OPTIMAL EMISSIONS UNDER EXOGENOUS AND ENDOGENOUS LEARNING

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Overview

Defining optimal emissions and carbon price trajectories is crucial to inform climate policy. Many integrated assessment models have been developed to do so. For instance, the representative emission pathways are an important output in the Intergovernmental Panel on Climate Change (IPCC) reports. Technological change plays an important role in the transition to the climate objectives. We distinguish between exogenous and endogenous technological change. We define exogenous learning as a reduction in abatement costs resulting from technological spill-overs from other sectors. For example, membrane technologies, which are developed for many purposes in the chemical industry, will reduce costs of hydrogen production. This process is "exogenous", in the sense that it only depends on time. By contrast, we define endogenous learning as the technological change where marginal abatement costs are a function of the cumulative abatement. For example, photovoltaic cells would still be expensive today if they would not have been deployed at large scale.

Yet, we show that many models integrate the dynamics of technological change only partially. Among the main widely used models and in the IPCC reports, many do not include endogenous learning dynamics in their optimisation. It is also the case in many bottom-up energy models. Learning is often only exogenously included. In order to support this claim, we reviewed a wide range of models and found that only 17% of the models reviewed include endogenous TC. Therefore, better understanding the effect of learning dynamics on the optimal path will help one's analysis of the scenarios produced by those models, which disregard the incentive created by learning by doing for early abatement.

In this paper, we aim to shed light on the differentiated impact of endogenous and exogenous learning on the optimal mitigation path. This is highly relevant for 3 main reasons: learning dynamics matter when looking at the optimal path; many models do not include endogenous learning; the question of the impact of endogenous (versus exogenous) learning is not sorted out in the literature (only a few papers focused on this particular question).

Firstly, we start with a theory section where we proof some analytical results. We start by comparing a model with learning and a model without any learning feature. Abatement starts lower but follows a steeper path in a model with learning. In the case of exogenous learning, the growth rate of the carbon price is merely affected by learning. Since abatement costs are decreasing over time, the same carbon price will lead to more abatement in the future. This 'decreasing cost effect' steepens the abatement path. In the case of endogenous learning, abating a tonne of CO_2 today will not only avoid a stream of marginal damages (the so-called social cost of carbon) but make future abatement cheaper. Therefore, on top of the social cost of carbon there is also a 'social gain from learning'. This 'learning effect' reduces the growth rate of the carbon price, resulting in a flatter price path. However, we show that abatement path is still steeper because the abovementioned 'decreasing cost effect' dominates the 'learning effect'. We also investigate cost-effectiveness analysis, which minimizes costs under a temperature constraint, in contrast to cost-benefit analysis with maximizes welfare. For a given steady state temperature, cost-effectiveness results in a steeper path (insufficiently ambitious at the start) compared to a welfare-maximizing path. Ignoring endogenous learning exacerbates this problem. This further deteriorates the dynamic properties of cost-effectiveness, because not only does it ignore the timing of damages, it also ignores the timing of the learning gains.

Secondly, to give an insight into the magnitude of the learning dynamics effect in models, we develop an integrated assessment model with both types of learning. We analyse central scenarios including the different types or the absence of learning. Next, we try to isolate the 'pure' effect of learning for identical abatement costs in each period. We start with a model with exogenous learning. We construct a static MAC curve that goes through all the combinations of abatement and abatement costs of our optimal path. We show numerically that in this case exogenous learning has no effect on the optimal carbon price nor on the abatement path. This is not true for a model with endogenous learning. The model with endogenous learning will initially have more abatement and a higher carbon price, due to the learning incentives. Indeed, abatement does not only avoid future damages, it also leads to lower future abatement costs (the 'social gain of learning').

Methods

We consider a cost-benefit model where marginal abatement costs depend on time directly (exogenous learning) or on cumulative abatement A (endogenous learning), such that we can write the decrease of marginal abatement costs (MAC) over time as the sum of both processes: $\frac{dMAC(t,A)}{dt} = \underbrace{\frac{\partial MAC}{\partial t}}_{exogenous\ learning} + \underbrace{\frac{\partial MAC}{\partial A}\frac{dA}{dt}}_{endogenous\ learning}$

We maximise welfare which is notably dependent on the level of abatement “a” (climate mitigation is costly, but the cost can be reduced thanks to learning), on abatement speed “v” (we assume a penalty on abatement speed because of inertia, stranding assets,…) and on cumulative emissions “S” (more emissions lead to more climate damages).

The welfare functional writes: $max \int_0^\infty e^{-(\delta-n+(\eta-1)g)t}\frac{c_{BAU_0}^{1-\eta}}{1-\eta}e^{(1-\eta)\left(-\frac{\varphi_t}{2}a^2(A/A_0)^{-\chi}-\theta_1 v-\frac{\theta_2}{2}v^2-\frac{\gamma}{2}\zeta^2 S^2\right)}$

We compute the current value Hamiltonian and the first order conditions. We obtain a system of 4 equations in 4 variables after substituting equations. We solve the model in Matlab as as a boundary value problem using bvp5c function.

We fit the parameters of our model to the scenarios database of IPCC (scenarios of the 1.5 special report) and NGFS (Network for Greening the Financial System). We minimise squared deviations from both the marginal abatement costs and the total abatement cost and obtain ’best fit’ learning parameters from the databases. Note that we also include inertia due to stranding costs in our abatement function. This framework allows us to investigate the consequences of learning on the optimal abatement path and to focus on the differences among the impact of endogenous, exogenous learning and the absence of learning.

We also developed a methodology to isolate respectively the exogenous and the endogenous effect thanks to a polynomial fit (which allow the models compared to have exactly the same slope of MAC).

Results

We look at the optimal emissions, carbon prices and temperatures paths considering 4 central scenarios (two scenarios without learning, one scenario with endogenous learning and one with exogenous learning). We also perform a sensitivity analysis on the learning parameters and on the discount rate.

Theoretically, endogenous learning modifies the optimality condition: the social cost of carbon is not only the sum of all discounted marginal damages anymore, it also includes the sum of all future gains from endogenous learning. This leads to more abatement and a higher carbon price. Looking at the equation of the growth rate of abatement (the Euler equation), we see that both exogenous and endogenous learning lead to a decreasing cost effect on abatement. As to the endogenous case, this decreasing cost effect on abatement dominates the early learning incentive. In fact, both learning dynamics lead to a steeper abatement path. We confirm those findings numerically in our central cases. Moreover, among the results of our central scenarios, we find out that slight negative emissions only occur in the endogenous case (from 2270).

Next, we compare the exogenous learning path with a model where there is no learning, but identical marginal abatement costs, by fitting a polynomial. There are no visible difference (e.g., the difference in emissions is only of 0.009 $GtCO_2$ in 2050) between the 2 paths, hence apparently the exogenous learning dynamic has no effect on the optimal trajectory. However, doing a similar exercise but including the endogenous learning dynamic, we obtain less emissions through the whole period until 2100 and hence less warming at the end of the century. For instance, there is a difference of 1.88 $GtCO_2$ in 2050 (9.11%) and of 0.56 $GtCO_2$ in 2100 (5.78%) while the temperature is 3.01% higher in the exogenous case in 2100 (2.184° compared to 2.118°). Note that if we consider a lower discount, the differences become more significant: e.g. about a 20% emissions difference in 2050 and a temperature in 2100 of 1.667° in the endogenous case and of 1.746° in the exogenous case.

Conclusions

Optimal emissions trajectories produced by integrated assessment and bottom-up energy models are of essential need to inform policies. In this paper, we sorted out the question of the differentiated impact of endogenous and exogenous learning on the optimal path. It was highly relevant to do so given the facts that learning dynamics matter when looking at the optimal path and that many widely used models do not include endogenous learning.

We showed that as long as the model is well calibrated, the isolated exogenous learning dynamic (which is time dependent) has absolutely no effect on the optimal path, compared to a model where the cost of abatement depends only on the level of abatement (and not on time). We believe that this fact has not been highlighted before and is of interest to modellers: as long as the cost calibration is accurate, including exogenous learning does not impact the results. On the contrary, the endogenous learning dynamic has a significant impact on the optimal trajectory: it leads to less emissions throughout the entire period until 2100 and hence less warming at the end of the century. Thus, the common practice of modelling endogenous learning as an exogenous process underestimates the optimal abatement, leading to a higher warming at the end of the century. This is a strong conclusion for policy makers and modellers: one should keep in mind that trajectories coming from models without endogenous learning might not be ambitious enough.