Research article

Fossil energy use and carbon emissions: An easy-to-implement technical policy experiment

Massimiliano Calvia*

Department of Management, Alma Mater Studiorum – University of Bologna, Italy

* Correspondence: Email: massimiliano.calvia2@unibo.it; massimiliano.calvia@yandex.com.

Abstract: Macroeconomic research on carbon policy mostly revolves around carbon pricing mechanisms such as carbon taxes, cap-and-trade-schemes, and a mix of them. Despite their relevance, however, carbon pricing is not the only policy available to mitigate carbon emissions. A richer and diversified arsenal of carbon policies may prove more effective in addressing carbon mitigation across different social, economic and geographic contexts. We proposed a policy experiment, which took the form of a *technical tax* on fossil energy use aiming at stabilizing carbon dioxide emissions. The *technical tax* responded to variations in all elements that are supposed to alter climatic phenomena, that is, domestic carbon emissions, domestic fossil energy use, and the industrial stock of atmospheric carbon dioxide, to which all world economies contribute. The macro-effects of the *technical tax* were simulated using an off-the-shelf Real Business Cycles (RBC) model targeting the economy of the United States and featuring a climatic block. The economy was perturbed by a technology shock and an energy-price shock. Special care was devoted to the processes of validation and calibration. The tax was responsive to the business cycle and showed positive aspects. When a technology shock hit the economy, it curbed carbon emissions with minor costs in terms of potential output losses. It also protected the economy from an increase in energy prices, mitigating the fall in output despite the drop in fossil energy use. Last but not least, the tax effectively stabilized carbon dioxide emissions by reducing their variance.

Keywords: carbon emission; carbon policy; fossil energy; fossil energy taxation; RBC model

JEL Codes: C63, E32, Q43, Q53, Q54

1. Introduction

Economic output and carbon emissions cannot exist without the other given the actual level of technology. Both outputs share fossil energy as a common production factor. On the one hand, fossil fuel production is expected to continue to play a non-negligible role in the short- and medium-term global energy scenario (Mohr et al., 2015). On the other hand, the burning of fossil fuels for productive processes is known to release in the atmosphere the carbon stored below ground for millions – if not hundreds of millions – of years (Seeley, 2017), thus contributing to global warming and climate change. Carbon pricing policies fall on the spectrum between the carbon tax and the cap-and-trade scheme. Despite their effectiveness, they should not be viewed as *passepartout* instruments fitting every social, economic, and geographical context (Finon, 2019). Furthermore, they must not be regarded as the only policy instrument available but rather as an essential tool of a diversified policy portfolio (Freebairn, 2020; Khan and Johansson, 2022; Haites et al., 2023).

We propose and simulate an easy-to-implement policy experiment directly targeting fossil energy use – and indirectly carbon emissions – which pursues a reduction in the variability of CO_2 emissions. The policy has been dubbed *technical tax* due its straightforward dependence on measurable physical quantities, namely variations in carbon emissions, fossil energy use, and industrial stock of CO_2. The policy is tested using an off-the-shelf Real Business Cycle (RBC) model calibrated on the United States economy, augmented so as to account for the twofold role fossil energy plays in fostering both output and CO_2 emissions, and hit by a technology shock and a price shock on fossil energy. Refraining from optimal taxation due to its degree of abstraction (Heady, 1993; Alm, 1996), the work explores almost in a pedagogical way (e.g., Costa Junior and Garcia-Cintado, 2018) the key features underlying macroeconomic models that address carbon emissions. A transparent validation of the model's ability to reproduce the cyclical behaviors of real economic and climatic variables and an *ad hoc* calibration are also provided.

The work is built as follows: In section 2, we provide a compact literature review; in section 3, we describe the dataset; in section 4, we detail the equations of the model; in section 5, we critically describe how the model is calibrated; in section 6, we deal with the model's validation; in section 7, we discuss the basic mechanisms of the model and the results; and in section 8, we summarize the conclusions of the analysis. Further details on empirical data and calibration details are included in the online appendices.

2. Literature review

Carbon mitigation policies relying on the pricing mechanisms are generally of three kinds: carbon tax, cap-and-trade, and mixes of the two. The carbon tax, a derivative of the Pigouvian tax (Pigou, 1932), sets a price on carbon emissions letting the market decide how much to emit. On the other hand, cap-and-trade schemes, whose origins can be traced back to the pioneering work of Montgomery (1972), keep the amount of carbon emissions fixed, leaving the market generate their price. In practical terms, the implementation and the acceptance of carbon taxes has proven complicated (Criqui et al., 2019), leading to a preference towards cap-and-trade schemes (Economides et al., 2018). Moreover, despite their effectiveness in triggering a reduction in carbon emissions, both policies failed to promote an actual shift towards zero-carbon technologies (Lilliestam et al., 2021).

The macroeconomic simulation of environmental policies is usually carried out through Environmental Dynamic Stochastic General Equilibrium (E-DSGE) models, which represent the leading laboratory for the simulation of macroeconomic phenomena in an open, transparent (Christiano

et al., 2018) and cheap (Lucas, 1980) way. Some E-DSGE models are built on a Real Business Cycle (RBC) framework (Kydland and Prescott, 1982), that is, neo-classical models assuming flexible prices and technological progress as the main source of economic fluctuations. As an example, Fischer and Springborn (2011) compare a cap on emissions, an emission tax and an intensity target. They find that a cap on emissions lowers economic volatility, while an emission tax increases it. The intensity target, instead, enhances production without altering the volatility of economic variables. Heutel (2012) studies the interaction between business cycle and environmental policy, operationalized in terms of a cap policy and a tax policy. Under a centralized economy, optimal policy makes emissions procyclical, the effect being dampened with respect to the no policy case; under a decentralized framework, optimal policy behaves in a procyclical fashion, thus decreasing during recessions and increasing during expansions. He also finds that carbon emissions in the United States are procyclical with the business cycle. Dissou and Karnizova (2016) outline a multi-sector model calibrated on the United States to compare the effects of the carbon tax and the cap-and-trade scheme. In case of non-energy shocks, the policies are equivalent. However, in the event of energy-shocks, the carbon tax is preferable as the cap-and-trade scheme, despite being able to tame macroeconomic volatility, entails higher welfare costs. Zhao et al. (2020) build a model for China to assess the effectiveness of the carbon tax, the emission trading systems, and a policy mix. The policies appear to have almost overlapping effects under different shocks. A policy mix, however, is recommended to avoid detrimental consequences on the economy.

Other E-DSGE models are developed around a New-Keynesian (NK) backbone, that is, RBC models extended to include sticky prices. Annicchiarico and Di Dio (2015) use this framework to compare the cap-and-trade scheme, the intensity target and the tax policy in the presence of nominal rigidities. They find that the cap-and-trade scheme is able to stabilize the economy dampening business cycle fluctuations. Furthermore, price stickiness appears to alter the performance of different carbon policies, including the optimal emission tax. Annicchiarico and Diluiso (2019) evaluate the role of the cap-and-trade scheme and the carbon tax in the transmission of shocks between open economies participating in intra-industry trade. The model suggests that carbon policies can effectively facilitate the cross-border spillover of shocks. Targeting the Chinese economy, Xiao et al. (2018) incorporate both energy consumption and energy efficiency to compare emission tax, emission cap, and emission intensity target. Results suggest the countercyclicality of all considered policies as well as the higher effectiveness of the intensity target in taming fluctuations. More recently, Eydam (2023) compares static and dynamic versions of a cap-and-trade-scheme. Under the dynamic rule, in particular, the price of emissions becomes less volatile, thus stabilizing the market of carbon permits.

Three points emerge from what has been highlighted so far. First, most of the E-DSGE literature revolves around comparisons between carbon pricing policies. Second, the policies analysed almost exclusively target carbon emissions, neglecting the importance of variables such as fossil energy use. Third, all policies focus exclusively on domestic variables, i.e., carbon emissions, without including global and measurable variables such as the atmospheric stock of anthropogenic CO_2. This being said, current carbon pricing policies are not the only tools available for mitigating carbon emissions. Different carbon policies may be better suited to specific social, economic or geographic contexts (Finon, 2019). Furthermore, multiple policies having different characteristics should be combined into packages to achieve actual effectiveness (Freebairn, 2020; Khan and Johansson, 2022; Haites et al., 2023). In light of the foregoing, this work contributes to the carbon policy debate by proposing a tool to add to the carbon policy arsenal, which could be potentially implemented independently or in combination with other existing policies. It takes the form of a tax on fossil energy use, which indirectly mitigates and stabilizes carbon emissions. As a point of innovation, its dynamics are

explicitly driven by those of all major measurable drivers of climate change, that is to say, fossil energy use, carbon emissions and atmospheric stock of carbon.

3. Data

The dataset contains series on economy, fossil energy use, and carbon emissions of the United States. It spans 47 years, from 1973 to 2019. The starting year is constrained by the unavailability of US carbon emission series prior to the year 1973. The last year is selected in order to avoid once-off cycles driven by health policies against Covid pandemics on the US economy. If, on the one hand, this might represent a limitation, on the other hand, lockdowns-triggered sharp recessions, modified energy use patterns and reduced carbon emissions (Aktar et al. (2021) might hit cyclical regularities in the short-run, thus, compromising the generalizability of model results.

The series considered are *output* (Y), *consumption* (C) (i.e., the aggregate of *non-durables* and *services*), *investment* (I) (i.e., the aggregate of *fixed private investment*, *durables*, and *changes in inventories*), *labor* (L) (i.e., the *hours worked in the non-farm business sector*), *fossil energy* (E) (i.e., the aggregate of energy consumption from *coal*, *gas*, and *oil*), *fossil energy price* (p_e) (i.e., a price index relative to gasoline and other energy goods), and *domestic CO_2 emissions* (M^d). Excluding labor, fossil energy use and domestic CO_2 emissions, all aggregates are expressed in *real* terms, i.e., they are deflated using the GDP deflator.

The dataset is shaped in *quarterly frequency* and all series are *seasonally adjusted*. Those series such as fossil energy use and domestic CO_2 emissions, originally supplied at monthly frequency without any preliminary seasonal adjustment, are properly aggregated and corrected for seasonality using TRAMO-SEATS in JDemetra+ (https://github.com/jdemetra/jdemetra-app/releases/tag/v2.2.2). Following macro-climatic literature, domestic CO_2 emissions, originally provided in *million metric tons,* are appositely converted into *giga tons of carbon* (*GtonC*) using the fact that $1\,TonCO_2 \approx (12/44)\,TonC$ (https://cdiac.ess-dive.lbl.gov/pns/convert.html#).

A few additional series are considered exclusively for calibration purposes. Nominal GDP, the energy-output ratio and household's expenditure on fossil energy are supplied at annual frequency. Total factor productivity corrected for capital utilization, instead, is available at quarterly frequency (Fernald, 2014). Further information concerning data is contained in Appendix A.

4. Model

The model describes an economy operating in a perfectly competitive fashion. It features three agents, i.e., household, firm, and government, and three factors of production, i.e., capital, labor, and fossil energy. A simplified climatic block impacts economic activities by affecting production. Figure 1 provides a general overview of the model and its components in order to clarify how they interact with each other.
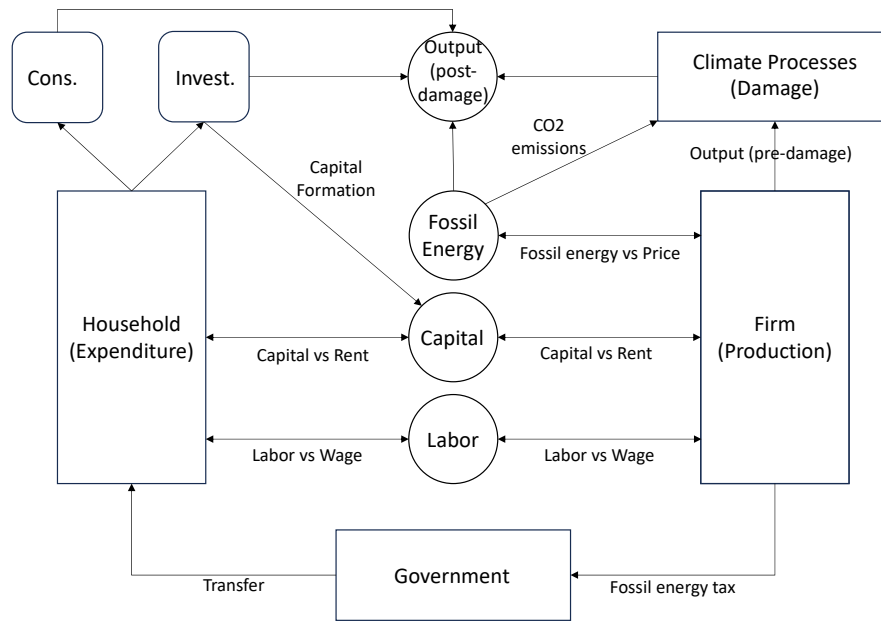
Figure 1. Framework of the RBC model.

4.1. Household

The infinitely lived representative household solves the following maximization problem:

$$\max_{C_t, L_t, K_{t+1}, u_t} \mathbb{E}_t \sum_{t=0}^{\infty} \beta^t \left[\frac{C_t^{1-\frac{1}{\sigma_c}}}{1-\frac{1}{\sigma_c}} + \chi \frac{(1-L_t)^{1-\frac{1}{\sigma_{le}}}}{1-\frac{1}{\sigma_{le}}} \right] \tag{1}$$

subject to

$$C_t + I_t \leq w_t L_t + z_t(u_t K_t) + F_t + \Pi_t \tag{2}$$

where $\beta \in (0,1)$ is the intertemporal discount factor measuring agent's impatience. The household consumes the bundle C_t and enjoys leisure $1 - L_t$, where L_t denotes market labor expressed as the number of hours worked. Parameter σ_c is the elasticity of intertemporal substitution (EIS), i.e., the consumer's willingness to substitute future for present consumption.

The Frisch elasticity of leisure ϵ_{le}, i.e., the elasticity of non-worked hours with respect to the wage rate keeping the marginal utility of consumption constant, is determined by the curvature of the utility function on leisure, i.e., $1/\sigma_{le}$.

The scaling parameter χ denotes the relative utility weight on leisure. Equation 2 formalizes the sequential budget constraint that the representative household faces in each period. As the owner of capital K_t and labor L_t, the representative household rents out the former in exchange for real capital rent z_t and supplies the latter in exchange for real wage w_t. Capital represents household's wealth within the model economy. Capital is not exploited at its maximum capacity, so its actual use is denoted by u_t.

As the owner of the firms, the household receives profits Π_t. It also receives a lump-sum transfer F_t from the government. The household employs the revenues to purchase consumption goods C_t and investment goods I_t. The stock of capital evolves according to

$$K_{t+1} = H(I_{t-1}, I_t)I_t + \left(1 - \delta(u_t)\right)K_t \tag{3}$$

where

$$\delta(u_t) = \delta_0 u_t^\nu \tag{4}$$

formalizes the capital depreciation rate δ as dependent on capital utilization. In particular, δ_0 represents the steady-state capital depreciation rate, while parameter ν governs the intensity of capital utilization. Equation 5

$$H(I_{t-1}, I_t) = \left[1 - \frac{\varphi}{2}\left(\frac{I_t}{I_{t-1}} - 1\right)^2\right] \tag{5}$$

denotes investment adjustment costs, that is, additional costs affecting the investment process, as function of the growth rate of investment. They are governed by parameter φ.

The following equilibrium conditions result from the above-stated problem:

$$C_t^{-\frac{1}{\sigma_c}} w_t = \chi(1 - L_t)^{-\frac{1}{\sigma_{le}}} \tag{6}$$

$$q_t = \beta \mathbb{E}_t \left\{ \left(\frac{C_{t+1}}{C_t}\right)^{-\frac{1}{\sigma_c}} [z_{t+1} u_{t+1} + q_{t+1}(1 - \delta_0 u_{t+1}^\nu)] \right\} \tag{7}$$

$$1 - q_t \left[1 - \frac{\varphi}{2}\left(\frac{I_t}{I_{t-1}} - 1\right)^2 - \varphi\left(\frac{I_t}{I_{t-1}} - 1\right)\frac{I_t}{I_{t-1}}\right] = \beta \mathbb{E}_t \left[q_{t+1}\left(\frac{C_{t+1}}{C_t}\right)^{-\frac{1}{\sigma_c}} \varphi\left(\frac{I_{t+1}}{I_t} - 1\right)\left(\frac{I_{t+1}}{I_t}\right)^2\right] \tag{8}$$

$$z_t = q_t \nu \delta_0 u_t^{\nu-1} \tag{9}$$

where q_t denotes marginal Tobin's Q, that is, the marginal value of installing one additional unit of capital expressed in terms of consumption. Equation 6 describes household's labor supply and captures the trade-off between consumption and leisure: the loss of utility determined by working more is counter-balanced by an adequate increase in consumption. Equation 7 describes household's intertemporal decision of consuming one unit today or saving it in the form of capital and postponing its consumption in the next period. Equation 8 captures the dynamics intrinsic to investment adjustment costs. According to Equation 9, the household choose capital utilization such that, at the margin, the benefits from capital rent equal the costs generated by the depreciation rate.

4.2. Firm

Firms are homogeneous and generate output Y_t according to a Cobb-Douglas production function that, mirroring Kim and Loungani (1992) and Dhawan and Jeske (2008), has the shape

$$Y_t = A_t D_t N_t^\alpha L_t^{1-\alpha} \tag{10}$$

where labor L_t appears explicitly, while capital K_t and fossil energy E_t are implicitly combined into the composite N_t. The latter, in particular, obeys a constant elasticity of substitution (CES) function shaped as

$$N_t = \left[\omega(u_t K_t)^\rho + (1-\omega)E_t^\rho\right]^{\frac{1}{\rho}} \tag{11}$$

where parameter ω reflects the weight of capital within the composite N_t, while ρ governs the degree of substitutability between capital and fossil energy, thereby implying an elasticity of substitution equal to $1/(1-\rho)$.

Equation 10 features a *damage function* D_t, which captures the percentage D_t of output net of the detrimental effect of climate change. The literature supplies several plausible damage functions (Nordhaus, 2008; Heutel, 2012). This work adopts that of Weitzman (2012) which, thanks to its non-linear nature, is able to capture also the catastrophic damages caused by very sharp increases in the global mean temperature T_t over the pre-industrial level (Botzen and van den Bergh, 2012). The damage is expressed by Equation 12

$$D_t = \frac{1}{1 + \left(\frac{T_t}{\pi_1}\right)^{\pi_2} + \left(\frac{T_t}{\pi_3}\right)^{\pi_4}} \tag{12}$$

which is governed by parameters π_1, π_2, π_3, and π_4.

Variable A_t is an exogenous technology shock, which is modelled as an $AR(1)$ process

$$ln(A_t) = (1-\rho^A)\,ln(\overline{A}) + \rho^A\,ln(A_{t-1}) + \varepsilon_t^A, \quad \varepsilon_t^A \sim \mathcal{N}(0,\sigma_A^2) \tag{13}$$

where $\rho^A \in (0,1)$, and ε_t^A is normally distributed with mean zero and standard deviation σ_A.

The representative firm decides its production plan by maximizing profit Π_t

$$\max_{L_t, K_t, E_t} \Pi_t = Y_t - w_t L_t - z_t(u_t K_t) - (1+\tau_t)p_{e,t}E_t \tag{14}$$

Avoiding overcomplications, the energy supply is assumed to be infinitely elastic, that is, all the quantity demanded is provided. As standard in the literature (e.g., Dhawan and Jeske, 2006, 2008; Dhawan et al., 2010), the real relative energy price[1] $p_{e,t}$ is treated exogenously and modelled as an ARMA(1,1) shock

$$ln(p_{e,t}) = (1-\rho^{pe})\,ln(\overline{p_e}) + \rho^{pe}\,ln(p_{e,t-1}) + \varepsilon_t^{pe} + \phi_{pe}\varepsilon_{t-1}^{pe}, \quad \varepsilon_t^{pe} \sim \mathcal{N}(0,\sigma_{pe}^2) \tag{15}$$

where $\rho^{pe} \in (0,1)$, and ε_t^{pe} is normally distributed with mean zero and standard deviation σ_{pe}.

The problem supplies three first-order conditions, namely Equations 16, 17, 18, which represent, respectively, labor demand, capital demand, and energy demand.

$$w_t = (1-\alpha)\frac{Y_t}{L_t} \tag{16}$$

$$z_t = \alpha\omega Y_t N_t^{-\rho}(u_t K_t)^{\rho-1} \tag{17}$$

$$(1+\tau_t)p_{e,t} = \alpha(1-\omega)Y_t N_t^{-\rho}E_t^{\rho-1} \tag{18}$$

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1 Note that wages, rental rate of capital and fossil energy price are expressed in real terms.

4.3. Energy, emissions and climate

The model assumes climate change to be the only environmental threat to the economy. For sake of simplicity, carbon dioxide, i.e., the greenhouse gas (GHG) *par excellence* (Economides et al., 2018), is assumed to be the only by-product of the burning of fossil fuels. This process is captured by Equation 19.

$$M_t^d = E_t^\gamma \tag{19}$$

where γ is the elasticity of domestic CO_2 emissions M_t^d with respect to fossil energy use E_t.

Once emitted, CO_2 undergoes the carbon cycle, that is, the series of transfers from and towards reservoirs (e.g., the atmosphere, the oceans, and the land biosphere) carbon goes through on a recurrent basis. This process is approximated and expressed recursively by Equation 20

$$V_{t+1} = \eta\left(M_t^d + M_t^{nd} + V_t\right) \tag{20}$$

where M_t^{nd} are non-domestic emissions, V_t is the industrial stock of CO_2 contributed by human activities, i.e., the excess of atmospheric CO_2 stock S_t over its *pre-industrial* level $\bar{S}$, while η represents the permanence rate of carbon in the atmosphere. Details on Equation 20 are presented in Appendix B.

Time plays a crucial role in modeling the CO_2-temperature relationship (Lacis et al., 2010; Stips et al., 2016). Ricke and Caldeira (2014) estimate an average of 10 years for the warming attributed to a certain CO_2 emission pulse to reach its maximum. Zickfeld et al. (2015) add that the larger the CO_2 emission pulse, the greater the delay necessary for the warming to reach its peak, the latter potentially happening even after centuries. Models such as Nordhaus (2008), Golosov et al. (2014), and Hassler et al. (2018) assume time-steps not lower than 5 years, frequently set at 10 years. Business cycles models, however, are characterized by periods of one *quarter* of year. The lack of knowledge about the dynamics between anthropogenic levels of carbon dioxide V_t and temperatures T_t in such short time-frames suggests to approximate their relationship with the best or – depending on the viewpoint – the "less bad" tool available in the literature, namely the Arrhenius equation (Hassler et al., 2016a)

$$T_t = \xi \frac{ln\left(\frac{\bar{S} + V_t}{\bar{S}}\right)}{ln2} \tag{21}$$

where climate sensitivity ξ represents the warming triggered by a doubling in the atmospheric stock of CO_2 (Knutti et al., 2017). For simplicity, Equation 21 assumes that any change in the stock of atmospheric CO_2 has an immediate effect on changes in the global mean temperature T_t over the pre-industrial level, thus abstracting from climate dynamics (Hassler et al., 2018).

4.4. Government and policy

The government runs a balanced budget

$$F_t = \tau_t p_{e,t} E_t \tag{22}$$

that is, it collects a tax on the use of fossil energy from firms, which is rebated to households by means of a lump-sum transfer F_t. The tax on fossil energy is expressed in terms of the fiscal-environmental rule

$$ln\left(\frac{1+\tau_t}{1+\bar{\tau}}\right) = \psi_1 ln\left(\frac{M_t^d}{\overline{M^d}}\right) + \psi_2 ln\left(\frac{E_t}{\overline{E}}\right) + \psi_3 ln\left(\frac{V_t}{\overline{V}}\right) \tag{23}$$

Specifically, Equation 23, expresses the percentage deviation of the gross tax from its steady-state as a function of the percentage deviations of domestic emissions, fossil energy, and anthropogenic stock of CO_2 from their steady-states. The experiment consists in simulating the aggregate dynamics set up by the *technical tax* on fossil energy use, where $\psi_1 \neq 0$, $\psi_2 \neq 0$, $\psi_3 \neq 0$ and $\bar{\tau} \neq 0$, and comparing them against two scenarios:

1. The no-tax scenario, where $\psi_1 = 0$, $\psi_2 = 0$, $\psi_3 = 0$ and $\bar{\tau} = 0$;
2. The constant tax scenario, where $\psi_1 = 0$, $\psi_2 = 0$, $\psi_3 = 0$ and $\bar{\tau} \neq 0$;

4.5. Equilibrium and resource constraint

The economy is characterized by the resource constraint, that is, the market clearing condition, expressed by Equation 24

$$Y_t = C_t + I_t + p_{e,t}E_t \tag{24}$$

which links the various sectors of the economy.

5. Calibration

The calibration of the model uses parameters both borrowed from the extant macro-economic literature on the US economy and calculated from scratch using the time series described in Appendix A. In line with Real Business Cycle (RBC) literature, the model is calibrated on a *quarterly* basis. The calibration of the household's block starts from two classical parametrizations characterizing the RBC modeling of the United States economy: first, the discount factor β is set to 0.99 so as to match a steady-state annual interest rate of 4%; second, the capital-energy share α is set at 33% of output, implying a labor's share of income $1 - \alpha$ equal to 67%. Following the comprehensive meta-analysis of Havranek et al. (2015), the elasticity of intertemporal substitution (EIS) σ_c for the US economy is set at 0.5940. The Frisch elasticity of labor ϵ_{la} for US economy is set equal to 3, i.e., the average between 2.9 and 3.1 (Peterman, 2016). Under the ordinary assumption that L_t equals 1/3 in steady-state, the relation $\epsilon_{la} = \sigma_{le}(1 - \overline{L})/\overline{L}$ (Huggett and Parra, 2010; Erosa et al., 2016) allows to recover the parameter $\sigma_{le} = 3/2$. Parameter φ, which governs investment adjustment costs, is endogenously calibrated at 0.9923 so as to pin down the relative standard deviation between consumption and output in the data, namely 0.59 (refer to Section 6 for a comprehensive list of *stylized facts*). The rate of capital utilization ν and the scaling parameter χ are determined within the model once steady-states are known; more specifically, in the no-tax case they result to be equal, respectively, to 1.7250 and 2.1433. It is worth emphasizing that the computation of the steady-states, as usual in DSGE model literature (e.g., Costa Junior & Garcia-Cintado, 2018), is achieved by exogenously assuming the following normalizations $\overline{A} = 1$, $\overline{q} = 1$, $\overline{u} = 1$, and $\overline{p}_e = 1$.

Table 1. Steady-states – Single variables and ratios.

Variables	Value (no-tax)	Value (tech. tax)	Description
$\overline{C}/\overline{Y}$	0.7879	0.7946	Consumption
$\overline{I}/\overline{Y}$	0.1672	0.1605	Investment-output ratio
$\overline{K}/\overline{Y}$	12	12	Capital-output ratio
$\overline{E}/\overline{Y}$	0.0449	0.0449	Energy-output ratio
$\overline{K}/\overline{E}$	267.08	267.08	Capital-energy output
$\overline{L}$	1/3	1/3	Labor
$\overline{D}$	0.9807	0.9807	Damage
$\overline{M}^{nd}/\overline{M}^{d}$	9.5483	9.5953	Nondomestic-domestic emissions ratio
$\overline{V}$	232.17	232.17	Industrial CO_2 stock (GTonC)
$\overline{T}$	2.6136	2.6136	Temperature change (°C)

With respect to the firm's block, the calibration starts by assuming fossil energy use and capital to be complements, i.e., $\rho < 0$. As the result of the sensitivity analysis provided in Section 6, ρ is set equal to -3. The goal is to target the capital-output ratio $\overline{K}/\overline{Y}$, whose value is set to 12 as standard in the literature (Dhawan and Jeske, 2008). The firms' energy-output ratio $\overline{E}/\overline{Y}$ is then calculated as the difference between the total energy-output ratio (available from the U.S. Energy Information Admnistration – EIA), which accounts for both households and firms, and the household's energy-output ratio, that is, the aggregate personal expenditure on non-durables and services related to fossil energy (available from the U.S. Bureau of Economic Analysis – BEA). This provides a value for the firm's energy-output ratio, i.e., $\overline{E}/\overline{Y}$ is equal to 0.0449. Knowing $\overline{K}/\overline{Y}$ and $\overline{E}/\overline{Y}$, it is trivial to calculate $\overline{K}/\overline{E}$ (267.08). Knowing these ratios and rearranging the steady-state versions of Equations 11, 18, 17 and 7, it is possible to retrieve the steady-state values of the depreciation rate δ_0 (0.0139) and of the CES weight ω (0.9999 $\approx$ 1).

Concerning the climatic side, the parameters of the damage function are borrowed directly from Weitzman (2012). This specification, identified by $\pi_1 = 20.46$, $\pi_2 = 2$, $\pi_3 = 6.081$, and $\pi_4 = 6.754$, captures the following relationship: an increase in global mean temperatures of 6°C (12°C) over the pre-warming level exerts a damage which keeps only 50% (1%) of the potential output or, in other words, implies an output reduction of 50% (99%). The value of η, which measures the airborne fraction of CO_2 remaining in the atmosphere each period net of the uptakes of carbon sinks, is set equal to 0.9985. This is obtained by retrieving the *e-folding* time, i.e., the time required for a certain substance to shrink to $1/e$ of its initial concentration, implied by the following *impulse-response functions* IRF_{CO_2} (Joos et al., 2013)

$$IRF_{CO_2}(t) = 0.2173 + 0.2240e^{-\frac{t}{394.4}} + 0.2824e^{-\frac{t}{36.54}} + 0.2763e^{-\frac{t}{4.304}} \qquad (25)$$

which captures the fraction of a certain CO_2 emission pulse remaining in the atmosphere after t years[2]. Equation 25 implicitly assumes an *e-folding time* of 165 years (660 quarters), resulting in $\eta = 1 - \frac{1}{(165 \cdot 4)} = 0.9985$. This differs slightly from the more popular specification of Reilly and Richards (1993), namely $\eta = 0.9979$, which implicitly assumes an *e-folding time* of 120 years. According to Joos et al. (2013), Equation 25 refers to a concentration of 828.57 GTonC (389 ppm). For this reason,

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2 Hassler et al. (2016b) consider a similar approach. It is relevant to notice that IRF_{CO_2} depends on the magnitude of the emissions (Joos et al., 2013); however, in this specific case, for sake of simplicity, Equation 25 is considered invariant.

the steady state value of V_t is calculated as the difference between the above-mentioned concentration of 828.57 GTonC and the pre-industrial stock of carbon of about 596.40 GTonC (280 ppm), that is, $\overline{V}$ = 232.17 GTonC (1 $ppm\ CO_2 \approx 2.13\ GTonC$, https://cdiac.ess-dive.lbl.gov/pns/convert.html#). The equilibrium climate sensitivity ξ in Equation 21 is set equal to 3 as suggested by Hassler et al. (2016a) and already implemented by Golosov et al. (2014). This implies that a doubling in the atmospheric stock of CO_2 with respect to its pre-industrial value leads to an increase of 3° Celsius. It is worth clarifying that the parameters of the damage function and the equilibrium climate sensitivity refer to global temperatures. As such, in absence of local data about the United States, they only approximate the potential climatic processes that might affect this country.

Other parameters are estimated by exploiting the available time series described in Appendix A. This is the case of γ, the elasticity between CO_2 emissions and fossil energy, whose value is obtained by estimating Equation 19. Its value results to be equal to 1.1285. The parameters of the technology shock are estimated minimizing the distance between total factor productivity simulated by the model and the utilization-adjusted total factor productivity from Fernald (2014). This procedure provides ρ^A = 0.9838 and σ^A = 0.0074. Following Dhawan and Jeske (2008) and Dhawan et al. (2010), the parameters of the energy price process are estimated via *maximum-likelihood* from Equation 15 using the natural logarithm of the GDP deflated price index relative to gasoline and other energy goods from the U.S. Bureau of Economic Analysis (BEA). The estimates are ρ^{pe} = 0.9221, ϕ^{pe} = 0.3373, and σ^{pe} = 0.0673. This calibration supplies a ratio between *non-domestic* and *domestic* carbon emissions equal to 9.5483. This is larger than the value employed by Heutel (2012), who fixes *non-domestic* carbon emissions as three times the steady-state value of *domestic* carbon emissions.

The steady-state value of the tax on energy is fixed at 15%. This is a hypothetical ethical tax, whose value hinges on the US share, i.e., impact, over the total worldwide level of CO_2 emissions in year 2019[3]. The tax aims at stabilizing domestic CO_2 emissions M^d by causing an arbitrary one-half reduction in their variance. With respect to Equation 24, this translates in calibrating parameters ψ_i, $i = 1, \ldots, 3$ by *minimizing* the following *loss function*

$$\min_{\psi_i} \left(\sigma_s^2(\psi_i) - \frac{1}{2}\sigma_d^2 \right)^2 \tag{26}$$

where σ_d is the *standard deviation* of the cyclical component of M_t^d obtained from actual data, and σ_s is the *standard deviation* of the cyclical component of $M_t^{d,s}$, that is, its simulated counterpart. In particular, given σ_d^2 = 5.3926, this calibration supplies the following parametrization[4]: ψ_1 = 2.1621, ψ_2 = 1.9158, and ψ_3 = −0.0002, to which corresponds $\sigma_{s,min}^2$ = 2.6963. All relevant steady-states concerning single variables and their ratios are collected in Table 1, while the results of this calibration are described in Table 2. The shift from pre- to the post-policy scenario produces only marginal changes to steady-states and endogenous parameters.

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3 Given that, in 2019, US and the world as a whole emitted, respectively, 4.8 Gt a 33 Gt of CO_2, the US emission share precisely amounts to about 14.55%. https://www.iea.org/articles/global-co2-emissions-in-2019.
4 Because of the structure of the model, when output is included in the policy exercise, this calibration procedure is unable to appropriately reduce the variance of CO_2 emissions. This does not happen when the policy rule excludes output.

Table 2. Calibration of parameters.

Parameter	Value (no-tax)	Value (tech. tax)	Description
α	1/3	1/3	Capital-energy share
β	0.9900	0.9900	Discount factor
χ	2.1433	2.1185	Utility of leisure
ν	1.7250	1.7554	Curvature parameter of capital utilization
φ	0.9923	0.9923	Sensitivity of investment
σ_c	0.5940	0.5940	Elasticity of intertemporal substitution (EIS)
σ_{le}	3/2	3/2	Frisch elasticity of leisure
δ_0	0.0139	0.0134	Steady-state depreciation rate of capital
ω	0.9999	0.9999	Share parameter of CES
ρ	-3.0000	-3.0000	Substitution parameter of CES
η	0.9985	0.9985	CO_2 airborne fraction
γ	1.1285	1.1285	CO_2 domestic emissions vs fossil energy - elasticity
π_1	20.46	20.46	1st damage parameter
π_2	2.0000	2.0000	2nd damage parameter
π_3	6.0810	6.0810	3rd damage parameter
π_4	6.7540	6.7540	4th damage parameter
ξ	3.0000	3.0000	Equilibrium climate sensitivity
ρ^A	0.9838	0.9838	Persistence of technology shock
σ^A	0.0074	0.0074	Standard deviation of technology shock
ϕ^{pe}	0.3373	0.3373	MA component of energy-price shock
ρ^{pe}	0.9221	0.9221	Persistence of energy-price shock
σ^{pe}	0.0673	0.0673	Standard deviation of energy-price shock

6. Validation

The calibrated model is used to generate artificial series (1000 simulations with a burn-in of 1000 periods each), whose core features are expected to match as much as possible those of original data. As witnessed by works such as Gregory and Smith (1991), Christiano and Eichenbaum (1992), King and Rebelo (1999) or, for a textbook-like exposition, DeJong and Dave (2012), how well a certain model is able to reproduce the actual features of the data is assessed through a "visual inspection" of the *stylized facts*, that is to say, a selection of statistical moments describing the cyclical features of the data. Stylized facts are obtained as follows. The Hodrick-Prescott filter (Hodrick and Prescott, 1997) is used to extract the cyclical components of previously log-transformed original and simulated series. The cyclical components are then multiplied by 100 so as to express them in percentage deviations from the trend. The cyclical component of output is used to operationalize the overall business cycle y_t, thus acting as the benchmark against which to compare any other variable of interest x_t. Four different moments are employed for this task. *Standard deviations* $std(x_t)$, which measure the *amplitude* of fluctuations in absolute terms; *relative standard deviations* $std(x_t)/std(y_t)$, which estimate the *variability* of each variable against output; *contemporaneous cross-correlations* with output $xcor(x_t, y_t)$, which capture the *co-movements* – procyclical if $xcor(x_t, y_t) > 0$, acyclical if $xcor(x_t, y_t) \approx 0$, or countercyclical if $xcor(x_t, y_t) < 0$ – between the cycle and any other aggregate of interest; *first-order autocorrelations* $acor(x_t, x_{t-1})$, which measure the *persistence* of each series.

6.1. Sensitivity analysis

A preliminary sensitivity analysis is carried out in order to inspect how the model behaves with respect to the substitution parameter ρ governing the CES production function. Motivated by similar

analyses in Kim and Loungani (1992) and Dhawan and Jeske (2008), three values of ρ are tested, namely −0.001, −0.7, −3. Table 3 provides several calibrations for the sensitivity of investment φ, the persistence of the technology shock ρ^A, and the standard deviation of the technology shock σ^A with respect to parameter ρ. In other words, different choices of ρ imply different calibrations. From a purely descriptive viewpoint, a gradual movement of ρ from −0.001 to −3 leads to slight decreases in φ and ρ^A and a small increase in σ^A.

Table 3. Sensitivity analysis as a function of the CES substitution parameter.

	$\rho = -0.001$	$\rho = -0.7$	$\rho = -3$	Description
φ	1.2351	1.0663	0.9923	Sensitivity of investment
ρ^A	0.9879	0.9852	0.9838	Persistence of technology shock
σ^A	0.0065	0.0071	0.0074	Std. deviation of technology shock

Table 4. HP-Filtered moments as function of the CES substitution parameter – Stylized facts.

Variable	ρ	$std(x_t)$	$std(x_t)/std(y_t)$	$xcor(x_t, y_t)$	$acor(x_t, x_{t-1})$
Y	−0.001	1.17	1.00	1.00	0.83
	−0.70	1.20	1.00	1.00	0.84
	−3	1.22	1.00	1.00	0.84
	data	**1.43**	**1.00**	**1.00**	**0.88**
C	−0.001	0.69	0.59	0.86	0.66
	−0.70	0.71	0.59	0.85	0.65
	−3	0.72	0.59	0.83	0.64
	data	**0.85**	**0.59**	**0.82**	**0.87**
I	−0.001	4.19	3.59	0.92	0.93
	−0.70	4.93	4.09	0.92	0.92
	−3	5.36	4.41	0.89	0.92
	data	**5.54**	**3.88**	**0.93**	**0.88**
L	−0.001	0.46	0.39	0.26	0.78
	−0.70	0.50	0.41	0.28	0.77
	−3	0.53	0.44	0.29	0.75
	data	**1.90**	**1.33**	**0.87**	**0.93**
E	−0.001	11.50	9.96	0.61	0.79
	−0.70	7.26	6.10	0.50	0.80
	−3	3.66	3.05	0.45	0.81
	data	**2.30**	**1.61**	**0.63**	**0.57**
p_e	−0.001	10.83	9.39	−0.54	0.79
	−0.70	10.83	9.12	−0.39	0.79
	−3	10.83	9.04	−0.26	0.79
	data	**9.80**	**6.86**	**0.14**	**0.76**
M^d	−0.001	12.98	11.24	0.61	0.79
	−0.70	8.19	6.89	0.50	0.80
	−3	4.13	3.44	0.45	0.81
	data	**2.32**	**1.63**	**0.62**	**0.59**

Notes:

1. Y: output; C: consumption; I: investment; L: labor; E: energy; p_e: energy price; M^d: domestic emissions.
2. Simulated moments for $\rho = -3$ (underline) are compared with empirical moments (bold).

The validation of the model, carried out in the absence of policies, is assessed in terms of Table 4, which presents the degree of similarity between the stylized facts from simulated and original series. The values of simulated moments are organized for each variable based on the descending value of the

substitution parameter ρ of the CES. The stylized moments of the economic variables remain relatively stable and similar to their counterparts in real data with respect to changes in ρ. On the other hand, moving ρ from −0.001 to −3 makes energy and climatic variables gradually approach the stylized moments characterizing real data. For this reason, as already mentioned in Section 5, the subsequent simulations and results purposely assume ρ equal to −3.

6.2. Inspecting original data

A first inspection of the empirical moments of the original series (bold in Table 4) suggests that pure economic aggregates behave in a similar way to the benchmark of King and Rebelo (1999): consumption is about half as volatile as output, investment is about four times more volatile than output, while labor is about as volatile as output. All of them are strongly procyclical with the overall cycle and very persistent. Carbon emissions, fossil energy use, and fossil energy price are relatively more volatile than output. The latter, in particular, is almost 7 times more volatile than output and shows a relatively large persistence (0.76). Fossil energy use and domestic CO_2 emissions are procyclical with output, though to a lesser extent than pure economic variables. The procyclicality between carbon emissions and the business cycle, in particular, is in line with extant literature such as Heutel (2012) or Calvia (2022).

6.3. Comparison between simulated and original moments

As Table 4 shows, the model works relatively well in capturing the empirical behavior of the main macroeconomic aggregates, as the simulated moments resemble (underlined in Table 4) the original ones in most cases. Mirroring the original series, simulated consumption is less volatile than simulated output, which, in turn, is less volatile than simulated investment. Simulated cross-correlations and first-order autocorrelations of the above-mentioned variables are very similar to their original counterparts. The model is not able to generate enough volatility for labor; this issue, however, is a well-known drawback of standard RBC models (DeJong and Dave, 2012). Overall, the model comes close to replicating the autocorrelations of almost all economic variables.

The model is relatively successful in reproducing all core features of energy prices except its cross-correlation with output: While data suggest a mild positive relationship, the model produces a negative one. Their values, however, are low in magnitude, thereby suggesting an almost acyclical behavior between energy price and output. It is worth underlying that Kim and Loungani (1992) find a negative correlation between energy price and output in annual data from 1949 to 1987, thus suggesting that such a discrepancy can be dependent on the period and frequency of analysis. The relative standard deviations of energy use and carbon emissions are approximated relatively well, in that they are more volatile than output and consumption, and less volatile than investment and fossil energy price. The model, however, tends to slightly underestimate cross-correlations with output and overestimate autocorrelations.

Differently from all other variables which, independent of their nature, are generated by economic processes, atmospheric stock of CO_2 and temperature change are governed by natural laws, whose times and features – not pertaining to the economic realm – are very far from being successfully simulated by standard RBC models. For this reason, they are purposely not considered, in that their reproducibility goes well beyond the simulating abilities of off-the-shelf RBC models.

7.   Results and discussion

The model economy is simulated under two exogenous shocks: Figure 2 and Figure 3 show the impulse response functions (IRFs) under the technology shock; Figure 4 and Figure 5 present the IRFs when the model is hit by the fossil energy price shock. As specified in Section 4.4, for each shock the *technical tax* scenario (green line) is compared to the constant tax scenario (red line) and the no-tax scenario (blue line), the latter representing the benchmark to highlight the model's core mechanisms. The long-run path of the unshocked value is the zero line (black). Variables are expressed in percentage deviations (%) from their steady-state. Any comparisons with similar models, although included, should be interpreted with caution, as this model might differ from them in terms of calibration and included variables. The model has been solved using Dynare 5.3 (Adjemian et al., 2011).

7.1. Technology shock
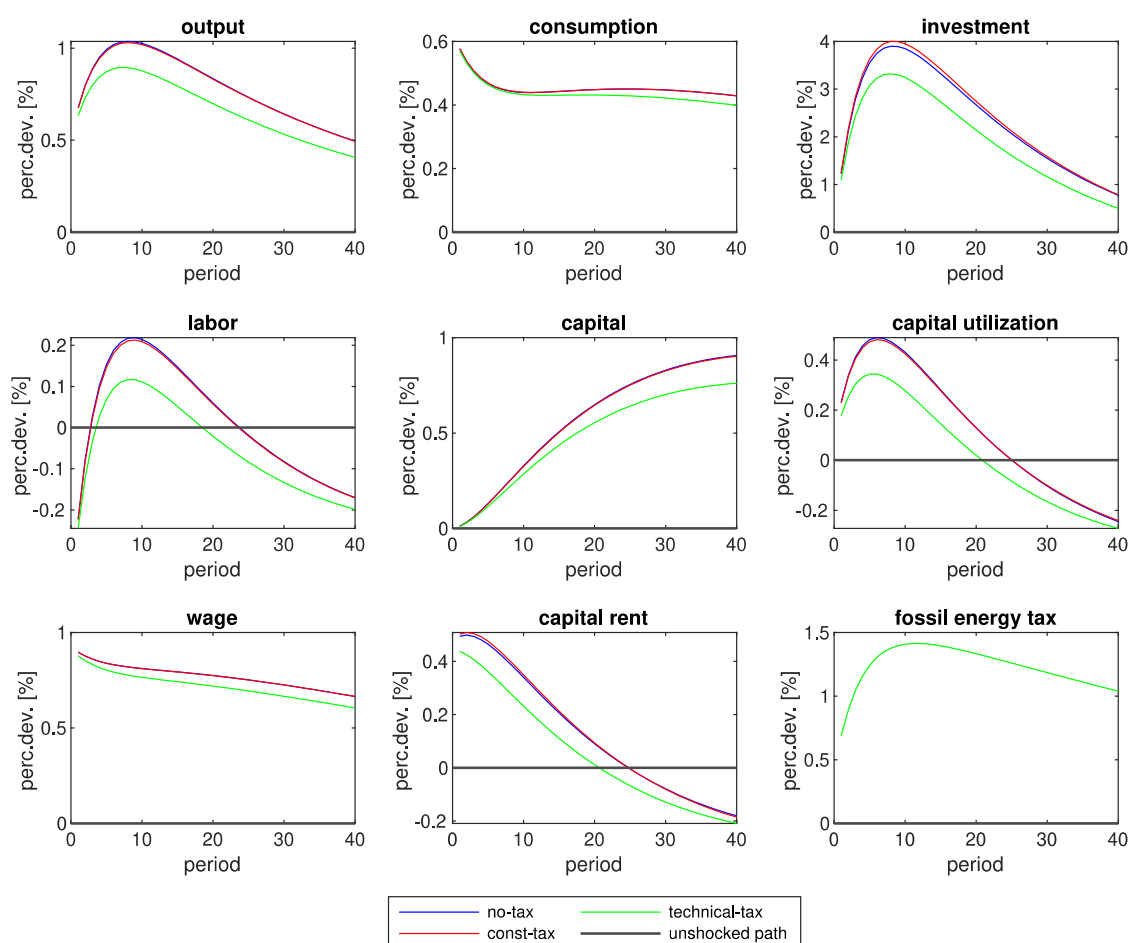
Figure 2. Effect of technology shock on economic variables.

Starting from the no-policy scenario, according to Figure 2, one standard deviation increase in total factor productivity pushes marginal productivities of labor and capital. In other words, the economy becomes more productive. This triggers firms' demand for production factors as witnessed

by the increase in real wage and capital rent, i.e., the prices of production factors. A positive income effect is, thus, experienced by the household, that increase their investment, thus fostering capital accumulation. The household experiences high wealth. This is, however, limited by investment adjustment cost. Aggregate demand – mostly in the form of consumption and investment – does not react much to the technology shock and remains relatively smooth. Given the higher level of wealth, the household is able to afford a certain level of consumption working less.

As witnessed by Figure 3, under complementarity between capital and fossil energy use, the push in output production results into a significant increase in fossil energy use and, thus, in domestic CO_2 emissions. The slow and positive path of accumulation concerning the industrial stock of CO_2 triggers a path of positive temperature changes.

The constant tax on fossil energy does not react with the business cycle and its impact on economic and non-economic variables almost overlaps with the no-tax case. Conversely, the *technical tax* is very reactive. Though mildly dampening the shock's impact on almost all economic variables, it strongly contains fossil energy use. The latter, in turn, influences the behavior of climate-related variables. CO_2 emissions grow lower than in the benchmark case, thereby mitigating global warming. This is clear by looking at the industrial stock of CO_2 and the temperature change that, despite the relatively small magnitudes, are characterized by lower profiles and smoother shapes compared to the benchmark case.

Compared to the static cap-and-trade scenario (e.g., Annicchiarico and Di Dio, 2015; Xiao et al., 2018; Eydam, 2023), the *technical tax*, inheriting dynamic features by construction, is obviously not able to lead to a zero-change in carbon emissions. However, it represents a valid complement to Eydam's (2023) dynamic cap-and-trade scheme, in that it features smoother and less oscillating dynamics of carbon emissions. The *technical tax* also presents a marked dampening in carbon emissions compared to the emission tax and the intensity target in Annicchiarico and Di Dio (2015) and Xiao et al. (2018). The latter two, on the other hand, do not seem to strongly affect the output dynamics with respect on the *no-policy* scenario.
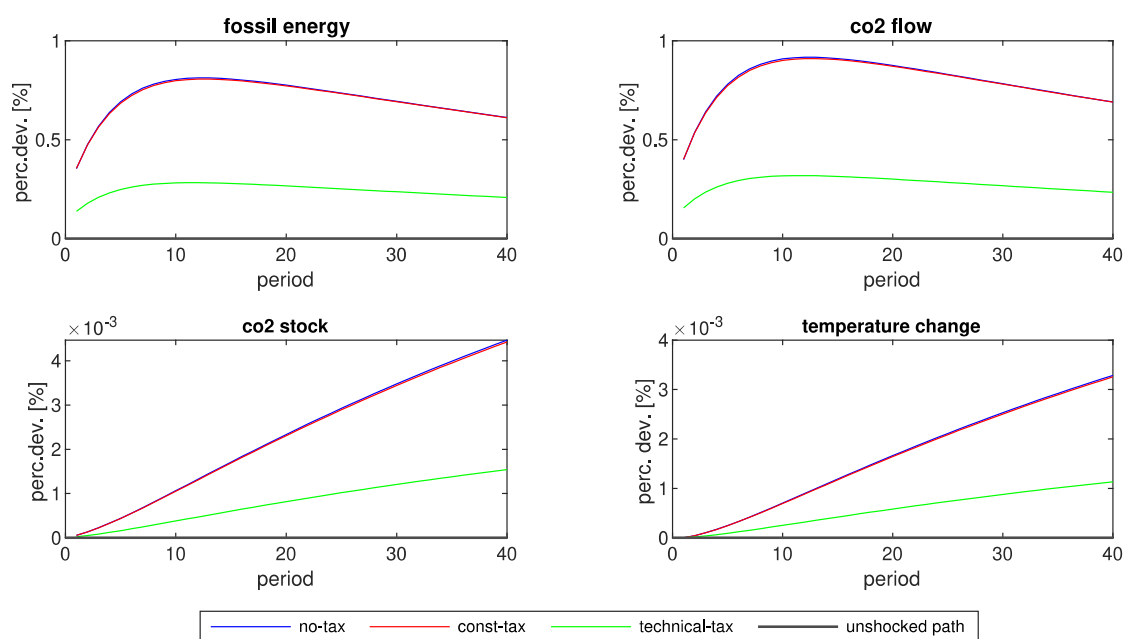

Figure 3. Effect of technology shock on fossil energy and climatic variables.

7.2. Fossil energy price shock

With respect to the no-tax scenario, one standard deviation increase in the price of fossil energy affects model variables in a way opposite to the technology shock. According to Figure 5, such a shock first lowers fossil energy use. As witnessed by Figure 4, capital utilization drops as well as capital rent. The household experiences a negative income effect, feeling poorer, ceasing investing and accumulating capital, the process resulting in the shrinking of household's wealth. As in the case of technology shock, investment adjustment costs do not allow aggregate demand to react too much to the fossil energy price shock. Households, thus, reduce consumption, invest less and simultaneously decide to work more even in a situation of falling wages. This fact reconciles the lower productivity induced by the energy-price shock with the smoothness of the aggregate demand.

According to Figure 5, the sharp decrease in the use of fossil energy due to a positive energy price shock has an impact – albeit modest – on climatic variables. More specifically, it leads to a significant instantaneous decrease in domestic CO_2 emissions, a gradual and mild fall in the industrial stock of CO_2 and, hence, in temperature change.
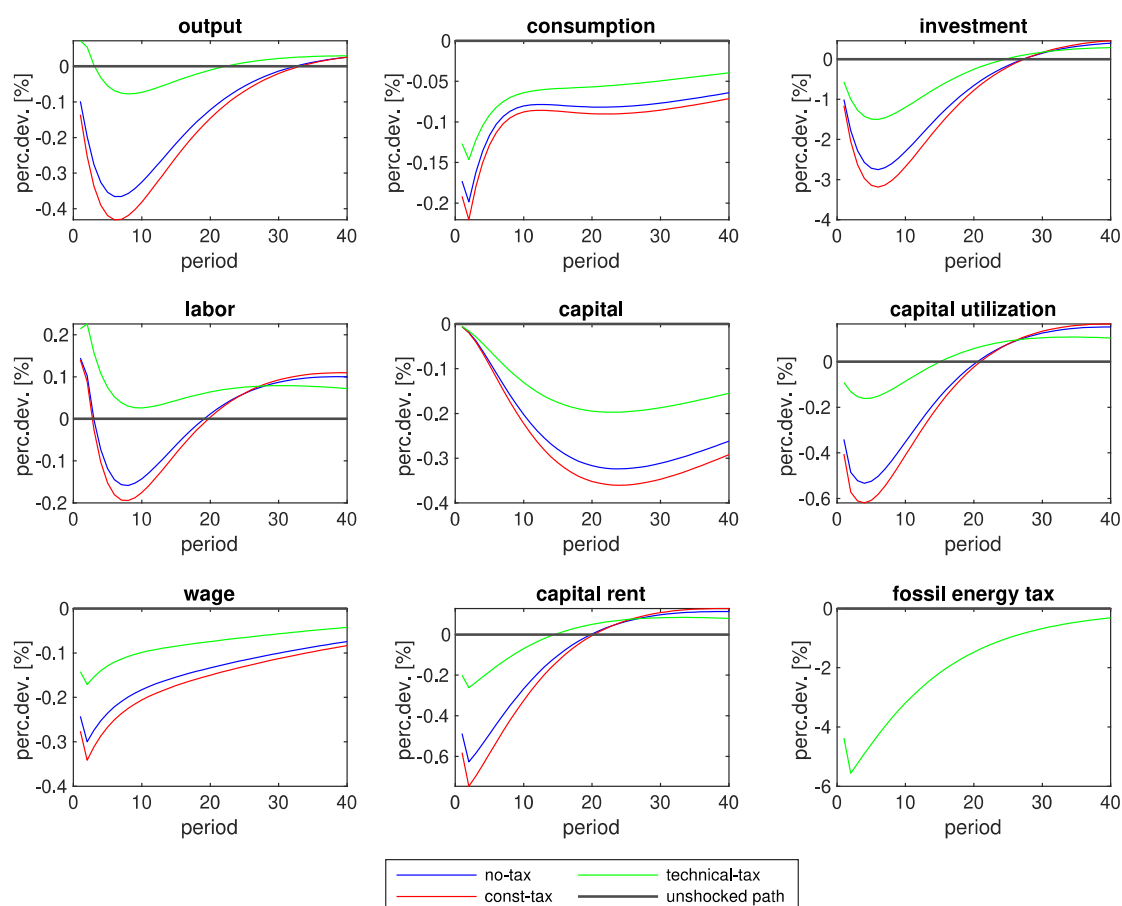

Figure 4. Effect of energy price shock on economic variables.

Mirroring the technology shock, the constant tax is not reactive and its outcome tends to stick close to that of the no-tax scenario. Due to its responsiveness to the business cycle, the effect of the

technical tax, on the other hand, is more net and diverse. The price shock pushes firms to reduce fossil energy use and, thus, their impact on climatic variables. Figure 5 shows an instantaneous drop in domestic CO_2 emissions, which translates into mild and gradual decreases in the industrial stock of CO_2 and temperature change. As a direct consequence, the reduction in energy use lowers the tax, thereby countering the increase in fossil energy price. The latter effect, however, is not strong enough – energy use does not drop considerably – and fossil energy value $p_{e,t}E_t$ keeps increasing pushed by the price effect. Given a certain level of consumption and investment, output reacts with a mild increase compared to the other scenarios. In other words, while energy is taxed and energy use drops, this policy is somehow able to counter the adverse effect of taxation on economic activity. This happens because labor is not taxed and can instantaneously adjust, thus replacing fossil energy.

As shown by Zhao et al. (2020) for China, standard policies such as the carbon tax, the carbon permits and the mix of them are able to negatively impact carbon emissions dynamics under an energy price shock; however, this happens at the cost of a net instantaneous reduction in output. Under the *technical tax*, instead, a milder reduction in carbon emissions is accompanied by and instantaneous moderate increase in output, which then slowly oscillates around the steady-state.
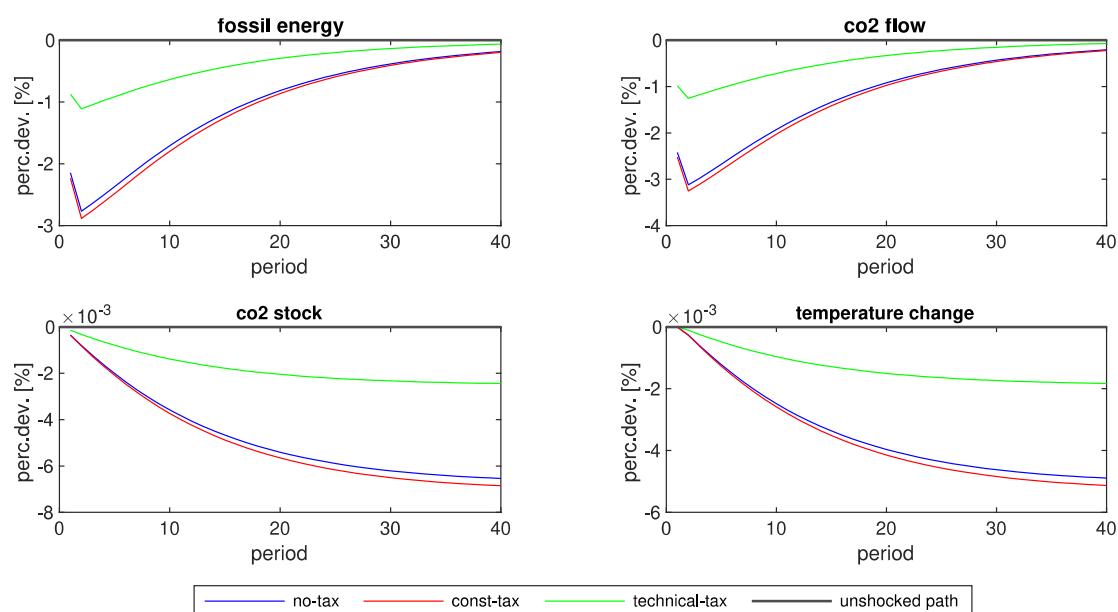

Figure 5. Effect of energy price shock on fossil energy and climatic variables.

7.3. Discussion

Similar to extant environmental policies (e.g., Eydam, 2023), the *technical tax* modifies aggregate economic and climatic dynamics quantitatively and not qualitatively with respect to the no-tax and the constant tax scenarios. The no-tax and the constant tax, which are characterized by the absence of dynamics ($\psi_1 = 0$, $\psi_2 = 0$, and $\psi_3 = 0$), almost overlap independent of the shock considered. The *technical tax*, being reactive to the business cycle, sustains a certain level of productivity and leads to a substantial limitation of domestic emissions in the case of the technology shock. With respect to the energy price shock, the reduction in fossil energy use lowers the effect of the tax, which counters, to

some extent, the increase in the price energy itself, thus mitigating its effect on output notwithstanding its negative impact on carbon emissions.

Despite its strong impact on domestic carbon emissions, the effect of the *technical tax* on climate variables is mild regardless of the shock considered. Results concerning climate variables should be interpreted qualitatively for two reasons. First, the climatic block provides only a stylized description of the carbon cycle. Second, the impact of the *technical tax* refers to a single country, namely the United States, while changes in global temperatures and in the industrial stock of atmospheric carbon dioxide are actually the result of global economic processes involving world emissions.

The *technical tax* accounts simultaneously for domestic variables such as fossil energy use and carbon emissions and for global variables such as the industrial stock of CO_2 in the atmosphere. The inclusion of the latter, despite its small weight compared to domestic variables ($\psi_3 = -0.0002$), emphasizes the need to extend carbon policy beyond domestic borders. In other words, each country adopting the *technical tax* would face the need to consider variations in the industrial stock of atmospheric carbon dioxide, to which all world economies jointly contribute. The implementation of the *technical tax* rests on the assumption that the policy maker knows the steady-state values of domestic emissions, fossil energy use and anthropogenic stock of CO_2. While the steady-state value of fossil energy use and carbon emissions can be determined endogenously, that of the atmospheric industrial stock of CO_2 can be set exogenously, for example, based on the values suggested by the existing literature. Furthermore, the *technical policy* gives the policy-maker a certain degree of flexibility in deciding how much to reduce the variance of, i.e., stabilize, carbon emissions. As for all carbon policies, international commitment would play a significant role in the implementation of the *technical tax*.

8. Conclusions

We propose a climate-oriented *technical* policy experiment targeting fossil energy use with the goal of stabilizing domestic CO_2 emissions. The *technical tax* represents an easy-to-implement policy rule, which responds to percent variations of measurable physical quantities such as fossil energy, domestic CO_2 emissions, and industrial stock of CO_2 from their steady-state values.

Within the limits posed by the methodology itself, the moments produced by the model are similar to those computed in the data for most macroeconomic aggregates, independent of their nature. The effect of the *technical tax* is compared with a constant tax and a no-tax scenario, i.e., the benchmark. The constant tax does not react with the business cycles, thus overlapping with the no-tax scenario for almost all variables, no matter the shock considered. The *technical tax*, on the contrary, is very responsive to the business cycle. When the economy is hit by a technology shock, the tax sustains a certain level of output with a relatively limited increase in the use of fossil energy, thus limiting carbon emissions and their contribution to the climatic issue. Under a positive energy price shock, the tax instantaneously reduces the use of fossil energy under its steady-state, hence mitigating its detrimental effect on production without fostering global warming. As a matter of fact, the adoption of the *technical tax* shows very positive aspects. In general, it is able to stabilize CO_2 emissions in terms of variability. When a technology shock hits the economy, it dampens domestic carbon emissions with minor costs in terms of potential output losses. It also protects the economy from an increase in energy

prices, mitigating the fall in production despite the drop in fossil energy use. In general, the *technical tax* has a strong impact on domestic carbon emissions. Its effects on global variables such as temperature change and atmospheric stock of carbon dioxide, despite qualitatively encouraging, should interpreted in light of the stylized description of the carbon cycle employed in this work and limited to the sole contribution of the United States.

As a direction for future research, the model could be further extended to account for the use of renewable energy. Such a model, if able to satisfactorily replicate the cyclical features of real data, would represent a useful framework to analyze the dynamics triggered by the *technical tax* or, more generally, by any other energy or carbon policy on the whole energy market. Moreover, the role of non-linearities in the damage function could be further explored for designing climate policies. In most E-DSGE models, policy functions are approximated through first-order perturbation methods around the steady-state. For this reason, non-linearities characterizing climate variables could be further addressed resorting to global solutions techniques. The *technical tax* might also be simulated under a New Keynesian framework including nominal rigidities as in Annicchiarico and Di Dio (2015). A paradigm-shift towards macroeconomic Agent-Based Models (ABM) (Fagiolo and Roventini, 2012), on the other hand, could provide a *flexible*, *bottom-up* alternative to understand how the *technical tax* interacts with those macro-dynamics set up by the behaviors of several heterogeneous individual agents.

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Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

Conflict of interest

The authors declare no conflict of interest.

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