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Boosting Sluggish Climate Policy: Endogenous Substitution, Learning, and Energy Efficiency Improvements*

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Abstract

There is widespread concern that climate policy is moving too slowly and that decarbonization of economic development is coming too late for effective climate protection. We analyze three different effects that emerge endogenously during decarbonization and amplify current policies: growing substitutability of dirty inputs with clean inputs, learning and scale effects in new renewables, and efficiency improvements in the application of energy. We employ the CITE simulation model, a computable general equilibrium (CGE) model with endogenous growth dynamics, to represent the macroeconomic framework of climate policy, calibrate the impacts, and obtain quantitative results. We use data for the Swiss economy and find that all three effects significantly accelerate decarbonization and markedly reduce the costs of climate policy, with increasing substitutability having the strongest impact. Targeted policies such as subsidies to clean energy and R&D may amplify these effects and thereby speed up the transition towards a carbon-free economy.

Keywords: CGE modelling, endogenous growth, energy efficiency, learning, elasticity of substitution, innovation, climate policy

JEL Classification: O31, O32, Q43, Q54, Q55, Q58

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1 Introduction

Current climate policies are increasingly considered insufficient and lagging behind necessary action (Depledge et al., 2022; Iyer et al., 2022). According to recent estimates, the target of maximum 1.5℃ warming will be missed due to geophysical, political, infrastructural, and technological inertia (Matthews & Wynes, 2022). However, predictions assume a linear development that disregards endogenous support mechanisms emerging during the transition to a low-carbon economy. Specifically, growing substitution possibilities as well as increased learning and scale effects support decarbonization efforts, thus amplifying current policy instruments and facilitating the energy transition. Disregarding these channels may lead to an overstatement of the economic costs of climate change mitigation. To date, most studies on environmental policies pay little attention to these channels and thus overlook their positive impact – potentially arriving to overly pessimistic conclusions.

In this paper, we study the policy implications of three effects supporting decarbonization: endogenously increasing substitutability of dirty inputs, induced learning effects in renewable energies, and policy-driven efficiency improvements in the use of energy. We use the computable general equilibrium model CITE (Bretschger et al., 2011), in which growth is fully endogenous, based on the increasing specialization of sector-specific intermediate varieties. CITE is the unique general equilibrium model that fully incorporates endogenous, innovation-driven growth in a multisector economy, providing an adequate modeling environment for dealing with the issues at hand. To quantify the effects, we calibrate the model for the Swiss economy. We find that the considered mechanisms can have a strong influence on the success of current climate policies and the optimal climate policy design. The three mechanisms in question – i.e. substitution, learning, and efficiency improvement – jointly reduce the optimal carbon tax in 2050 under a net-zero goal from 401 CHF to 232 CHF per ton of CO_2.

While the concepts of learning and scale effects have been scrutinized in empirical literature, in climate policy analysis they are often integrated as exogenous, stand-alone processes.[1] Such an approach overlooks the fact that policy itself might amplify these effects by stimulating investments in low-carbon and energy-efficient technologies, thereby accelerating the transition to a low-carbon economy. To the best of our knowledge, this is the first paper that integrates endogenous feedback effects of climate policy through the channels of learning, improving energy efficiency, and substitution intensity between clean and dirty energy inputs. Moreover, we add to the literature by combining endogenous growth based on the achievement of new growth theory (Romer, 1990; Grossman & Help-

[1] Gillingham et al. (2008), Pizer & Popp (2008), and Farmer et al. (2015) provide detailed reviews on the empirical evidence and modelling practices for technological change in climate policy assessment.

man, 1994) with endogenous substitution, learning and scale effects in a numerical CGE model. By accounting for empirically relevant feedback channels, we show that restrictive climate policies are less costly than commonly assumed. In the following, the three feedback effects and their empirical evidence in the decarbonization process are presented.

The elasticity of substitution between clean and dirty inputs is one of the major factors determining the feasibility and ease of the energy transition in macroeconomic frameworks. It governs the extent of possible expansion for renewable energy and thus the pace of decarbonization of the economy (Acemoglu et al., 2012; Carrara & Marangoni, 2017). Recent empirical findings suggest that the elasticity of substitution varies with time and relative use of renewable energies in production processes (Papageorgiou et al., 2017; Jo & Miftakhova, 2022). Despite the strong intuition that substitutability between clean and dirty inputs may change over time as renewable energy technologies and infrastructure evolve, this parameter has so far been treated as exogenous and constant in numerical studies of climate policy. It is therefore critical to take this dynamic property into account when designing climate policy, as the positive feedbacks resulting from the expansion of renewable energies could fundamentally change the outcome. This paper is the first attempt to integrate dynamic, endogenous elasticity of substitution into a numerical general equilibrium model. In our model, the degree of substitutability between clean and dirty energy updates with the expansion of clean technologies in production. We quantify the effect of having a dynamic endogenous elasticity of substitution as opposed to a constant exogenous counterpart and find that the former reduces the costs of climate policy by more than a half.

The feasibility of a rapid expansion of renewable energies is often questioned by the public and scientific community; among other things, because it is generally assumed that economic costs of the energy transition increase disproportionately with increasing abatement.[2] While this concept of "low-hanging-fruits" is certainly true for some sectors, the opposite is true for fast-developing renewable technologies such as wind and solar. For these technologies, costs decrease with increasing deployment due to strong learning and scale effects. The concept of learning-by-doing pioneered by Arrow (1971) is a well-documented, stylized fact within energy economics: Since 2010 alone, the costs for key renewable energy technologies have fallen substantially with the expansion of installed generation capacities: by more than 80% for solar PV and by more than 45% for onshore wind energy. A large body of research shows that learning rates (see, e.g., Rubin et al., 2015; McDonald & Schrattenholzer, 2001) and knowledge spillovers intensities (see, e.g.,

[2]For example, the DICE model assumes that costs increase as emissions are reduced (Barrage & Nordhaus, 2023), while Bretschger (2024) argues that learning and economies of scale in new energies reduce the costs of mitigation and accelerate decarbonization.

Bretschger & Zhang, 2017a; Dechezleprêtre et al., 2014) are generally higher for newer and cleaner energy technologies than for mature fossil fuel-based technologies. Besides, the expansion of production in the solar and wind sectors may follow a highly nonlinear process that includes tipping points and disruptive changes (Sharpe & Lenton, 2021; Lenton, 2020). Thus, the common approach of a linear extrapolation of past developments in these sectors is rather unrealistic (Way et al., 2022). In order to capture the higher learning potential and associated cost reductions, we introduce a non-linear scale effect for the wind and solar energy sectors.[3] The learning effect is triggered endogenously by climate policy (e.g. a carbon tax), which discourages the use of fossil fuels and promotes the expansion of renewable energies. Our simulations reveal a reinforcement effect between policy and learning: Both carbon tax and targeted subsidies can notably elevate learning rates for renewable energy sectors. Learning, in turn, can greatly amplify the effect of a policy and retain this effect even if the policy is phased out. Although learning *per se* does not have a major impact on the overall cost of reducing carbon emissions, it appears essential for growth and capital accumulation in the renewable energy sectors.

Energy inevitably enters the production process of every sector. A mitigation policy makes fossil fuels relatively more expensive and increases the incentives to substitute fossil energy sources with other inputs. As part of their mitigation strategy, producers may invest in the development and adoption of technologies that reduce their energy demand. In fact, there is ample empirical evidence that environmental policy promotes energy efficiency (Jaffe & Palmer, 1997; Popp, 2002; Gillingham et al., 2009; Bretschger, 2015; Da Cruz, 2022). Contrary to this intuition, the conventional CES specification of a production function in macroeconomic analyses implies that emission intensity can be reduced only by substituting away from fossil energy within a predetermined production process (that is, along a given isoquant). In our model, we include a mechanism of endogenous energy-efficiency improvements that arise from additional sectoral investments induced by a carbon policy. Since the incentives for innovations in the model are microeconomically based, it provides a unique modeling environment for capturing energy efficiency improvements as a function of sector-specific investments. We find that a carbon policy can induce substantial (up to 62%) energy efficiency improvements and R&D subsidies can accelerate the progress.

Our results contribute to the broad literature that suggests technological progress and clean energy expansion should be listed among the targets for an effective climate policy (Acemoglu et al., 2012; Gans, 2012; Greaker et al., 2018; Hart, 2019; see Popp, 2019 for the latest review). We adopt a comprehensive view of technological progress by jointly

[3] Here, we focus on the solar and wind sectors as they are expected to take on the major share of the expansion of renewables in the upcoming energy transition in Switzerland (SFOE, 2020).

modelling three policy-relevant channels of technological change and analysing their interplay in a multi-sectoral general equilibrium framework with endogenous growth. We highlight the importance of endogenising learning, innovation and energy efficiency for an appropriate assessment of climate policy.

Our most notable finding is that mitigation policy not only directly discourages the use of fossil fuels, but also stimulates innovation through the three internal channels mentioned above. Among these channels, endogenous substitution intensity has the strongest impact on the cost of mitigation and the growth path of the economy. A carbon tax alone can increase substitutability and substantially ease the achievement of the net-zero target. Combining the tax with subsidies to clean energy might further reduce the overall costs of mitigation thanks to the synergy between the two policy instruments. Subsidizing renewable energy also facilitates learning in these sectors, which proves crucial for sectoral growth. We also find a strong synergy between the two mechanisms of endogenous substitutability and learning, in that the learning rates are substantially higher when the degree of substitutability is determined endogenously. Finally, our analysis shows that a carbon tax promotes investments in sectoral energy efficiency improvements; complementary R&D subsidies can further strengthen the incentives to invest in energy-saving technologies.

The rest of the paper is organized as follows. Section 2 describes the CITE model and its calibration. Section 3 introduces the three effects and their individual implications. Section 4 presents a joint analysis of the three mechanisms and policy outcomes. Section 5 discusses the results and concludes.

2 CITE model

This section outlines the main features of the CITE model. The growth mechanism in CITE is endogenous and is based on increasing gains from the diversification of production driven by innovation and knowledge accumulation. As a result, sectoral output can grow not only by increasing input quantities, but also by expanding the number of intermediate varieties.

Production

The economy in the CITE model is represented by 18 economic sectors, which include ten non-energy sectors, three fossil energy sectors, and five renewable energy sectors. Figure 1 provides an overview of the production structure for each sector of the economy. The production process in every sector i comprises three levels. At the top level, final good, Y_i, is produced out of sector-specific intermediate composite, Q_i, as well as aggregate

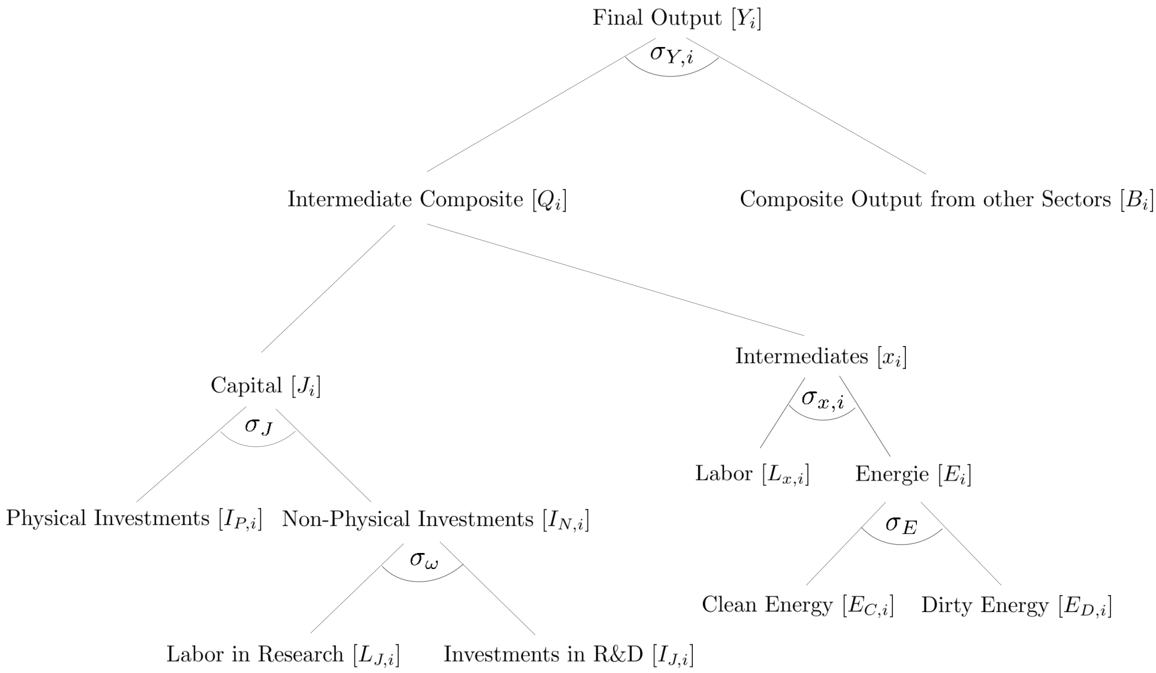

Figure 1: Sectoral production structure of the economy

input from all other non-energy sectors, B_i, using a CES production function[4]

$$Y_i = \left[\alpha_i Q_i^{\frac{\sigma_{Y,i}-1}{\sigma_{Y,i}}} + (1-\alpha_i) B_i^{\frac{\sigma_{Y,i}-1}{\sigma_{Y,i}}}\right]^{\frac{\sigma_{Y,i}}{\sigma_{Y,i}-1}}, \tag{1}$$

with α_i corresponding to the share parameter and $\sigma_{Y,i}$ to the elasticity of substitution. The parameter $\sigma_{Y,i}$ is sector-specific (see Table A.3 for the parameter values) and smaller than unity, so that the intermediate composite and intermediate inputs from other sectors are only substitutable to a limited extent. B_i corresponds to the output from the other sectors and captures the underlying input-output structure of the economy, i.e. the intersectoral linkages.

The production of each intermediate $x_{i,j}$ requires labor and energy as inputs (see below); the intermediates are then aggregated into sector-specific composite, Q_i, via Dixit-Stiglitz production function,

$$Q_i = \left[\int_{j=0}^{J_i} x_{i,j}^{\kappa} dj\right]^{\frac{1}{\kappa}}, \tag{2}$$

where $0 < \kappa < 1$ is a measure for the substitutability between the intermediate varieties. The number of varieties (or, equivalently, intermediate firms) in each sector, J_i,

[4]We omit the time indices wherever they are not critical for understanding the model's structure.

is determined by the amount of capital which is accumulated from physical ($I_{P,i}$) and non-physical ($I_{N,i}$) investments according to

$$J_{i,t+1} = \left[\upsilon_i I_{P,i,t}^{\frac{\sigma_J - 1}{\sigma_J}} + (1-\upsilon_i) I_{N,i,t}^{\frac{\sigma_J - 1}{\sigma_J}}\right]^{\frac{\sigma_J}{\sigma_J - 1}} + (1-\delta) J_{i,t} \ , \tag{3}$$

where υ_i denotes the share parameter, σ_J is the elasticity of substitution, and δ is the depreciation rate. Non-physical investments require labor in research, $L_{J,i}$, and non-labor inputs in R&D, I_J, according to

$$I_{N,i} = \left[\beta_i L_{J,i}^{\frac{\sigma_\omega - 1}{\sigma_\omega}} + (1-\beta_i) I_{J,i}^{\frac{\sigma_\omega - 1}{\sigma_\omega}}\right]^{\frac{\sigma_\omega}{\sigma_\omega - 1}} , \tag{4}$$

with β_i denoting the share parameter and σ_ω representing the elasticity of substitution between L_J and I_J. While the markets for final goods are perfectly competitive, intermediate firms operate under monopolistic competition and earn a mark-up $1/\kappa$ on top of the marginal costs of production – such that it covers investment costs. Hence, each sector can grow through either devoting more resources (labor and energy) to production of each intermediate or expanding the number of intermediates via intentional investment.

Intermediate goods $x_{i,j}$ are produced by monopolistic firms using labor, $L_{X,i}$, and energy E_i as inputs,

$$x_{i,j} = \left[\nu_i L_{X,i}^{\frac{\sigma_{x,i} - 1}{\sigma_{x,i}}} + (1-\nu_i) E_i^{\frac{\sigma_{x,i} - 1}{\sigma_{x,i}}}\right]^{\frac{\sigma_{x,i}}{\sigma_{x,i} - 1}} , \tag{5}$$

with ν_i denoting the share parameter and $\sigma_{x,i}$ representing the elasticity of substitution between the inputs. Here, too, we assume $\sigma_{x,i}$ to be sector specific and below unity (see Table A.3 for the parameter values). Finally, the energy aggregate required for intermediates' production is made out of clean ($E_{C,i}$) and dirty ($E_{D,i}$) energy,

$$E_{i,t} = \left[\phi_i E_{C,i,t}^{\frac{\sigma_E - 1}{\sigma_E}} + (1-\phi_i) E_{D,i,t}^{\frac{\sigma_E - 1}{\sigma_E}}\right]^{\frac{\sigma_E}{\sigma_E - 1}} , \tag{6}$$

with ϕ_i referring to the share parameter and σ_E to the elasticity of substitution between clean and dirty energy. Clean energy includes hydropower, solar energy, wind power and nuclear energy, while dirty energy comprises fossil fuels such as oil and gas. Table A.2 lists both energy and non-energy sectors in this economy.

Consumption

A household's aggregate consumption includes the consumption of energy and regular goods aggregated in a nested-CES fashion, as illustrated in Figure A.1. The country's population comprises five household groups, each group h representing an income and activity category.[5] The households are infinitely lived, forward-looking, have perfect foresight and preferences described by a CIES utility function. The instantaneous utility from consumption and leisure is discounted at the rate ρ. The households maximize their intertemporal utility, U_h, by choosing their consumption, $C_{h,t}$, and leisure, $L_{U,h,t}$, at each time t,

$$U_h = \sum_{t=0}^{\infty} \left[\frac{1}{1+\rho}\right]^t \frac{\left(C_{h,t} + L_{U,h,t}\right)^{1-\zeta} - 1}{1-\zeta}, \tag{7}$$

where ζ is the intertemporal elasticity of substitution. We consider no population growth and normalize total labor endowment to unity,

$$L_{U,t} + L_{X,t} + L_{J,t} = 1. \tag{8}$$

The representative households own all the assets in this economy, and therefore distribute their income between consumption and investments. The budget constraint of a household balances their total income from wages, capital rents, and transfers from the government with their consumption expenses, tax payments, and investment:

$$\sum_i p_{J,i,t+1} J_{h,i,t+1} = w_t(L_{X,h,t} + L_{J,h,t}) + \sum_i (1+r_t) p_{J,i,t} J_{h,i,t} - p_{C,t} C_{h,t} + T_{h,t}, \tag{9}$$

where w_t stands for wage, r_t for interest rate, and T_t for net transfers at time t. Maximizing (7) with respect to (9) gives the optimal consumption growth rate $g_C \equiv \frac{C_{t+1}}{C_t}$ that resembles the standard Keynes-Ramsey rule

$$g_C = \left[\frac{1+r_{t+1}}{1+\rho} \frac{p_{C,t}}{p_{C,t+1}}\right]^{\frac{1}{\zeta}}, \tag{10}$$

where $P_{C,t}$ is the price of consumption in period t. According to Equation (10), a higher interest rate r stimulates growth by inducing more savings, whereas a higher discount rate ρ gives incentives to increase current consumption, at the expense of future growth. The discount rate follows from the equilibrium growth path in (10). Along the BGP, it must hold that $\frac{P_{C,t}}{P_{C,t+1}} = 1 + r$, so that the discount rate is determined endogenously by

$$\rho = \frac{(1+r)^2}{g_C^{\zeta}} - 1. \tag{11}$$

[5] The households are split into three working groups (with low, medium, and high income levels) and two retired groups (with low and high income levels). For the calibration purposes, leisure is defined as the complement of the labor force participation rate, based on the data on income and labor force participation rate provided by the Swiss Federal Office of Statistics. More details on households' categories and the calibration of the consumption side can be found in Karydas & Zhang (2017).

We assume that the intertemporal elasticity of substitution $1/\zeta$ is equal to 0.85, which yields a rather conservative discount rate of 0.03%, implying very high intergenerational altruism in the spirit of the Stern Review (Stern, 2007). A full list of the parameters' values used in calibration is provided in Table A.3 of the Appendix.

International Trade

CITE considers an economy that is open to trade on the goods market and takes foreign prices as exogenous. We model international trade following the Armington approach (Armington, 1969), according to which domestically produced and imported goods are imperfect substitutes in each sector. The imported and domestic goods are combined into aggregate Armington goods represented by the composite input B_i, which enters the the production of final goods at the top level. The economy exports and imports regular and energy goods and also purchases oil and natural gas from abroad. Trade is balanced in every period and asset trade is disregarded. A more detailed describtion of the nesting strcuture is provided in the Section A.1 of the Appendix.

Calibration and Solution

We calibrate the CITE model to represent the Swiss economy based on the Swiss Input-Output Table (IOT), Energy Input-Output Table (EIOT), and the Household Budget Survey data (HABE) for the year 2014.[6]

The economy is assumed to be in equilibrium prior to any interventions. In the dynamic setting, this assumption translates into the balanced growth path (BGP), along which all sectors and the key variables grow at the same rate. A growth rate of 1% per year approximates the expansion of the Swiss economy over the last two decades.[7] The interest rate for capital, r, is set to 0.6% to reflect the average value of the interest rate set by the Swiss National Bank (SNB).[8]

The model is written in a mixed-complementatiry format using the General Algebraic Modeling System (GAMS) and its MPSGE subsystem (Rutherford, 1999) and solved by the PATH solver (Ferris & Munson, 2000). Our analysis spans 25 years – from 2025 to 2050 – with a time step of 5 years.

Baseline and Policy Scenarios

We consider three types of scenarios summarized in Table 1. In the baseline scenario, a carbon tax ensures reaching a given policy target. Policy targets are defined as the

[6]The IOT and HABE data are provided by the Federal Statistical Office of Switzerland. Nathani et al. (2019) document the EIOT. 2014 is the latest year for which the EIOT is available.

[7]According to the World Bank Open Data, the last 10- and 20-year average growth rates for GDP per capita in Switzerland are 1% and 1.03% correspondingly. The data can be retrieved from https://data.worldbank.org/indicator/NY.GDP.PCAP.KD.ZG?locations=CH.

[8]The data on the interest rate policy of the SNB can be retrieved from the website of the Bank for International Settlements (BIS) at https://www.bis.org/statistics/cbpol.htm.

amount of CO_2 emissions allowed in 2050 in percent of the initial emissions level in 2025. For example, a baseline scenario with a 40% target implies that only 40% of the initial emissions level can be emitted in 2050 (that is, the emissions are reduced by 60% within the modeled period). The carbon tax increases gradually over time until this target is reached.[9] Taxing carbon emissions leads to an increase in fossil fuel prices and thus influences profit opportunities of individual intermediate goods producers in each sector. As a result, the incentives to invest in new capital varieties differ across sectors, which affects, among others, the structural composition of the economy, the interest rate, consumer prices and the growth rate of consumption in (10). Most of the figures below present the results across different policy targets, but we keep our focus on the net-zero case. By definition, none of the three mechanisms are considered in the baseline scenario. Instead, the effects of each of the mechanisms and additional policy instruments are compared to the baseline outcomes.

The second type of scenarios engage the three endogenous mechanisms and demonstrate their individual and joint implications. These scenarios, just like the baseline scenario, use carbon tax as a sole instrument to reach a policy target. They therefore demonstrate the effect of accounting for the supporting mechanisms on the economy's pathway to its carbon target.

Baseline Scenario	**Scenarios with Feedback Mechanisms**	**Scenarios with Feedback Mechanisms & Complementary Policies**
Carbon tax Nuclear phase out by 2035 NET/CCS from 2035	Carbon tax Nuclear phase out by 2035 NET/CCS from 2035	Carbon tax Nuclear phase out by 2035 NET/CCS from 2035
	Endogenous feedback mechanisms: Endogenous substitution Learning mechanism Energy efficiency mechanism	**Endogenous feedback mechanisms:** Endogenous substitution Learning mechanism Energy efficiency mechanism
		Complementary policies: Output subsidy for wind and solar R&D subsidy for non-energy sectors

Table 1: Overview of scenarios

The last set of the scenarios is aimed at exploring the potential of additional, targeted policy instruments to engage and amplify each of the three endogenous effects. The additional instruments considered here are output subsidies for renewable energy sectors and R&D subsidies for non-energy sectors. The following sections explain the relevance of each instrument to one or more of the mechanisms.

To obtain realistic predictions for the transformation of the Swiss energy sector, all simulated scenarios include nuclear phase-out as planned by the Swiss government. In

[9] Note that we do not use a business-as-usual scenario that would have no policy in place. Instead, all simulations are compared to the baseline scenario where none of the three mechanisms are in place and carbon tax is the sole policy instrument used.

accordance with the schedule in the Energy Perspectives 2050+ (SFOE, 2020), the generation of nuclear energy is phased out to zero by 2035.

Furthermore, in all simulated scenarios, negative emission technologies and carbon capture and storage technologies (NET/CCS) are assumed to be available starting from 2035. Their availability is limited to the amount specified in the Energy Perspectives 2050+ (SFOE, 2020). Arguably, the assumption on the costs of these technologies is highly speculative in the absence of reliable estimates or projections. Here, we assume the costs to be 300 CHF/tCO_2. A sensitivity analysis shows that the level of these costs affects the optimal values for the carbon tax required to achieve the reduction targets; however, it does not affect qualitative conclusions of our study.

Here, we abstract from the distributional and fairness considerations, in that we consider lump-sum redistribution of the tax revenues; subsidies in the follow-up scenarios are also collected from consumers.[10]

3 Endogenous effects during decarbonization

In this section we introduce three endogenous mechanisms that might interact with decarbonization policies and amplify their effects. By way of illustration, Figure 2 locates these mechanisms in the model's production structure: The endogenous elasticity of substitution in the production of the energy aggregate (highlighted in purple) determines the degree of substitutability between clean and dirty energy inputs. The mechanism for improving energy efficiency (marked in blue) determines how much energy is used in the respective sectors for the production of intermediates. The learning mechanism (highlighted in red) is reflected in the speed of capital accumulation from physical and non-physical investments. In the following, we discuss the implementation, calibration, and implications of each of the mechanisms in CITE.

3.1 Endogenous elasticity of substitution

The elasticity of substitution between clean and dirty inputs plays a critical role in evaluating the impact and costs of a policy in climate policy analysis; in extreme cases the very feasibility of a policy target depends on this value. To illustrate this, we simulate climate policy outcomes in the CITE model using different values for the elasticity of substitution. Figure 3 shows the aggregate welfare level as a function of the value for

[10] An interested reader is referred to Rausch et al. (2011) and Landis et al. (2019) for analyses of the impact of carbon taxation and other policy measures across heterogeneous households. Ohlendorf et al. (2021) offer a meta-study of the empirical evidence on the distributional impacts of market-based climate policies. Karydas & Zhang (2017) consider both efficiency and fairness of using carbon tax revenues to reduce the existing tax distortions. Future research would inarguably benefit from an exploration in the spirit of this literature.

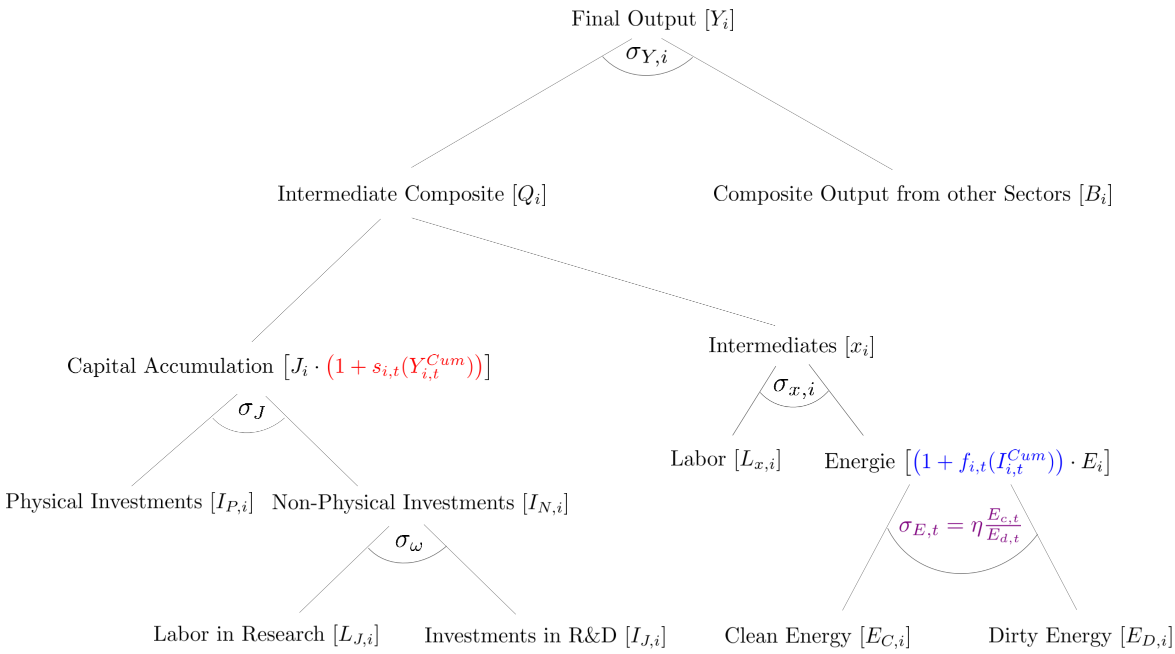

Figure 2: Location of the three feedback channels in the CITE model

constant elasticity of substitution in the energy composite when policies of different stringencies are in place. The costs of a policy in terms of welfare corresponds to the difference between the level of welfare under the policy and the level under the business-as-usual scenario, here normalized to one. A simple examination of the welfare implications of the degree of substitutability between clean and dirty energy suggests that it is a key determinant of policy costs.

For example, if emissions are reduced to 40% of their benchmark level ("0.4" line on the graph), an initial increase in elasticity of 0.5 leads to an increase in welfare levels of around 2 percentage points. The costs only flatten out when the elasticity exceeds the value of 3. This figure alone suggests that the expansion of clean energies is associated with a higher substitutability, which is supported by the empirical literature (Jo & Miftakhova, 2022). Therefore, policies that can exploit the positive feedback effects of clean energy expansion can greatly ease the path to the ultimate policy goal.

To integrate the concept of endogenous elasticity of substitution between clean and dirty energy, we extend the CES formulation for the energy aggregate by allowing its elasticity parameter to adjust dynamically,

$$E_{i,t} = \left[\phi_i E_{C,i,t}^{\frac{\sigma_{E,t}-1}{\sigma_{E,t}}} + (1 - \phi_i) E_{D,i,t}^{\frac{\sigma_{E,t}-1}{\sigma_{E,t}}} \right]^{\frac{\sigma_{E,t}}{\sigma_{E,t}-1}}. \tag{12}$$

The possibility to substitute clean energy for dirty grows with the expansion of renewable

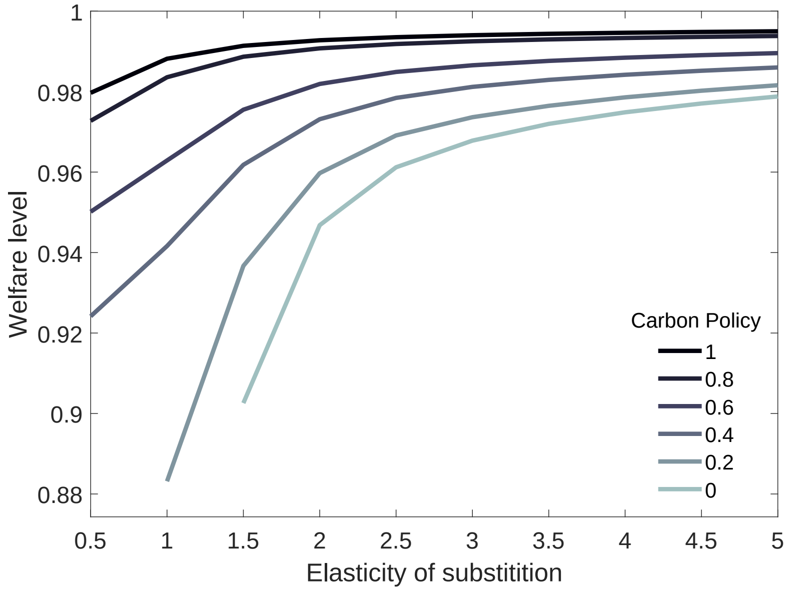

Figure 3: Welfare level as a function of constant values for the elasticity of substitution between clean and dirty energy, for policies of increasing stringency. Policy stringency corresponds to CO_2 emissions target in 2050 as a percentage of the benchmark emissions in 2025. The benchmark welfare level in the business-as-usual scenario is normalized to unity.

energy – such that the elasticity of substitution, $\sigma_{E,t}$, is determined by their ratio,

$$\sigma_{E,t} = \eta \frac{E_{C,t}}{E_{D,t}} \ , \tag{13}$$

where η refers to the substitutability parameter that governs this relationship. Based on the empirical estimation in Jo & Miftakhova (2022), we set η to 3.076.[11,12]

The elasticity of substitution between clean and dirty energy is therefore an endogenous dynamic variable that essentially reflects the economy's transition to clean energy. Figure 4 shows the resulting dynamics for the elasticity of substitution under policies of increasing stringency. Starting from the initial value of slightly below 3 in 2025, the

[11]The estimation of η is based on plant-level data from the French manufacturing sector, the Enquête sur les Consommations d'Énergie dans l'Industrie (EACEI). The dataset provides information on energy consumption and expenditure over the period 1989–2017. The data exhibits large variation both in the demand and price of clean and dirty energy at the micro level, which facilitates the identification of the parameter of interest. Specifically, η is estimated by regressing the CES estimates of the elasticity of substitution on the contemporaneous share of clean to dirty energy. See Jo & Miftakhova (2022) for the details of the data structure and estimation.

[12]To solve the model with the endogenous elasticity of substitution numerically, we update the value for the elasticity of substitution iteratively until it converges to the value specified in (13). The stopping rule for the iterative algorithm is $|\sigma^{old}_{E,t} - \sigma^{new}_{E,t}| < \varepsilon$, with a tolerance criterion $\varepsilon = 10^{-6}$. We apply the same iterative strategy for the two other mechanisms described below. For each mechanism, we compare this iterative approach with including the nonlinear relationship (e.g., Equation (13)) directly in the optimization problem. We find that the two approaches yield similar results. We thus resort to the iterative approach as it eases the joint analysis of the three mechanisms.

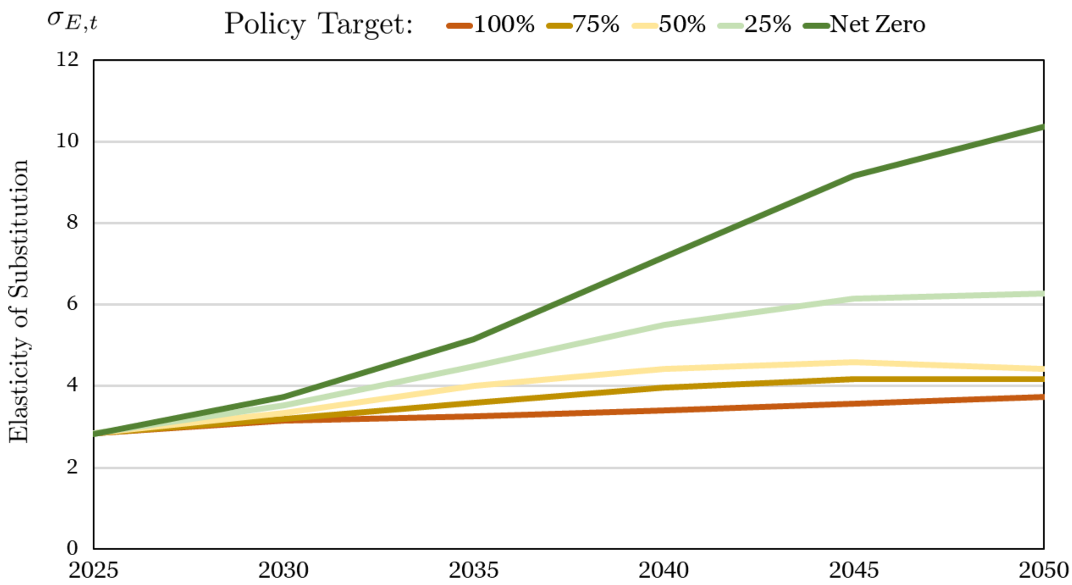

Figure 4: Dynamics of the endogenous elasticity of substitution under policies of increasing stringency. Policy stringency corresponds to the CO_2 emissions target in 2050 as a percentage of the benchmark emissions in 2025.

elasticity of substitution only moderately increases in the first five years. However, already by 2035 the differences in its dynamics across policy targets become apparent – the values range from just above 3 for moderate policies to 5 for the case of full decarbonization. Even the mildest policy target of non-increasing emissions (i.e., policy stringency of 100%) increases the elasticity of substitution slightly, raising it to a value of almost 4 by 2050. Under the net-zero target, the value for the elasticity of substitution exceeds 10 by mid-century. The disproportionate increase in this parameter following the carbon reductions above 50% indicates that strict policies are enforcing the expansion of clean energy.

More aggressive carbon policy, apart from being more costly, ensures a steeper substitutability profile – which in turn enables faster and *less* costly decarbonization. To quantify this positive feedback effect for the economy, Figure 5 compares the policy costs in terms of welfare between a constant and a dynamic substitution elasticity. In the presence of the endogenous substitutability mechanism, the policy costs do increase with stricter emissions targets, but they stay below 0.5% of the aggregate welfare level even in the case of full decarbonization. In the absence of this mechanism – that is, in the baseline scenario – these costs can be up to two times higher.

Figure 6 translates these results into the economy's growth rates. Stringent carbon policies expectedly lead to slower growth for the economy. This effect, however, can be offset to a large extent by higher energy substitutability. In the extreme case of the net-zero target, this offset amounts to 0.063 percentage points of difference in the economy's annual growth rates.

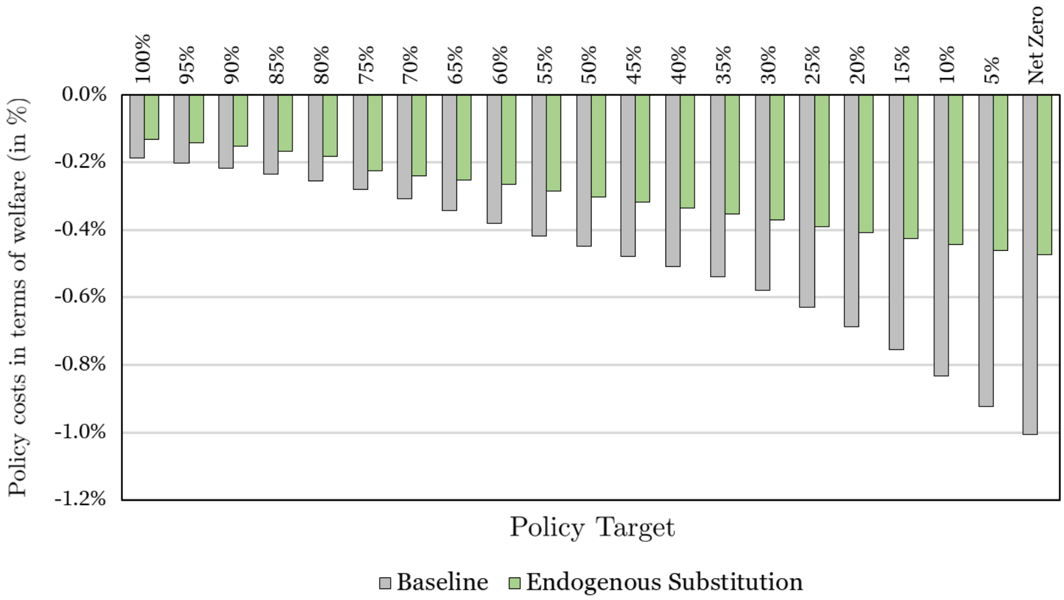

Figure 5: Policy costs in terms of welfare in the cases of constant (baseline) and dynamic (endogenous) elasticity of substitution, in percentages of the baseline welfare level.

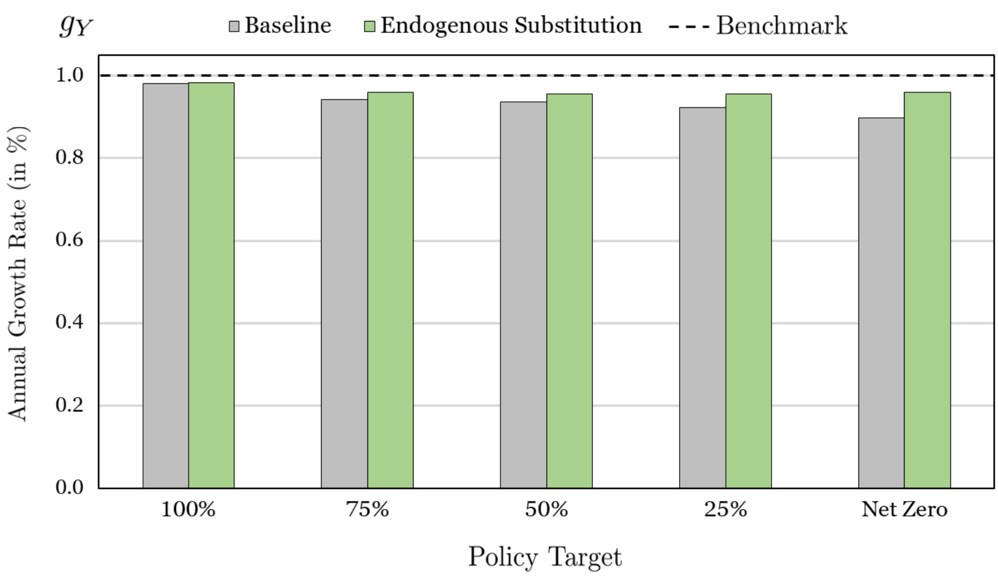

Figure 6: Annual aggregate growth rates of economy in the cases of constant and dynamic (endogenous) elasticity of substitution under policies of increasing stringency.

Complementary Policy: Output Subsidy for Wind and Solar

Notably, the pronounced effect of endogenous substitutability on the economy's decarbonization path is driven solely by carbon tax, which drives clean energy expansion. One possibility to engage this mechanism directly is to introduce subsidies to renewable energy. Here, we explore two scenarios of output subsidies to the solar and wind sectors – one with constant and one with decreasing subsidy profile. In the first scenario, a constant subsidy of 30% is given to the producers in the two sectors throughout the modelled

Policy Scenarios		
Year:	Constant subsidy:	Decreasing subsidy:
2025	30%	30%
2030	30%	25%
2035	30%	20%
2040	30%	15%
2045	30%	10%
2050	30%	5%

Table 2: Output subsidy profiles for wind and solar energy sectors

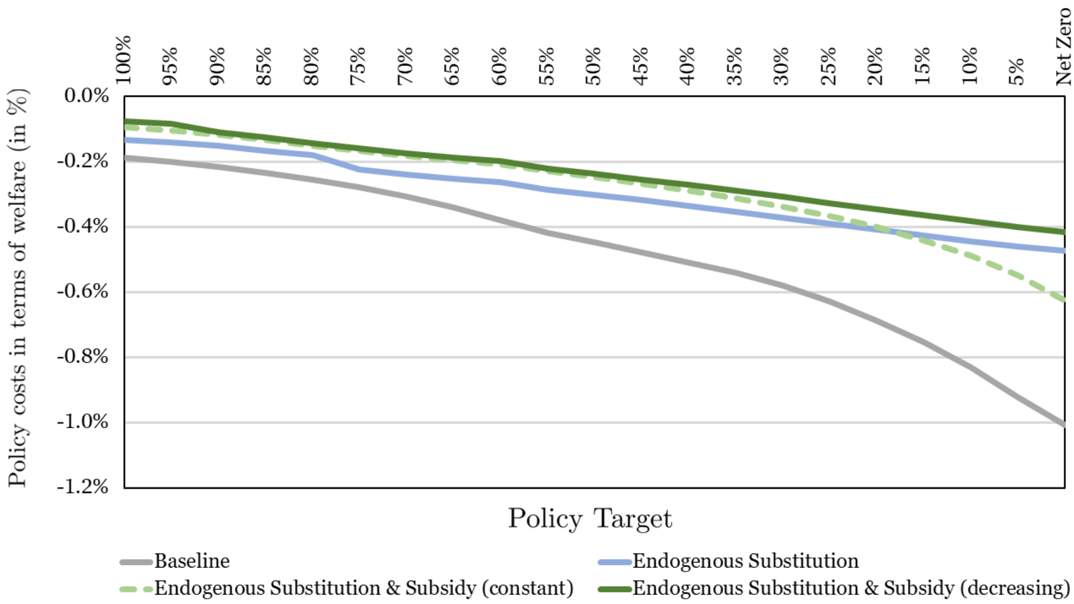

Figure 7: The effect of output subsidies on the policy costs when the elasticity of substitution is endogenous (in percentages of the benchmark welfare level).

period. In the alternative scenario, the subsidy to both sectors also starts at the level of 30% but is gradually reduced to 5% by 2050. We summarize both subsidy profiles in Table 2.

Figure 7 shows the resulting costs of mitigation. When combined with moderate levels of carbon tax (up to 60% reduction in CO_2 emissions), both types of subsidies appear welfare-improving. However, under stringent policy targets, they have opposite outcomes: decreasing subsidy stays beneficial, whereas the constant subsidy is not cost-efficient anymore. Even though it stimulates the transition to renewable energy, the subsidy loses its relevance as the economy approaches net-zero target, indicating that only a temporary subsidy is necessary and optimal in terms of welfare to decarbonize the economy.

3.2 Learning effects for wind and solar energy sectors

Learning is an important driver of the costs reductions in renewable energy sectors. In order to reflect their learning potential, we introduce a learning mechanism for the wind and solar energy sectors. Under a carbon policy, which makes fossil energy relatively more expensive, the cumulative output for renewable energy sectors is higher than its benchmark level specified by the balanced growth path. This excess cumulative output represents the stock of additional experience, which increases the productivity of investment in the corresponding sector. In the model, this relation is represented by a learning factor, $s_{i,t}$, which augments investments in capital accumulation according to:

$$J_{i,t+1} = (1 + s_{i,t}) \left[\upsilon_i I_{P,i,t}^{\frac{\sigma_J - 1}{\sigma_J}} + (1 - \upsilon_i) I_{N,i,t}^{\frac{\sigma_J - 1}{\sigma_J}} \right]^{\frac{\sigma_J}{\sigma_J - 1}} + (1 - \delta_t) J_{i,t}, \tag{14}$$

where the subscript i refers to the wind or solar sector. The learning factor $s_{i,t}$ depends on the (excess) cumulative output $y_{i,t}$ in a non-linear fashion:

$$s_{i,t} = \begin{cases} \frac{\beta_i}{1+\left(\frac{\omega}{y_{i,t}}\right)^{\gamma_i}} & \text{if} \quad y_{i,t} > 0, \\ 0 & \text{if} \quad y_{i,t} \leq 0, \end{cases} \quad \text{with} \quad y_{i,t} = \frac{Y_{i,t}^{Cum} - \bar{Y}_{i,t}^{Cum}}{\bar{Y}_{i,t}^{Cum}}, \tag{15}$$

where $Y_{i,t}^{Cum}$ corresponds to the actual and $\bar{Y}_{i,t}^{Cum}$ to the benchmark cumulative output. Each time the cumulative output exceeds its benchmark level, the corresponding sector can gain additional experience and thus increase the efficiency of capital formation in subsequent periods. The functional specification for the learning factor $s_{i,t}$ is widely used in energy economic models (see e.g. Kverndokk & Rosendahl, 2007; Kalkuhl et al., 2012 and Mattauch et al., 2015) and reflects the fact that production expansion in the wind and solar industries follows a highly nonlinear process. This learning mechanism leads to a positive nonlinear deviation from the balanced growth path and thus provides scope for policy interventions that promote the development of clean energy sectors and thereby decrease the costs of greenhouse gas mitigation.

It is important to distinguish the learning effect in energy transition in CITE from the already existing endogenous growth mechanism based on gains from specialisation according to the new growth theory (Romer, 1990; Grossman & Helpman, 1994). Intuitively, the main difference between productivity gains through sector-wise learning and endogenous technological change based on gains from specialisation is that the latter considers technological innovation as an economic activity. The incentives to invest in new varieties stem from the monopoly rent (monopolistic power) and thus the possibility for an inventor to make profit with a new product. In contrast, the learning mechanism in the wind and solar sectors arises as a pure by-product of output production without any costs. The schematic representation in Figure 8 demonstrates the positive feedback

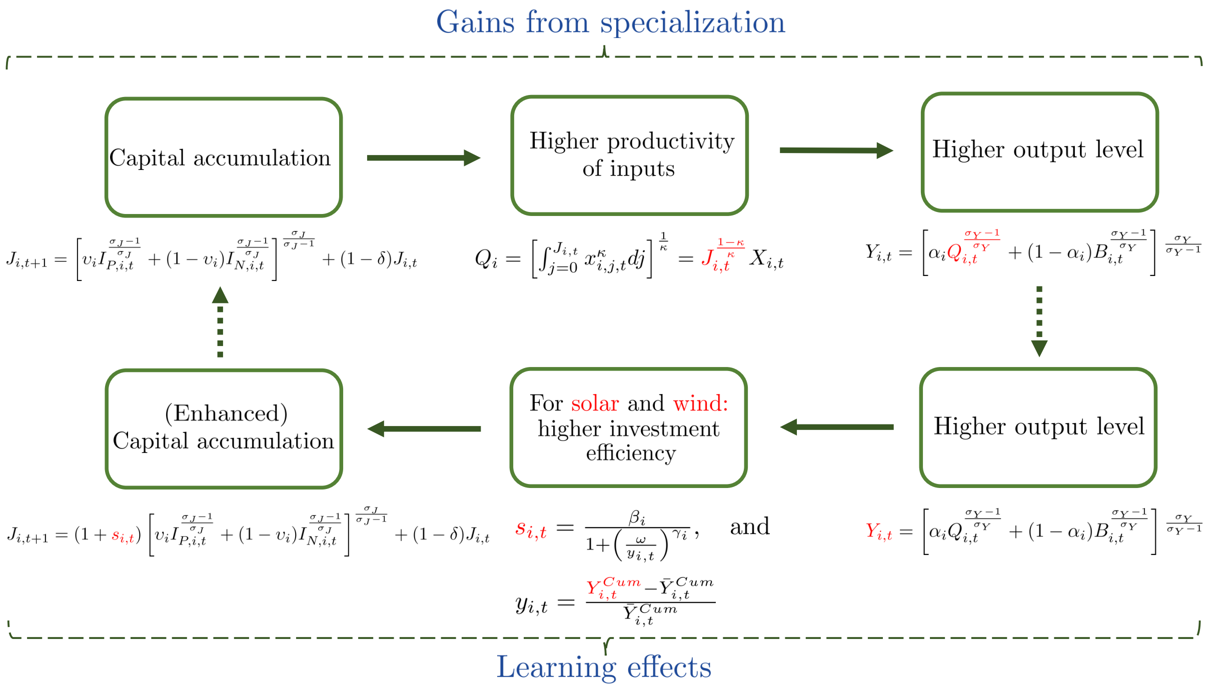

Figure 8: Gains from specialization and scale effect in energy transition

loop formed by the two endogenous growth channels. The upper part of the figure represents the existing endogenous growth mechanism based on gains from specialisation. New capital (J) is formed by physical (I_P) and non-physical (I_N) investments. The level of accumulated sectoral capital determines the number of intermediates and hence the extent of gains from diversification at the intermediate production level (Q). These gains translate to higher levels of sectoral output (Y). The lower part displays the newly introduced learning effect in the energy transition. For the sectors with high learning potential, i.e., the wind and solar energy sectors, higher output is associated with a learning effect, captured by $s_{i,t}$, which in turn increases investment efficiency for these sectors. In other words, with increasing production experience (represented by the excess cumulative sectoral output), the efficiency of investments in the wind and solar sector is enhanced, allowing more capital to be accumulated in the subsequent periods. This process repeats itself, establishing a self-reinforcing cycle.

The extent to which the investment efficiency can be improved depends on three parameters in (15) – the curvature of learning curve, γ, scaling parameter, ω, and maximal productivity, β. Table 3 summarizes the values for the three parameters for solar and wind technologies based on the existing literature (Mattauch et al., 2015; Kalkuhl et al., 2012).

Figure 9 shows the evolution of the learning factor for wind (s_{Wind}) and solar (s_{PVP}) energy under the assumption that the Swiss economy reaches the net-zero target by 2050. Consistent with the literature on learning rates for renewable energy technologies (see e.g. Rubin et al., 2015), our results suggest that the learning factor for wind energy is slightly

Parameters:	PVP	Wind
Maximal productivity, β_i	11	8
Scaling parameter, ω	200	200
Learning exponent, γ_i	0.2	0.27

Table 3: Parameters' values for the learning effects in the solar and wind energy sectors (based on Mattauch et al., 2015 and Kalkuhl et al., 2012).

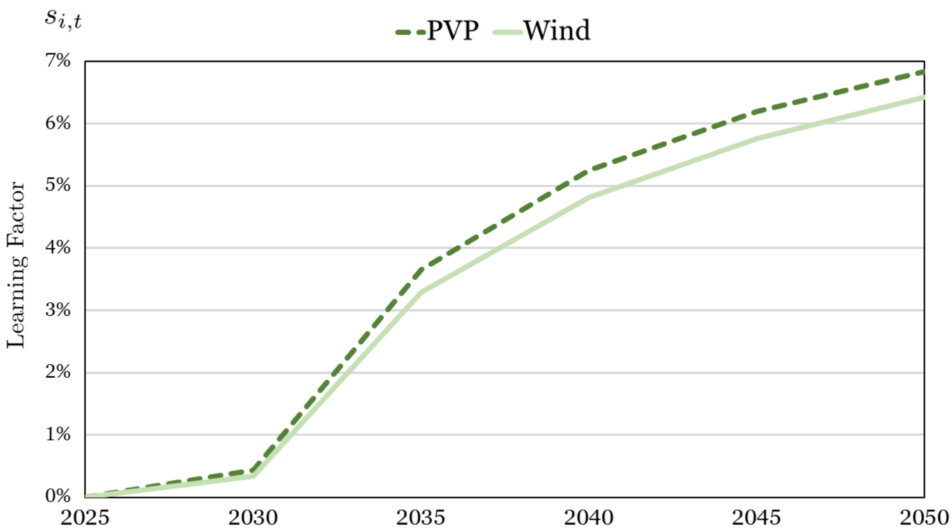

Figure 9: Learning factors for solar (s_{PVP}) and wind (s_{Wind}) under the net zero target. Learning is measured as percentage increase in the productivity of investment in the corresponding sector.

lower than for solar energy. The learning factors develop along an S-shaped curve reflecting current growth patterns of solar and wind energy capacities. From 2030, the learning rates accelerate and flatten out towards the middle of the century.[13] The learning effects resulting from the decarbonization target alone are around 7% and 6.5% for solar and wind power respectively, which are induced by the increased output in these sectors under a carbon tax.

Complementary Policy: Output Subsidy for Wind and Solar

To explore whether a policy can amplify the learning effect, we consider two additional scenarios where constant or decreasing output subsidies are given to solar and wind energy sectors. This instrument can directly increase cumulative sectoral output and thereby amplify the learning effect in (15).[14] Similar to the scenarios in Section 3.1 (see Table 2), the constant subsidy is set to 30% over the entire time horizon and the decreasing

[13]These results are consistent with Kverndokk & Rosendahl (2007) who state that technological progress resulting from learning-by-doing calls for early investment. See also Bretschger (2024), who assumes an S-shaped productivity curve for renewable energies in a dynamic macroeconomic model.

[14]It is straightforward to see that the condition $(1 + \tau_{c,t})Y_{i,t}^{Cum} > \bar{Y}_{i,t}^{Cum}$ is more likely to hold in the presence of the introduced output subsidies denoted by $\tau_{c,t}$.

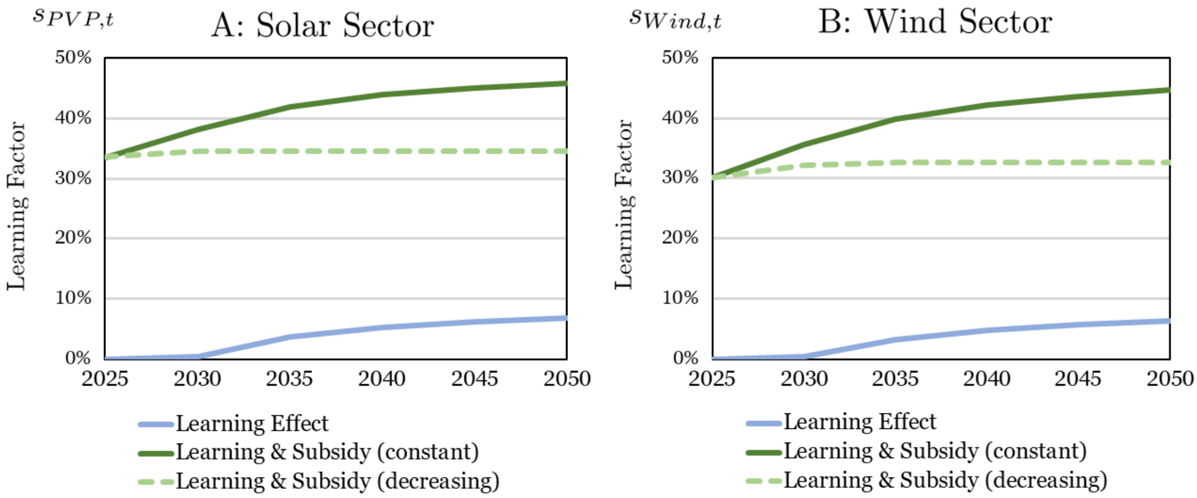

Figure 10: Implemented learning effect in energy transition for solar (A) and wind (B) sectors and the effect of output subsidies (with constant and decreasing profiles) on learning. Learning is measured as percentage increase in the productivity of investment in the corresponding sector.

subsidy falls from 30% in 2025 to 5% in 2050.[15]

As shown in Figure 10, the two sectors benefit from a remarkable increase in their learning factors when output subsidies are used as additional policy instruments to promote the expansion of production capacities. A decreasing subsidy profile leads to constant learning factors of up to 34% for the solar sector and up to 32% for the wind sector. Maintaining a constant subsidy increases the learning factor of the solar (wind) sector to almost 45% (43%) by 2050. Targeted policies in the form of output subsidies can therefore have a significant impact on sectoral growth by exploiting the learning potential of the renewable energy sectors.

The presence of the learning mechanism, in turn, reinforces and sustains the effect of subsidies even when the policy itself expires. This is shown by Figure 11, which depicts the impact of the learning effect on capital formation in the two sectors assuming that the Swiss economy reaches the net-zero target by 2050. The amount of accumulated capital increases slightly due to the sole learning effect in the two sectors. In both sectors, a constant subsidy policy (left) can boost capital accumulation by up to 65% by 2050 even in the absence of learning. What is striking, however, is the extent of synergy between the constant subsidy policy and learning, which together increase the capital index by around 145%. Even in the case of a declining subsidy profile (right), a strong synergy

[15]These scenarios, although different from the currently implemented policies, serve as a proxy for potential governmental action. At the time of writing this paper, the Swiss federal government uses one-off payments to promote photovoltaic (PV) systems. The one-off payments for small PV systems (up to an output of 100 kW) and for large systems (from 100 kW) amount to a maximum of 30% of the investment costs of reference systems. The one-off payments for PV systems without self-consumption amount to up to 60% of the costs of reference systems. New wind turbines with an output of at least 2 MW can receive an investment contribution up to 60% of the eligible costs (SFOE, 2021).

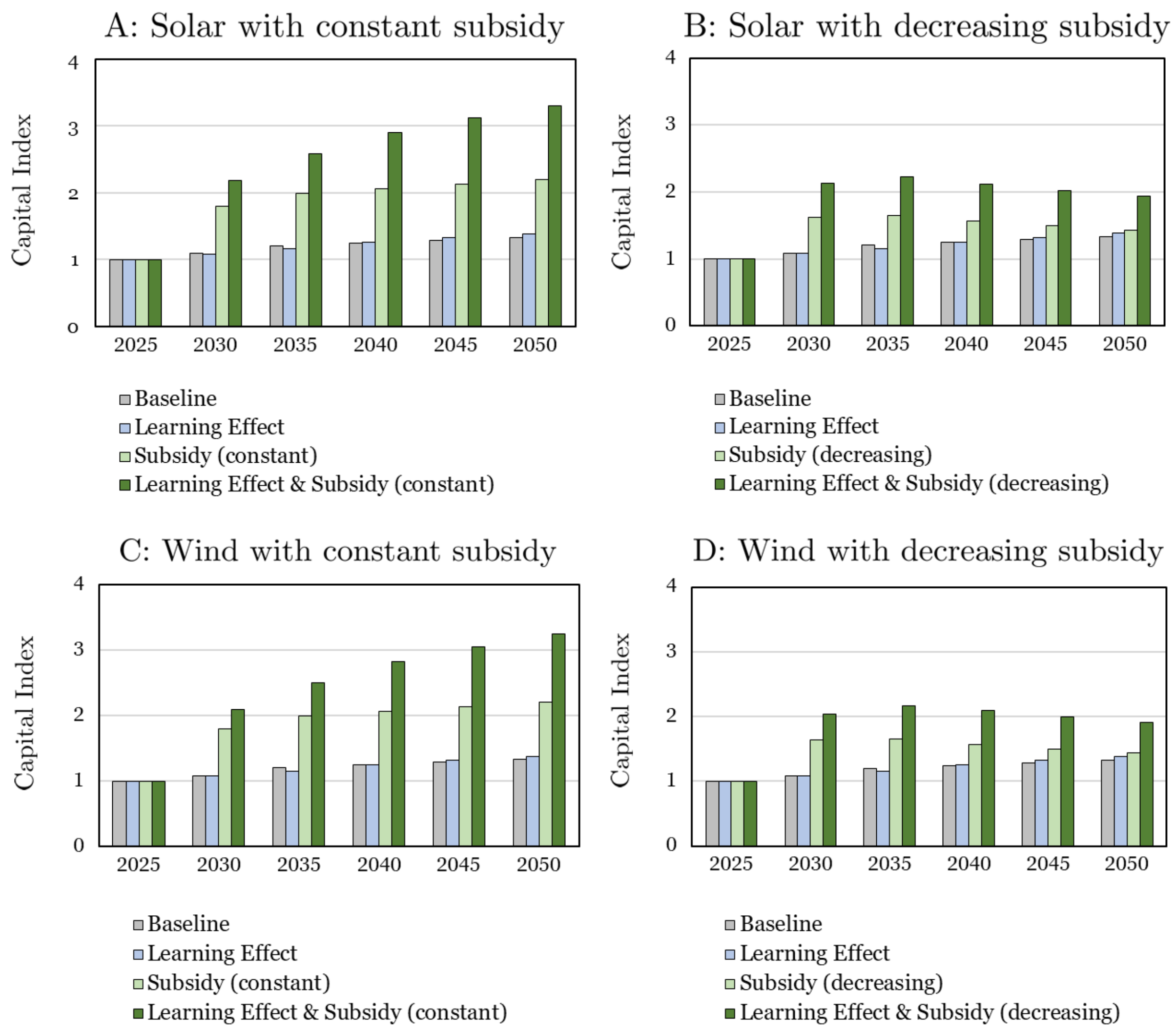

Figure 11: Capital accumulation in solar (top) and wind (bottom) sectors under the baseline scenario, scenario with the learning mechanism, and under constant (left) and decreasing (right) subsidy profiles for the net-zero policy target. The amount of capital is measured as index normalized to 1 in the initial year 2025.

effect persists once triggered by the policy.

Synergy between the effects

A prominent synergy effect occurs between the learning and endogenous substitution mechanisms. As Figure 12 shows, learning factors are up to three times higher by 2050 when energy substitution is endogenous. Intuitively, an increasing substitutability profile (e.g. due to advances in fossil-free infrastructure), facilitates the expansion of production in the two energy sectors, allowing more experience to be gained, which in turn translates into higher learning rates. Conversely, higher learning rates can only marginally affect the degree of substitutability between clean and dirty energy inputs. The provision of a fossil-free infrastructure is therefore of great importance for the expansion of the production capacities of renewable technologies and thus for reducing the costs of en-

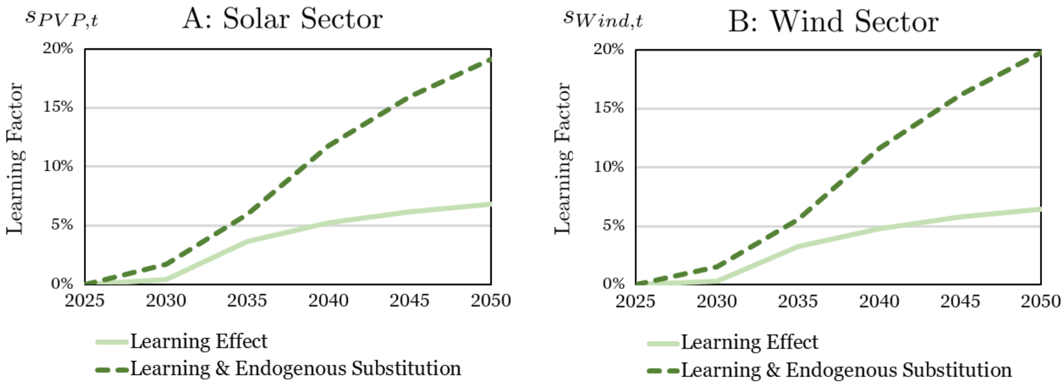

Figure 12: The synergy between the learning effect and the endogenous elasticity of substitution mechanism for the wind and solar sectors under the net-zero target

ergy generation via the learning channel. In Section A.2 of the Appendix, we show that complementary policies can exploit this synergy to further increase the learning factors in the solar and wind energy sectors. In particular, we show that a decreasing output subsidy profile increases learning rates disproportionately when energy substitutability is endogenous.

At the aggregate level, the learning mechanism has a very modest impact on the overall economy's path to the net-zero target: In our simulations, the optimal carbon tax remains almost unchanged (less than 1% difference) when learning effects are taken into account, even in the net-zero scenario. Likewise, the cost of the policy in terms of welfare can only be reduced by a negligible amount and the growth rate of the economy remains essentialy unchanged. The learning mechanism is important mostly for growth and capital accumulation in the renewable energy sectors and not for the overall climate policy costs.

3.3 Endogenous energy efficiency improvements

A carbon tax on fossil fuels inevitably increases the incentives to substitute fossil energy sources with other inputs. In addition to this substitution effect, intermediate firms may invest in energy-augmenting technical progress – they can redirect their investment activities in favor of energy-saving technologies. Energy-augmenting technical progress is often modelled as an exogenous process by so-called autonomous energy efficiency improvement (AEEI), which reduces energy use depending on sectoral energy intensity projections.[16] We develop this idea further and introduce *endogenous* energy efficiency

[16]The many examples of the use of AEEI for climate policy modelling include DICE (Nordhaus & Sztorc, 2013), MERGE (Manne et al., 1995), MiniCAM (Brenkert et al., 2003), and EPPA (Paltsev et al., 2005). For comparison, the ENTICE (Popp, 2004) and WITCH (Bosetti et al., 2007) models integrate endogenous energy improvements based on investments in energy R&D. See Webster et al. (2008) for a numerical, Kaufmann (2004) for an empirical, and Gillingham et al. (2008) for a theoretical

Sector	k_i
Machinery industry (MCH)	1.4%
Chemical industry (CHM)	1.4%
Other industry (OIN)	1.4%
Construction (CON)	1.4%
Agriculture (AGR)	1.4%
Other Services (OSE)	2.0%
Health (HEA)	2.0%
Banking & Financial Services (BNK)	2.0%
Transport (TRN)	1.6%
Insurance (INS)	2.0%

Table 4: Sector-specific values for k_i based on the projected physical energy efficiency (EE) (Bhadbhade et al., 2020).[18]

improvements that arise through sector–specific investment activities.

As energy enters sectoral production at the level of the intermediate varieties in CITE, energy intensity is reflected in the share of energy used in the production at this level. Using labor ($L_{X,i}$) and energy (E_i) as inputs, intermediate goods (x_i) are now produced according to the following CES production function:

$$x_{i,t} = \left[\nu_i L_{X,i,t}^{\frac{\sigma_{x,i}-1}{\sigma_{x,i}}} + (1-\nu_i)\left[(1+f_{i,t})\, E_{i,t}\right]^{\frac{\sigma_{x,i}-1}{\sigma_{x,i}}} \right]^{\frac{\sigma_{x,i}}{\sigma_{x,i}-1}}, \tag{16}$$

where $f_{i,t}$ represents the energy efficiency improvements mechanism; the subscript i refers to the corresponding non-energy sector. We assume that energy efficiency increases endogenously with excessive sectoral investment (on top of the benchmark level)[17] such that

$$f_{i,t} = \begin{cases} (1+k_i)^{t-1} \cdot \min\left[1, z_{i,t}\right] - 1 & \text{if} \quad z_{i,t} > 0, \\ 0 & \text{if} \quad z_{i,t} \leq 0, \end{cases} \quad \text{with} \quad z_{i,t} = \frac{I_{i,t}^{Cum} - \bar{I}_{i,t}^{Cum}}{\bar{I}_{i,t}^{Cum}}, \tag{17}$$

where k_i is a sector-specific parameter that measures the intensity of efficiency improvements, $I_{i,t}^{Cum}$ represents actual and $\bar{I}_{i,t}^{Cum}$ benchmark cumulative investments. Each time the cumulative sectoral investments exceed their benchmark level, i.e. $I_{i,t}^{Cum} > \bar{I}_{i,t}^{Cum}$,

discussion on the importance of endogenizing the efficiency improvements.

[17]It should be noted that only excess investments contribute to the improvement in energy efficiency, which corresponds to around 40-50% of total investments in CITE. This is in line with the estimates in Bhadbhade & Patel (2024), who examined energy efficiency investments in Swiss industry and found that currently around 35% of investments are targeted to improve energy efficiency.

[18]The physical energy efficiency (EE) measure represents the contribution (per annum) of technical progress to EE improvement and is calculated based on the energy efficiency index (ODEX). See Bosseboeuf et al. (2005) for a detailed description.

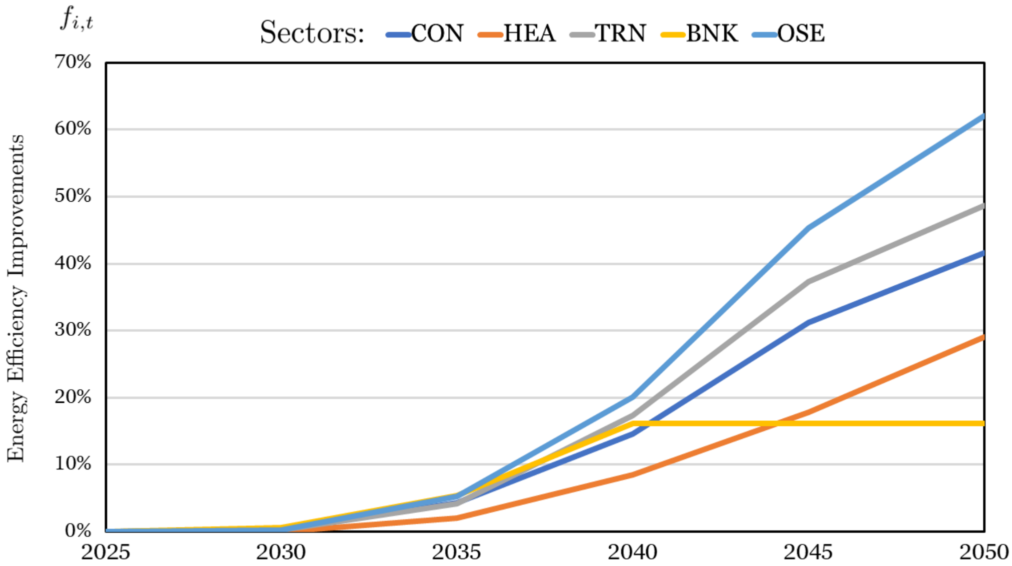

Figure 13: Trajectories of the energy efficiency effect for different non-energy sectors given the net-zero target by 2050.

energy efficiency in the respective non-energy sector can be improved. The parameter k_i takes the sector-specific values (see Table 4) required for the Swiss economy to reach the emissions reduction target for 2050 (Bhadbhade et al., 2020).[19] The term $(1+k_i)^{t-1}$ represents the potential energy efficiency improvements based on the sector-specific estimates required to achieve the policy target. The extent of the actual improvement achieved by a sector in a given scenario is determined by the amount of excess cumulative investments in that sector induced by the policy. Investments thus entail positive spillover effects that are not internalized by policy.

Figure 13 shows the trajectories of the efficiency improvement effect for the different non-energy sectors in the CITE model under the assumption that the Swiss economy reaches its net-zero target by 2050. This stringent climate policy creates incentives for five non-energy sectors to reduce their energy use significantly through additional investment in energy-saving technologies – their improvements in energy efficiency range from 16% (for the banking sector) to 62% (for the other service sectors) by 2050.

Figure 14 shows that the inclusion of the energy efficiency mechanism reduces the overall costs of climate policy by about 0.2 p.p. for policies of medium and high stringency. In addition, the improvements achieved in energy efficiency slightly increase the growth rate of the economy compared to the baseline scenario; this difference in growth rates amounts to 0.02 percentage points for the net zero target as is shown in Figure 15.

Complementary Policy: R&D Subsidy for Non-Energy Sectors

[19] As we focus on the future scenarios of emissions reductions, we adopt these *projected* rates for the main scenario and provide analogous results for the case of *observed* average annual rates in the Section A.3 of the Appendix.

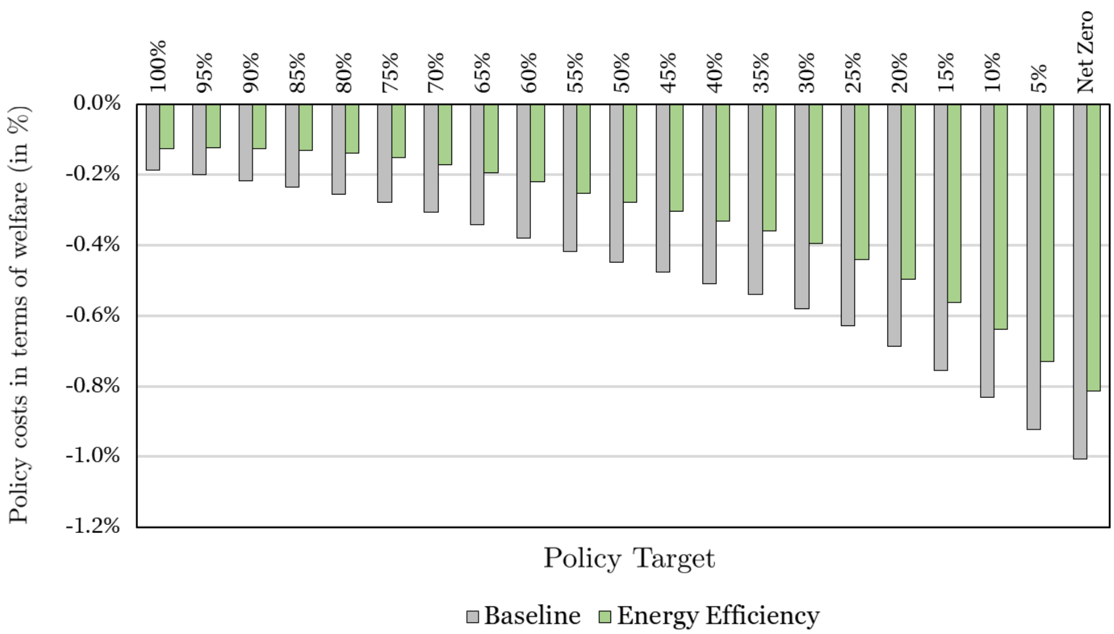

Figure 14: The overall costs of climate policy in terms of welfare across policies of increasing stringency in the baseline scenario and with the energy efficiency improvement mechanism.

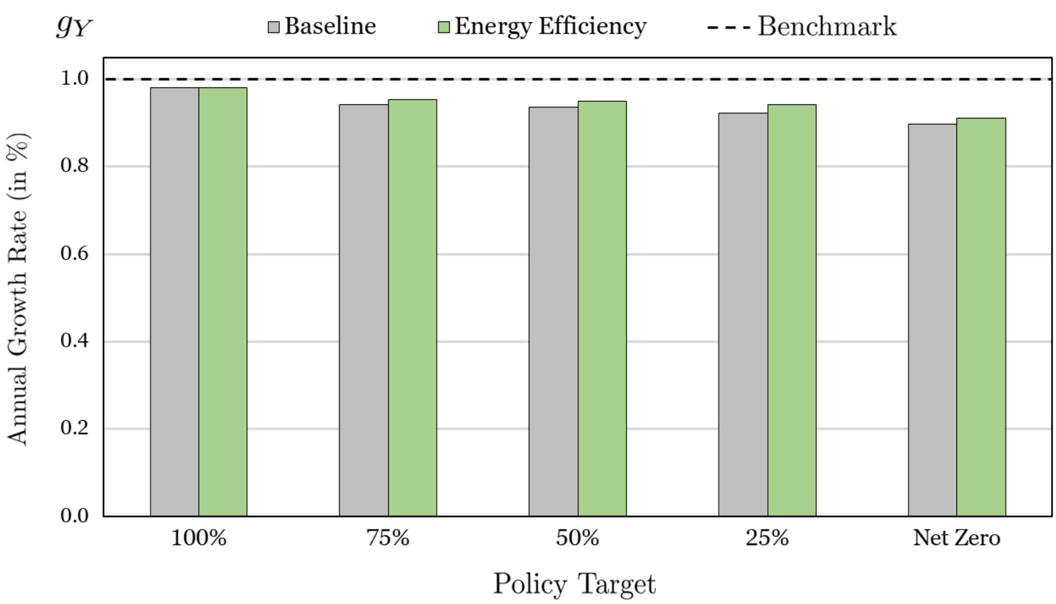

Figure 15: Annual aggregate growth rates of the economy in the baseline scenario and with improvements in energy efficiency in place.

Here, we explore whether complementary policies can stimulate this particular mechanism. Since a sector's energy efficiency depends on its innovation activity, we examine whether innovation subsidies can spur additional energy efficiency improvements. In particular, an R&D subsidy of 20% is offered to all non-energy sectors. Figure 16 illustrates that this policy instrument can both accelerate the adoption of energy-saving technologies and increase the ultimate level of the sectoral energy efficiency. In addition, three

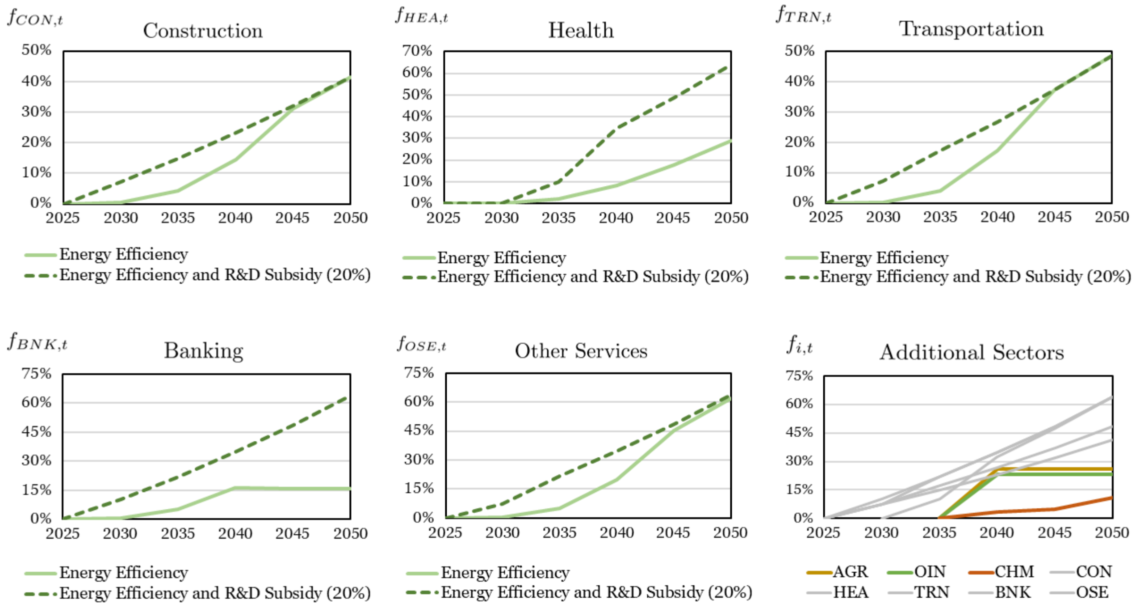

Figure 16: Trajectories for the energy efficiency effect for different sectors with and without R&D subsidies in the net-zero scenario.

other non-energy sectors (CHM, OIN, AGR) can now benefit from the energy efficiency mechanism due to the stimulated investment activity. The corresponding efficiency improvements range from 12% for the chemical sector to 27%-28% for other indusries and agriculure. In health and banking sectors, the efficiency improves by 35 and 48 percentage points respectively by the time the policy target is reached. The other three sectors reach their given energy efficiency levels faster; for example, the efficiency factor of the transportation sector is 13 percentage points higher in 2035 than it would be without a complementary policy intervention. Such higher trajectory implies earlier reductions in energy demand per unit of production, which ultimately translates to lower levels of cumulative emissions over the entire period (even if the final value for the energy efficiency improvement stays unchanged).

4 Putting it all together

The previous sections have highlighted the importance of each of the three mechanisms that can directly or indirectly promote climate policy. Not only can these mechanisms strongly affect the economy's path to the policy target, but they might also have nontrivial synergy effects when enabled jointly. By considering all three mechanisms collectively, the adverse impact on welfare stemming from climate policy can be curtailed by over 60%, transitioning from -1.01% to a more favorable -0.043%, as shown in Figure 17. A significant portion of this improvement is attributable to the endogenous elasticity mechanism, followed by the mechanism of endogenous energy efficiency improvements.

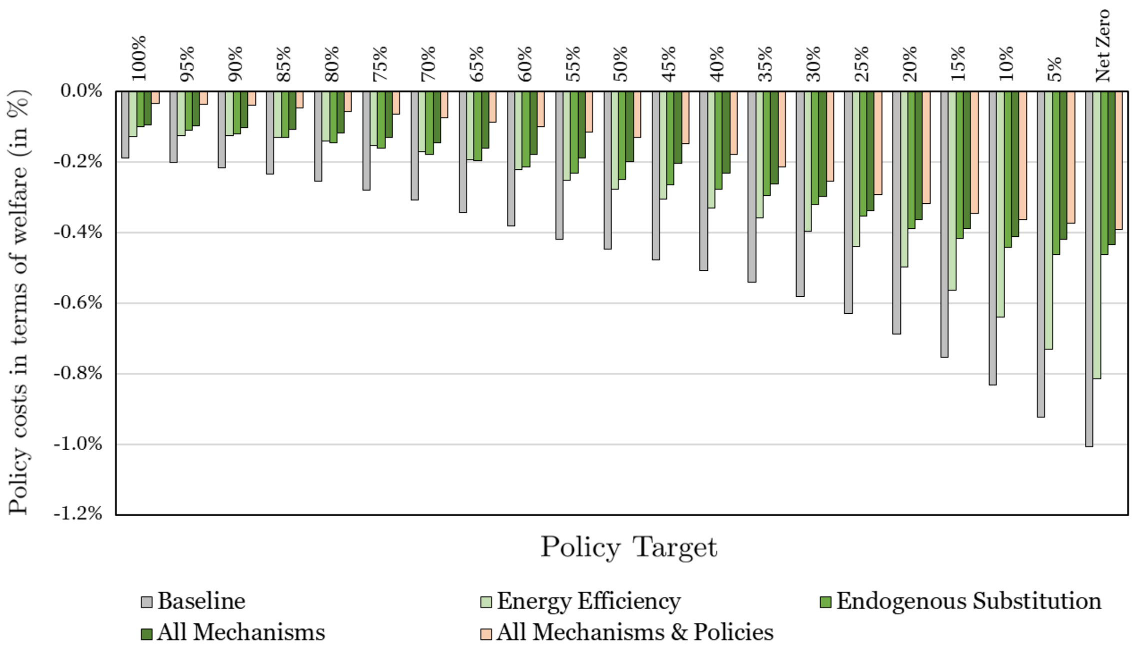

Figure 17: The overall costs of climate policy in terms of welfare across policies of increasing stringency in the baseline scenario, with endogenous energy efficiency, with endogenous elasticity of substitution and with all three mechanisms in place.

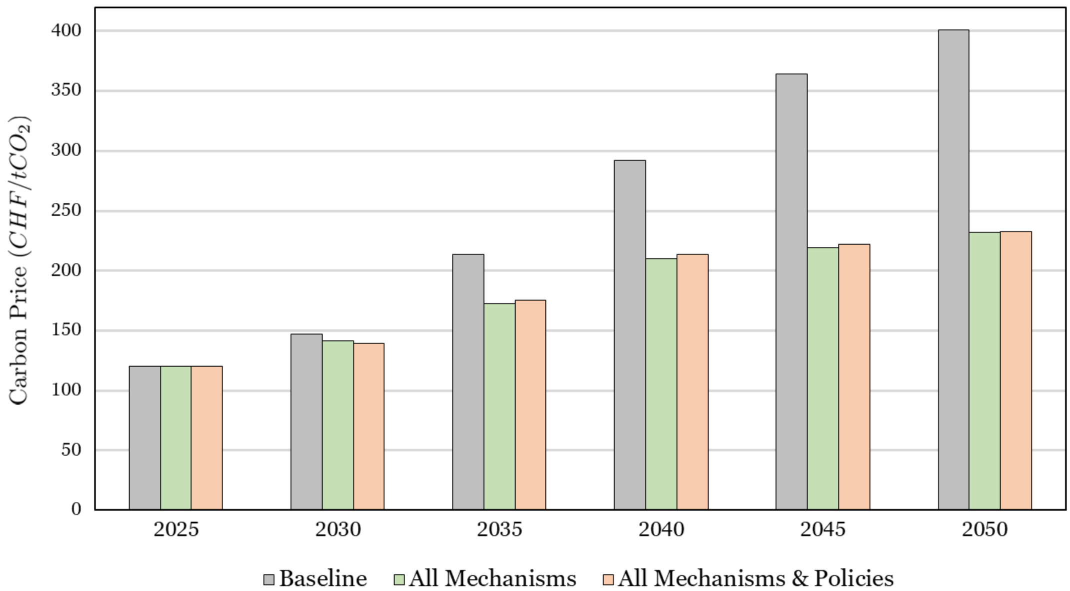

Figure 18: Optimal carbon tax under a net-zero target in the baseline scenario and with all three feedback channels in place.

The learning mechanism does not have a strong influence on the aggregate dynamics of the economy. Section A.4 reports and discusses the resulting values for all three mechanisms.

Furthermore, policy can additionally boost the introduced feedback mechanisms and thus further reduce costs in terms of welfare. In the "All mechanisms and policies" scenario, we assume that all feedback mechanisms are implemented simultaneously with the decreasing production subsidy profile for the wind and solar sectors and the constant R&D

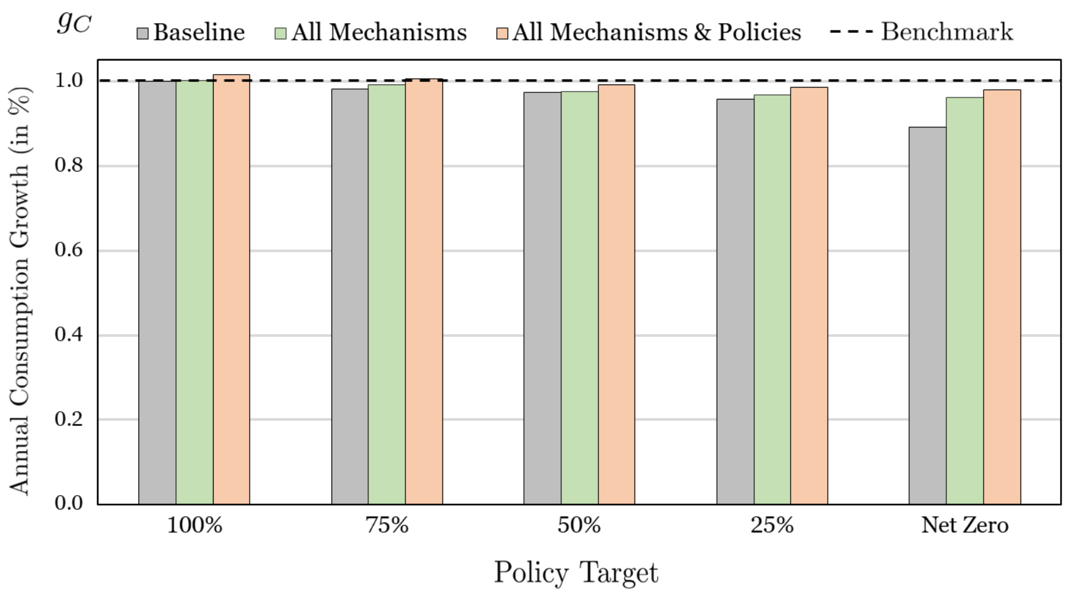

Figure 19: Optimal carbon tax under a net-zero target in the baseline scenario and with all three feedback channels in place.

subsidy for the non-energy sectors, which further reduces the costs of decarbonization in terms of welfare to -0.036% by 2050.

Figure 18 demonstrates that the presence of all feedback channels lowers the level of carbon tax required to reach the net-zero target by 2050: With all mechanisms in place, the carbon price only increases to 232 CHF/tCO_2, while in the baseline scenario a carbon price of 401 CHF/tCO_2 is required to reach the net-zero target for the Swiss economy. Given the lower costs of the policy and lower tax levels required for reaching its targets, the three mechanisms implicitly promote economic growth and allow for higher consumption levels in equilibrium (Figure 19). This translates into the growth rate of consumption being up to 0.07 percentage points higher than in the baseline scenario. When the mechanisms are boosted with the complementary policies, the carbon price stays at the same level; however, the consumption growth rate is 0.08 percentage points higher compared to the baseline scenario.

Overall, the results above offer two key insights. First, in the absence of the three mechanisms, both the optimal carbon price and the overall costs for climate policies might be notably overestimated. Second, by engaging the corresponding channels, a policy can trigger the mechanisms that may reinforce it and partially alleviate the associated economic burden.

5 Conclusions

Using a dynamic general equilibrium model with endogenous growth dynamics for the Swiss economy, we have quantified the policy implications of three empirically relevant feedback channels that evolve endogenously during decarbonization: increasing substitutability of dirty inputs by clean inputs, learning effects in renewable energy, and efficiency improvements in the use of energy. Accounting for these endogenous feedback dynamics results in significantly lower economic costs of mitigating climate change, with the increasing substitution intensity between clean and dirty inputs having the strongest impact. We show that climate policy can trigger and amplify these feedback effects, thereby boosting the transition to a low carbon economy.

Our analysis suggests that even the baseline carbon policy that increases the costs of fossil energy implicitly engages the economic mechanisms that might in turn facilitate reaching the policy's target. Additional policies that support innovation and adoption of green technology and renewable energy may directly target the incentives of economic agents to transition away from fossil fuels and steer the economy towards a more attractive pathway of decarbonization.

We have intentionally abstracted from the factors that might hamper the implementation of a climate policy (such as lock-ins, the presence of uncertainty, or political tension) and instead focus on the channels that indirectly foster its effects.

In our study we have disregarded the important positive effects of phasing out fossil fuels, such as avoided climate damages, health benefits, or reduced dependence on foreign energy supply. Contributions on these topics are complements to our paper.[20] We therefore focus on reporting the estimated costs of climate policy in terms of welfare and leave balancing it against the associated benefits to future research.

We acknowledge that the sectoral results of the paper have to be interpreted with caution as the nested-CES framework of the CITE model offers only an aggregated look at the economy's structure. A more rigorous representation would combine a bottom-up technology-based model and a top-down macroeconomic model.[21] Even though it would provide more details, such framework would largely complicate the joint implementation of the three mechanisms. We therefore adhere to the present structure of the model, which enables an analysis of both individual and joint macroeconomic effects induced by the presence of the discussed mechanisms.

[20] See, for example, Diaz & Moore (2017); Howard & Sterner (2017); Bretschger & Pattakou (2019) for a discussion of the role of damage and benefits estimates in climate policy analysis.

[21] Tapia-Ahumada et al. (2015) and Delzeit et al. (2020) discuss the ability of top-down general equilibrium models to deliver results consistent with detailed bottom-up models and the suitability of the aggregated top-down approach for analyzing climate policy in presence of intermittent energy sources.

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A Appendix

A.1 Details of the CITE Model

Household

In Figure A.1, we provide the consumption structure of the individual households in CITE.

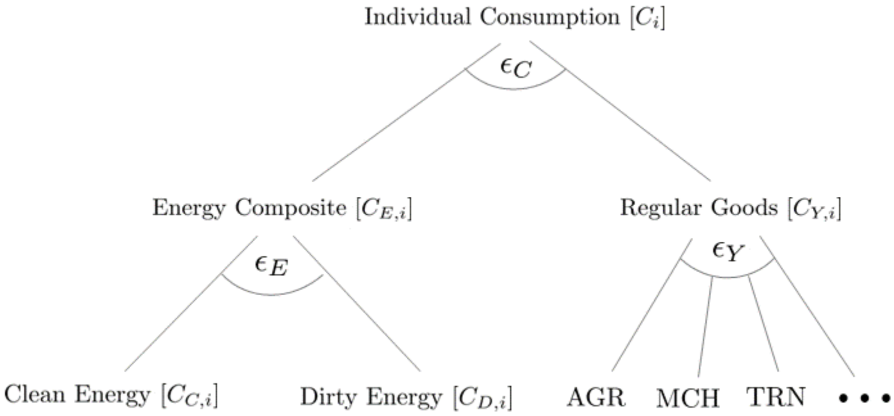

Figure A.1: Consumption structure of individual households

International trade

International trade is modeled under the assumption of Armington aggregation (Armington, 1969), i.e. each sectoral good is an imperfect substitute for an imported sectoral product in consumption. For each sector i, domestic D_i and the imported goods M_i are combined according to the following CET function:

$$A_{i,t} = \left[\iota D_{i,t}^{\frac{\sigma_{\xi,i}-1}{\sigma_{\xi,i}}} + (1-\iota) M_{i,t}^{\frac{\sigma_{\xi,i}-1}{\sigma_{\xi,i}}} \right]^{\frac{\sigma_{\xi,i}}{\sigma_{\xi,i}-1}}, \tag{18}$$

where ι and $1-\iota$ are the value shares and $\sigma_{\xi,i}$ denotes the sector-specific elasticity of substitution between domestic and foreign goods (see Table A.3 for the parameter values).

A.2 Synergy between the learning mechanism and endogenous substitution

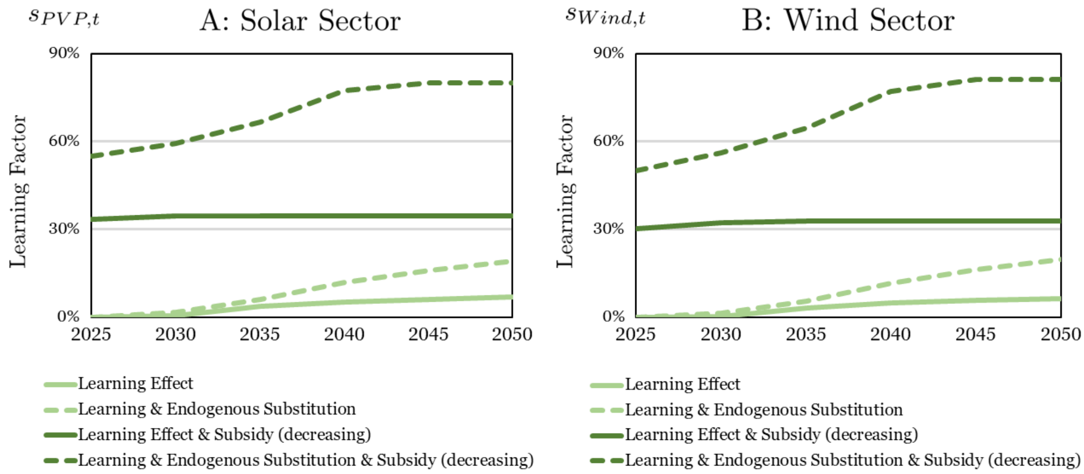

Figure A.2: Synergies between learning and endogenous substitution mechanism for the wind and solar sectors with (dark green) and without (light green) a decreasing output subsidy policy in the net-zero scenario.

Output subsidies for wind and solar energy can further promote the synergies between learning and endogenous substitution as described in Section 3.2. The learning factor for both the solar and wind sectors experiences a disproportionate increase in the presence of the endogenous growth mechanism, reflecting the synergy between the two effects. This synergy can be exploited even with relatively low and temporary subsidies. Here, too, we implement a subsidy that starts at 30% in 2025 and gradually phases out by 2050. As shown by Figure A.2, a decreasing production subsidy can promote the learning factor in both sectors significantly more if the mechanisms are jointly enabled. These results suggest that the technological advances and the infrastructure development reflected by the expanding substitutability are important for the learning potential to be fully exploited.

A.3 Current rates for energy efficiency improvements

In this section, we provide the results for the energy efficiency improvements based on the observed, as opposed to projected, rates for the period 2000-2016 as reported in Table A.1

Sector:	k_i:
Machinery industry (MCH):	1.0%
Chemical industry (CHM):	1.0%
Other industry (OIN):	1.0%
Construction (CON):	1.0%
Agriculture (AGR):	1.0%
Other Services (OSE):	1.2%
Health (HEA):	1.2%
Banking & Financial Services (BNK):	1.0%
Transport (TRN):	1.5%
Insurance (INS):	1.0%

Table A.1: Observed annual sector-specific values for k_i for the 2000-2016 period based on Bhadbhade et al. (2020).

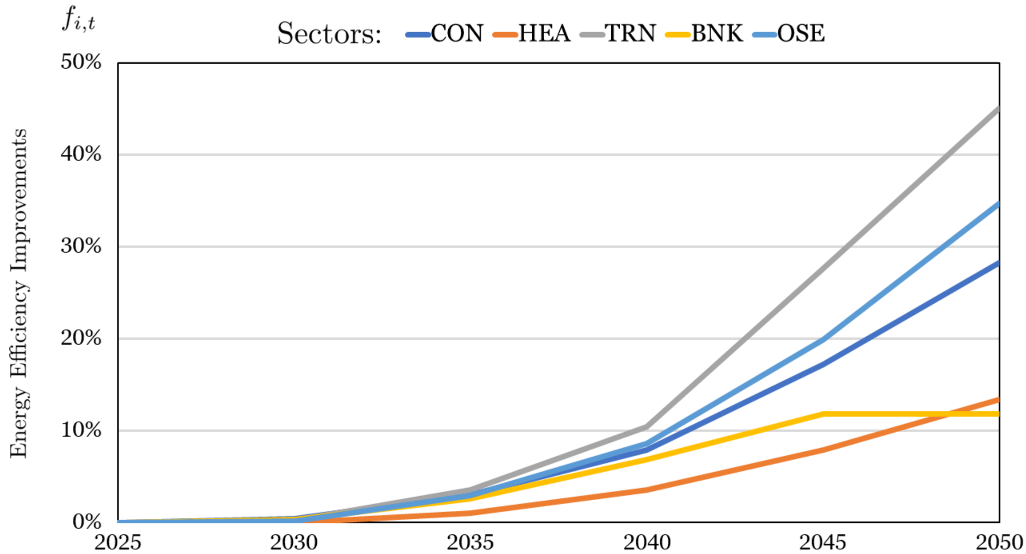

Figure A.3: Trajectories of the energy efficiency effect for different non-energy sectors based on observed efficiency rates (2000-2016) given the net-zero target by 2050.

Figure A.3 shows the resulting trajectories of the efficiency improvement effect for the non-energy sectors under the assumption that the Swiss economy is fully decarbonized by 2050. The energy efficiency improves in the same five non-energy sectors reaching levels between 12% (banking sector) and 45% (transportation sector) by 2050.

Note that the level and speed of energy efficiency improvements are lower than those reported in Section 3.3 due to the more conservative assumption on the values for k_i.

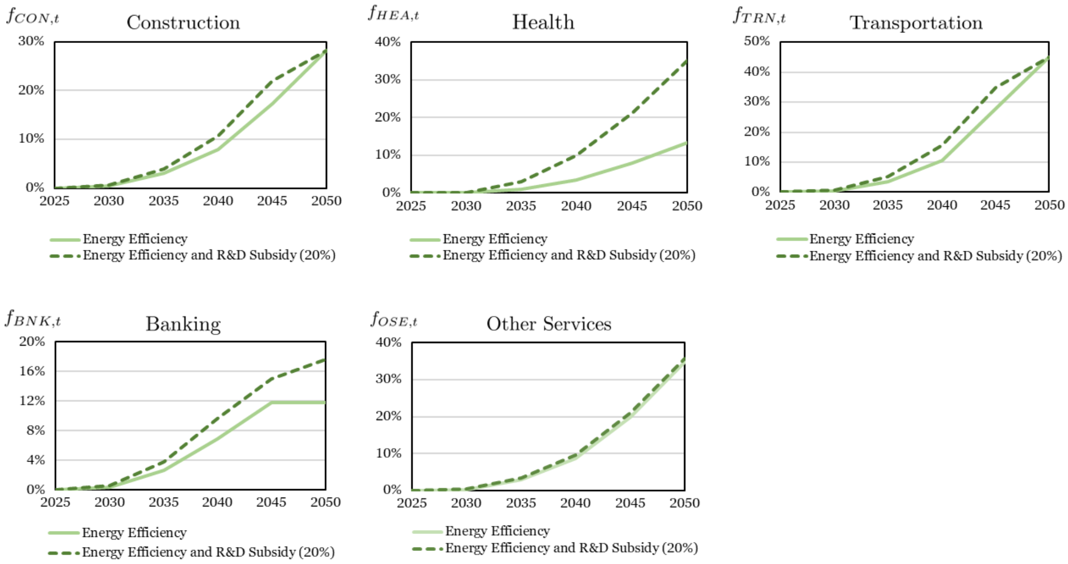

Figure A.4: Trajectories for the energy efficiency effect for different sectors with and without R&D subsidies in the net-zero scenario.

Figure A.4 illustrates that R&D subsidies can trigger additional innovations that improve energy efficiency in the respective non-energy sectors. For example, the improvements in energy efficiency in the health (banking) sector are 22 (6) percentage points higher in 2050 when R&D subsidies are used as a complementary policy instrument.

A.4 Putting all together

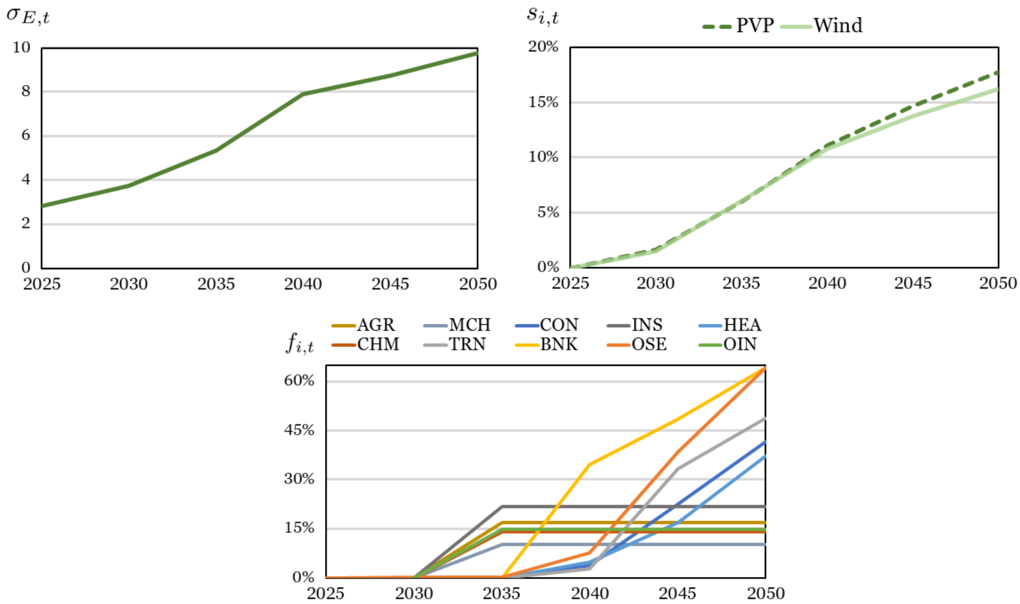

Figure A.5: Evolution of the elasticity of substitution ($\sigma_{E,t}$), the learning factors ($s_{i,t}$) and the energy efficiency improvements ($f_{i,t}$) in the case of the net-zero target when all three feedback mechanisms are in place.

Here, we report the values for the key indicators for each of the three mechanisms and compare them with the individual levels reported in the corresponding sections. As shown in Figure A.5, the value of the elasticity of substitution almost reaches 10 in the case of the net-zero target – a trajectory similar to one reported in Figure 4. The learning factors for the wind and solar sectors are notably higher in the presence of all mechanisms compared to the case when the learning mechanism alone is active (Figure 9). These factors reach 29% and 18% for the solar and wind sectors correspondingly. The levels of energy efficiency improvements are also substantially higher than those reported in Figure 13 when all three mechanisms are in place. Besides, five more sectors enjoy moderate improvements in their energy efficiency.

A.5 Sectors and parameters in CITE

Sector label	Description	NOGA Divisions
Non-energy sectors		
AGR	Agriculture	01 - 03
CHM	Chemical Industry	20 - 21
MCH	Machinery and Equipment	26 - 30, 33
CON	Construction	41 - 43
TRN	Transport	49 - 52
BNK	Banking and Financial Services	64
INS	Insurances	65
HEA	Health	86
OSE	Other Services	36 - 39, 45 - 47, 53 - 63, 68 - 97
OIN	Other Industries	05 - 18, 22 - 25, 31 - 32
Energy sectors		
OIL	Oil	19
GAS	Gas	35
HET	Heat	35
PVP	Solar	35
WIN	Wind	35
NUC	Nuclear	35
HYD	Hydro	35
ELE	Other Electricity	35

Table A.2: Mapping of NOGA divisions to sectors in CITE

Table A.3: Description and values of the parameters used in the economic model

(Endogenous) Supporting Channels		
Parameter	Description	Value
Endogenous elasticity of substitution		
η	Substitutability parameter	3.07
Endogenous learning mechanism		
β_i	Maximal productivity	$\star$
γ_i	Learning exponent	$\star\star$
ω	Scaling parameter	200
Endogenous energy efficiency improvements		
k_i	Intensity of efficiency improvement	$\diamond$
Model Parameters		
Parameter	Description	Value
Elasticities of substitution for production activities		
$\sigma_{Y,i}$	Intermediate composite Q and inputs B from other sectors	$*$
$\sigma_{x,i}$	Labour and energy in intermediate good production	$**$
σ_E	Clean and dirty energy for intermediate goods production	2.00
σ_{fos}	Types of fossil energy in intermediate production	1.00
σ_J	Physical investment $I_{P,i}$ and non-physical investments $I_{N,i}$	0.30
σ_ω	Labor in research $L_{J,i}$ and investments in R&D $I_{J,i}$	0.30
κ	Intermediate varieties	0.70
υ	Elasticity of substitution between sectoral outputs for the input B_i	0
Elasticities of substitution for consumption		
ϵ_C	Energy and regular goods in consumption	0.50
ϵ_E	Energy goods in consumption	2.00
ϵ_{fos}	Types of fossil energy in consumption	1.00
ϵ_Y	Different regular goods	0.50
Elasticities of substitution for welfare		
$1/\zeta$	Intertemporal elasticity of substitution	0.85
ϵ_L	Consumption and leisure	0.65
Other parameters		
$\sigma_{\xi,i}$	Trade elasticities	$***$
$\bar{r}$	Benchmark Interest rate	0.006
$\bar{\delta}$	Benchmark depreciation rate	0.07
g_K	Benchmark growth rate of capital	0.007
g_Y, g_C	Benchmark growth rate of output and consumption	0.01
ρ	Discount rate	0.0003

$\star$: 11 (PVP); 8 (Wind) $\star\star$: 0.2 (PVP); 0.27 (Wind)
$\diamond$: 1.6% (TRN); 1.4% (AGR, MCH, CHM, OIN, CON); 2% (INS, BNK, HEA, OSE)
$*$: 0.392 (AGR); 0.568 (OIN); 1.264 (CON); 0.848 (Fossil, CHM); 0.518 (MCH); 0.352 (TRN); 0.100 (Electricity); 0.492 (others)
$**$: 0.7 (AGR, MCH, Electricity, Fossil); 0.52 (CON); 0.55 (CHM, TRN, OIN); 0.4 (others)
$***$: 3.52 (AGR); 5.06 (MCH); 4.18 (Electricity, OIN); 3.19 (others)

Sources: η Jo & Miftakhova (2022); β_i Mattauch et al. (2015); γ_i Mattauch et al. (2015) and Kalkuhl et al. (2012); ω Mattauch et al. (2015) and Kalkuhl et al. (2012); k_i Bhadbhade et al. (2020); $\sigma_{Y,i}$ Ban & Okagawa (2008); $\sigma_{x,i}$ Mohler & Müller (2012) and Van der Werf (2008); σ_E Jo (2020) and Papageorgiou et al. (2017); σ_{fos} and ϵ_{fos} Bretschger & Zhang (2017b); $\sigma_J, \sigma_\omega, \sigma_{\xi,i}$ Bretschger et al. (2011); ϵ_C and ϵ_Y Vöhringer et al. (2007); $1/\zeta$ Hasanov (2007); ϵ_L Imhof (2012); $\sigma_{\xi,i}$ Donnelly et al. (2004); υ Paltsev et al. (2005)

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21/365 E. Komarov
Capital Flows and Endogenous Growth

21/364 L. Bretschger, A. Jo
Complementarity between labor and energy: A firm-level analysis

21/363 J. A. Bingler, C. Colesanti Senni, P. Monnin
Climate Transition Risk Metrics: Understanding Convergence and Divergence across Firms and Providers

21/362 S. Rausch, H. Yonezawa
Green Technology Policies versus Carbon Pricing: An Intergenerational Perspective

21/361 F. Landis, G. Fredriksson, S. Rausch
Between- and Within-Country Distributional Impacts from Harmonizing Carbon Prices in the EU

21/360 O. Kalsbach, S. Rausch
Pricing Carbon in a Multi-Sector Economy with Social Discounting

21/359 S. Houde, T. Wekhof
The Narrative of the Energy Efficiency Gap

21/358 F. Böser, H. Gersbach
Leverage Constraints and Bank Monitoring: Bank Regulation versus Monetary Policy

21/357 F. Böser
Monetary Policy under Subjective Beliefs of Banks: Optimal Central Bank Collateral Requirements

21/356 D. Cerruti, M. Filippini
Speed limits and vehicle accidents in built-up areas: The impact of 30 km/h zones

21/355 A. Miftakhova, C. Renoir
Economic Growth and Equity in Anticipation of Climate Policy

21/354 F. Böser, C. Colesanti Senni
CAROs: Climate Risk-Adjusted Refinancing Operations

21/353 M. Filippini, N. Kumar, S. Srinivasan
Behavioral Anomalies and Fuel Efficiency: Evidence from Motorcycles in Nepal

21/352 V. Angst, C. Colesanti Senni, M. Maibach, M. Peter, N. Reidt, R. van Nieuwkoop
Economic impacts of decarbonizing the Swiss passenger transport sector

21/351 N. Reidt
Climate Policies and Labor Markets in Developing Countries