DREAM
Danish Research institute for Economic Analysis and Modelling

GREEN REFORM

Implementation of input-displacing abatement technologies in GreenREFORM

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1. Introduction

This memo describes how information on input-substituting technologies are directly integrated into production functions of nested CES-function in GreenREFORM.

The production in GreenREFORM consists of CES-functions. A central feature of these functions are constant elasticities of substitution between different production inputs. This means that firms react to e.g., increasing energy prices, by substituting energy for other inputs, e.g., capital. One way of interpreting these elasticities of substitution is that they are a "reduced-form" representation of a portfolio of technologies that firms can employ as a response to changes in input prices. In this interpretation, technologies should be broadly understood to include new machines, management practices, and workflows. In many cases, the elasticities of substitution can be estimated based on historical data (Kronborg et al., 2019). This is indeed what we aim to do in the GreenREFORM model.

In some cases, however, data exists on the costs and effects of specific technologies that firms can use. This information is available in so-called technology catalogs, which detail the costs and effects of concrete technologies. Incorporating such catalogs can be important when dealing with a field such as the green transition, where newly developed technologies may allow for more substitution – or substitution of a different kind – than what can be estimated using historic data. However, incorporating this type of information at a detailed level in a large-scale CGE model such as GreenREFORM is not an easy feat.

However, Berg, Leisner and Nielsen (2020) have recently developed a method of integrating technology catalogs in a large-scale CGE model. This companion memo outlines the specific implementation of the method in the GreenREFORM model. We start by briefly describing the method and discussing specifics of the implementation in GreenREFORM, We then proceed to outline some potential issues with the method and discuss how they are handled.

2. Input-displacing technologies in GreeenREFORM

We first discuss the methodological framework in the simplest possible form and we then discuss a series of extensions to the simple model that are used in GreenREFORM

2.1 The framework

The framework of Berg et al. (2020) can be described in following way. We consider a firm, which uses two energy inputs *i* and *j* in quantities and prices (q_i, p_i) and (q_j, p_j). The two types of energy is nested together in a CES-function to form the composite input q.

Consider a technology, which can reduce the use of energy input *i* at a cost. This technology is described in a technology catalog, from which we know that the technology can reduce a share $\theta_{i,i}$ of input i q_i at a cost of c per saved GJ. The convention is that a reduction corresponds to a $\theta_{i,i} < 0$.[1]

Consider for instance, a technology, which saves on gas input (q_i) in industrial drying processes by using a more energy-efficient dryer design. This new dryer can save a total of 10% of gas input, but at the cost of using more expensive machinery. The firm will apply the technology if savings exceed costs, i.e. if $p_i > c$.

We can rewrite this condition in terms of unit savings per energy input. We also introduce a price index for technology costs, p_k:

$$p_i > c \Rightarrow -\theta_{i,i} p_i > p_k \left(\left(\frac{c}{p_k} \right) * (-\theta_{i,i}) \right) \equiv p_k \theta_k$$

In this formulation, θ_k can be interpreted as the quantity of technological capital, which multiplied by the price, p_k, gives the technology unit costs per GJ saved. Another way to interpret this is to note that total costs of the technology are costs per saved GJ (c) times saved GJ. Saved GJ is equal to total baseline energy input q_i times savings potential $(-\theta_{i,i})$. So total costs are $c * (-\theta_{i,i}) * \frac{p_k}{p_k} q_i = p_k \theta_k q_i$, and unit costs are therefore $p_k \theta_k$.

Initially, this can be perceived as a discrete choice problem. Either the technology is applied or it is not. In GreenREFORM however, for technical reasons, this must be formulated as a problem with a continuum of possible solutions.

To bridge the gap, we introduce a continuous approximation of a discrete indicator function to control the use of the technology in the model. Specifically, we use the normal cumulative distribution function, and we call it the instantaneous adoption function:

$$f = \Phi \left(\frac{\theta_{i,i} p_i - p_k \theta_k}{\sigma} \right) \quad (1)$$

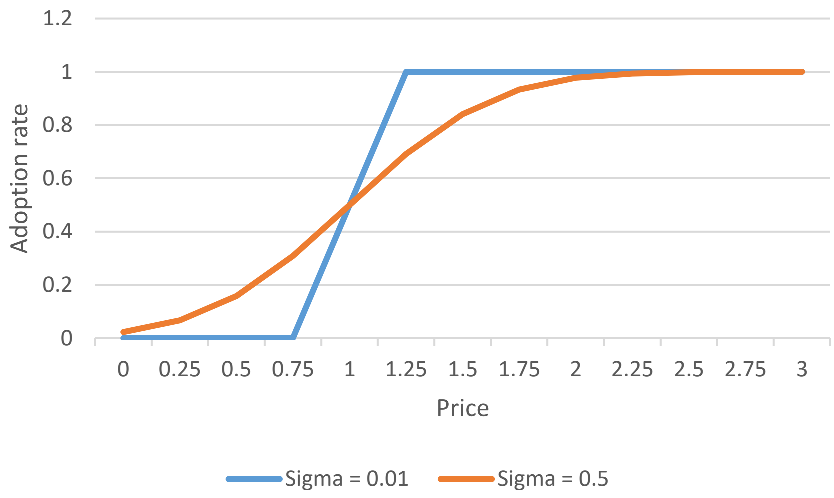
[1] This corresponds to the height and length of a single "step" on a standard stair-case shaped marginal abatement cost curve, which is often drawn as a summary figure illustrating the contents of a technology catalog.

The parameter σ controls the degree of smoothing. High values of σ reduce numerical complexity, but also introduce an interval of prices and costs, where only a share of the technology is adopted, i.e. where (1) evaluates to some value between 0 and 1.

Consider a simple example, where $\theta_i = -0{,}1$ and$c = 1$, i.e., a technology that can reduce the use of input i by 10% at a cost of 1 per reduced unit of input. This means that it is profitable to employ the technology when the price of q_i is above 1, ie. $p_i > 1$

Figure 2.1 illustrates the behaviour of the indicator for two different values of sigma for different prices.

Figure 2.1
Instantaneous adoption at different prices



Source: Own illustration

2.2 Baseline adoption of technologies

It often occurs that technologies described in technology catalogs appear to be profitable at current costs and prices, but are nevertheless not adopted. There are several potential explanations, including high discount rates (for an example on Danish data, see Andersen et al., 2020)) asymmetric information and mismeasurement of technology costs (e.g., Allcott & Greenstone, 2012).

It does, however, pose a practical problem for the method described here, as the model will predict adoption of technologies today, even when this is not true. In order to counteract this, we introduce a "cost multiplier", λ, in the indicator function. This means that firms only adopt the technology when the benefit is above some multiple of the cost. The modified expression for instantaneous technology adoption is therefore:

$$f = \Phi\left(\frac{-\theta_{i,i}p_i - p_k\theta_k\lambda}{\sigma}\right) \quad (2)$$

We calibrate a single λ that applies to all technologies. This preserves relative cost differences between technologies. However, it means that even technologies that are not profitable at the current prices now need an even larger increase in profitability before they are adopted.

The cost multiplier λ enters into the adoption function, but does not affect actual costs paid by the firm when they decide to use the technology. One way to interpret λ is therefore that technologies should be "sufficiently profitable" before they are adopted. This is similar in spirit to the assumption of "hurdle rates" of the IntERACT model, where firms are assumed to discount investments in new technologies at higher rates than the rate at which purchased equipment depreciates.

For some technologies, we may have a baseline adoption forecast. We therefore introduce a technology-specific "shadow tax", τ, which we calibrate in order to hit a baseline adoption rate. The shadow tax is not a proper tax, i.e., it is not paid by the firm. But the firm adopts technology *as if* it was paying this tax. This means that we expand (3) to the following expression:

$$f = \Phi\left(\frac{-\theta_{i,i}p_i - p_k\theta_k\lambda - \tau}{\sigma}\right) \quad (3)$$

2.3 Sluggish adoption

The method described above implies that when a technology becomes profitable, this technology is immediately adopted, i.e. adoption jumps immediately to the instantaneous adoption f in (3).

This may not be realistic. For instance, the variable costs of an old machine may be lower than the sum of the rental price and the variable costs of a new, more energy-efficient machine. In this case, the firm will not purchase a new machine before the old machine is no longer economically viable. In order to capture such effects, we model new adoption of technology as sluggish.

Also, when adoption is sluggish, it may not be optimal to adopt to the instantaneous adoption level at all. If agents are forward-looking, and they expect that the technology again will be less profitable in the future, e.g. if a technology subsidy disappears or if energy prices change, it may not be worthwhile to install the new technology to gain the temporary benefit of the new technology.

One way to model these effects would be to introduce a proper capital stock for each technology, and add convex installation costs on capital investments. However, this would introduce a lot of numerical complexity in the model in the presence of many technologies. Instead, we opt for a novel and more practical approach:

Actual adoption, $\bar{f}$, is controlled by a weighted average between the preferred adoption, $\hat{f}(t)$ and the actual adoption of last period, $\bar{f}(t-1)$:

$$\bar{f}(t) = a(x_t)\hat{f}(t) * (1 - a(x_t)) * \bar{f}(t-1)$$

The definition of the weight $a(x_t)$ gives flexibility in how actual adoption behaves. It has to satisfy that $a(0) = 1$ and that $\lim_{x\to\infty} a(x) = \lim_{x\to-\infty} a(x) = 0$. In the following, we use $a(x) =$

$e^{-x^2/\rho}$, where ρ controls how fast the function approaches 0 as the absolute value of x increases. This can for instance be calibrated by fixing how much adoption is expected in year 1, if a technology suddenly becomes profitable, i.e. if preferred adoption jumps from 0 to 1.[2]

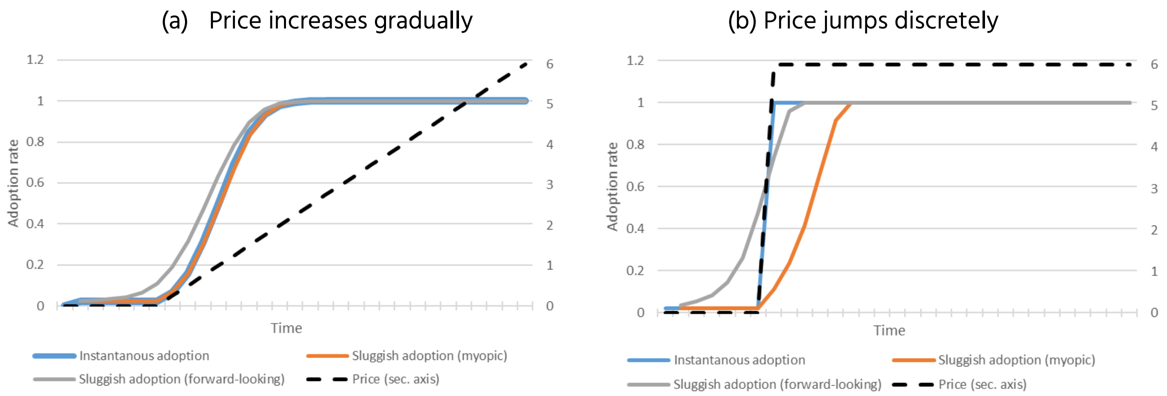
We further define $x_t = \hat{f}(t) - \bar{f}(t-1)$, i.e., as the difference between preferred adoption of the current period and last period's actual adoption. If the difference is high, the weight ($a(x)$) will tend towards 0, and if it is small it will tend towards 1. The formulation thus ensures, that adoption always moves sluggishly towards the preferred adoption, cf. figure 2.2 and 2.3.

If firms are not forward-looking in their technology adoption choice, we can model myopic adoption by letting 'preferred adoption' be equal to 'instantaneous adoption, i.e., $\hat{f}(t) = f(t)$ with $f(t)$ defined as in equation (3).

It is, however, relatively simple to introduce forward-looking behavior by letting preferred adoption be a forward-looking function of future preferred adoption rates: $\hat{f}(t) = \beta\hat{f}(t+1) + (1-\beta)f(t)$. This implies that the preferred adoption rate in year t is a weighted average between the instantaneous adoption rate in year t and preferred adoption in year t+1. It can be shown that this is the closed-form solution to infinite-period forward-looking behavior of the form $\hat{f}(t) = (1-\beta)\sum_{s=t}^{\infty}\beta^{s-t}f(s)$, where β is the time discount rate. We add an additional terminal condition in the final model year T, namely that $\hat{f}(T) = f(T)$.

In figure 2.2, we illustrate the behaviour of myopic and forward-looking sluggish adoption for two different scenarios. In figure 2.2.a, the price increases gradually over time. In figure 2.2.b, the price jumps discretely to a new, higher price.

Figure 2.2
Technology adoption when the price of energy subject to abatement increase

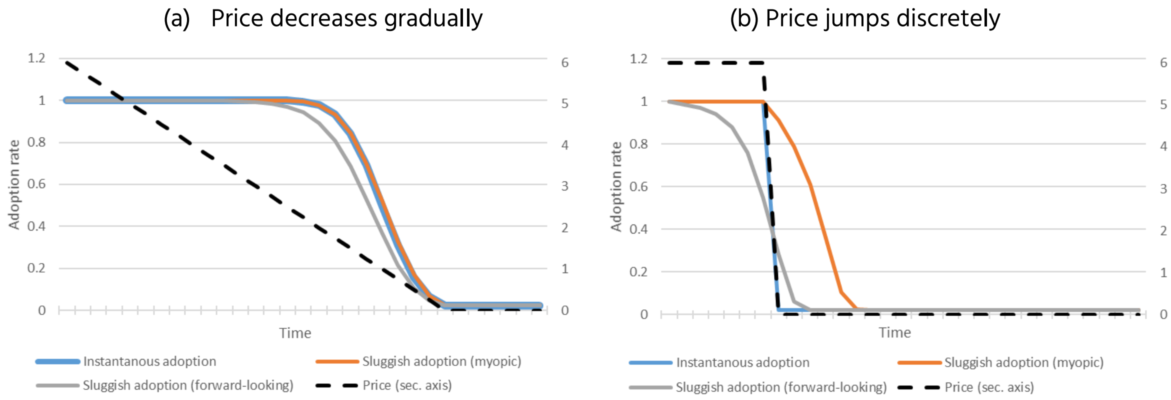


Source: Own illustration.
Note: $\sigma = 0.5, \rho = 0.4, \beta = 0.5.$

[2] For $\hat{f}(t) = 1$ and $\bar{f}(t-1)$, adoption of the technology in the first period, t, is $\bar{f}(t) = a(1) = e^{-1/\rho}$. For instance, for $\rho = 0.4$,, this means that first period adoption is around 8% of the total potential of the technologuy.

In figure 2.3, we illustrate the behaviour of sluggish adoption when prices fall and the technology is no longer profitable.

Figure 2.3 **Technology adoption when the price of energy subject to abatement fall**



Source: Own illustration
Note: $\sigma = 0.5, \rho = 0.4$. For the forward, looking expectations, we have used $\beta = 0.5$.

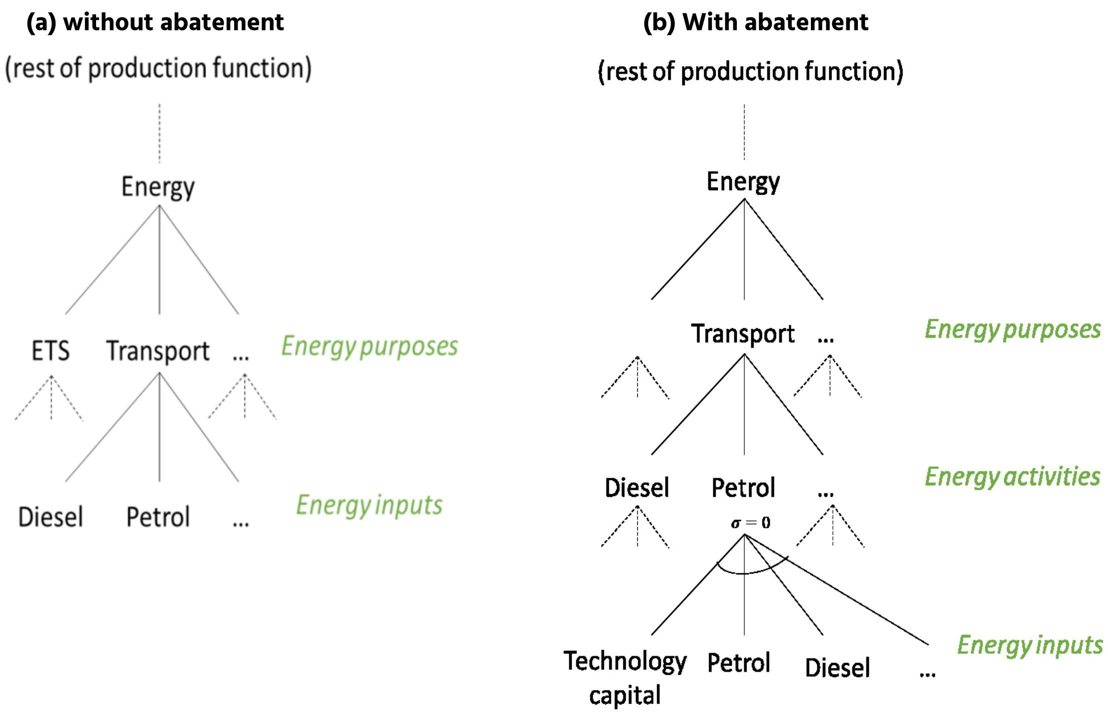
2.4 Integration

In this subsection, we describe how abatement adoption is integrated in GreenREFORM. However, before we do so, we introduce some additional model equations that complete our description of the framework of Berg et al. (2020) from section 2.1. The equations ensure that 1) abatement costs are paid as a substitute cost for using energy and 2) the framework extends to the case where a technology implies that energy demand *switches* from one type of input to another, i.e., if a diesel-powered truck is replaced by an electric one.

First, we introduce an additional Leontief nest in the production function. This nest aggregates "energy inputs" and abatement capital into "energy activites". The energy activities take the place of standard energy inputs in the model without abatement. In the absence of active abatement technologies, each energy activity take only one input, i.e. the oil-energy activity uses only oil as an input. However, when firms abate, the oil-activity reduces its demand for oil, but increases the demand for abatement capital. Such shifts are captured by $\theta_{i,j}$-parameters. The nesting structure is illustrated in figure 2.4 We now denote the energy activity q_i and the demand for energy into the energy activity q_i as $q_{i,j}$, where $q_i = q_{i,i}$ in the absence of abatement.[3]

[3] The equations of section 2.1 generalize to this more general framework; see Berg et al. (2020) for a more detailed discussion.

Figure 2.4
Nesting structure of energy with and without technological abatement



Source: Own illustration based on Berg et al. (2020).

When new technologies are introduced, q_i becomes a composite of energy input and other complementary inputs. It thus no longer has a readily interpretable unit of measurement. It does however do the task at hand of carrying the costs of both energy and any additional capital costs into the general modelling of the choice of production inputs in GreenREFORM. The demand for abatement capital as a means to reduce use of input *i* is now given as:

$$q_{tech} = \mu_{tech} q_i = f * \theta_k * q_i$$

The key idea is that the demand for technological abatement is proportional to the demand for the energy activity q_i; however, the Leontief parameter μ_{tech}, that controls how much technological capital that is required per q_i, is itself endogenous and is determined by technology use.

In a similar way, the demand for energy input j is now:

$$q_{i,j} = u_{i,j} q_i, \text{ where } u_{i,j} = \mu_{i,j} + f * \theta_{i,j} \quad (4)$$

In order to integrate the abatement module with the rest of the GreenREFORM model, two types of links are required. First, we need to specify what the abstract quantities and prices that firms pay in order to abate is made of and from where it is derived. Second, we need to specify how the changes to energy demand that arises from the abatement module is integrated into the rest of the model. We address these two issues in turn.[4]

Abatement costs: We assume that the costs of abatement technologies are made of the same composite good as other machinery investements that firms make in GreenREFORM. We can thus simply add the abatement costs as an extra demand component in the market for the machinery investment good. This also implies that the cost of abatement technologies should evolve proportionally to the cost of the investment good[5].

Changes in energy demand: The abatement module is constructed in such a way that the CGE model can run with or without the abatement module. This is accomplished with two adjustment terms in the CGE model in the key equations for quantities and prices of each energy activity.

The abatement module contains a price index for energy activities and new equations for energy demanded of type *i*, which includes energy demanded of type *i* by all energy activities, i.e., if a technology replaces diesel-powered trucks with electric ones, the demand for the diesel-activity is partly met through input of electricity. The total demand for electricity (*i*) is therefore the sum of electricity input demand across energy activities (*j*) and can be written as:[6]

$$q_i^{energy} = \sum_j q_{j,i}$$

The price index for the energy activity *i* is defined as:

$$p_i \ q_i \ = \sum_j [q_{i,j} * p_{i,j}] \ + f * c$$

The model integration feature the possibility to turn the abatement module on and off. When the abatement module is switched on, it determines the energy activity prices. This is done by exogenizing a set of adjustment terms in the CGE-model. In practice, the adjustment term equations in the CGE-model are specified as follows (for a single energy purpose in a single sector):

$$p_i = p_{i,i} + j_i$$
$$q_i^{energy} = q_i + j_i^q$$

When the abatement module is turned off, (i.e. when the j-terms are zero), energy activity prices are equal to energy prices. Further, the quantity of input demanded is equal to the quantity of the demanded activity.

2.5 Calibration

The calibration of the parameters is slightly complicated. This is caused by 1) the need to calibrate the cost multiplier before the shadow tax and 2) numerical issues owing to the

[4] We note here, that we started out by defining θ_k as $\theta_k \equiv \left(\frac{c}{p_k}\right) * (-\theta_{i,i})$. However, since technology potentials can vary over time, we allow the total technology cost in the model to change with changing potentials. Therefore, in the model, we actually calibrate $\tilde{\theta}_k \equiv \left(\frac{c}{p_k}\right)$ using the technology catalog information, and then use $\tilde{\theta}_k * (-\theta_{i,i})$ in place of a time-constant θ_k .

[5] This default approach may not always be optimal. If data permits, it is an easy extension of the model to change this so that abatement requires input from some other sector, or a vector of sectors.

[6] For ease of illustration, we continue to only consider the presence of a single technology, but results generalize easily

smoothness of the indicator function. The numerical issues stem from the fact that the indicator function (1) never truly evaluates to zero or one. This means no technology will have a true zero baseline adoption rate, although for low values of σ, baseline adoption can be very small.

The calibration procedure is done in two steps. First, the Leontief parameters (μ's) are calibrated using data in the years where data is available. As is standard in the model, the parameters are assumed to be constant in subsequent simulations. In the second step, technology adoption forecasts are used (where available) to calibrate technology-specific shadow taxes.

An issue with the procedure is that when there are technologies that allow secondary energy inputs to increase (as discussed in the end of section 2.1), this procedure can give rise to counterintuitive results. The reason for this is as follows: In the baseline data, energy activity *i* only uses energy inputs of type *i*. We calibrate Leontief parameters of the input of energy type *j* into energy activity *i* using equation (4), reproduced here for convenience:

$$q_{i,j} = u_{i,j} q_i, \text{ where } u_{i,j} = \mu_{i,j} + f * \theta_j.$$

In years where data is available, it is always the case that $u_{i,j} = 0$, i.e., only input *i* is used to produce the activity *i*. Therefore, when baseline adoption is nonzero, i.e. $f > 0$, we calibrate a negative $\mu_{i,j}$ in order to ensure that $u_{i,i} = 0$. If technology adoption then falls in the model forecast due to e.g. increases in technology costs, we will get $u_{i,j} < 0$, which implies that the sector will use a *negative* amount of energy of type *j*, which is of course not realistic. As these negative values will be quite small (since maximum baseline adoption is small), we do not expect that they will have any practical implications for the model, but we note it here for completeness and as a precautionary note for our own work.

3. References

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