Tradable Renewable Quota vs. Feed-In Tariff vs. Feed-In Premium under Uncertainty

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Abstract: We study the performance under uncertainty of three renewable energy policy instruments: a Tradable Renewable Quota (TRQ) requires producers of electricity from fossil-fuel sources to buy a given number of green certificates per unit of output. A Feed-In-Tariff (FIT) pays a fixed premium price to suppliers of electricity from renewable energy sources, while a Feed-In-Premium (FIP) pays them a fixed subsidy on top of the market price. We develop a stylized two-period, two-sector model of the electricity market, where renewables are characterized by a positive learning externality, which the regulator aims to internalize. Assuming shocks on the level of the two supply curves or on total electricity demand, we analytically derive the dominance conditions that determine the instruments' relative welfare ranking. Although our results generally confirm the key role of the slopes of marginal benefits and costs associated with the policy, the specific instrument ranking depends on which type of uncertainty is considered, and whether shocks are permanent or transitory. However, we find that a high learning rate generally favours the FIT, and that TRQ is mostly dominated by the other two instruments. The latter result is also confirmed by a numerical application to the US electricity market.

1. Introduction

Policies aiming to increase the share of electricity from renewable sources (RES-E) are now widely employed.[1] A prominent example is Germany, where the introduction of Feed-In-Tariffs (FIT) in the year 2000 has led to a considerable expansion of renewable energy capacity.[2] Under a Feed-In-Tariff, a fixed price (above the market price) is guaranteed to producers of RES-E for a period of typically ten to 20 years. While such policies might be motivated by various reasons such as green jobs, energy security, or as a second-best measure for reducing the risks and negative externalities of nuclear power or carbon emissions (see, e.g., Fischer and Preonas 2010), their main justification from the perspective of economic theory is the internalization of an external effect, which would cause a market failure if no policy intervention occurs. In the case of renewables, it is widely assumed that positive knowledge spillovers constitute such an externality. Namely, it is argued that renewable technologies are still in a relatively early stage of their development, and that therefore further capacity expansion as well as R&D will lead to lower costs in the future, but that this effect–because it cannot be fully appropriated–is not taken into account properly by individual firms (e.g. Rivers and Jaccard, 2006).

As a consequence, a regulatory intervention to increase the share of renewables within total electricity is needed. It was the choice of Germany to use a FIT for this purpose, but this is not the only policy instrument available: a Tradable-Renewable-Quota (TRQ) was employed, e.g. in the UK and in many states of the US[3] (where it is often labelled RPS - Renewable Portfolio Standard), and Denmark currently resorts to a Feed-In-Premium (FIP) [4]. The latter, the FIP, seems to be similar to a FIT, offering a fixed mark-up on the market price (in effect an output subsidy) to producers of RES-E. The former, the TRQ, 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 RES-E, who receive one certificate for each unit of output. They are then traded on a dedicated market for such certificates.

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 RES-E 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.

[1] See, e.g., the overview given in Table 1 of Fischer and Preonas (2010).
[2] A comprehensive overview in German: http://de.wikipedia.org/wiki/Erneuerbare-Energien-Gesetz
[3] See, e.g., data presented in the review of Schmalensee (2012).
[4] http://www.eclareon.eu/sites/default/files/denmark_-_res_integration_national_study_nreap.pdf

In the presence of such informational 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)).[5] 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*.

The research question addressed in our contribution is directly related to this real-world example: would the overshoot have been avoided or at least reduced if not a FIT but instead a FIP or a TRQ had been employed, i.e. would these other instruments have performed better? More generally, how do the three different policy instruments pass on shocks in underlying parameters onto the resulting output level of renewable electricity, and what does this imply for their respective expected net-benefit?

Although–to the best of our knowledge–our study is the first to propose a full formal analysis of the three instruments under uncertainty, it is not the first which compares different renewable energy policies. For example, Menanteau et al. (2003), in a qualitative analysis without formal model, illustrate and compare the different mechanics of FIT and TRQ, 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 TRQ. They find that while in theory FIT again offers a superior performance, the TRQ 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 (2013) 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 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. Tamas et al. (2010) study the difference between FIT and TRQ 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.

[5] See also Fig.(1) in Quaschning (2011).

Noteworthy, they report an increasing preference for TRQ as the instrument of choice for stimulating the deployment of renewables.

Finally, in the review provided by Schmalensee (2012), the performance of FIT and the TRQ-like Renewable Portfolio Standard (RPS) is compared both by means of empirical evidence from the US and the EU, and within a very simple theoretical model. Based on the latter, he objects to the widely held notion that FIT is preferable because it involves a lower risk for investors, since this view ignores the risk posed by FIT to society at large, which may well be lower under RPS. His model incorporates uncertainty on the intercept of the supply curve of renewables and shares some other features with ours (two-sector structure, inelastic total demand, increasing marginal costs for renewables), but it does not incorporate the learning (or any other) externality. Moreover, the way the RPS is modelled–namely as an instrument which allows to directly set the total output of renewables–differs significantly from the market-based TRQ system considered by us, and the FIP is not considered at all.

In sum, the existing literature has not yet provided a full formal analysis of which of the three instruments yields the higher expected net benefits under second-best conditions, in which–similar to the seminal prices vs. quantities analysis of Weitzman (1974)–the regulator has only imperfect knowledge of the parameters needed to optimally set the policy. To keep our basic analysis as transparent as possible, we have to ignore several aspects that might also influence instrument choice, such as risk aversion (Butler and Neuhoff 2008; Fagiani et al. 2013), the ability of FIT or FIP to price-discriminate (Fischer and Preonas 2010), the overlap and interaction with other policies like CO_2 emission control (Böhringer and Rosendahl 2010, Fischer and Preonas 2010), and the different way in which the cost burden is distributed (e.g., the German FIT system is self-financed by a levy added to the electricity bill of end-consumers).

The remainder of this article is organized as follows: Section 2 introduces our model of the electricity market and the three policy instruments, and derives the optimal policy intervention in the absence of uncertainty. Section 3 characterizes the effect of permanent shocks on the three instruments by deriving for each one the expected net benefits. Section 4 describes how these results change if shocks are assumed as transitory. Section 5 presents a numerical application of the model to the US electricity market. Section 6 concludes.

2. A Simple Model of the Electricity Market and the three Policy Instruments

2.1 Definition of the Model

Consider the following two-period model of the electricity market: demand $d>0$ is inelastic and, for simplicity, identical across both periods.[6] Electricity is supplied by two competitive sectors, the

[6] The assumption of a fixed demand allows us to abstract from the distributional aspects arising in this context, e.g. the TRQ is financed by the fossil-based sector and consumers, while the FIT could be financed either from the government's general budget or–as in Germany–by a levy on the electricity bill. Although politically relevant, for our present analysis of uncertainty performance we deliberately want to defer these issues, as there is no one-to-one correspondence between instruments and the financing mechanism, i.e. each instrument could be financed in various ways, making it more difficult to arrive at a clear-cut discrimination between them.

renewables sector (characterized by the letter '*r*') and the fossil-fuel sector ('*f*'). Denoting by $q_{s,t}$ the output q of sector $s \in \{r,f\}$ in period $t \in \{1,2\}$ we have

$$d = q_{r,t} + q_{f,t} \quad \text{with } t = 1,2 \tag{1}$$

Like Schmalensee (2012), we assume an upward sloping linear supply curve in the renewables sector, justified by the increasing scarcity of suitable sites. In addition, we incorporate a learning-by-doing effect that leads to a downward shift of the supply curve in period 2, in proportion to the output $q_{r,1}$ of period 1. This specification formalizes the idea that learning-by-doing drives down the unit production costs (e.g. $/Watt generation capacity), from which all future output benefits and which is stronger the more experience was gained. At the same time, it preserves the scarcity of sites (slope of supply curve). In formal terms, costs c in the renewable sector are thus given by

$$c_{r,1} = \frac{smc_r}{2}\left(q_{r,1}\right)^2 + imc_r * q_{r,1} \tag{2}$$

$$c_{r,2} = \frac{smc_r}{2}\left(q_{r,2}\right)^2 + \left(imc_r - le\, q_{r,1}\right) q_{r,2} \tag{3}$$

where $c_{r,1}$, $c_{r,2}$ is the sector's cost for period 1 and 2, respectively, smc_r the slope of the marginal cost (or supply curve), imc_r the intercept of the marginal cost, and $le \geq 0$ the learning effect. For the fossil-fuel sector we assume the same functional forms, with the exception of the learning effect, which we assume to be negligible due to the much higher maturity of this technology.[7]

$$c_{f,t} = \frac{smc_f}{2}\left(q_{f,t}\right)^2 + imc_f * q_{f,t} \qquad \text{with } t = 1,2 \tag{4}$$

There are several models in which marginal costs in the fossil-based sector are assumed to be constant (e.g. Schmalensee 2012); however, scarcity of fossil resources, increasing extraction costs and capacity constraints suggest that increasing marginal costs are quite plausible (as in, e.g., Fischer and Preonas 2010; Schmidt and Marschinski 2009, Fischer and Newell 2008). Nevertheless, to take this issue into account one may assume that the increase is lower than for renewables, i.e. $smc_r > smc_f > 0$.[8]

Finally, we constrain our model to interior solutions, i.e. equilibria with $q_{s,t}>0\ \forall t,s$ which requires:

$$imc_f - imc_r > -d\ smc_f \tag{5}$$

$$imc_f - imc_r < d\,(smc_r - le) \tag{6}$$

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[7] The no-learning assumption in the fossil-sector is a didactic exaggeration for keeping the analysis as clear as possible, but it is also commonly adopted in the literature (e.g. Fischer and Newell 2008; Kalkuhl et al. 2012).

[8] Note that we ignore system costs (grid, storage capacity, etc.), which are generally expected to rise when the relative share of renewables increases, due to the variability of sources like wind or sunlight (Ueckerdt et al. 2013). In this our model may at first sight seem less plausible than the one of Schmalensee (2012), who incorporates this aspect by assuming the marginal costs of fossil-generated electricity to be the sum of a constant term and one that is proportional to the ratio of renewable and fossil-generated output. However, his particular specification is mathematically equivalent to simply adding a constant term to the marginal costs of renewables. Therefore our model comprises Schmalensee's, and is more general as it allows for a non-zero slope of the fossil-based supply curve.

Intuitively, the first condition prevents the fossil-based sector to take all the market, and the second prevents the renewable sector to take all the market (at the optimum). Note that the above equations also imply

$$le < smc_r + smc_f \tag{7}$$

which is a condition that will be used frequently.[9]

2.1 Social Optimum

In the present setting, welfare maximization coincides with the minimization of the total costs *tc* incurred for meeting the constant demand *d* in period 1 and 2:[10]

$$\min_{\{q_{r,1}, q_{r,2}, q_{f,1}, q_{f,2}\}} tc = c_{r,1} + c_{r,2} + c_{f,1} + c_{f,2} \tag{8}$$

$$s.t.: \quad d = q_{r,t} + q_{f,t} \qquad t = \{1,2\}$$

Given an interior solution, the optimal output – which we identify with a superscript 'OPT' – is characterized by a pair of first-order conditions with respect to $q_{r,1}$ and $q_{r,2}$:

$$smc_r \; q_{r,1}^{OPT} + imc_r = smc_f \; q_{f,1}^{OPT} + imc_f + le \; q_{r,2}^{OPT} \tag{9}$$

$$smc_r \; q_{r,2}^{OPT} + imc_r - le \; q_{r,1}^{OPT} = smc_f \; q_{f,2}^{OPT} + imc_f \tag{10}$$

Intuitively, the second efficiency condition–relating to period 2–simply equates marginal costs in the renewable and fossil-based sector, where the former's costs are reduced by the learning effect induced by the output of the previous period. The first efficiency condition equates period-1 marginal costs in the renewable sector with period-1 marginal costs in the fossil-based sector and the cost-saving effect realized in period 2. Note that the two equations are perfectly symmetric: taking one, the other can be obtained by switching the time index. As a consequence, also the optimal outputs must be symmetric and hence the last two equations simplify into one, namely

$$smc_r \; q_r^{OPT} + imc_r = smc_f \; (d - q_r^{OPT}) + imc_f + le \; q_r^{OPT} \tag{11}$$

where we have additionally substituted $q_f^{OPT} = d - q_r^{OPT}$. This expression has a straightforward interpretation from a cost-benefit perspective: the costs of renewables (LHS) are justified by the avoided costs for fossil-based supply (RHS, 1st and 2nd term), plus the learning effect (RHS, 3rd term). The avoided marginal costs of fossil-based output is decreasing, while the learning effect is increasing in renewables output. The efficiency condition can be readily solved, yielding

$$q_r^{OPT} = \frac{imc_f - imc_r + d \; smc_f}{smc_f + smc_r - le} \tag{12}$$

[9] A further noteworthy simplification of our model is that, to keep the model tractable, it uses 'instantaneous' electricity supply curves and hence ignores the distinction between investment cost and variable cost.
[10] We ignore discounting and for now assume equal parameters in both periods for the sake of simplicity.

By Eqs.(7) and (5) the denominator and the numerator, respectively, are always positive. It might seem surprising that the optimal amount of renewables is the same in both periods, even though the marginal cost function of renewables is shifted downwards in the second period, and hence marginal costs are lowered by $le * q_{r,1}$ compared to the first period. However, it is only the 'instantaneous' marginal costs that are higher in the first period, which is justified by the additional cost-saving effect on the second period. Naturally, the optimal fossil-generated supply also becomes symmetric, with (using the demand constraint):

$$q_f^{OPT} = \frac{imc_r - imc_f + d\,(smc_r - le)}{smc_f + smc_r - le} \tag{13}$$

To verify that we are facing a cost minimum, we express total costs solely in terms of the $q_{r,1}$ ($q_{r,2}$ can be expressed in terms of $q_{r,1}$ by the second efficiency condition Eq.(10)) and take the second derivative, yielding

$$\frac{d^2 tc}{d(q_{r,1})^2} = \frac{1}{smc_f + smc_r}\left(\left(smc_f + smc_r\right)^2 - le^2\right) > 0 \tag{14}$$

where the positive sign follows directly from the constraint in Eq.(7).

2.2 Competitive Market Equilibrium

Competitive firms take the electricity price p_1 and p_2 for periods 1 and 2 as given and produce electricity such as to maximize their profits π. For simplicity we assume one representative firm per sector and time period, yielding the following four maximization problems:

$$\max_{q_{s,t}} \pi_{s,t} = p_t\, q_{s,t} - c_{s,t} \tag{15}$$

The corresponding four first-order conditions, together with the demand constraints, yield for the equilibrium output of renewable electricity in period 1 and 2, respectively:

$$q_{r,1}^{NP} = \frac{imc_f - imc_r + d\,smc_f}{smc_f + smc_r}, \quad q_{r,2}^{NP} = \frac{\left(imc_f - imc_r + d\,smc_f\right)\left(smc_f + smc_r + le\right)}{\left(smc_f + smc_r\right)^2} \tag{16}$$

where we introduced the superscript shorthand '^{NP}' to indicate the 'no policy' case. Comparison with Eq.(12) for q_r^{OPT} shows that if *le>0*, then $q_{r,1}^{NP} < q_{r,2}^{NP} < q_r^{OPT}$. In other words, the market provides too little renewables in both periods, especially in period 1, and thus leads to higher total costs than in the social optimum whenever *le>0*.

This outcome is of course not surprising, since by assumption market participants do not internalize the learning effect. However, the fact that period 2 supply of renewables nevertheless increases because some learning does occur highlights how the regulator's problem in this model is to implement the optimal supply of renewables in period 1, as the period 2 market equilibrium will be optimal by itself if the right amount of learning is induced.

2.3 Policy Instruments

The policy instruments are applied only in period 1, since there is no externality associated with the level of $q_{r,2}$ or $q_{f,2}$. We now formalize FIP, FIT, and TRQ, and derive their optimal setting for the deterministic case.

FIT: feed-in-tariff, i.e. a guaranteed fixed price for renewables output

Under a FIT policy the representative firm's profit in the first period becomes

$$\pi_{r,1}^{FIT} = fit\ \ q_{r,1}\ - c_{r,1} \tag{17}$$

(where we denote by '*fit*' the level of the instrument), leading to an associated output of

$$q_{r,1}^{FIT} = \frac{fit - imc_r}{smc_r} \tag{18}$$

The regulator sets FIT optimally by equating it to the marginal costs implied by q_r^{OPT} from Eq.(12):

$$fit = imc_r + smc_r\ q_r^{OPT} = \frac{imc_r\big(smc_f - le\big) + (imc_f + d\ smc_f)smc_r}{smc_f + smc_r - le} \tag{19}$$

Chosen this way, the FIT induces the optimum level $q_{r,1}^{OPT}$ of renewables output, and hence also of all other model variables. As can be confirmed easily, for *le=0* the optimal FIT would simply become equal to the price realized in a 'laisser-faire' market equilibrium.

FIP: feed-in-premium, i.e. a per-unit subsidy for renewables added to the electricity price

Under this instrument, the first-order condition for profit maximization of the representative firm in the renewables sectors implies

$$p_1 + fip = imc_r + smc_r\ q_{r,1} \tag{20}$$

leading to an output level of

$$q_{r,1}^{FIP} = \frac{fip + imc_f - imc_r + d\ smc_f}{smc_f + smc_r} \tag{21}$$

Comparing the producers' efficiency condition Eq.(20) from above with the social efficiency condition Eq.(11) immediately shows that producers respond optimally to the market price p_1 if the FIP is set to

$$fip = \frac{le(imc_f - imc_r + d\ smc_f)}{smc_f + smc_r - le} = le\ \ q_r^{OPT} \tag{22}$$

In line with intuition, the optimal FIP strictly increases with the strength of the learning effect and equals zero if *le=0*.

TRQ: tradable renewable quota, i.e. a share α of renewables per unit of fossil-generated output

Under this instrument, the regulator requires producers of fossil-generated electricity to buy a number α of 'green' certificates for every unit of their output. The resulting relative market share of renewables becomes $\alpha/(1+\alpha)$, which we assume to be above the no-policy 'NP' case. Green certificates are awarded to renewable producers for each unit of their output. Being freely tradable, the price p^c of these certificates is determined by the market.

The period-1 profit functions of the renewable and fossil-based representative firm are thus given by

$$\pi_{r,1}^{TRQ} = (p_1 + p^c)\, q_{r,1} - c_{r,1} \tag{23}$$

$$\pi_{f,1}^{TRQ} = (p_1 - \alpha\, p^c)\, q_{f,1} - c_{f,1} \tag{24}$$

Together with the market clearing condition

$$\alpha\, q_{f,1} = q_{r,1} \tag{25}$$

the implied equilibrium can be readily computed and implies a price of electricity and of the green certificates given by

$$p_1 = \frac{(1+\alpha)\left(imc_f + \alpha\, imc_r\right) + d\left(smc_f + \alpha^2\, smc_r\right)}{(1+\alpha)^2} \tag{26}$$

$$p^c = \frac{(1+\alpha)\left(imc_r - imc_f\right) - d\left(smc_f - \alpha\, smc_r\right)}{(1+\alpha)^2} \tag{27}$$

and a resulting output of renewables

$$q_{r,1}^{TRQ} = \frac{d\,\alpha}{1+\alpha} \tag{28}$$

To minimize total costs, the regulator has to choose α as the ratio of the optimal renewables and optimal fossil-generated output:

$$\alpha = \frac{q_r^{OPT}}{q_f^{OPT}} = \frac{imc_f - imc_r + d\, smc_f}{imc_r - imc_f + d\,(smc_r - le)} \tag{29}$$

Note that in this case α increases with *le*, but does not become zero for *le=0*. This is consistent, since for *le=0* the laisser-faire market equilibrium is optimal, which would nevertheless comprise a share of renewables that is greater than zero.

In sum, all instruments, if set at their optimal value, yield the optimal value of $q_{r,1}$, and hence of $q_{f,1}$, $q_{r,2}$, and $q_{f,2}$, and thus also the optimal welfare. The different instruments are graphically illustrated in Fig.(1), which compares (for period 1 only) the no-policy case with the social optimum and indicates the optimally set instruments FIT, FIP, and TRQ. The figure shows how the regulator's challenge consists of increasing $q_{r,1}$ from the static marginal-cost intersection – where the positive external effect from learning is ignored – to the point where fossil-based marginal costs become equal to the *adjusted* marginal costs of renewables, which include future cost-savings. Overall, this provides us with a simple but useful framework to analyse the instruments' performance under uncertainty, which will be done in the next section.

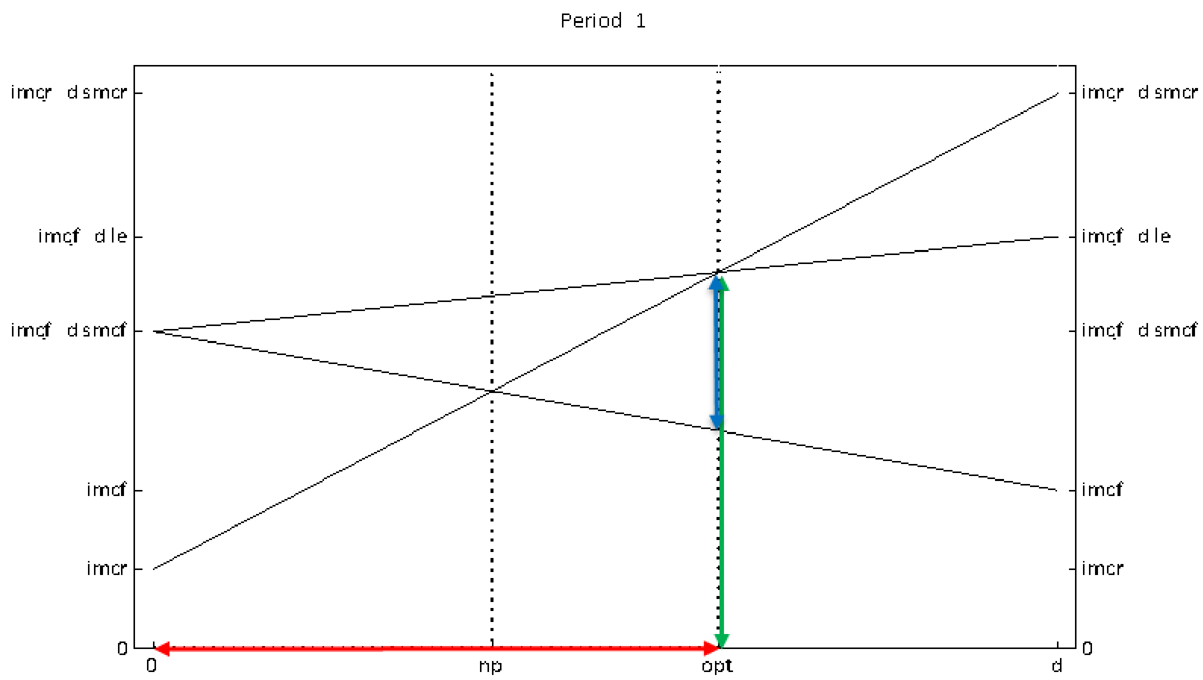

Figure 1: Graphical illustration of the model (d=4;imc_f=1;smc_f=0.25;imc_r=0.5;smc_r=0.75;le=0.4), for period 1. Shown are (rising from left to right) the renewables sector's plain (dotted, with slope smc_r) and adjusted marginal cost curve resulting from the optimization (solid, with slope smc_r-le), as well as (rising from right to left) the marginal costs curve of the fossil-based sector. Social optimum ($q_{r,1}^{OPT}$) and no-policy market equilibrium ($q_{r,1}^{NP}$) are indicated. The optimally set policy instruments are highlighted in green (FIT), blue (FIP), and red (TRQ).

3. Instrument Performance under Uncertainty: Permanent Shocks

This section formally analyses the three instruments' robustness for three different sources of uncertainty. Each instrument should minimize total expected cost, which is equivalent to maximizing net surplus (or welfare) if demand–as in our case–is inelastic. We assume that the regulator, being affected by uncertainty, sets each instrument to its ex-ante optimal level, while firms have perfect information (as in Weitzman's 1974 model).

Another basic assumption of our model is that shocks occur only in the first period. The reason for this restriction is that the second period is not subject to policy intervention (and should not be, as the policy intervention is justified only by the positive external effect associated with period 1 renewables output), and hence uncertainty in this period would not affect instrument choice. Note that uncertainty on the learning parameter *le* is therefore not considered here. The reason for this perhaps unexpected choice–given that *le* is evidently uncertain–is that considering uncertainty on *le* would not lead to a discrimination between the different policy instruments in terms of their robustness. Namely, if *le* turns out to be lower than expected (and vice versa), all three of them would yield the exact same excess output of renewables in the first period, and hence induce the same efficiency loss.

Finally, a specific assumption of this section (but later reversed) is that shocks are permanent. In other words, all model parameters have the same value in period 1 and 2. The 'shock' can be interpreted as a false estimation of the system's parameters by the regulator, leading to the implementation of an ex-post non-optimal renewables target $q_{r,1}$, and hence to excess costs. Importantly, the permanency of shocks implies that the full formal symmetry between period 1 and 2 – as discussed in Section 2.1 and reflected in Eq.(11) – is preserved. Under this condition, total costs are uniquely determined by the value of $q_{r,1}$ (with given parameter values). Eq.(14) shows that this minimization problem is strictly convex with a constant second derivative, allowing us to reduce the uncertainty analysis to a simple comparison of how shocks impact the first-order condition for $q_{r,1}$ under the various instruments.[11]

The model admits uncertainty on three model parameters: (i) the level imc_f of the marginal costs of fossil-generated output (driven by volatility of fossil fuel prices, possibly also of a carbon price), (ii) the level imc_r of the marginal costs of renewables-based output (uncertain short-term production costs and site availability), and (iii) total demand d (uncertainty driven by business cycle fluctuations).[12] In formal terms, we introduce an additive uncertainty δ_f on the level imc_f of the marginal costs of fossil-generated power (equivalently: on the level of the supply curve), such that the expected value is $E[\delta_f]=0$ and the standard deviation $SD[\delta_f]=\sigma_f$. Analogously, δ_r defines an additive uncertainty on the level imc_r of the marginal costs of renewables, with $E[\delta_r]=0$ and standard deviation $SD[\delta_r]=\sigma_r$. Finally, δ_d denotes the additive uncertainty on demand d, again with expected value $E[\delta_d]=0$ and standard deviation $SD[\delta_d]=\sigma_d$.

3.1 Formal analysis: The Weitzman perspective

Given the formal similarity of our problem to the one addressed by Weitzman (1974), and the prominence of his homonymic 'rule' of the relative slopes of marginal costs and benefits, we first discuss those cases in which the ranking between instruments can be determined by applying this rule. As will be seen, depending on the uncertainty at hand, the different policy instruments will varyingly act as price or quantity instrument. For instance, the FIT formally fixes the price for renewables, but by doing so it also fixes the level of renewables output if uncertainty is linked exclusively to demand or the supply curve of the fossil-based sector. Hence, a FIT acts as a quantity instrument in the latter two cases and as a price instrument when uncertainty is linked to imc_r.

Since $q_{r,2}$ will automatically be optimal if $q_{r,1}$ is optimal, only the first period needs to be considered. The efficiency condition Eq.(11) can be written as

$$smc_r\, q_{r,1}^{OPT} + imc_r = \left(le\ - smc_f\right) q_{r,1}^{OPT} + imc_f + smc_f\ \ d \tag{30}$$

where the left-hand side corresponds to the price of renewables, i.e. their marginal costs, which becomes fixed by a FIT. The right-hand side, as discussed before, represents the marginal benefits from employing renewables. Under uncertainty on imc_f or imc_r the TRQ acts as a quantity instrument, since it sets the output level of $q_{r,1}$ directly through Eq.(28). Consequently, the Weitzman rule can be applied to FIT vs. TRQ for these two sources of uncertainty. As by Eq.(30), the slope of the marginal

[11] In addition, we also assume that all uncertainties are *uncorrelated*. This seems to be a natural starting point, given that the assumption of correlation would complicate the analysis significantly.

[12] The slopes of the marginal cost curves, representing, e.g., the declining quality of grades for renewables, are considered to be known by the regulator, an assumption also made in the uncertainty analysis of Weitzman (1974).

costs is given my smc_r, while the absolute slope of the marginal benefits is abs(le-smc_f). Hence, we obtain the following two results:

- with marginal cost uncertainty due to shocks on imc_r, a price instrument FIT is more efficient than a quantity instrument TRQ if smc_r>abs(le-smc_f), which by Eq.(7) simplifies to smc_r+le>smc_f;
- with shocks on imc_f uncertainty only affects marginal benefits, and hence–as per Weitzman's rule–price (FIT) and quantity (TRQ) regulation become equivalent.

Using the rule to assess the FIP instrument becomes straightforward when rearranging the efficiency condition Eq.(11) into

$$\left(smc_r + smc_f\right)q_{r,1}^{OPT} - smc_f\ d + imc_r - imc_f = le\ q_{r,1}^{OPT} \tag{31}$$

Here, the left-hand side represents the wedge between the marginal costs in the renewable and fossil-based sector – which is precisely what is fixed by a FIP. Because any such wedge leads to a deviation from the cost-minimum for total supply in period 1, the LHS also represents the marginal excess costs associated with renewable employment beyond the free-market equilibrium. The right-hand side captures the corresponding marginal benefit, namely the cost reduction from learning. Under a FIP the marginal costs (i.e. the wedge) are fixed, but not the resulting output quantity $q_{r,1}$. Conversely, in the absence of demand shocks a TRQ fixes $q_{r,1}$, but leaves the marginal cost difference undetermined. For uncertainty on demand d and imc_f, also the FIT acts as a quantity instrument. Hence, given the slope smc_r+smc_f of the marginal costs, and le of the marginal benefits, the Weitzman rule can be applied to four further cases of instrument choice:

- with cost-uncertainty due to shocks in imc_f or imc_r, the price instrument FIP is more efficient than the quantity instrument TRQ if smc_r+smc_f>le, which by Eq.(7) always holds;
- with cost-uncertainty due to shocks in imc_f, the price instrument FIP is more efficient than the quantity instrument FIT if smc_r+smc_f>le, which by Eq.(7) always holds;
- with cost-uncertainty due to demand shocks, the price instrument FIP is more efficient than the quantity instrument FIT if smc_r+smc_f>le, which always holds, unless smc_f=0, in which case uncertainty drops out of Eq.(31) and both instruments become first-best.

The results obtained so far already allow to fully characterize the instruments' relative performance under uncertainty on imc_f, as summarized in the following statement:

Proposition 1.1 (permanent uncertainty on imc_f): *Consider the model defined by Eqs.(1)-(7). If uncertainty occurs in form of permanent shocks affecting the level of the marginal cost curve in the fossil-based sector, then a FIP is always more efficient than both FIT and TRQ, while the latter two are equivalent.*

In Fig.(2) we graphically illustrate the impact of a -25% shock of imc_f on the optimum and on the output of $q_{r,1}$ implied by the three instruments. Intuitively, if fossil-based electricity has higher (lower) costs than expected, then a greater (lower) share of renewables would be required to meet the social optimum. However, both FIT and TRQ are–once the instrument level is set–insensitive to the price signal from the fossil sector and hence do not respond to shocks. Only under the FIP does the price signal reach the renewables sector and induces an adjustment in the right direction. However, this adjustment remains weaker than optimal as long as le>0, demonstrating that the FIP falls short of being an optimal instrument. This is the case because a FIP defines a fixed mark-up on the price of renewables, while the size of the external effect it aims to internalize increases with the level of $q_{r,1}$. Said differently, the effect of a FIP is to shift the marginal cost curve of the renewable sector downwards, while the optimal correction, as can be seen in Fig.(2), would be a rotation of the curve.

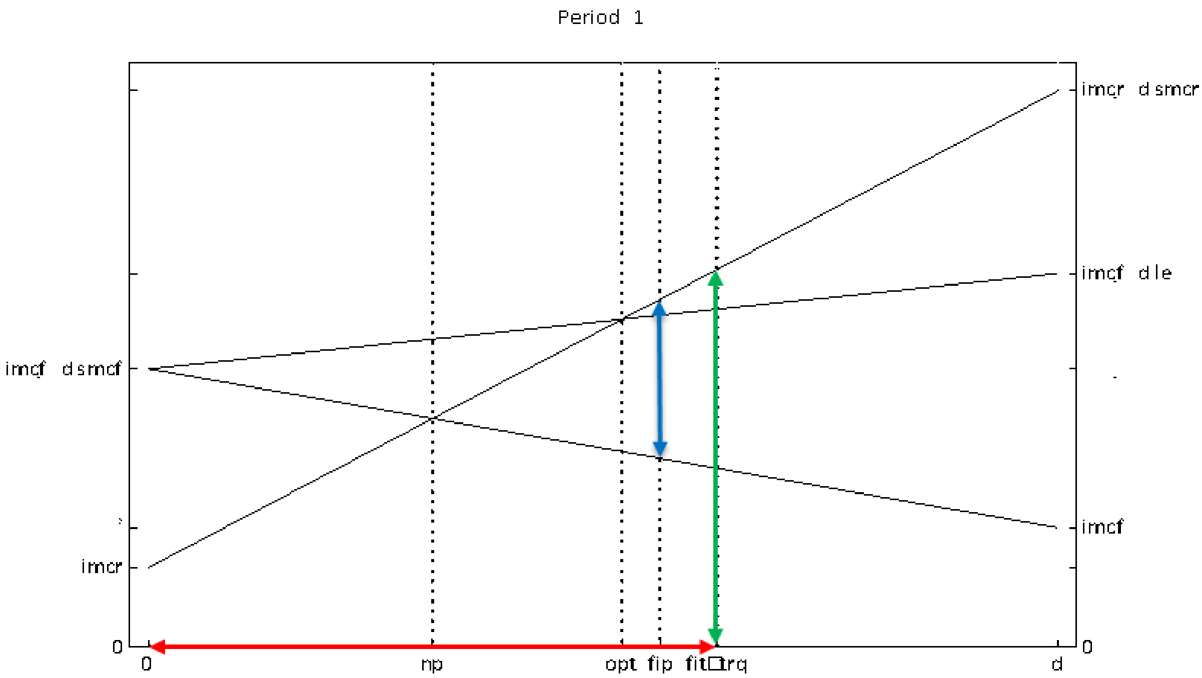

Figure 2: Illustration of a shock of -25% on imc_f (all other parameter values as in Fig.(1)). The ex-post optimum for $q_{r,1}$ becomes lower than in Fig.(1), while output under FIT (green) and TRQ (red) remains unchanged. Only for FIP (blue) a reduction of renewables output can be observed, albeit insufficient.

3.2 Formal analysis: General perspective

The previous application of Weitzman's rule allowed determining the instrument ranking for six out of nine possible cases, with FIT vs. TRQ and FIP vs. TRQ for demand uncertainty, as well as FIT vs. FIP for uncertainty on imc_r as the remaining three cases. To derive the corresponding dominance conditions, the efficiency condition for $q_{r,1}^{OPT}$ can be re-analysed in the following way: substitute $q_{r,1}^{OPT}$ by the considered (and optimally set) policy instrument. E.g. for a FIT, using Eq.(18), Eq.(30) becomes

$$fit = \left(le - smc_f\right)\frac{fit - imc_r}{smc_r} + imc_f + smc_f\, d \tag{32}$$

The instrument leads to an optimal outcome as long as the equation is satisfied, i.e. when the fixed marginal costs on the LHS equal the 'unfixed' marginal benefits on the RHS. In presence of a shock on imc_f, imc_r, or d this will generally no longer be the case, and the size of the resulting wedge will become a measure of the incurred inefficiency. In other words, the extent to which any of these shocks lead to a violation of the instrument-specific efficiency condition directly captures the instrument's robustness. Under a FIT shocks in imc_f, imc_r, or d yield an inefficiency-wedge proportional to the corresponding partial derivative, namely 1, $(smc_f\text{-}le)/smc_r$, and smc_f, respectively.

Notice that the second coefficient implies that under uncertainty on imc_r a FIT becomes a first-best instrument whenever smc_f=le, as in this case the coefficient becomes zero. Next, consider the FIP: from Eqs.(21) and (31) the required form of the efficiency condition is obtained as

$$fip = le\ \frac{fip + imc_f - imc_r + d\ smc_f}{smc_f + smc_r} \tag{33}$$

implying coefficients of $le/(smc_f+smc_r)$, - $le/(smc_f+smc_r)$, and $(le\ smc_f\ )/(smc_f+smc_r)$ for shocks in imc_f, imc_r, and d, respectively. Finally, for the TRQ we use Eq.(28) for the substitution, yielding

$$\left(smc_r\ + smc_f - le\right)\ \frac{d\ \alpha}{1+\alpha} = imc_f - imc_r + d\ smc_f \tag{34}$$

and thus implying robustness coefficients 1, -1, and α/(1+α) (smc_f+smc_r-le) – smc_f. Notice that the equation shows that a TRQ becomes a first-best instrument under demand uncertainty only if imc_f=imc_r, since in this case d can be eliminated from the condition.

Comparing the coefficients' absolute magnitude yields the dominance conditions. In particular, for shocks on imc_f the coefficients of FIP, FIT, and TRQ are $le/(smc_f+smc_r)$, 1, and 1, respectively, meaning that a FIP is always more efficient than FIT and TRQ (by Eq.(7) its coefficient is below unity), and that the latter two are equivalent, which confirms the result of the previous section.

For uncertainty on imc_r the (absolute value) coefficients for FIP, FIT and TRQ become $le/(smc_f+smc_r)$, abs(smc_f-le)/smc_r, and 1, respectively. The FIP evidently dominates the TRQ, and so does the FIT if $smc_r+le>smc_f$, as already found in the previous section. As a new case, the FIT is superior to the FIP if $le/(smc_f+smc_r)$ > abs(smc_f-le)/smc_r. For $0<smc_f<le$, this simplifies to $le<smc_f+smc_r$, which by Eq.(7) always holds, while $smc_f>le$ leads to the non-trivial condition $le>smc_f\ (smc_f\ +smc_r)/(smc_f\ +2\ smc_r)$; in the limit case of smc_f=0 both instruments become equivalent. The following proposition summarizes:

Proposition 1.2 (permanent uncertainty on *imc*$_r$): *Consider the model defined by Eqs.(1)-(7). If uncertainty occurs in form of permanent shocks affecting the level of the marginal cost curve in the renewables sector, then*

- *(i)* *FIP is always more efficient than TRQ*
- *(ii)* *FIT is more efficient than TRQ if* $le > smc_f - smc_r$
- *(iii)* *FIT is more efficient than FIP if* $le > smc_f\ \left(smc_f +\ smc_r\right)/\left(smc_f + 2\ smc_r\right)$*, except for* smc_f*=0, in which case they are equivalent instruments.*

Hence, the TRQ is not a good choice in this case, as it is dominated by the FIP. The FIT might be an even better choice if the marginal cost curve in the fossil sector is relatively flat and if learning is high. Intuitively, lower (higher) than expected costs for renewables imply that they should supply a higher (lower) share of electricity. The TRQ, however, fixes the share and hence does not respond. The FIP reacts exactly as for uncertainty on imc_f, i.e. the cost-shock is passed on to the market, albeit imperfectly. The FIT also reacts and adjusts in the right direction, but may overshoot. This is illustrated graphically in Fig.(3).

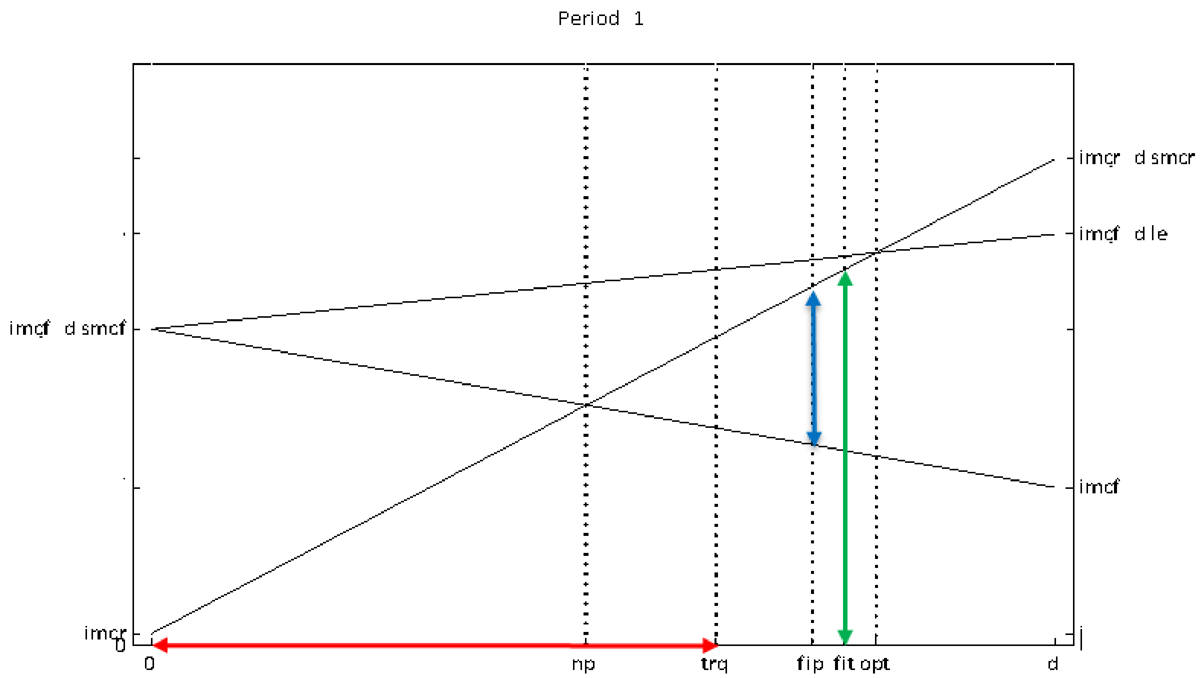

Figure 3: Illustration of a shock of -80% on imc_r (all other parameter values as in Fig.(1)). The ex-post optimum for $q_{r,1}$ becomes higher than in Fig.(1). Output under TRQ remains unchanged, while it is increased under FIP and, even more so, under FIT.

Fig.(3) also illustrates why the FIT is first-best if $smc_f=le$: because in this case marginal benefits are flat and can therefore be perfectly internalized by a constant price. As a consequence, the FIT will dominate both TRQ and FIP whenever smc_f and le are sufficiently close.

Shocks in total demand constitute the last source of uncertainty to consider. In general a positive demand shock means that the optimal quantity of both renewable and fossil-generated electricity should increase. This, intuitively, might favour the TRQ, which so far did not show any particular advantage vis-à-vis the other two instruments. For FIT and FIP we found coefficients of smc_f and $(le\ smc_f)/(smc_f+smc_r)$, respectively, thus confirming the last section's result that under demand uncertainty FIP always dominates FIT, unless $smc_f=0$, in which case they become equivalent.

The TRQ coefficient was $\alpha/(1+\alpha)\ (smc_f+smc_r\ -le)\ -\ smc_f$. To derive specific dominance conditions the instrument's parameter α needs to be replaced. This, as before, will be done by using the optimal value found in the initial analysis without uncertainty, i.e. Eq.(29). Note, however, that in the present case this does not correspond to the ex-ante optimal value that minimizes expected total costs. The two only coincide when the ex-post output of $q_{r,1}$ is linear in the shock as well as in the instrument's parameter, e.g. as in Eqs.(18) and (21) for FIT and FIP. For the TRQ this was the case for uncertainty on imc_f and imc_r. However, it is no longer true for the present case of demand uncertainty, since the ex-post output of $q_{r,1}$ now depends on the product of the shock and α (see Eq.(28)). Nevertheless, for reasons of exposition and because it seems quite plausible that a regulator would indeed choose the certainty value, we still proceed this way.[13]

[13] We also report results corresponding to the case where demand uncertainty is optimally taken into account by the regulator. The value for α that minimizes expected costs is given by $\frac{d(\mathrm{imc}_f-\mathrm{imc}_r+d\ \mathrm{smc}_f)+\mathrm{smc}_f\ \sigma_d}{d(\mathrm{imc}_r-\mathrm{imc}_f+d(\mathrm{smc}_r-\mathrm{le}))+(\mathrm{smc}_r-\mathrm{le})\sigma_d}$,

Comparing FIT and TRQ shows that the former dominates the latter if

$$smc_f < abs\left[\left(\frac{\alpha}{1+\alpha}\right)\left(smc_f + smc_r - le\right) - smc_f\right] \tag{35}$$

which, by using Eq.(29) becomes

$$smc_f < abs\left[\frac{1}{d}\left(imc_f - imc_r + d\ smc_f\right) - smc_f\right] = \frac{1}{d}\ abs\left[imc_f - imc_r\right]. \tag{36}$$

By Eq.(5), the condition can only be fulfilled if imc_f-imc_r>$d\ smc_f$. Finally, a FIP is more efficient than TRQ if (simply replacing the LHS of Eq.(36) with the FIP's coefficient)

$$\frac{smc_f\ le}{smc_f + smc_r} < \frac{1}{d}\ abs\left[imc_f - imc_r\right]. \tag{37}$$

In sum, for uncertainty on total demand the instruments' relative performance can be characterized as follows:

Proposition 1.3 (permanent uncertainty on *d*): *Consider the model defined by Eqs.(1)-(7). If uncertainty occurs in form of permanent shocks affecting the level of total electricity demand, then*

- *(i)* *FIP is more efficient than FIT, except if marginal costs in the fossil-based sector are constant, in which case they are equivalent (and both ex-post optimal).*
- *(ii)* *FIT is more efficient than TRQ if imc_f-imc_r>$d\ smc_f$.*
- *(iii)* *FIP is more efficient than TRQ if abs(imc_f-imc_r) > ($d\ le\ smc_f$)/(smc_r +smc_f)*

As the result shows, TRQ is not a 'silver-bullet' instrument for demand uncertainty, which stems from the fact that the optimal percentage share of renewables does generally not stay constant under demand variations. This would only be the case if imc_f equals imc_r, and hence the relative difference between them – set in relation to total demand *d* – becomes a measure of the TRQ's expected error.

On the other side, a FIT decouples the renewables sector from the electricity market and thereby prevents it from reacting to demand shocks. This, in general, leads to a suboptimal outcome, except if the fossil sector's supply curve is flat, in which case it is optimal that all demand shocks are absorbed exclusively by the latter. Hence, the slope smc_f of the supply curve becomes a measure of the FIT's expected error. Finally, the FIP always improves upon the FIT, but the induced adjustment of the renewables output generally remains insufficient (except for smc_f=0, for the same reason as for FIT). This can also be understood by thinking in terms of the effective subsidy provided: in case of a permanent positive demand shock, the benefits from learning increase, and hence the per-unit subsidy offered to the renewables sector should become higher. However, under a FIP it stays by definition constant, while under a FIT – being the difference between laisser-faire price and *fit* – it even decreases (and under a TRQ it generally becomes too high).

The behavior of all three instruments is illustrated in Fig.(4). Clearly, if demand uncertainty is the regulator's main concern, the instrument choice comes down to deciding between the FIP and TRQ.

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and in fact only leads to a slight modification of the dominance conditions given in Proposition 1.3 (ii) and (iii), namely the replacement of *d* with $d\sqrt{(1+\sigma_d/d)}$.

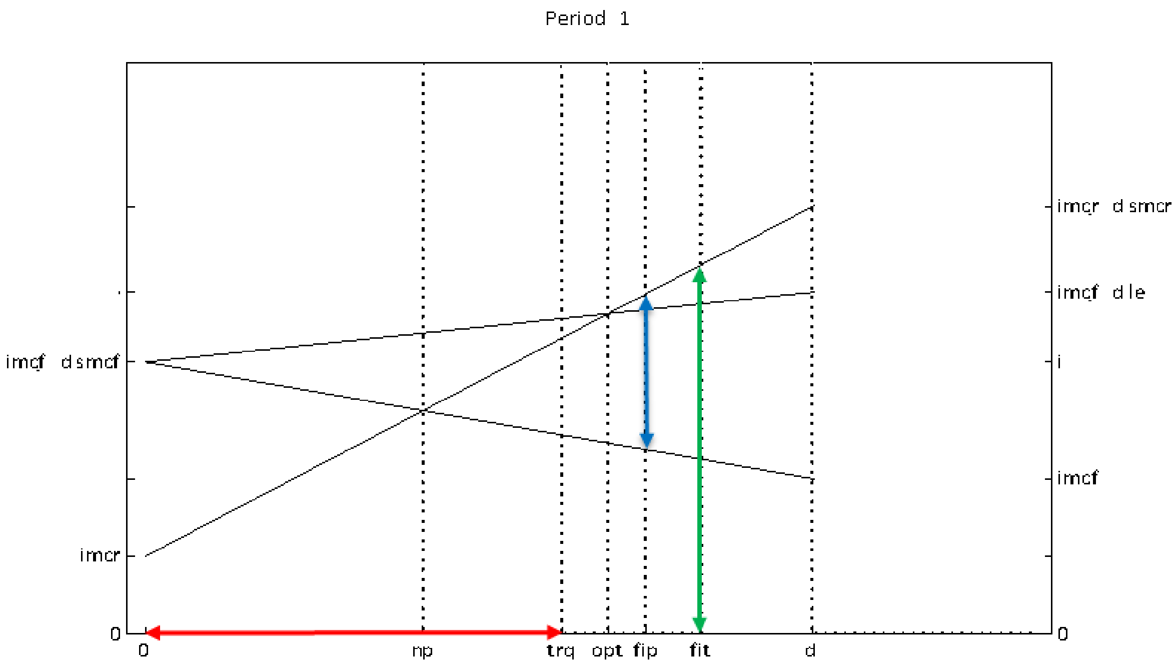

Figure 4: Illustration of a shock of -25% on demand d (all other parameter values as in Fig.(1)). The ex-post optimum for $q_{r,1}$ becomes lower than in Fig.(1). Output under FIT remains unchanged, it becomes lower – but not enough – under FIP and also – but too much so – under TRQ.

4. Instrument Performance under Uncertainty: Transitory Shocks

Especially at shorter time-scales (e.g. less than one business cycle) it might seem plausible to assume transitory rather than permanent shocks. Therefore, this section takes a brief look at how the dominance conditions would change in this case. As we will see, the conditions remain very similar.

In formal terms, the efficiency condition for an ex-post optimal output of renewables becomes more complicated than Eq.(11), as it now depends explicitly on the different parameter values of the first and the second period. If we denote by $imc_{r,1}$, $imc_{f,1}$, and d_1 the respective parameters' ex-post values for the first period, the efficiency conditions for a social optimum read (analogous to Eqs.(9) and (10)):

$$smc_r\, q_{r,1}^{opt} + imc_{r,1} - le\, q_{r,2}^{opt} = smc_f\left(d_1 - q_{r,1}^{opt}\right) + imc_{f,1} \qquad (38)$$

$$smc_r\, q_{r,2}^{opt} + imc_r - le\, q_{r,1}^{opt} = smc_f\left(d - q_{r,2}^{opt}\right) + imc_f \quad . \qquad (39)$$

The second equation can be used to the substitute the dependent period-2 output of renewables:

$$smc_r\, q_{r,1}^{opt} + imc_{r,1} = smc_f\left(d_1 - q_{r,1}^{opt}\right) + imc_{f,1} + le\left(\frac{le\, q_{r,1}^{opt} + smc_f\, d - imc_r + imc_f}{smc_r + smc_f}\right) \qquad (40)$$

The instruments are still set optimally by choosing the value found in the deterministic analysis of Section 2 (except TRQ under demand uncertainty, where we nevertheless assume such a setting, as explained above). Hence, we can introduce the instruments one by one in Eq.(40), and then compute the uncertainty coefficients as the partial derivatives with respect to the three different possible shocks. In particular, for the FIT we use Eq.(18) – replacing imc_r by the first period ex-post value $imc_{r,1}$ – to substitute the renewables output in Eq.(40):

$$fit = smc_f \left(d_1 - \frac{fit - imc_{r,1}}{smc_r}\right) + imc_{f,1} + le \left(\frac{le \left(\frac{fit - imc_{r,1}}{smc_r}\right) + smc_f\, d - imc_r + imc_f}{smc_r + smc_f}\right) \quad (41)$$

Taking the partial derivatives with respect to $imc_{f,1}$, $imc_{r,1}$ and d_1 provides the corresponding uncertainty coefficients $1, smc_f/smc_r - le^2/\left(smc_r(smc_r + smc_f)\right)$, and smc_f. We proceed analogously for the FIP, using Eq.(21) to re-write Eq.(40) as

$$fip = \frac{le}{smc_r + smc_f}\left(le \left(\frac{fip + imc_{f,1} - imc_{r,1} + d_1\, smc_f}{smc_f + smc_r}\right) + smc_f\, d - imc_r + imc_f\right), \quad (42)$$

allowing to obtain the three uncertainty coefficients $le^2/\left(smc_r + smc_f\right)^2, le^2/\left(smc_r + smc_f\right)^2$, and $\left(le^2\, smc_f\right)/\left(smc_r + smc_f\right)^2$. Finally, for TRQ we can substitute using Eqs.(28) and (29), yielding

$$\left(smc_r + smc_f\right) \frac{d_1\, \alpha}{1 + \alpha} + imc_{r,1} = smc_f\, d_1 + imc_{f,1} + le \left(\frac{le\, \frac{d_1\, \alpha}{1+\alpha} + smc_f\, d - imc_r + imc_f}{smc_r + smc_f}\right) \quad (43)$$

and uncertainty coefficients 1, 1, and $\left(smc_r + smc_f - \frac{le^2}{smc_r + smc_f}\right) \frac{\alpha}{1+\alpha} - smc_f$. By comparing the absolute value of these coefficients the following results can be derived in a straightforward manner, starting with uncertainty on the marginal costs in the fossil-based sector:

Proposition 2.1 (transitory uncertainty on *imc_f*): *Consider the model defined by Eqs.(1)-(7). If uncertainty occurs in form of transitory shocks affecting the level of the marginal cost curve in the fossil-based sector, then a FIP is always more efficient than both FIT and TRQ, while the latter two are equivalent.*

Proof: The coefficient for FIP is $le^2/\left(smc_r + smc_f\right)^2$, which by Eq.(7) is below unity, while we get a coefficient of 1 for both FIT and TRQ. □

Hence, the ranking remains exactly the same as in the case with permanent shocks. Next, consider uncertainty on the supply curve in the renewables sector:

Proposition 2.2 (transitory uncertainty on *imc_r*): *Consider the model defined by Eqs.(1)-(7). If uncertainty occurs in form of transitory shocks affecting the level of the marginal cost curve in the renewables sector, then*

- *(i) FIP is always more efficient than TRQ*
- *(ii) FIT is more efficient than TRQ if* $le^2 + smc_r^2 > smc_f^2$
- *(iii) FIP is more efficient than FIT if* $le < \left(smc_f + smc_r\right)\sqrt{smc_f/\left(smc_f + 2smc_r\right)}$.

Proof: See Appendix.

In qualitative terms, the ranking of instruments does not change compared to the permanent uncertainty case: the FIP always dominates the TRQ, and the position of the FIT could be anywhere from best to worst choice. However, in quantitative terms the FIT's performance deteriorates, i.e. the conditions for it to be superior to TRQ or FIP are less likely to be met under transitory than under permanent shocks. This is a consequence of the FIT's tendency to overshoot, which was illustrated in Fig. 4, and which has a less severe effect if a shock makes renewables permanently more (or less) attractive, rather than just temporarily. Finally, the case of demand uncertainty:

Proposition 2.3 (transitory uncertainty on *d*): *Consider the model defined by Eqs.(1)-(7). If uncertainty occurs in form of transitory shocks affecting the level of total electricity demand, then*

(i) *FIP is more efficient than FIT, except if marginal costs in the fossil-based sector are constant, in which case they are equivalent (and both ex-post optimal).*

(ii) *FIT is more efficient than TRQ if* $imc_f - imc_r > \frac{d\ smc_f\ (smc_f + smc_r - le)}{(smc_f + smc_r + le)}$*, or if* $smc_f = 0$

(iii) *FIP is more efficient than TRQ unless* $\frac{d\ le\ smc_f}{(smc_f + smc_r)}\frac{(smc_f + smc_r - le)}{(smc_f + smc_r + le)} < imc_r - imc_f < \frac{d\ le\ smc_f}{(smc_f + smc_r)}$

Proof: See Appendix.

As for permanent shocks, FIT and FIP become first-best instruments if marginal costs in the fossil-based sector are flat, but otherwise the FIT is dominated by the FIP. Also as before, the relative performance of the TRQ depends on the size of the term (imc_f-imc_r)/d, but the dominance conditions also show that under transitory shocks TRQ has a smaller likelihood to be preferable over FIT or FIP than under permanent shocks. This can be explained by the tendency of the TRQ to overreact, as seen in Fig.(5), which leads to a smaller efficiency loss if the parameter change to which it reacts persists throughout the second period.

	***imc*$_f$ uncertain**		***imc*$_r$ uncertain**		***demand* uncertain**	
	perm.	*trans.*	*perm.*	*Transitory*	*perm.*	*Transitory*
FIT vs TRQ	equal	Equal	$smc_r + le > smc_f$	$smc_r^2 + le^2 > smc_f^2$	$Imc_f - imc_r > d\ smc_f$, or if $smc_f=0$	$imc_f - imc_r > \frac{d\ smc_f\ (smc_r + smc_f - le)}{(smc_r + smc_f + le)}$, or if $smc_f=0$
FIP vs TRQ	FIP sup	FIP sup	FIP sup	FIP sup	$abs(imc_f - imc_r) > (d\ le\ smc_f)/(smc_r+smc_f)$	$imc_r - imc_f < \frac{d\ le\ smc_f}{(smc_r + smc_f)}\frac{(smc_r + smc_f - le)}{(smc_r + smc_f + le)}$ or $imc_r - imc_f > \frac{d\ le\ smc_f}{(smc_r + smc_f)}$
FIP vs FIT	FIP sup	FIP sup	$le < (smc_r + smc_f)/\left(1 + 2\frac{smc_r}{smc_f}\right)$	$le < (smc_r + smc_f)/\sqrt{1 + 2\frac{smc_r}{smc_f}}$	FIP sup, equal only if $smc_f=0$	FIP sup, equal only if $smc_f=0$

Table 1: Overview of analytical results. If the stated condition is met, then the first instrument dominates the latter.

Table 1 summarizes all analytical findings, allowing highlighting the following insights: First, under uncertainty on imc_f, the ranking of instruments is unaffected by whether uncertainty is permanent or transitory: FIP is always the most efficient choice, and FIT and TRQ are equivalent. This is the case because both TRQ and FIT are unresponsive to shocks in the marginal costs of fossil-based supply. They act as quantity instruments and Eq.(31) shows that as such they are dominated – because of the steepness of marginal costs – by the price instrument FIP.

Second, in case uncertainty is on imc_r, we again find an unambiguous superiority of FIP over TRQ, independent of permanent or transitory uncertainty. As before, this is due to the TRQ's behaviour as a quantity instrument and the ensuing lack of responsiveness to shocks. On the other side, the rank of the FIT is ambiguous: depending on parameter values, it could theoretically be the first-, second-, or third-best instrument choice. However, it always fares relatively better under permanent than transitory shocks, which – as said before – can be explained by its tendency to overshoot, whereas the other two instruments always react too little to shocks. If the shock is 'neutralized' in the second period, the error of overshooting in the first period becomes relatively more expensive.

Third, under demand uncertainty FIP dominates FIT, independent of whether uncertainty is transitory or permanent. The reason is that under demand uncertainty the FIT acts as a quantity instruments, fully equivalent to the TRQ under shocks in imc_r – and that marginal costs are steeper than marginal benefits. The relative performance of TRQ under demand uncertainty is a case in which the value of new parameters comes into play, namely $(imc_f\text{-}imc_r)/d$. It captures the error of TRQ and hence if this parameter is sufficiently large relative to smc_f, then TRQ will be dominated by both FIP and FIT. This is more likely more to be the case for the FIP than for the FIT, and under transitory than under permanent uncertainty. The latter can be explained by noting that FIP and FIT always under- respectively not react to a demand shock, which leads to less costly errors if the shock is transitory. The TRQ, on the other side, has a tendency to overreact, as illustrated in Fig.(3).[14]

Overall – if no further knowledge on the relative importance of the three sources of uncertainty is available – the FIP emerges as the most robust choice, as even in the worst possible case it still ranks 1st, 2nd, and 2nd with respect to uncertainty on imc_f, imc_r, and demand. This is in line with economic intuition: a per-unit subsidy on renewables most directly conforms to the idea of internalizing a positive learning externality. Indeed, in our model the FIP would be an optimal instrument if it were not for the scale-effect of learning which it does not capture – i.e. the fact that the benefit of a given cost-reduction is not constant but positively dependent on the future employment of renewables, since for each unit a benefit is realized. In other words, an optimal subsidy would not be constant, like the FIP, but increase with the size of the future renewables supply. This calls for a FIP set at a higher level for relatively expansive renewable sources, e.g. higher for PV than for onshore wind, and higher in locations with moderate wind speeds or sunlight than in locations with high wind speeds or sunlight. Note that some real-world renewable support systems (e.g. the FIT in Germany or France) already feature such differentiation but with a different rationale, namely to limit the differential rent for renewables in sites with the most productive resource. Our conclusions identify an alternative justification for this practice.

[14] For demand uncertainty, the four conditions regarding the performance of TRQ change if one considers the truly optimal setting of α for TRQ. However, the rigorous conditions are easily obtained by replacing d with $d\sqrt{(1+\sigma_d/d)}$, which makes it relatively easier for TRQ to meet the dominance conditions. In addition, the term 'imc_f-imc_r' must be changed into $abs(imc_f\text{-}imc_r)$.

If the size of the learning effect *le* is large, the FIP's error will also become large, which might justify the use of a FIT, especially if uncertainty is mainly associated with the renewables sector's costs and if the fossil-based sector's supply curve is relatively flat. The latter implies a weak interaction between renewables and fossil-based sector, which favours the FIT's effect of sealing off the renewables sector. Conversely, a TRQ might be justified if learning *le* is low, the fossil-based sector's supply curve is steep, and uncertainty is mainly rooted in demand. However, the TRQ will generally be prone to large inefficiencies if there is a marked difference in the marginal costs of the first output units between the two sectors ($(imc_f\text{-}imc_r)/d$).

Table 1 shows our results in full generality, where no assumptions on the cost structure of the renewable and fossil-based sector were made except that it must be consistent with an interior solution where both types of electricity are in the market. To allow for more conclusive insights, we may make two additional assumptions which are frequently found in the literature (e.g. Schmalensee 2012), namely that the supply curve of the fossil-based sector is relatively flat ($smc_f<smc_r$) and that the marginal costs of the first units of renewable electricity are lower than of fossil-based electricity ($imc_f>imc_r$). The resulting dominance conditions are listed in Table 2, showing that these additional assumptions drive out the TRQ completely, in particular when fossil-based supply is flat.

	imc_f uncertain		**imc_r uncertain**		***demand* uncertain**	
	perm.	*trans.*	*perm.*	*Transitory*	*perm.*	*Transitory*
FIT vs TRQ	=	=	FIT	FIT	→FIT for smc_f→ 0	→FIT for smc_f→ 0
FIP vs TRQ	FIP	FIP	FIP	FIP	→FIP for smc_f→ 0	FIP
FIP vs FIT	FIP	FIP	→FIT for smc_f→ 0	→FIT for smc_f→ 0	FIP, but equality if $smc_f=0$	FIP, equality if $smc_f=0$

Table 2: Analytical dominance conditions under additional assumption $smc_f<smc_r$,$imc_r<imc_f$, $le\neq0$.

5. Numerical Application to the US Electricity Sector

An analytical model cannot, by definition, inform on the quantitative difference in expected costs across instruments. Hence, based on the stylized US electricity sector model designed by Fischer and Newell (2008), this section provides numerical estimate of the instruments' performance. We incorporate three modifications of the original model so that it corresponds exactly to our analytical specification. First, we merge coal and gas into a single fossil electricity sector. Second, we exclude hydro and nuclear, assuming, as Fischer and Newell, that their supply is unaffected by the policies considered. Third, we assume that demand is inelastic and set it at its baseline value.

To calculate the value of *le* compatible with Fischer and Newell's model, we take their elasticity of learning of 0.15 and equalize it to our model's elasticity of the marginal cost in period 2 with respect to the amount of renewables in period 1: $\frac{\partial mc^{r,2}}{\partial q^{r,1}} \frac{q^{r,1}}{mc^{r,2}} = lr$ where *lr* is the learning rate. This calibration leads to the parameter values shown in Table 3.

Parameter	Value	Unit
imc_r	**0.059**	**\$/kWh**
imc_f	**0.0439**	**\$/kWh**
smc_r	**1.2*10^-13**	**\$/kWh²**
smc_f	**9.9*10^-15**	**\$/kWh²**
d	**3.05606*10^12**	**kWh**
le	**7.11764*10^-14**	**\$/kWh²**

Table 3: Values of the parameters for the numerical application.

The next step is to quantify each source uncertainty. To this aim, we use three real-world 'surprises', which happened after the Fischer-Newell model was calibrated: the decrease in fossil fuel prices in the US electricity sector due to the development of shale gas, the massive drop in PV cost after 2008, and the electricity consumption decrease due to the economic downturn in 2008-2009. In each case, we use a very simple way to quantify the magnitude of the shock, i.e. we compare the observed relevant variable after the shock to a hindcast based on a linear projection of the pre-shock trend. Since the relevant shocks have not vanished yet, we apply the model with permanent uncertainty. We calculate the total cost of meeting the electricity demand without the shock and, for each instrument, with the shock, which allows calculating, for each instrument, the extra cost compared to the *ex post* optimum.

For the uncertainty on the cost of fossil fuel-based electricity, we take the cost of coal, petroleum and natural gas for the electric power industry provided by the US DOE EIA (2013a). We calculate a linear trend for 2002-2008, extend the trend up to 2012 and compare this hindcast to the observed price for 2012 (latest year with published data). The difficulty is to build a counterfactual for the share of natural gas vs. coal, which is highly dependent on relative price of these two fuels. Using back-of-the-envelope calculation, we take -1 c\$/kWh as the illustrative shock on imc_f.

Concerning renewables cost, we illustrate uncertainty by the unexpected drop in PV cost which has happened since 2008, using data from Feldman et al. (2012, Figure 14). In 2008, the average analyst expectation for module selling price for 2010 Q4 in the US was 2.6 \$/W while the ex post observed average was 1.8, i.e. 30% below. Since PV is only one the renewable energies used to produce electricity and since wind power cost decreased also, but by a lower rate, we take -20% of p_1^{np} as the illustrative shock on imc_r.

Finally, we take the sales of electricity to final consumers in the US (US DOE EIA, 2013b) for 2001-2007 (i.e. just before the crisis), continue the trend line until 2012 and compare with the actual 2012 value, which is around 9% lower, so we take -9% as the illustrative shock on demand *d*.

Table 4 below displays the excess cost (compared to the *ex post* optimum and to the best instrument) of each instrument for each source of uncertainty.

	FIP excess cost		FIT excess cost		TRQ excess cost	
uncertainty	compared to ex post optimum	compared to best instrument	compared to ex post optimum	compared to best instrument	compared to ex post optimum	compared to best instrument
imc_f : - 1 c$/kWh	**396**	0	1317	921	1317	921
imc_r : -20% of p_1^{np}	1281	168	**1113**	0	4267	3154
d : -9%	29	5	98	74	**24**	0

Table 4: Excess costs of the instruments compared to the ex post *optimum (million US dollars of 2004). The excess cost of the best instrument is shown in bold.*

Although in each case total social costs are minimized by a different instrument, the FIP is either the best choice or very close behind, with an extra cost of only 168 million dollars in the worst case (compared to FIT under uncertainty on imc_r). Conversely, the TRQ generates a significant extra cost compared to FIP under uncertainty in imc_f (921 million dollars) and compared to both FIP and FIT under uncertainty on imc_r (respectively 3 and 3.2 billion dollars). It follows that in quantitative terms, if one assumes a similar probability for each of the three shocks considered, the overall preferred instrument is FIP, followed by FIT, and TRQ emerging as the worst one.

6. Conclusion

This contribution investigates the comparative performance under uncertainty of three types of renewable electricity support policies: (i) feed-in tariffs have been widely used in, e.g., Germany, (ii) tradable renewable quotas in some states of the US as well as in some European countries, and (iii) feed-in premia most recently, e.g., in Finland or Denmark (Ragwitz et al. 2012). The main economic rationale for employing these policies is to correct the potential market failure associated with external learning effects and imperfect appropriation of private R&D.

However, renewables being relatively young technologies, their future costs, e.g. the price of solar PV panels, are subject to considerable uncertainty. In such a setting, also the impact of renewable policies becomes highly uncertain, as illustrated by the solar PV explosion in Germany. Likewise, the price of fossil-based electricity and total electricity demand are inherently volatile due to, respectively, shocks in fossil fuel or CO_2 permit prices and business cycle dynamics.

To capture these stylized facts and assess their implications for policy instrument choice, this paper developed a theoretical model of an electricity market with a learning externality in the renewables sector. The simple structure of the model allows deriving the formal conditions that determine the welfare ranking of the three support schemes.

Reflecting the formal relatedness of our analysis to “Prices vs. Quantities” (Weitzman 1974), most of these dominance conditions are a function of the relative slopes of marginal costs and benefits associated with the policy, where the latter includes the learning effect. However, the specific instrument ranking depends on which type of uncertainty is considered, and whether shocks are permanent or transitory. In general we find that a high learning rate favours the FIT, and that TRQ is mostly dominated by the other two instruments. The latter result can be explained by the fact that the TRQ’s response to exogenous shocks, namely to preserve the relative share of fossil and renewable energy, is never optimal for cost shocks occurring in one of these two sectors, and only in very particular parameter settings for shocks in overall demand. The FIP, on the other side, performs increasingly bad if the size of the externality is large, because its underlying assumption of a *constant* positive external effect becomes increasingly at odds with the non-linearly increasing benefits from learning. Nevertheless, overall the FIP emerges as a robust choice that–if some common assumptions on the relative slopes are made–always figures as first or second-best performing policy.

The latter result is confirmed by a numerical application of our theoretical framework to the US electricity market, which builds on the stylized model of Fischer and Newell (2008). Although in each case total social costs are minimized by a different instrument, the FIP is either the best choice or very close behind, with an extra cost of only 168 million dollars in the worst case (compared to FIT under uncertainty on imc_r).

Naturally, several other and equally relevant criteria exist along which the three instruments may be compared, and where a different conclusion may be reached. This includes, e.g., the compatibility of the TRQ with political renewable targets which are often expressed in terms of a target share (EU strategy), the political economy argument that a FIT is easier to implement than a TRQ because it hands out a subsidy more directly (but at the same time may induce more rent-seeking behaviour), or the ability to overcome market power and strategic behaviour of large fossil-based utility companies. For instance, under a binding FIT the renewables sector becomes effectively isolated from the electricity market, as the price for suppliers is invariably fixed. Thereby it can counteract any prevailing market power of fossil-based firms. Conversely, in case of a TRQ, the green certificates markets efficiency may be reduced by the market power of large electricity producers, as seems to be the case in Flanders (Dubois et al. 2013).

Another aspect repeatedly emphasized in the literature is the importance of risk and how different instruments allocate risk across the involved actors (e.g. Fagiani et al. 2013). In particular, the low risk exposure to investors in renewable capacity has been seen as one of the main reasons for the effectiveness of the FIT (Butler and Neuhoff 2008). This low risk reduces the cost of capital (especially for smaller investors) and hence the cost of deploying a given amount of renewables (Gavard 2013). However, the higher risk to consumers implied by this scheme should also not be neglected, as they might face considerable uncertainty on future electricity prices, especially when the renewable policy instruments are financed through a levy on the consumer electricity price (or the risk to the public budget in case of direct state subsidies).

The implications of other differences between the three instruments are less obvious: e.g. to some the inability of the TRQ to discriminate between different renewable technologies represents a drawback, while to others it is a merit because it prevents the government from trying to choose a winner. Finally, an open but highly relevant question for future research is the one of instrument choice under policy overlap, i.e. the instruments' uncertainty performance in simultaneous presence of a cap-and-trade policy like the EU ETS.

In the real world many different aspects must be taken into account when choosing the most appropriate instrument, which is why it is so challenging to arrive at clear-cut conclusions. In view of this, we must qualify the contribution of our paper: it developed a model that is able to isolate one aspect–uncertainty–and show how the three different instruments are able to cope with it.

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Appendix

Proof of Proposition 2.2 (transitory uncertainty on *imc*^{r}):

First consider claim *(i)*: the coefficient for FIP is $le^2/(smc_r + smc_f)^2$, which by Eq.(7) is smaller than the coefficient of 1 found for TRQ. For *(ii)*: The coefficient of FIT is smaller than the one of TRQ if $abs\left(smc_f - \frac{le^2}{smc_r+smc_f} \right) < smc_r$, which for a positive valued parenthesis directly leads to the result, whereas in the case with a negative value one finds $le^2 - smc_r\, smc_f > smc_f{}^2$, i.e. a more stringent condition (one that is sufficient, but not necessary). To derive *(iii)*, one needs to evaluate

$$\frac{le^2}{(smc_r + smc_f)^2} < \frac{1}{smc_r} abs\left(smc_f - \frac{le^2}{smc_r + smc_f} \right) \qquad (A1)$$

Taking the parenthesis on the RHS to be positive, one obtains the condition. For a negative value one finds the condition $smc_f + smc_r < le$ that contradicts Eq.(7) and hence can never be fulfilled. □

Proof of Proposition 2.3 (transitory uncertainty on *d*):

We have the following coefficients (FIT, FIP, TRQ): smc_f , $(le^2\, smc_f)/(smc_r + smc_f)^2$, $\left(smc_r + smc_f - \frac{le^2}{smc_r+smc_f}\right) \frac{\alpha}{1+\alpha} - smc_f$. Claim *(i)* is shown by invoking Eq.(7) and noting that both coefficients become zero for smc_f=0. For claim *(ii)* we have to consider

$$smc_f < abs\left[\left(smc_r + smc_f - \frac{le^2}{smc_r + smc_f} \right) \frac{\alpha}{1+\alpha} - smc_f \right] \qquad (A2)$$

Evidently, this condition can only be met if the value in brackets is positive. By using the fact that α/(1+α) – the share of renewables – can be expressed as the ratio of the ex-ante optimal renewables output Eq.(12) and demand *d* the last equation becomes

$$2\, smc_f (smc_r + smc_f) < \left((smc_r + smc_f)^2 - le^2 \right) \frac{1}{d} \left(\frac{imc_f - imc_r + d\, smc_f}{smc_r + smc_f - le} \right) \qquad (A3)$$

which further simplifies to

$$\frac{2\, smc_f (smc_r + smc_f)}{(smc_r + smc_f + le)} < \frac{imc_f - imc_r}{d} + smc_f \qquad (A4)$$

Bringing smc_f to the LHS and further simplifying then yields the claim. Finally, for claim (iii) we depart from

$$\left(le^2\, smc_f\right)/\left(smc_r + smc_f\right)^2 < abs\left[\left(smc_r + smc_f - \frac{le^2}{smc_r + smc_f}\right)\frac{\alpha}{1+\alpha} - smc_f\right] \qquad (A5)$$

If the expression in brackets is positive, we get

$$\left(le^2/\left(smc_r + smc_f\right)^2 + 1\right) smc_f < \left(\frac{(smc_r + smc_f)^2 - le^2}{(smc_r + smc_f)}\right)\frac{\alpha}{1+\alpha} \qquad (A6)$$

The term α/(1+α) can be substituted by the ratio of ex-ante optimal renewables output and demand:

$$\left(le^2/\left(smc_r + smc_f\right)^2 + 1\right) smc_f < \left(\frac{(smc_r + smc_f)^2 - le^2}{(smc_r + smc_f)}\right)\frac{1}{d}\left(\frac{imc_f - imc_r + d\, smc_f}{smc_r + smc_f - le}\right) \qquad (A7)$$

which can be simplified to

$$\left(\frac{le^{\,2}}{\left(smc_r + smc_f\right)^2} - \frac{le}{smc_r + smc_f}\right) smc_f < \left(1 + \frac{le}{smc_r + smc_f}\right)\left(\frac{imc_f - imc_r}{d}\right) \qquad (A8)$$

and

$$-\frac{smc_f\, le}{\left(smc_r + smc_f\right)}\left(\frac{smc_r + smc_f - le}{smc_r + smc_f + le}\right) < \left(\frac{imc_f - imc_r}{d}\right) \qquad (A9)$$

Conversely, if the expression in brackets is negative we obtain

$$\left(le^2\, smc_f\right)/\left(smc_r + smc_f\right)^2 < \frac{-smc_f\, le}{\left(smc_r + smc_f\right)} - \left(1 + \frac{le}{\left(smc_r + smc_f\right)}\right)\left(\frac{imc_f - imc_r}{d}\right) \qquad (A10)$$

and

$$-\left(\frac{smc_f\, le}{smc_r + smc_f}\right) > \left(\frac{imc_f - imc_r}{d}\right) \qquad (A11)$$

which, together with the previous result, corresponds to claim *(iii)*. □

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