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Modelling Complex Emissions Intensity Targets with a Simple Simulation Algorithm

CAMA Working Paper 33/2013 June 2013

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Abstract

Designing, modelling and analysing global emissions policies are becoming increasingly complex undertakings. Pressure on developing economies to make quantifiable emissions reduction commitments has led to the introduction of intensity based emissions targets, where reductions in emissions are specified with reference to some measure of output, generally gross domestic product. The Copenhagen commitments of China and India are two prominent examples. From a modelling perspective, intensity targets substantially increase the complexity of analysis, with respect to both theoretical design and computational implementation. Here, a clear and practically relevant theoretical design is used to present a new algorithm that can be applied to frameworks that model the complex interaction that occurs between emissions policy instruments, emissions levels and output effects under an emissions intensity target. The coding of the algorithm has been simplified to allow for easy integration into a range of modelling frameworks. Further development of the algorithm that allows for more complex theoretical design structures is possible.

Keywords

JEL Classification

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ABSTRACT

Designing, modelling and analysing global emissions policies are becoming increasingly complex undertakings. Pressure on developing economies to make quantifiable emissions reduction commitments has led to the introduction of intensity based emissions targets, where reductions in emissions are specified with reference to some measure of output, generally gross domestic product. The Copenhagen commitments of China and India are two prominent examples. From a modelling perspective, intensity targets substantially increase the complexity of analysis, with respect to both theoretical design and computational implementation. Here, a clear and practically relevant theoretical design is used to present a new algorithm that can be applied to frameworks that model the complex interaction that occurs between emissions policy instruments, emissions levels and output effects under an emissions intensity target. The coding of the algorithm has been simplified to allow for easy integration into a range of modelling frameworks. Further development of the algorithm that allows for more complex theoretical design structures is possible.

Introduction

Designing, modelling and analysing global emissions policies are becoming increasingly complex undertakings. Pressure on developing economies to make quantifiable emissions reduction commitments has led to the introduction of intensity based emissions targets, where reductions in emissions are specified with reference to some measure of output, generally gross domestic product (GDP). The Copenhagen commitments of China and India are two prominent examples. An intensity target for emissions allows there to be a range of possible emission and output combinations that are consistent with the intensity target. From a developing economy perspective, the intent is to increase flexibility and allow for continued growth and development¹ – for a given emissions intensity target, higher levels of GDP allow for higher emission levels. From a modelling perspective, intensity targets substantially increase the complexity of analysis, with respect to both theoretical design and computational implementation.

Theoretical design involves specifying the criteria for selecting a *particular* emissions and output combination that is consistent with the intensity target. This allows policy instruments to be modelled and heterogeneous policy options to be consistently compared across economies. In practice, theoretical design may involve balancing the economic and political implications of a wide range of policies that affect output.

Computational implementation involves developing the modelling tools capable of accounting for the complex interaction that occurs between emissions policy instruments, emissions levels and output effects under an emissions intensity target.² In this paper, a new algorithm, capable of balancing these effects in a modelling framework, is introduced. Specifically, the simulation algorithm is designed to generate a policy instrument path that results in a GDP and emissions level combination that: a) is consistent with an emissions intensity target for a given year; and b) minimises economic loss, as measured by the deviation in GDP from the baseline projection in the absence of policy. The coding of the

¹ For theoretical discussions on emissions intensity targeting, see Ellerman and Sue Wing (2003), Sue Wing et al. (2006), Quirion (2005), Jotzo and Pezzey (2007) and Marschinski and Edenhofer (2010). ² An emissions tax, for example, will affect both the level of emissions and the level of output. If an emissions

^{2} An emissions tax, for example, will affect both the level of emissions and the level of output. If an emissions intensity (emissions per unit of GDP) target is to be met, then these effects must be balanced in a way that meets the target.

algorithm has been simplified to allow for easy integration into a range of modelling frameworks. Further development of the algorithm that allows for more complex theoretical design structures is possible.

Debate over the effectiveness and efficiency of emissions intensity targets is beyond the scope of this paper. Lu *et al.* (2013) consider this debate with modeling results based on the algorithm presented here. The motivation here is to enable further research in this area by providing a relatively simple solution to the complex problem of modeling emissions intensity in a way that enables consistent comparison with emissions level targets.

Preliminary Assumptions

The problem under consideration is to find a single policy instrument path that results in an emissions and GDP combination that is consistent with an emissions intensity target for a particular target year. As discussed in the introduction, any given emissions intensity target could be satisfied with a range of emissions and GDP level combinations, and the first step in generating a solution is to define the criteria for selecting a particular combination.

In the algorithm presented here, the level of emissions and GDP are chosen so as to minimize any loss in GDP that results from the policy. This is defined as minimizing the deviation in GDP with reference to the model baseline projection for GDP in the target year³. This specification is relatively straightforward to implement and, given that the promotion of emissions intensity targets in international climate agreements has been driven by developing economies arguing against limits to growth, the specification is also relevant and appealing from a practical viewpoint.

To define the problem and its solution explicitly, let $R = (-\infty, \infty)$, $R_+ := [0, \infty)$, and $R_{++} := (0, \infty)$. Let $\varepsilon \in R_+$ be the emissions intensity target in year t and let $\tau \in R$ be the

³ Baseline model projections provide a 'base' from which to analyse alternative policy and shock scenarios. Projections of key variables generated from baseline assumptions are not necessarily designed to represent a forecast of the future – they are generally constructed conservatively under 'no policy' or 'no shock' assumptions so that the impact of alternative policies and shocks can be effectively analysed.

carbon policy that is implemented in year *s*, such that $s \le t$.⁴ In the scope of this paper, the carbon policy is assumed to be a carbon tax, or its price equivalence in a cap-and-trade system.⁵

Let *G* and *E* be model projections such that $G(\tau,t)$ and $E(\tau,t)$ correspond to the level of GDP and emissions in year *t* given policy τ , and $G(\tau,t)$, $E(\tau,t) \in R_+$. The baseline projections are denoted G(0,t) and E(0,t). For future reference, let us define the auxiliary function \hat{E} such that $\hat{E}(\tau,t) = \varepsilon \times G(\tau,t)$, and note that a fixed point exists where $\hat{E}(\tau,t) = \varepsilon \times G(\tau,t) = E(\tau,t)$.

The algorithm is intended to complement an existing, and generally complex, modeling methodology for assessing emissions and other climate related economic policy responses. The aim is to enhance the existing model properties, without compromising the complex dynamics on which the model runs and without sacrificing usefulness and relevance in the model results. The following four assumptions are designed to achieve this balance.

Assumption 1 There exists at least one policy $\tau^* \in R_{++}$ such that $E(\tau^*) = \hat{E}(\tau^*)$.

This assumption ensures that there is a solution to the problem.

Let τ_m be the minimum of all τ^* 's that satisfy $E(\tau^*) = \hat{E}(\tau^*)$. By Assumption 1, τ_m exists.

Assumption 2 The projection function E is continuous and weakly decreasing in τ .

This assumption implies that the policy instrument is effective for domestic emissions reduction. Assumption 1 ensures that increasing the carbon tax results in a reduction in the level of emissions.

⁴ The value of τ can be but not necessarily be negative.

⁵ Note that, with a variety of policy instruments (such as regulation, technology subsidies, or carbon planting) emissions intensity targets could be reached with a range of growth policies that may result in an increase in the level of emissions. Algorithm Assumption 2 rules out this possibility here but there is an important debate over the effectiveness of emissions intensity targets that needs further discussion. At this stage, it is not clear how the emissions intensity targets of China and India will be met in practice and what the outcome for the level of emissions will be. Lu et al. (2013) discuss these ideas further with specific reference to China.

Assumption 3 The auxiliary function \hat{E} is continuous. It satisfies $\hat{E}(\tau) = \varepsilon \times G(\tau) > \varepsilon \times G(\tau_m) = \hat{E}(\tau_m)$ for all $\tau \in [0, \tau_m)$; and \hat{E} is weakly decreasing on $[\tau_m, \infty)$.

Assumption 3 states that achieving the emissions intensity target incurs a higher economic cost than not doing so or doing less, and that the adverse impact of the carbon tax on economic output gradually becomes unambiguous. This assumption is satisfied when the projection function *G* is continuous and strictly decreasing in τ . A carbon tax is generally regarded as a negative policy shock to output. It is however possible that with a secondary tax revenue-recycling effect, GDP may jump up in response to the imposition of a sizable carbon tax. This secondary effect is most likely to occur when the carbon tax revenue is recycled to households as a lump sum transfer or used to cut the rates of other distortionary taxes, such as capital taxes. Rebound effects of this type have been noted by McKibbin *et al.* (2010) and Lu *et al.* (2012). McKibbin et al (2012) contains a discussion of different carbon tax revenue recycling schemes. Assumption 3 allows for this type of rebound effect⁶ (see e.g. Fig. 1 (c)) . It also allows for the possibility that overall gdp is unaffected, perhaps via structural adjustment mechanisms. Assumptions 2 and 3, together, ensure that τ_m leads to the highest GDP and emissions level combination (or, conversely, the smallest deviation in GDP).

Assumption 4
$$\frac{E(0,t)}{G(0,t)} > \varepsilon$$
; or equivalently, $E(0,t) > \hat{E}(0,t)$.

This is a necessary condition for the algorithm. The projections E(0) and G(0) are the "business as usual" (BAU) projections of emissions and GDP in the absence of an active carbon policy. Assumption 4 implies that the BAU carbon intensity projection will be higher than the economy's target and that an active carbon policy is therefore needed.

⁶ In an integrated assessment framework, GDP rebound due to avoided climate damage can be much more complex. This is not considered in the scope of this paper.

Fig. 1 contains some examples where Assumptions 1 - 4 are satisfied and Fig. 2 contains some examples where at least one of the assumptions are violated. More specifically, in Fig. 1, Example (a) corresponds to the scenario where only one policy solution to the emissions intensity target exists; Example (b) corrresponds to the scenario where there are two solutions – the algorithm will converge on solution b1, but it can be used to find all possible solutions (see footnote 4); Example (c) corresponds to the scenario where the rebound effects discussed above are prominent and the carbon tax is sufficiently low. It shall be shown that the algorithm works for all three examples. By contrast, in Fig. 2, Example (a) violates Assumption 1 as there is no policy solution to the emissions intensity target; Example (b) violates Assumption 3 which unrealistically states that carbon tax will continue to increase GDP over quite a wide spectrum; and Example (c) violates Assumption 4 because the baseline emission intensity is lower than the target and thus no mitigation is needed.

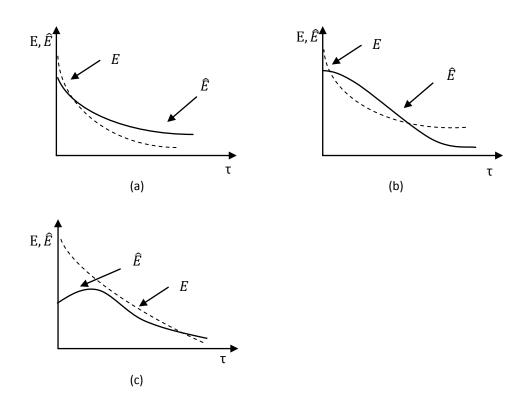


Fig.1 Examples Where the Algorithm Can Be Applied

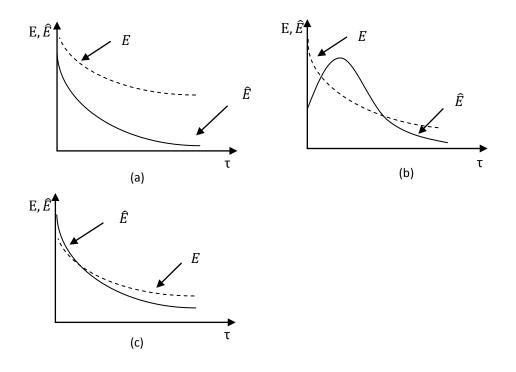


Fig. 2 Examples Where the Algorithm Cannot Be Applied

The Algorithm

For $k \ge 0$ and $\tau_k \ge 0$, define the operator T such that $\tau_{k+1} = T(\tau_k)$ and τ_{k+1} solves $E(\tau_{k+1}) = \varepsilon \times G(\tau_k)$.

Under Assumptions 1 - 4, the carbon policy that results in the smallest output loss can be found by the following algorithm⁷.

Algorithm: Searching	for a carbon	policy with	highest GE	P and emissions
- ingointening	101 0 000 000	, , , , , , , , , , , , , , , , , , ,	mgnese op	

set $\tau_0 = 0$	
Repeat	
set $\tau_{k+1} = T(\tau_k)$	
until $\tau_{k+1} = \tau_k$	
return $\tau^* = \tau_k$	

⁷ The algorithm can be extended to exhaust all solutions to a carbon intensity target, if more than one exists. The general method is to perturb the last solution, and then either follow the algorithm when solving for the odd solution, or reverse the algorithm when solving for the even solution. In example (b) of Panel A in Fig. 1, after solving for point E, it is possible to (1) perturb τ^* for ξ to the right, solve for τ' such that $E(\tau^* + \xi) = \varepsilon \times G(\tau')$; (2) continue solving for τ'' such that $E(\tau') = \varepsilon \times G(\tau')$ until it converges to the second solution τ^{**} .

An Illustrative Example

Consider Example (a) in Fig. 1. Assume an emissions intensity target of ε for year *t*. Step 1 involves setting the policy option to 0 (no active policy) and generating a baseline or 'business as usual' projection of GDP for the target year, denoted G(0,*t*) (see Step A1 in Fig. 3). In practice, the process of generating baseline projections can be complex and further discussion is beyond the scope of this paper. A detailed discussion can be found in McKibbin *et al.* (2007, 2009).

Under Step 2, an intermediate 'target' level of emissions, \hat{E} , is constructed using the equation $\hat{E}(0,t) = \varepsilon \times G(0,t)$. The operator *T* is then used to find $\tau_{k+1} = \tau_1 = T(\tau_0)$. τ_{k+1} is the policy path that generates a projected level of emissions equal to $\hat{E}(0,t)$ in the target year *t*. For example, if an economy has an emissions level target of $\hat{E}(0,t)$ for year *t*, τ_{k+1} could be the carbon tax rate profile that ensures this 'target' is met. Again, in parctice, the process by which this policy path is found can be complex and there are a variety of modelling techniques that can be used to define and estimate *T*. The algorithm presented here is designed to be flexible in its implementation and can be integrated with a range of policy projection frameworks. T is therefore left undefined. A practical illustration of its use in a dynamic general equilibrium modelling framework can be found in McKibbin *et al.* (2011) and Lu *et al.* (2012).

The policy projection τ_1 , has an associated GDP projection, $G(\tau_1, t)$ and an associated emissions projection, $E(\tau_1, t)$. The next step involves constructing $\hat{E}(1,t) = \varepsilon \times G(1,t)$ (Step B1 in Fig. 3). If $\hat{E}(\tau_1, t) \neq E(\tau_1, t)$, iterate over Step 2 for k > 1, until $\hat{E}(\tau_k, t) = E(\tau_k, t)$ and $\tau_{k+1} = \tau_k$. This process is depicted in Fig. 2. τ^* is the policy path associated with projections of GDP $G(\tau^*, t)$ and emissions, $E(\tau^*, t)$ in year t, that satisfy $E(\tau^*, t) = \varepsilon \times G(\tau^*, t)$ or equivalently, $\frac{E(\tau^*, t)}{G(\tau^*, t)} = \varepsilon$.

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Algorithm Properties

The algorithm is characterised by the following properties:

Property 1 For any $k \ge 0$ and $0 \le \tau_k < \tau_m$, $\tau_{k+1} \ge \tau_k$.

Proof. Suppose for a contradiction that $\tau_{k+1} < \tau_k$. Then by Assumption 2,

$$\hat{E}(\tau_k) = E(\tau_{k+1}) \ge E(\tau_k)$$

Since $E(0) > \hat{E}(0)$, if $\hat{E}(\tau_k) > E(\tau_k)$, then by continuity there exists $\tau_a \in [0, \tau_m)$ such that $E(\tau_a) = \hat{E}(\tau_a)$, contradicting the definition of τ_m ; if $\hat{E}(\tau_k) = E(\tau_k)$, then τ_k is a fixed point and by definition of τ_m we have $\tau_k \ge \tau_m$, again a contradiction.

Property 2 For any $k \ge 0$ and $0 \le \tau_k < \tau_m$, $\tau_{k+1} \le \tau_m$.

Proof. Suppose for a contradiction that $\tau_{k+1} > \tau_m$. Then by Assumptions 2 and 3,

$$\hat{E}(\tau_k) = E(\tau_{k+1}) \le E(\tau_m) = \hat{E}(\tau_m) < \hat{E}(\tau_k)$$

which is a contradiction.

Property 3 Let $\tau_0 = 0$. The sequence (τ_k) converges to τ_m .

Proof. This follows readily from Properties 1 and 2, and the monotone convergence theorem.

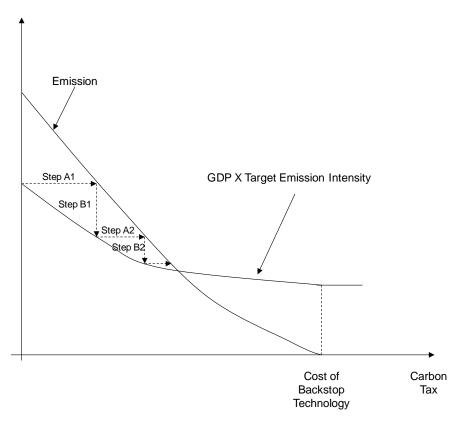


Fig. 3 The tatonnement process to targeted emissions intensity

Conclusion

The algorithm presented here provides a simple solution to the complex problem of modelling climate policy commitments specified in terms of an emissions intensity target. In practice, a variety of GDP and emission levels may satisfy an emissions intensity target in a given year and may be reached with a range of policy instruments. Within the current state of economic modelling however, assessing and consistently comparing policies that involve emissions intensity targets requires the specification of a particular policy path, and generally, a single comparable policy instrument. The assumptions made here are designed to balance the tradeoff that exists between transperant and practical model design and practically useful and relevant model results. The algorithm provides an attractive solution to the problem; one that minimises the economic loss, as measured by the deviation in GDP from a baseline projection in the absence of policy. Alternative specifications are possible, based on more complicated criteria for the particular policy path, by augmenting the basic algorithm presented here and are currently being explored in further research.

Acknowledgement

The authors gratefully acknowledge support from ARC (Australian Research Council) Discovery Grant DP0988281.

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