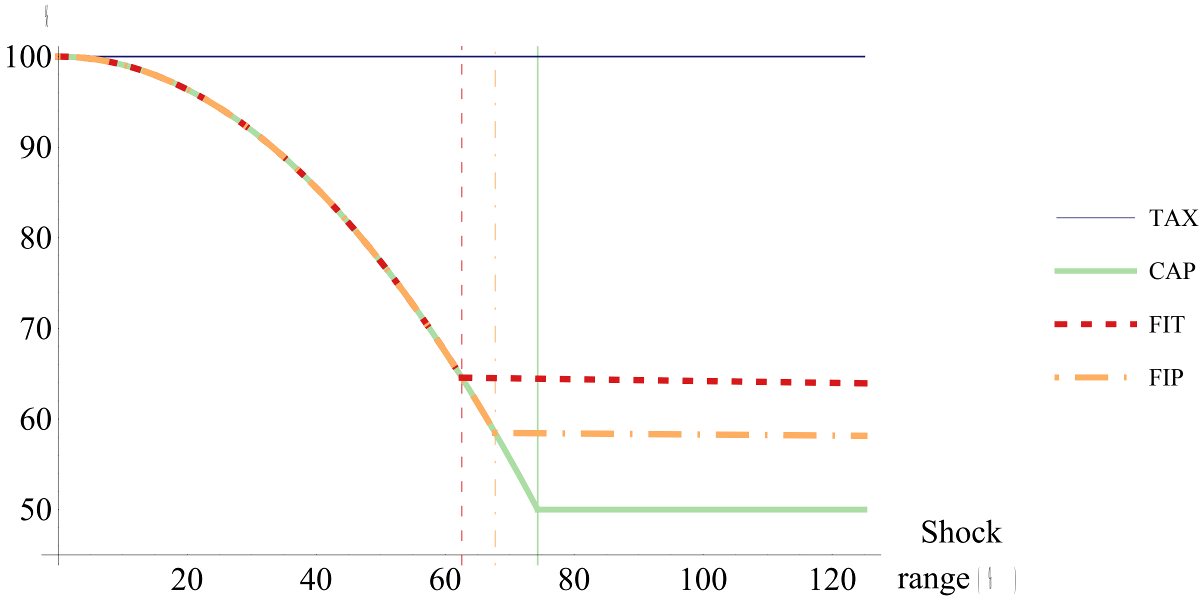
The x-axis presents the shock range as a percentage of the electricity price under the no-policy scenario.

3.6 Results with uncertain cost of gas

In general, the price of gas has an ambiguous impact on CO_2 emissions since it is in competition with coal which is more CO_2-intensive but also with the other energy sources which are less CO_2-intensive. Hence, depending on the model, a nil CO_2 price may be provoked by a high *or* a low gas price – or by neither. In our numerical model, the latter situation occurs. As shown in Figures 11 to 13, qualitatively, the model outcome is the same as under a shock to the cost of renewables.

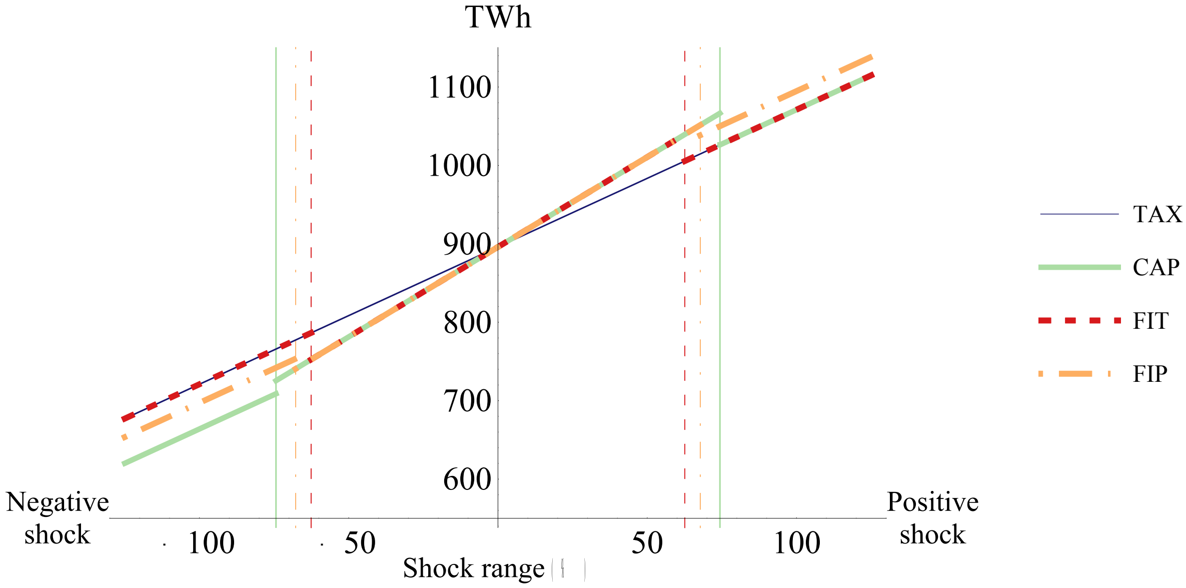
However a very big uncertainty is required for the CO_2 price to collapse: the cost of gas-based electricity generation has to drop by more than 60%. Hence, as for the cost of renewables, this uncertainty alone is unlikely to generate a corner solution, but, it may contribute to it if combined with a drop in electricity demand and/or in renewable energy cost.

Figure 11. Expected welfare gain from policy packages when gas cost is uncertain



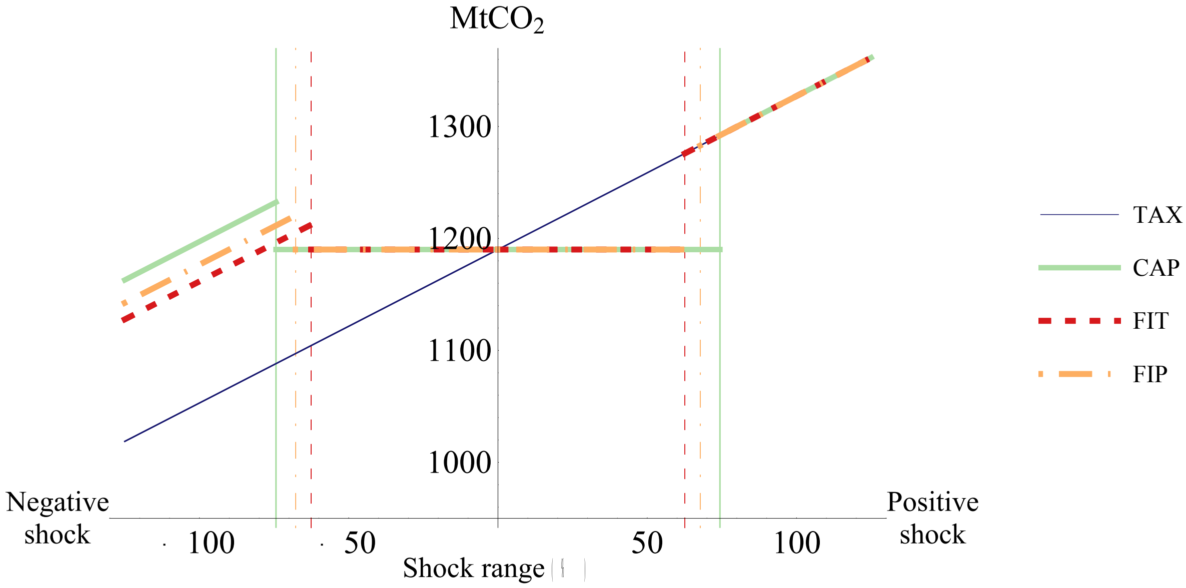
The x-axis presents the shock range as a percentage of the electricity price under the no-policy scenario.
The y-axis presents the expected welfare gain compared to the no-policy scenario, as a percentage of the first-best policy.

Figure 12. Electricity production by renewables when gas cost is uncertain



The x-axis presents the shock range as a percentage of the electricity price under the no-policy scenario.

Figure 13. CO_2 emissions when gas cost is uncertain



The x-axis presents the shock range as a percentage of the electricity price under the no-policy scenario.

Conclusion

Evidence reviewed in this paper indicates that over-allocation has occurred during at least part of the history of most existing Emissions Trading Systems around the world. There are good reasons to consider that this prevalence of over-allocation is not only due to bad luck or to teething problems, but that it stems from unavoidable uncertainty about business-as-usual emissions and costs. This uncertainty means that there is also a risk of generating over-allocation in the next phases of the EU

ETS: our simulations indicate that a 10% drop in electricity demand compared to forecast, which is well within in the range of the typical error margin, would be sufficient to reduce emissions below the ex-ante-optimal emissions cap.

Applying both an analytical and a numerical model to the European electricity industry, we show that the very possibility of over-allocation justifies the existence of subsidies to renewable energies, even when climate change mitigation is the only benefit from renewables taken into account. Moreover, uncertainty over electricity demand, renewable energy costs or gas prices favours a feed-in tariff rather than a feed-in premium, while the opposite conclusion is reached only under uncertainty over coal prices. This conclusion casts doubts on the switch from feed-in tariffs to feed-in premiums that is currently taking place in Europe following the European Commission (2014) guidelines on State aid for energy, and has been challenged on other grounds by several leading European energy economists (Fabra et al. 2014). At the very least, a deeper analysis of the way these subsidies react to uncertainty should be undertaken, featuring their interactions with the EU ETS.

Our conclusion is based on the premise that a CO_2 tax cannot be implemented in Europe, which is justified by the failures of the proposals that have been tabled by the Commission since 1992, and by the unanimity rule governing fiscal decisions in the EU – as opposed to environmental decisions which are subject to a qualified majority rule. Likewise, if a CO_2 price floor were set at the marginal damage level in the EU ETS, our conclusions would no longer be valid, but such a reform, while advocated by many researchers (Knopf et al. 2014; Branger et al. 2015) is not part of the Commission's proposals to reform the EU ETS. Moreover, our conclusions would remain qualitatively valid for a price floor lower than the environmental marginal damage level, while quantitatively the expected benefit from renewables subsidies would diminish.

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Table 1. Variables and parameters in the analytical model

	Illustrative dimension	Description
f	MWh	Electricity from fossil fuels
r	MWh	Electricity from renewable sources
p	€/MWh	Wholesale power price
ω	€/tCO_2	Carbon price
ρ	€/MWh	Feed-in tariff
θ	€/MWh	Feed-in premium
Ω	tCO_2	Emissions cap
Θ	€/MWh	Effective marginal revenue of renewables (included policy)
σ_d	MWh^2/€	Slope of demand function
σ_r	MWh^2/€	Slope of RE supply function
σ_f	MWh^2/€	Slope of fossil-based electricity supply function
δ	€/tCO_2	Marginal environmental damage
$\varDelta^2$	MWh^2	Variance of demand
γ^2	€^{2}/MWh^2	Variance of the marginal cost of renewables or fossils
ι_d	MWh	Intercept of demand function
μ	tCO_2/MWh	CO_2-intensity of fossil-based electricity
x	€/MWh	Random variable denoting the uncertainty on the future marginal cost of fossil production
y	€/MWh	Random variable denoting the uncertainty on the future marginal cost of renewable production
z	MWh	Random variable denoting the uncertainty on the future demand for electricity

Appendix

A.1. Table 2.

Table 2. Variables and parameters in the numerical model

	Value	Dimension	Description
q_r^0	839.02	TWh	Electricity from renewable sources, no-policy scenario
q_n^0	1117.28	TWh	Electricity from nuclear and hydro, no-policy scenario
q_c^0	1143.13	TWh	Electricity from coal (including lignite and oil) , no-policy scenario
q_g^0	640.17	TWh	Electricity from gas, no-policy scenario
σ_r	0.12	MWh^2/€	Slope of renewable electricity supply function
σ_n	0.93	MWh^2/€	Slope of fossil-based electricity supply function
σ_c	0.045	MWh^2/€	Slope of coal-based electricity supply function
σ_g	0.028	MWh^2/€	Slope of gas-based electricity supply function
μ_c	0.96	tCO_2/MWh	CO_2-intensity of fossil-based electricity
μ_g	0.37	tCO_2/MWh	CO_2-intensity of fossil-based electricity
δ	60	€/tCO_2	Marginal environmental damage
p^0	89.12	€/MWh	Wholesale power price, no-policy scenario
ε	0.1	none	Price-elasticity of demand at p^0
i_d	4113.56	TWh	Intercept of the demand curve
σ_d	4.19614	MWh^2/€	Slope of the demand curve

A.2 Demonstration of Proposition 1:

The FOCs are the same for all the policy sets:

$$p = \mu\omega + \frac{f}{\sigma_f} + \mathrm{x}$$
$$\Theta = y + \frac{r}{\sigma_r}$$
$$f + r + p\sigma_d = \iota_d + \mathrm{z}$$
$$f = \Omega$$

The marginal cost of renewable and fossil production, included shocks, should be equal to marginal revenues, and the electricity and emissions allowance markets should clear, given the possible shock on demand. Solving for the reaction functions for the market variables gives:

$$f = \Omega$$
$$r = (-y + \Theta)\sigma_r$$
$$p = \frac{z - \Omega + \iota_d + y\sigma_r - \Theta\sigma_r}{\sigma_d}$$
$$\omega = \frac{-\Omega\sigma_d + z\sigma_f - \Omega\sigma_f + \iota_d\sigma_f - x\sigma_d\sigma_f + y\sigma_f\sigma_r - \Theta\sigma_f\sigma_r}{\mu\sigma_d\sigma_f}$$

Once the reaction functions have been reinjected in the welfare function, the expected welfare function (EW^{LOW}) depends on the source of uncertainty:

$$EW_{FOS}^{LOW} = -\frac{\Omega\left(-2\iota_d\sigma_f + 2\delta\mu\sigma_d\sigma_f + \Omega\left(\sigma_d + \sigma_f\right)\right) + 2\Theta(\Omega - \iota_d)\sigma_f\sigma_r + \Theta^2\sigma_f\sigma_r(\sigma_d + \sigma_r)}{2\sigma_d\sigma_f}$$

$$EW_{REN}^{LOW} = -\frac{1}{2\sigma_d\sigma_f}(\Omega(-2\iota_d\sigma_f + 2\delta\mu\sigma_d\sigma_f + \Omega(\sigma_d + \sigma_f)) + 2\Theta(\Omega - \iota_d)\sigma_f\sigma_r + \Delta^2\sigma_f\sigma_r(\sigma_d + \sigma_r) + \Theta^2\sigma_f\sigma_r(\sigma_d + \sigma_r))$$

$$EW_{DEM}^{LOW} = -\frac{\Delta^2\sigma_f + \Omega(-2\iota_d\sigma_f + 2\delta\mu\sigma_d\sigma_f + \Omega(\sigma_d + \sigma_f)) + 2\Theta(\Omega - \iota_d)\sigma_f\sigma_r + \Theta^2\sigma_f\sigma_r(\sigma_d + \sigma_r)}{2\sigma_d\sigma_f}$$

Where LOW stands for low uncertainty (hence an interior solution). When maximized with respect to Ω and Θ, all three expected welfare functions yield the same result:

$$\Omega^* = \frac{\sigma_f(\iota_d - \delta\mu(\sigma_d + \sigma_r))}{\sigma_d + \sigma_f + \sigma_r} \Longrightarrow \mathbb{E}_{DEM}[\omega] = \delta$$
$$\Theta^* = \frac{\iota_d + \delta\mu\sigma_f}{\sigma_d + \sigma_f + \sigma_r} = p^*$$

The expected carbon price should be equal to the marginal damage, and the (implicit) subsidy to renewables should be nil. The optimal welfare levels are hence also the same:

$$EW^{*LOW} = \frac{-2\delta\mu\iota_d\sigma_d\sigma_f(\sigma_d + \sigma_r) + \delta^2\mu^2\sigma_d\sigma_f(\sigma_d + \sigma_r)^2 + \iota_d^2(\sigma_d + \sigma_r)(\sigma_f + \sigma_r) + \Delta^2\sigma_r(\sigma_d + \sigma_f + \sigma_r)}{2\sigma_d(\sigma_d + \sigma_r)(\sigma_d + \sigma_f + \sigma_r)}$$

A.3 Demonstration of Proposition 2:

A.3.1 Optimal expected welfare

The FOCs with nil carbon price are the following:

$$p = \frac{f}{\sigma_f} + \mathrm{x}$$
$$\Theta = y + \frac{r}{\sigma_r}$$
$$f + r + p\sigma_d = \iota_d + \mathrm{z}$$
$$\omega = 0$$

The marginal cost of renewable and fossil production, included shocks, should be equal to marginal revenues, and the electricity market should clear, given the possible shock on demand. Solving for the reaction functions for the market variables gives:

$$f \to \frac{\sigma_f(z + \iota_d - v\sigma_d + y\sigma_r - \Theta\sigma_r)}{\sigma_d + \sigma_f}$$
$$r \to (-y + \Theta)\sigma_r$$
$$p \to \frac{z + \iota_d + v\sigma_f + y\sigma_r - \Theta\sigma_r}{\sigma_d + \sigma_f}$$
$$\omega \to 0$$

The expected welfare expressions depend on the source of uncertainty, because the expectation operator depends on which random variable is taken into account. Moreover, the reaction functions to use are state- and policy-dependant. When considering the case of a corner solution, the carbon price drops to zero in states of low demand and low renewable cost, that is for a negative shock. When computing the expected welfare function with a corner solution, two different sets of FOCS and reaction functions have hence to be used to replace policy variables in the high and low states.

Moreover, while the FIP binds whatever the state, the FIT may be set between the price level in the low state and the price level in the high state, meaning that he may bind only when the electricity price is low. The reaction functions used will then be different, because they will feature a FIT in the low case and no renewable policy in the high case. As the intuition suggests, a comparison with a setting featuring a FIT binding in both cases reveals that it is not optimal (not shown here). The expected welfare (EW) functions are:

$$\begin{aligned}EW_{REN}^{CAP} = {} & \frac{1}{4\sigma_d\sigma_f(\sigma_d + \sigma_r)(\sigma_d + \sigma_f + \sigma_r)}(-\Omega^2\sigma_d(\sigma_d + \sigma_f + \sigma_r)^2 + 2\Omega\sigma_d\sigma_f(\sigma_d + \sigma_f + \sigma_r)(\iota_d \\ & + \Delta\sigma_r - \delta\mu(\sigma_d + \sigma_r)) + \sigma_f(-2\iota_d\sigma_d\sigma_f(\Delta\sigma_r + \delta\mu(\sigma_d + \sigma_r)) + \Delta\sigma_d\sigma_r(2\Delta\sigma_d(\sigma_d \\ & + \sigma_f) + \Delta(2\sigma_d + \sigma_f)\sigma_r + 2\delta\mu\sigma_f(\sigma_d + \sigma_r)) + \iota_d^2(2\sigma_r(\sigma_f + \sigma_r) + \sigma_d(\sigma_f + 2\sigma_r))))\end{aligned}$$

$$\begin{aligned}EW_{REN}^{FIP} = {} & \frac{1}{4\sigma_d\sigma_f(\sigma_d + \sigma_r)(\sigma_d + \sigma_f + \sigma_r)}(-2\iota_d\sigma_d\sigma_f(\Delta\sigma_f\sigma_r + \delta\mu\sigma_f(\sigma_d + \sigma_r) - \Omega(\sigma_d + \sigma_f + \sigma_r)) \\ & + \iota_d^2\sigma_f(2\sigma_r(\sigma_f + \sigma_r) + \sigma_d(\sigma_f + 2\sigma_r)) + \sigma_d(-\Omega^2(\sigma_d + \sigma_f + \sigma_r)^2 - 2\Omega\sigma_f(\sigma_d + \sigma_f \\ & + \sigma_r)(-\Delta\sigma_r + \delta\mu(\sigma_d + \sigma_r)) + (\Delta + \theta)\sigma_f\sigma_r(2\Delta\sigma_d(\sigma_d + \sigma_f) - 2\theta\sigma_d(\sigma_d + \sigma_f) \\ & + \Delta(2\sigma_d + \sigma_f)\sigma_r - \theta(2\sigma_d + \sigma_f)\sigma_r + 2\delta\mu\sigma_f(\sigma_d + \sigma_r))))\end{aligned}$$

$$EW_{REN}^{FIT} = \frac{1}{4\sigma_d\sigma_f(\sigma_d+\sigma_f)(\sigma_d+\sigma_r)}(2\iota_d\sigma_d\sigma_f(\Omega(\sigma_d+\sigma_f) - \delta\mu\sigma_f(\sigma_d+\sigma_r) + \rho\sigma_r(\sigma_d+\sigma_r) + \Delta\sigma_r(-\sigma_f+\sigma_r)) + \iota_d^2\sigma_f(2\sigma_f\sigma_r + \sigma_d(\sigma_f+\sigma_r)) + \sigma_d(-\Omega^2(\sigma_d+\sigma_f)(\sigma_d+\sigma_f+\sigma_r) - 2\Omega\sigma_f(\sigma_d+\sigma_f)(-\Delta\sigma_r + \delta\mu(\sigma_d+\sigma_r)) + \sigma_f\sigma_r(2\Delta(\sigma_d+\sigma_r)(\delta\mu\sigma_f - \rho\sigma_r) + \Delta^2(2\sigma_d(\sigma_d+\sigma_f) + \sigma_f\sigma_r - \sigma_r^2) - \rho(\sigma_d+\sigma_r)(-2\delta\mu\sigma_f + \rho(\sigma_d+\sigma_f+\sigma_r)))))$$

$$EW_{DEM}^{CAP} = \frac{1}{4\sigma_d\sigma_f(\sigma_d+\sigma_r)(\sigma_d+\sigma_f+\sigma_r)}(-\Omega^2\sigma_d(\sigma_d+\sigma_f+\sigma_r)^2 + 2\Omega\sigma_d\sigma_f(\sigma_d+\sigma_f+\sigma_r)(\Delta+\iota_d - \delta\mu(\sigma_d+\sigma_r)) + \sigma_f(2\Delta\sigma_d\sigma_f(-\iota_d + \delta\mu(\sigma_d+\sigma_r)) + \Delta^2(2\sigma_r(\sigma_f+\sigma_r) + \sigma_d(\sigma_f + 2\sigma_r)) + \iota_d(-2\delta\mu\sigma_d\sigma_f(\sigma_d+\sigma_r) + \iota_d(2\sigma_r(\sigma_f+\sigma_r) + \sigma_d(\sigma_f+2\sigma_r)))))$$

$$EW_{DEM}^{FIP} = \frac{1}{4\sigma_d\sigma_f(\sigma_d+\sigma_r)(\sigma_d+\sigma_f+\sigma_r)}(-\Omega^2\sigma_d(\sigma_d+\sigma_f+\sigma_r)^2 - 2\Omega\sigma_d\sigma_f(\sigma_d+\sigma_f+\sigma_r)(-\iota_d + \delta\mu(\sigma_d+\sigma_r)) + 2\Delta\sigma_d\sigma_f(-\iota_d\sigma_f + \delta\mu\sigma_f(\sigma_d+\sigma_r) + \Omega(\sigma_d+\sigma_f+\sigma_r)) + \Delta^2\sigma_f(2\sigma_r(\sigma_f+\sigma_r) + \sigma_d(\sigma_f+2\sigma_r)) + \sigma_f(-2\delta\mu\iota_d\sigma_d\sigma_f(\sigma_d+\sigma_r) - \theta\sigma_d\sigma_r(2\theta\sigma_d(\sigma_d+\sigma_f) + \theta(2\sigma_d+\sigma_f)\sigma_r - 2\delta\mu\sigma_f(\sigma_d+\sigma_r)) + \iota_d^2(2\sigma_r(\sigma_f+\sigma_r) + \sigma_d(\sigma_f+2\sigma_r))))$$

$$EW_{DEM}^{FIT} = \frac{1}{4\sigma_d\sigma_f(\sigma_d+\sigma_f)(\sigma_d+\sigma_r)}(\Delta^2\sigma_f(2\sigma_f\sigma_r + \sigma_d(\sigma_f+\sigma_r)) + \iota_d^2\sigma_f(2\sigma_f\sigma_r + \sigma_d(\sigma_f+\sigma_r)) + 2\Delta\sigma_d\sigma_f(\Omega(\sigma_d+\sigma_f) + \iota_d(-\sigma_f+\sigma_r) + (\sigma_d+\sigma_r)(\delta\mu\sigma_f - \rho\sigma_r)) + 2\iota_d\sigma_d\sigma_f(\Omega(\sigma_d+\sigma_f) + (\sigma_d+\sigma_r)(-\delta\mu\sigma_f + \rho\sigma_r)) - \sigma_d(2\delta\mu\Omega\sigma_f(\sigma_d+\sigma_f)(\sigma_d+\sigma_r) + \Omega^2(\sigma_d+\sigma_f)(\sigma_d+\sigma_f+\sigma_r) + \rho\sigma_f\sigma_r(\sigma_d+\sigma_r)(-2\delta\mu\sigma_f + \rho(\sigma_d+\sigma_f+\sigma_r))))$$

When maximized with respect to policy instruments, those expressions lead to following optimal policy instruments and expected welfare level for demand uncertainty:

$$\Omega_{DEM}^{*CAP} = \Omega_{DEM}^{*FIT} = \Omega_{DEM}^{*FIP} = \frac{\sigma_f(\Delta + \iota_d - \delta\mu\sigma_d - \delta\mu\sigma_r)}{\sigma_d+\sigma_f+\sigma_r}$$

$$\rho_{DEM}^{*} = \frac{-\Delta + \iota_d + \delta\mu\sigma_f}{\sigma_d+\sigma_f+\sigma_r}$$

$$\theta_{DEM}^{*} = \frac{\delta\mu\sigma_f(\sigma_d+\sigma_r)}{2\sigma_d^2 + \sigma_f\sigma_r + 2\sigma_d(\sigma_f+\sigma_r)}$$

$$EW_{DEM}^{*CAP} = \frac{-4\delta\mu\iota_d\sigma_d\sigma_f + \delta^2\mu^2\sigma_d\sigma_f(\sigma_d+\sigma_r) + 2\Delta^2(\sigma_f+\sigma_r) + 2\iota_d^2(\sigma_f+\sigma_r)}{4\sigma_d(\sigma_d+\sigma_f+\sigma_r)}$$

$$EW_{DEM}^{*FIT} = \frac{-4\delta\mu\iota_d\sigma_d\sigma_f(\sigma_d+\sigma_f) + 2\Delta^2(\sigma_d+\sigma_f)(\sigma_f+\sigma_r)}{4\sigma_d(\sigma_d+\sigma_f)(\sigma_d+\sigma_f+\sigma_r)} + \frac{2\iota_d^2(\sigma_d+\sigma_f)(\sigma_f+\sigma_r) + \delta^2\mu^2\sigma_d\sigma_f(\sigma_d^2 + 2\sigma_f\sigma_r + \sigma_d(\sigma_f+\sigma_r))}{4\sigma_d(\sigma_d+\sigma_f)(\sigma_d+\sigma_f+\sigma_r)}$$

$$EW_{DEM}^{*FIP} = \frac{\delta^2\mu^2\sigma_d\sigma_f(\sigma_d+\sigma_f)(\sigma_d+\sigma_r)^2 - 2\delta\mu\iota_d\sigma_d\sigma_f(2\sigma_d^2 + \sigma_f\sigma_r + 2\sigma_d(\sigma_f+\sigma_r))}{2\sigma_d(\sigma_d+\sigma_f+\sigma_r)(2\sigma_d^2 + \sigma_f\sigma_r + 2\sigma_d(\sigma_f+\sigma_r))} + \frac{\Delta^2(\sigma_f+\sigma_r)(2\sigma_d^2 + \sigma_f\sigma_r + 2\sigma_d(\sigma_f+\sigma_r)) + \iota_d^2(\sigma_f+\sigma_r)(2\sigma_d^2 + \sigma_f\sigma_r + 2\sigma_d(\sigma_f+\sigma_r))}{2\sigma_d(\sigma_d+\sigma_f+\sigma_r)(2\sigma_d^2 + \sigma_f\sigma_r + 2\sigma_d(\sigma_f+\sigma_r))}$$

And for renewable uncertainty:

$$\Omega_{REN}^{*CAP} = \Omega_{REN}^{*FIT} = \Omega_{REN}^{*FIP} = \frac{\sigma_f(\iota_d + \Delta\sigma_r - \delta\mu(\sigma_d + \sigma_r))}{\sigma_d + \sigma_f + \sigma_r}$$

$$\rho_{REN}^{*} = \frac{\iota_d + \delta\mu\sigma_f - \Delta\sigma_r}{\sigma_d + \sigma_f + \sigma_r}$$

$$\theta_{REN}^{*} = \frac{\delta\mu\sigma_f(\sigma_d + \sigma_r)}{2\sigma_d^2 + \sigma_f\sigma_r + 2\sigma_d(\sigma_f + \sigma_r)}$$

$$EW_{REN}^{*CAP} = \frac{-4\delta\mu\iota_d\sigma_d\sigma_f + 2\iota_d^2(\sigma_f + \sigma_r) + \sigma_d(2\Delta^2(\sigma_d + \sigma_f)\sigma_r + \delta^2\mu^2\sigma_f(\sigma_d + \sigma_r))}{4\sigma_d(\sigma_d + \sigma_f + \sigma_r)}$$

$$EW_{REN}^{*FIT} = \frac{-4\delta\mu\iota_d\sigma_d\sigma_f(\sigma_d + \sigma_f) + 2\Delta^2(\sigma_d + \sigma_f)(\sigma_f + \sigma_r)}{4\sigma_d(\sigma_d + \sigma_f)(\sigma_d + \sigma_f + \sigma_r)} + \frac{2\iota_d^2(\sigma_d + \sigma_f)(\sigma_f + \sigma_r) + \delta^2\mu^2\sigma_d\sigma_f(\sigma_d^2 + 2\sigma_f\sigma_r + \sigma_d(\sigma_f + \sigma_r))}{4\sigma_d(\sigma_d + \sigma_f)(\sigma_d + \sigma_f + \sigma_r)}$$

$$EW_{REN}^{*FIP} = \frac{\delta^2\mu^2\sigma_d\sigma_f(\sigma_d + \sigma_f)(\sigma_d + \sigma_r)^2 - 2\delta\mu\iota_d\sigma_d\sigma_f(2\sigma_d(\sigma_d + \sigma_f) + (2\sigma_d + \sigma_f)\sigma_r)}{2\sigma_d(\sigma_d + \sigma_f + \sigma_r)(2\sigma_d(\sigma_d + \sigma_f) + (2\sigma_d + \sigma_f)\sigma_r)} + \frac{\Delta^2(\sigma_f + \sigma_r)(2\sigma_d(\sigma_d + \sigma_f) + (2\sigma_d + \sigma_f)\sigma_r) + \iota_d^2(\sigma_f + \sigma_r)(2\sigma_d(\sigma_d + \sigma_f) + (2\sigma_d + \sigma_f)\sigma_r)}{2\sigma_d(\sigma_d + \sigma_f + \sigma_r)(2\sigma_d(\sigma_d + \sigma_f) + (2\sigma_d + \sigma_f)\sigma_r)}$$

Knowing that all parameters are positive, a direct comparison of the corresponding optimal expected welfare expressions gives the desired result about ordering policy sets (given the shock variance is above the specified threshold discussed below).

A.3.2 Counterfactual optimal cap on the low state only

The optimal counterfactual cap on the low state is obtained by maximizing a counterfactual welfare expression (CW) whose variables are replaced by the reaction functions of an interior solution (positive carbon price):

$$CW_{DEM}^{FIT} = \frac{2\Omega\iota_d\sigma_d\sigma_f + \Delta^2\sigma_f\sigma_r + \iota_d^2\sigma_f\sigma_r - 2\Delta\sigma_f(\Omega\sigma_d + \iota_d\sigma_r) - \Omega\sigma_d(2\delta\mu\sigma_f(\sigma_d + \sigma_r) + \Omega(\sigma_d + \sigma_f + \sigma_r))}{2\sigma_d\sigma_f(\sigma_d + \sigma_r)}$$

$$CW_{DEM}^{FIP} = \frac{2\Omega\iota_d\sigma_d\sigma_f + \Delta^2\sigma_f\sigma_r + \iota_d^2\sigma_f\sigma_r - 2\Delta\sigma_f(\Omega\sigma_d + \iota_d\sigma_r) - \sigma_d(\theta^2\sigma_d\sigma_f\sigma_r + \Omega(2\delta\mu\sigma_f(\sigma_d + \sigma_r) + \Omega(\sigma_d + \sigma_f + \sigma_r)))}{2\sigma_d\sigma_f(\sigma_d + \sigma_r)}$$

$$CW_{REN}^{FIT} = \frac{\iota_d^2\sigma_f\sigma_r + 2\iota_d\sigma_d\sigma_f(\Omega + \Delta\sigma_r) + \sigma_d(-2\Delta\Omega\sigma_f\sigma_r + \Delta^2\sigma_d\sigma_f\sigma_r - \Omega(2\delta\mu\sigma_f(\sigma_d + \sigma_r) + \Omega(\sigma_d + \sigma_f + \sigma_r)))}{2\sigma_d\sigma_f(\sigma_d + \sigma_r)}$$

$$C\cancel{E}W_{REN}^{FIP} = \frac{\iota_d^2\sigma_f\sigma_r + 2\iota_d\sigma_d\sigma_f(\Omega + \Delta\sigma_r) + \sigma_d(-2\Delta\Omega\sigma_f\sigma_r + \Delta^2\sigma_d\sigma_f\sigma_r - \theta^2\sigma_d\sigma_f\sigma_r - \Omega(2\delta\mu\sigma_f(\sigma_d + \sigma_r) + \Omega(\sigma_d + \sigma_f + \sigma_r))}{2\sigma_d\sigma_f(\sigma_d + \sigma_r)}$$

Leading to following cap when maximized (the renewable subsidy is nil):

$$\tilde{\Omega}_{DEM} = -\frac{\sigma_f(\Delta - \iota_d + \delta\mu\sigma_d + \delta\mu\sigma_r)}{\sigma_d + \sigma_f + \sigma_r}$$

$$\tilde{\Omega}_{REN} = \frac{\sigma_f(\iota_d - \delta\mu\sigma_d - \Delta\sigma_r - \delta\mu\sigma_r)}{\sigma_d + \sigma_f + \sigma_r}$$

Which, when reinjected into the reaction function for the electricity price, gives:

$$\tilde{p}_{DEM} = \frac{-\Delta + \iota_d + \delta\mu\sigma_f}{\sigma_d + \sigma_f + \sigma_r}$$

$$\tilde{p}_{REN} = \frac{\iota_d + \delta\mu\sigma_f - \Delta\sigma_r}{\sigma_d + \sigma_f + \sigma_r}$$

A comparison with the optimal policy levels yields the desired results:

$$\rho^*_{DEM} = \tilde{p}_{DEM}$$

$$\theta^*_{DEM} + p^-_{DEM} = \tilde{p}_{DEM} - \frac{\delta\mu\sigma_d\sigma_f}{2\sigma_d^2 + 2\sigma_d\sigma_f + 2\sigma_d\sigma_r + \sigma_f\sigma_r}$$

$$\rho^*_{REN} = \tilde{p}_{REN}$$

$$\theta^*_{REN} + p^-_{REN} = \tilde{p}_{REN} - \frac{\delta\mu\sigma_d\sigma_f}{2\sigma_d^2 + 2\sigma_d\sigma_f + 2\sigma_d\sigma_r + \sigma_f\sigma_r}$$

Where p^- is the price in the low demand and renewable cost state, when the carbon price is zero.

A.3.3 Variance threshold levels

The regulator actually chooses to implement a given renewable support policy only when it increases welfare (when available). To know for which level of shock this happens, we compare the optimal expected welfare expressions with and without a corner solution (a zero carbon price) and search for the shock value for which the expected welfare with corner solution is higher:

$$EW^{*CAP}_{DEM} > EW^{*LOW} \Leftarrow \Delta > \frac{\delta\mu(\sigma_d + \sigma_r)}{\sqrt{2}}$$

$$EW^{*FIP}_{DEM} > EW^{*LOW} \Leftarrow \Delta > \frac{\delta\mu\sqrt{\sigma_d}(\sigma_d + \sigma_r)\sqrt{\sigma_d + \sigma_f + \sigma_r}}{\sqrt{2\sigma_d(\sigma_d + \sigma_f) + (2\sigma_d + \sigma_f)\sigma_r}}$$

$$EW^{*FIT}_{DEM} > EW^{*LOW} \Leftarrow \Delta > \frac{\delta\mu\sqrt{\sigma_d}\sqrt{\sigma_d + \sigma_r}\sqrt{\sigma_d + \sigma_f + \sigma_r}}{\sqrt{2}\sqrt{\sigma_d + \sigma_f}}$$

$$EW^{*CAP}_{REN} > EW^{*LOW} \Leftarrow \gamma > \frac{\delta\mu(\sigma_d + \sigma_r)}{\sqrt{2}\sigma_r}$$

$$EW^{*FIP}_{REN} > EW^{*LOW} \Leftarrow \gamma > \frac{\delta\mu\sqrt{\sigma_d}(\sigma_d + \sigma_r)\sqrt{\sigma_d + \sigma_f + \sigma_r}}{\sigma_r\sqrt{2\sigma_d(\sigma_d + \sigma_f) + (2\sigma_d + \sigma_f)\sigma_r}}$$

$$EW^{*FIT}_{REN} > EW^{*LOW} \Leftarrow \gamma > \frac{\delta\mu\sqrt{\sigma_d}\sqrt{\sigma_d + \sigma_r}\sqrt{\sigma_d + \sigma_f + \sigma_r}}{\sqrt{2}\sqrt{\sigma_d + \sigma_f}\sigma_r}$$

Since the variance of the demand and renewable shock distributions are respectively Δ^2 and γ^2, we can thus define a variance threshold, above which the effect of the shock is to make the optimal expected welfare with a corner solution higher than with an interior solution, and a positive subsidy to renewables desirable:

$$\tilde{V}^{CAP}_{DEM} = \frac{1}{2}\delta^2\mu^2(\sigma_d + \sigma_r)^2$$

$$\tilde{V}^{FIP}_{DEM} = \frac{\delta^2\mu^2\sigma_d(\sigma_d + \sigma_r)^2(\sigma_d + \sigma_f + \sigma_r)}{2\sigma_d(\sigma_d + \sigma_f) + (2\sigma_d + \sigma_f)\sigma_r}$$

$$\tilde{V}_{DEM}^{FIT} = \frac{\delta^2\mu^2\sigma_d(\sigma_d+\sigma_r)(\sigma_d+\sigma_f+\sigma_r)}{2(\sigma_d+\sigma_f)}$$
$$\tilde{V}_{REN}^{CAP} = \frac{\delta^2\mu^2(\sigma_d+\sigma_r)^2}{2\sigma_r^2}$$
$$\tilde{V}_{REN}^{FIP} = \frac{\delta^2\mu^2\sigma_d(\sigma_d+\sigma_r)^2(\sigma_d+\sigma_f+\sigma_r)}{\sigma_r^2(2\sigma_d(\sigma_d+\sigma_f)+(2\sigma_d+\sigma_f)\sigma_r)}$$
$$\tilde{V}_{REN}^{FIT} = \frac{\delta^2\mu^2\sigma_d(\sigma_d+\sigma_r)(\sigma_d+\sigma_f+\sigma_r)}{2(\sigma_d+\sigma_f)\sigma_r^2}$$

A direct comparison of the thresholds and their derivative with respect to δ yield the desired results:

$$\frac{\partial\tilde{V}_{DEM}^{CAP}}{\partial\delta} > \frac{\partial\tilde{V}_{DEM}^{FIP}}{\partial\delta} > \frac{\partial\tilde{V}_{DEM}^{FIT}}{\partial\delta}$$

$$\frac{\partial\tilde{V}_{REN}^{CAP}}{\partial\delta} > \frac{\partial\tilde{V}_{REN}^{FIP}}{\partial\delta} > \frac{\partial\tilde{V}_{REN}^{FIT}}{\partial\delta}$$

A.3.4 Variations in expected welfare

Computing the difference between expected welfare between policy sets gives:

$$\Delta EW_{FIP-CAP}^{*} = EW_{DEM}^{*FIP} - EW_{DEM}^{*CAP} = EW_{REN}^{*FIP} - EW_{REN}^{*CAP} = \frac{\delta^2\mu^2\sigma_f^2\sigma_r(\sigma_d+\sigma_r)}{4(\sigma_d+\sigma_f+\sigma_r)(2\sigma_d^2+\sigma_f\sigma_r+2\sigma_d(\sigma_f+\sigma_r))}$$

$$\Delta EW_{FIT-CAP}^{*} = EW_{DEM}^{*FIT} - EW_{DEM}^{*CAP} = EW_{REN}^{*FIT} - EW_{REN}^{*CAP} = \frac{\delta^2\mu^2\sigma_f^2\sigma_r}{4(\sigma_d+\sigma_f)(\sigma_d+\sigma_f+\sigma_r)}$$

$$\Delta EW_{FIT-FIP}^{*} = EW_{DEM}^{*FiT} - EW_{DEM}^{*FIP} = \frac{\delta^2\mu^2\sigma_d\sigma_f^2\sigma_r}{4(\sigma_d+\sigma_f)(2\sigma_d^2+\sigma_f\sigma_r+2\sigma_d(\sigma_f+\sigma_r))}$$

Comparing the partial derivatives with respect to δ yield the desired results:

$$\frac{\partial(\Delta EW_{FIT-CAP}^{*})}{\partial\delta} > \frac{\partial(\Delta EW_{FIP-CAP}^{*})}{\partial\delta} > \frac{\partial(\Delta EW_{FIT-FIP}^{*})}{\partial\delta}$$

A.3.4 Comparison with the first-best production and price levels

The first-best solution is found by setting the carbon price at the marginal damage level in all states, e.g. through a carbon tax. Such a setting gives following FOCS and reaction functions:

$$p = \mu\omega + \frac{f}{\sigma_f} + x$$
$$p = y + \frac{r}{\sigma_r}$$
$$f + r + p\sigma_d = \iota_d + z$$

$$f = \frac{\sigma_f(z + \iota_d - x\sigma_d - \mu\omega\sigma_d - x\sigma_r + y\sigma_r - \mu\omega\sigma_r)}{\sigma_d + \sigma_f + \sigma_r}$$

$$r = \frac{(z + \iota_d - y\sigma_d + x\sigma_f - y\sigma_f + \mu\omega\sigma_f)\sigma_r}{\sigma_d + \sigma_f + \sigma_r}$$

$$p = \frac{z + \iota_d + x\sigma_f + \mu\omega\sigma_f + y\sigma_r}{\sigma_d + \sigma_f + \sigma_r}$$

When optimizing the expected welfare function after replacing the market variables by their respective reaction function, one immediately finds that the carbon tax should be set at the marginal level. The expected value of production (ΔEQ) and price (ΔEP) can then easily be obtained from the reaction functions, and yield following desired result:

$$\Delta EQ^*_{CAP} = \mathbb{E}^{CAP}_{DEM}[f + r] - \mathbb{E}^{TAX}_{DEM}[f + r] = \mathbb{E}^{CAP}_{REN}[f + r] - \mathbb{E}^{TAX}_{REN}[f + r] = \frac{\delta\mu\sigma_d\sigma_f}{2(\sigma_d + \sigma_f + \sigma_r)} > 0$$

$$\Delta EQ^*_{FIP} = \mathbb{E}^{FIP}_{DEM}[f + r] - \mathbb{E}^{TAX}_{DEM}[f + r] = \mathbb{E}^{FIP}_{REN}[f + r] - \mathbb{E}^{TAX}_{REN}[f + r]$$
$$= \frac{\delta\mu\sigma_d\sigma_f(\sigma_d + \sigma_r)}{2\sigma_d^2 + \sigma_f\sigma_r + 2\sigma_d(\sigma_f + \sigma_r)} > 0$$

$$\Delta EQ^*_{FIT} = \mathbb{E}^{FIT}_{DEM}[f + r] - \mathbb{E}^{TAX}_{DEM}[f + r] = \mathbb{E}^{FIT}_{REN}[f + r] - \mathbb{E}^{TAX}_{REN}[f + r] = \frac{\delta\mu\sigma_d\sigma_f}{2(\sigma_d + \sigma_f)} > 0$$

$$\Delta EP^*_{CAP} = \mathbb{E}^{CAP}_{DEM}[p] - \mathbb{E}^{TAX}_{DEM}[p] = \mathbb{E}^{CAP}_{REN}[p] - \mathbb{E}^{TAX}_{REN}[p] = -\frac{\delta\mu\sigma_f}{2(\sigma_d + \sigma_f + \sigma_r)} < 0$$

$$\Delta EP^*_{FIP} = \mathbb{E}^{FIP}_{DEM}[p] - \mathbb{E}^{TAX}_{DEM}[p] = \mathbb{E}^{FIP}_{REN}[p] - \mathbb{E}^{TAX}_{REN}[p] = -\frac{\delta\mu\sigma_f(\sigma_d + \sigma_r)}{2\sigma_d^2 + \sigma_f\sigma_r + 2\sigma_d(\sigma_f + \sigma_r)} < 0$$

$$\Delta EP^*_{FIT} = \mathbb{E}^{FIT}_{DEM}[p] - \mathbb{E}^{TAX}_{DEM}[p] = \mathbb{E}^{FIT}_{REN}[p] - \mathbb{E}^{TAX}_{REN}[p] = -\frac{\delta\mu\sigma_f}{2(\sigma_d + \sigma_f)} < 0$$

$$\Delta EQ^*_{FIP} > \Delta EQ^*_{FIT} > \Delta EQ^*_{CAP}$$

$$\Delta EP^*_{FIP} < \Delta EP^*_{FIT} < \Delta EP^*_{CAP}$$

A.4 Demonstration of Proposition 3:

A.4.1 Optimal expected welfare

With a shock on the cost of fossil production, the carbon price decreases with the shock, so in a corner solution the carbon price drops to zero in the high state (contrary to the two other sources of uncertainty considered). The electricity price rises with the shock, meaning that a FIT can only be binding in the both states. Setting a FIT only in the low state is possible, but would be equivalent to no FIT at all, since the carbon price is positive and the optimal renewable subsidy is zero. The expected welfare functions are thus obtained by replacing the market variables by the reaction functions with positive carbon price in the low state an nil carbon price in the high state:

$$EW_{FOS}^{CAP} = \frac{1}{4\sigma_d\sigma_f(\sigma_d+\sigma_r)(\sigma_d+\sigma_f+\sigma_r)}\Big(-\Omega^2\sigma_d(\sigma_d+\sigma_f+\sigma_r)^2 + 2\Omega\sigma_d\sigma_f(\sigma_d+\sigma_f+\sigma_r)(\iota_d+(\Delta-\delta\mu)(\sigma_d+\sigma_r)) + \sigma_f\Big(-2(\Delta+\delta\mu)\iota_d\sigma_d\sigma_f(\sigma_d+\sigma_r)+\Delta(\Delta+2\delta\mu)\sigma_d\sigma_f(\sigma_d+\sigma_r)^2 + \iota_d^2\big(2\sigma_r(\sigma_f+\sigma_r)+\sigma_d(\sigma_f+2\sigma_r)\big)\Big)\Big)$$

$$EW_{FOS}^{FIT} = -\frac{\Omega\left(2\delta\mu\sigma_d\sigma_f+\Omega(\sigma_d+\sigma_f)\right)+2\rho\Omega\sigma_f\sigma_r+\rho^2\sigma_f\sigma_r(\sigma_d+\sigma_r)-2\iota_d\sigma_f(\Omega+\rho\sigma_r)}{2\sigma_d\sigma_f}$$

$$EW_{FOS}^{FIP} = \frac{1}{4\sigma_d\sigma_f(\sigma_d+\sigma_r)(\sigma_d+\sigma_f+\sigma_r)}(2\iota_d\sigma_d\sigma_f(-(\Delta+\delta\mu)\sigma_f(\sigma_d+\sigma_r)+\Omega(\sigma_d+\sigma_f+\sigma_r)) + \iota_d^2\sigma_f(2\sigma_r(\sigma_f+\sigma_r)+\sigma_d(\sigma_f+2\sigma_r)) + \sigma_d(2(\Delta-\delta\mu)\Omega\sigma_f(\sigma_d+\sigma_r)(\sigma_d+\sigma_f+\sigma_r) - \Omega^2(\sigma_d+\sigma_f+\sigma_r)^2 + \sigma_f(\Delta^2\sigma_f(\sigma_d+\sigma_r)^2 + 2\delta\Delta\mu\sigma_f(\sigma_d+\sigma_r)^2 - \theta\sigma_r(2\theta\sigma_d(\sigma_d + \sigma_f) + \theta(2\sigma_d+\sigma_f)\sigma_r - 2\delta\mu\sigma_f(\sigma_d+\sigma_r)))))$$

Maximizing those expressions with respect to the policy variables gives following optimal values:

$$\Omega_{FOS}^{*CAP} = \frac{\mathrm{\sigma f(\iota d} + (\Delta-\delta\mu)(\mathrm{\sigma d + \sigma r}))}{\mathrm{\sigma d + \sigma f + \sigma r}}$$

$$\Omega_{FOS}^{*FIT} = \frac{\sigma_f(\iota_d(\sigma_d+\sigma_f)-\delta\mu(\sigma_d+\sigma_f)(\sigma_d+\sigma_r)+\Delta\sigma_d(\sigma_d+\sigma_f+\sigma_r))}{(\sigma_d+\sigma_f)(\sigma_d+\sigma_f+\sigma_r)}$$

$$\rho_{FOS}^{*} = \frac{\iota_d+\delta\mu\sigma_f}{\sigma_d+\sigma_f+\sigma_r}$$

$$\Omega_{FOS}^{*FIP} = \frac{\sigma_f(\iota_d+(\Delta-\delta\mu)(\sigma_d+\sigma_r))}{\sigma_d+\sigma_f+\sigma_r}$$

$$\theta_{FOS}^{*} = \frac{\delta\mu\sigma_f(\sigma_d+\sigma_r)}{2\sigma_d^2+\sigma_f\sigma_r+2\sigma_d(\sigma_f+\sigma_r)}$$

$$EW_{FOS}^{*CAP} = \frac{-4\delta\mu\iota_d\sigma_d\sigma_f+(2\Delta^2+\delta^2\mu^2)\sigma_d\sigma_f(\sigma_d+\sigma_r)+2\iota_d^2(\sigma_f+\sigma_r)}{4\sigma_d(\sigma_d+\sigma_f+\sigma_r)}$$

$$EW_{FOS}^{*FIT} = \frac{-4\delta\mu\iota_d\sigma_d\sigma_f(\sigma_d+\sigma_f)+2\iota_d^2(\sigma_d+\sigma_f)(\sigma_f+\sigma_r)}{4\sigma_d(\sigma_d+\sigma_f)(\sigma_d+\sigma_f+\sigma_r)} + \frac{\sigma_d\sigma_f(2\Delta^2\sigma_d(\sigma_d+\sigma_f+\sigma_r)+\delta^2\mu^2(\sigma_d^2+2\sigma_f\sigma_r+\sigma_d(\sigma_f+\sigma_r)))}{4\sigma_d(\sigma_d+\sigma_f)(\sigma_d+\sigma_f+\sigma_r)}$$

$$EW_{FOS}^{*FIP} = \frac{-2\delta\mu\iota_d\sigma_d\sigma_f(2\sigma_d(\sigma_d+\sigma_f)+(2\sigma_d+\sigma_f)\sigma_r)+\iota_d^2(\sigma_f+\sigma_r)(2\sigma_d(\sigma_d+\sigma_f)+(2\sigma_d+\sigma_f)\sigma_r)}{2\sigma_d(\sigma_d+\sigma_f+\sigma_r)(2\sigma_d(\sigma_d+\sigma_f)+(2\sigma_d+\sigma_f)\sigma_r)} + \frac{\sigma_d\sigma_f(\sigma_d+\sigma_r)(\delta^2\mu^2(\sigma_d+\sigma_f)(\sigma_d+\sigma_r)+\Delta^2(2\sigma_d(\sigma_d+\sigma_f)+(2\sigma_d+\sigma_f)\sigma_r))}{2\sigma_d(\sigma_d+\sigma_f+\sigma_r)(2\sigma_d(\sigma_d+\sigma_f)+(2\sigma_d+\sigma_f)\sigma_r)}$$

Comparing the expected welfare expressions yields following desired result:

$$EW_{FOS}^{*CAP} < EW_{FOS}^{*FIP}$$

$$EW_{FOS}^{*CAP} < EW_{FOS}^{*FIT} \Leftarrow \gamma < \frac{\delta\mu}{\sqrt{2}}$$

The latter is impractical, given that when the shock is below this value, the expected welfare is higher with an interior solution (i.e. the cases where a FIT would bring something are all dominated by interior solutions with a positive carbon price and no effective renewable subsidies):

$$EW_{FOS}^{*FIT} > EW^{*LOW} \Leftarrow \gamma > \frac{\delta\mu}{\sqrt{2}}$$

Note that these two limit values do not necessarily coincide when several fossil technologies are considered, as in the numerical application.

A.4.2 Counterfactual optimal cap on the low state only

The optimal counterfactual cap on the low state is obtained by maximizing a counterfactual welfare expression (CW) whose variables are replaced by the reaction functions of an interior solution (positive carbon price):

$$CW_{DEM}^{FIP} = \frac{2\Omega\iota_d\sigma_d\sigma_f + \iota_d^2\sigma_f\sigma_r - \sigma_d(\theta^2\sigma_d\sigma_f\sigma_r + \Omega(2\Delta\sigma_f(\sigma_d+\sigma_r) + 2\delta\mu\sigma_f(\sigma_d+\sigma_r) + \Omega(\sigma_d+\sigma_f+\sigma_r)))}{2\sigma_d\sigma_f(\sigma_d+\sigma_r)}$$

Leading to following cap when maximized (the renewable subsidy is nil):

$$\tilde{\Omega}_{FOS} = \frac{\sigma_f(\iota_d - \Delta\sigma_d - \delta\mu\sigma_d - \Delta\sigma_r - \delta\mu\sigma_r)}{\sigma_d+\sigma_f+\sigma_r}$$

Which, when reinjected into the reaction function for the electricity price, gives:

$$\tilde{p}_{FOS} = \frac{\iota_d + \Delta\sigma_f + \delta\mu\sigma_f}{\sigma_d+\sigma_f+\sigma_r}$$

A comparison with the optimal policy levels yields the desired results:

$$\theta_{FOS}^* + p_{FOS}^+ = \tilde{p}_{FOS} - \frac{\delta\mu\sigma_d\sigma_f}{2\sigma_d^2 + 2\sigma_d\sigma_f + 2\sigma_d\sigma_r + \sigma_f\sigma_r}$$

Where p^+ is the price in the high fossil cost state, when the carbon price is zero.

A.4.3 Variance threshold levels and expected welfare vairations

A setting with FIP in a corner solution is preferable when the EW function is higher:

$$EW_{FOS}^{*CAP} > EW^{*LOW} \Leftarrow \gamma > \frac{\delta\mu}{\sqrt{2}}$$

$$EW_{FOS}^{*FIP} > EW^{*LOW} \Leftarrow \gamma > \frac{\delta\mu\sqrt{\sigma_d}\sqrt{\sigma_d+\sigma_f+\sigma_r}}{\sqrt{2\sigma_d(\sigma_d+\sigma_f) + (2\sigma_d+\sigma_f)\sigma_r}}$$

A variance threshold can thus be defined, above which the effect of the shock is to make the optimal expected welfare with a corner solution higher than with an interior solution, and a positive subsidy to renewables desirable:

$$\tilde{V}_{FOS}^{CAP} = \frac{\delta^2\mu^2}{2}$$

$$\tilde{V}_{FOS}^{FIP} = \frac{\delta^2\mu^2\sigma_d(\sigma_d+\sigma_f+\sigma_r)}{2\sigma_d(\sigma_d+\sigma_f) + (2\sigma_d+\sigma_f)\sigma_r}$$

A direct comparison of the thresholds and their derivative with respect to δ yield the desired results:

$$\frac{\partial\tilde{V}_{FOS}^{CAP}}{\partial\delta} > \frac{\partial\tilde{V}_{FOS}^{FIP}}{\partial\delta}$$

Computing the difference in expected welfare between policy sets gives the same result than for the other sources of uncertainty:

$$EW_{FOS}^{*FIP} - EW_{FOS}^{*CAP} = \Delta EW_{FIP-CAP}^{*}$$

A.4.4 Comparison with the first-best production and price levels

Using the same first best carbon tax setting than in the previous section, computing the expected electricity production and prices show exactly the same expressions :

$$\mathbb{E}_{FOS}^{CAP}[f+r] - \mathbb{E}_{FOS}^{TAX}[f+r] = \Delta EQ_{CAP}^{*}$$

$$\mathbb{E}_{FOS}^{FIP}[f+r] - \mathbb{E}_{FOS}^{TAX}[f+r] = \Delta EQ_{FIP}^{*}$$

$$\mathbb{E}_{FOS}^{CAP}[p] - \mathbb{E}_{FOS}^{TAX}[p] = \Delta EQ_{CAP}^{*}$$

$$\mathbb{E}_{FOS}^{FIP}[p] - \mathbb{E}_{FOS}^{TAX}[p] = \Delta EQ_{FIP}^{*}$$

$$\Delta EQ_{FIP}^{*} > \Delta EQ_{CAP}^{*}$$

$$\Delta EP_{FIP}^{*} < \Delta EP_{CAP}^{*}$$