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An Operational Framework for a Low-carbon, Green Growth Economy: CO-STIRPAT Dynamic System

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ABSTRACT

This paper presents an operational framework for assessing the trajectories of production, energy, emissions, and capital accumulation to ensure the implementation of Nationally Determined Contributions (NDCs). The framework combines widely used methodologies (STIRPAT, system dynamics, and optimization) to simulate the pathways of variables until a target year. The CO-STIRPAT dynamic system allows us to identify the spillover pathways from carbon policy to economic growth based on output optimization principles; to conduct a more systematic analysis of the interconnections between the main drivers that determine carbon emissions; to develop a cost-effective climate policy mix that is a backbone for the right combination of carbon pricing, energy efficiency, and carbon intensity; and to assess NDC targets with respect to ambition gaps, implementation gaps, and feasibility.

KEYWORDS

Nationally Determined Contributions (NDCs); STIRPAT, carbon emission; energy efficiency; carbon intensity; system dynamics

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1. Introduction

Countries have pledged their Nationally Determined Contributions (NDCs) under the Paris Agreement. Meeting NDC targets is critical to reducing emissions and limiting global warming through collective action around the world. The probability of keeping warming below 2°C under current trends is only 5% but increases to 26% if all countries meet their NDCs and continue to reduce emissions at the same rate after 2030 (Liu and Raftery 2021). However, their fully statistically based probability framework shows that the probability of meeting NDCs for the largest emitters is low. If countries fail to meet their NDCs, the credibility of the global agreement to combat climate change could be undermined, making it urgent to explore feasible climate policy options.

Countries may consider a variety of policy instruments to fulfill their NDCs: carbon pricing, improving energy efficiency, reducing carbon intensity, etc. First, introducing a carbon pricing mechanism (such as a carbon tax or cap-and-trade system) can create economic incentives to reduce emissions. Establishing mechanisms for green finance and investment in sustainable projects can accelerate the transition to a low-carbon economy. Another policy option is to encourage energy efficiency in industrial processes, transportation, buildings, and appliances to significantly reduce emissions. Promoting circular economy principles (such as recycling and waste reduction) can contribute to energy efficiency by reducing resource consumption. As a next option, governments can provide incentives, subsidies, and tax breaks to attract investment in renewable energy infrastructure and technologies. Funding R&D for low-carbon technologies and innovations can catalyze progress toward meeting NDC targets more effectively.

This paper aims to provide a practical operational framework for assessing the feasibility of individual climate policy options and deriving the optimal combination of instruments to achieve NDC goals. NDCs may be incompatible with current climate policy instruments, resulting in an ambition gap and an implementation gap. The ambition gap relates to the difference between the carbon budget implied by the 1.5° or 2.0°C corridor set by the Paris Agreement and the level of NDCs committed by countries (Friedlingstein et al. 2022). Assessing the ambition of NDCs is particularly important because the Paris Agreement calls for regular reviews of national contributions (Höhne et al. 2018). The implementation gap captures the difference between the policies implemented and the emission reduction pathway targeted in the NDC (Perino et al. 2022). The level of ambition gap and implementation gap varies widely across countries, and some countries appear to have set unrealistic NDC targets. Countries that set overly ambitious targets may face greater challenges in achieving them, increasing the likelihood of NDC failure. An accurate assessment of the feasibility of announced NDC targets depends on the flexibility of the operational framework to reflect progress in energy efficiency and carbon intensity reduction in an appropriate way. We combine CO-STIRPAT (Component-Oriented STIRPAT) with system dynamics and optimization methodologies to link NDC targets to manageable quantified performance indicators. We aim to keep the framework as simple as possible by focusing on the essentials but with enough flexibility to ensure that important issues relevant to climate policy are covered in the framework.

Assessing the feasibility of NDC targets can provide valuable insights into the effectiveness of current climate policy actions to reduce carbon emissions. By analyzing the likelihood of achieving NDC targets, policymakers can identify areas where more effort and resources are needed to increase the probability of success. The operational framework in this paper can guide policymakers to implement climate policy measures more effectively. By translating the gap between the pathway predicted by current climate technologies and the NDC target pathway into the necessary level of policy indicators (carbon price, clean energy share, energy efficiency, carbon intensity), the framework can help the general public assess whether the targets are feasible under current conditions and whether they are ambitious enough to achieve the goals of the Paris Agreement. This research can also contribute to broader solutions for international cooperation to achieve global climate goals. By analyzing the likelihood of achieving NDC targets in different countries and regions, researchers can identify challenges and opportunities for more effective global cooperation to address the climate crisis.

The paper proceeds as follows. We first review the related literature and introduce the analytical backbone. Next, we describe the design for the numerical analysis and present the data. We then present the quantitative results of applying the framework to the Korean NDC targets. Finally, we conclude the paper with conclusions and future research directions.

2. Literature review

This research is deeply related to four research streams: NDC goal attainability, drivers of carbon emissions, the nexus between GDP, energy, and emissions, and system dynamics. In this section, we briefly introduce key findings related to each research stream that is relevant to this paper. First, several studies have assessed if countries are on track to fulfill their NDCs as promised in the Paris Agreement. As presented in Panel A of Table 1, the current policies across scenarios are evaluated to analyze whether countries are on track to meet their NDC targets. Next, many studies have used the IPAT, the ImPACT (as a widely recognized instance, the Kaya identity), and the STIRPAT framework for analyzing the key drivers of carbon emissions. As presented in Panel C of Table 1, many papers analyze individual factors of the Kaya identity to identify relevant drivers of carbon emissions. Next, there is a large amount of research on issues related to the nexus of GDP, energy, emission, NDC, and climate policy. As shown in Panel C of Table 1, several studies have analyzed the causal links between GDP, energy consumption, and carbon emissions with objectives close to ours. Most previous studies focus on whether GDP or energy consumption affects carbon emissions. In contrast, our study seeks to determine how carbon emission reductions through NDCs affect GDP or energy consumption. Finally, much of the recent work on climate policy has utilized system dynamics, as summarized in Panel D of Table 1. They develop simulation models based on system dynamics to examine the impact of the adoption of climate policy instruments.

3. Methods

3.1. IPAT, ImPACT, STIRPAT, and CO-STIRPAT

The theoretical basis of this paper is a commonly used framework in the field of sustainability studies to understand the drivers and impacts of economic activities on carbon emission: IPAT, ImPACT, and STIRPAT. These theoretical concepts are often used as a starting point to understand the complex interactions between human activities and the environment. As discussed in early papers(Commoner 1971; Ehrlich and Holdren 1972), IPAT (Impact, Population, Affluence, and Technology) is a simple equation that expresses the environmental impact (I) as the product of population (P), affluence (A), and technology (T). IPAT emphasizes the role of population growth, increasing affluence patterns, and technological advancements in shaping environmental degradation. As an extended IPAT framework reconceptualized by (Waggoner and Ausubel 2002), ImPACT (Integrated Model of Population, Affluence, Consumption, and Technology) includes an additional factor: consumption (C). ImPACT focuses on the interconnections between population dynamics, economic development, consumption patterns, technological choices, and their combined impacts on the environment. As a statistical version of IPAT reconstructed from related research(Dietz and Rosa 1994; Rosa and Dietz 1998), STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) seeks to explain environmental impacts by using regression analysis to estimate the influence of PAT (population, affluence, technology) on environmental outcomes. CO-STIRPAT is a component-oriented version of STIRPAT described in Jin (2023) that incorporates a stochastic term in the dynamic causal relationship for each component of ImPACT (or the Kaya identity). These four approaches share a common focus on understanding the relationship between human activities and environmental impacts although they differ in terms of their complexity and the variables they consider.

Table 1. Relevant research examples and key findings.

Feasibility of committed NDCs	
Paper	Finding
den Elzen et al. (2019)	Some of the G20 economies are on track to meet their NDCs.
Dong et al. (2018)	There will be a shortfall in achieving targets by seven countries out of the top ten CO2 emitters.
Liobikienė and Butkus (2017)	The EU countries should attempt more to reduce energy consumption and to increase the share of RES to seek targets.
Liu and Raftery (2021)	The probabilities of meeting their nationally determined contributions for the largest emitters are low.
Roelfsema et al. (2020)	The countries evaluated are found to not achieve their pledged contributions with implemented policies (implementation gap).
Drivers of carbon emissions	
Paper	Finding
Ang and Zhang (2000)	The Kaya identity helps quantitatively analyze the impact of interest on the intensity or total amount of carbon emissions.
Hwang et al. (2020)	The indirect effects of the decomposed variables in the Kaya identity on the carbon emission are significant.
Jin and Kim (2017)	It is necessary to have sufficient public finances to implement measures contained within NDC.
Wang et al. (2021)	From the STIRPAT perspective, the robust U-shaped EKC was confirmed for 198 countries between 1990 and 2018.
York, Rosa, and Dietz (2003)	The STIRPAT allows for a more precise specification of the sensitivity of environmental impacts to the forces driving them.
Nexus between GDP, energy, and emission	
Paper	Analysis
Gyimah et al. (2023)	Renewable energy and fossil fuel cause carbon emissions in Ghana whereas economic growth has no relevant effect on carbon emissions.
Khan et al. (2022)	The causality between GDP growth and carbon emission and the bidirectional causality between economic growth and energy use are identified.
Raihan et al. (2022)	Renewable energy use and technological innovation can reduce Malaysia's carbon emissions while economic growth deteriorates the environmental quality.
Sohag, Chukavina, and Samargandi (2021)	The use of renewable energy in the production process spurs TFP in the long run through different macroeconomic channels.
Wen et al. (2021)	The EKC hypothesis is confirmed in the South Asian region; at the early stages of development, environmental pollution also increases when economic growth increases.
System dynamics for climate policy	
Paper	Analysis
Ahmad et al. (2015)	Constructed a system dynamics model that investigates the role of feed-in tariff policy in Malaysia till 2050.
Al-Refaie and Abdelrahim (2021)	Developed a system dynamics model to analyze the effect of green transportation and logistics on the total transportation cost.
Daneshgar and Zahedi (2022)	Developed a dynamic production profitability model to analyze the operation of a hydro reservoir system in Iran.
Nair et al. (2021)	Examined the impact of renewable energy in the energy mix for energy supply in Malaysia using a system dynamics approach.
Smit, Musango, and Brent (2019)	Investigated issues about energy fuel choice, energy bias, energy switching, and energy access through system dynamics.

Notes: This table provides an overview of papers in four research streams that are closely related to our analysis: feasibility of committed NDCs, drivers of carbon emissions, nexus between GDP, energy, and emissions, and system dynamics for climate policy. The panel for each research stream lists the author names, year of publication, and key findings of relevant papers.

3.2. System dynamics

We utilize system dynamics to simulate the behavior of complex CO-STIRPAT systems over time.[1] At its core,

[1]System dynamics was established in the 1950s and has since been widely used in various disciplines, including

we seek to analyze the interconnections and feedback loops within a system to gain insights into its dynamic behavior: production, energy consumption, carbon emission, and capital evolution. The representative agent is assumed to have the goal of maximizing profits through a process of optimizing outputs and inputs to achieve the highest possible profit level. In a competitive market with prices given, the agent seeks to choose an optimal level of production at which marginal revenue equals marginal cost. In our model, climate policy options (carbon pricing, energy efficiency enhancement, and carbon intensity reduction) are interconnected within the context of NDCs, especially through the profit maximization principle. As shown below, our dynamic system consists of five elements of the system: an objective function (profit) and causal relationship constraints (production Q, labor L, capital K, carbon-intensive energy EC, carbon-free energy EF, and emission C). For a given set of prices $\{r_Q, r_L, r_K, r_{EC}, r_{EF}, r_C\}$, each component describes the key aspects that determine the dynamics of the national economy.[2]

$$\max_{Q}\left(r_Q Q_t - r_L L_t - r_K K_{t-1} - r_{EC} EC_t - r_{ER} EF_t - r_C C_t\right) \quad (1-1)$$

$$Q_t = f(K_{t-1}, L_t) \quad (1-2)$$

$$E_t = EC_t + EF_t = g(Q_t; t) \quad (1-3)$$

$$C_t = h(EC_t; t) = h(\omega_t E_t; t) \quad (1-4)$$

Where: $\omega_t = EC_t / E_t$.

$$K_t - K_{t-1} = i(Q_t; t) \quad (1-5)$$

First, the profit function (Equation 1-1) includes terms related to energy consumption and carbon emissions, unlike traditional cost structures that focus only on capital and labor inputs. The relationship between revenue, production costs, energy price, and carbon price is now integrated into a unified decision problem. This describes the economic incentive to consider additional constraints such as energy efficiency and carbon intensity. The framework allows the previously externalized cost of carbon emissions to be internalized through carbon pricing.[3]

The second element of our system dynamic model (Equation 1-2) is the production function with two conventional inputs: capital and labor. We use the constant elasticity of substitution (CES) production function to describe the relationship between two inputs and the output in a production process.[4] The CES production function provides a flexible framework for analyzing production processes, input substitution possibilities, and the impact of changes in factor prices on output levels.

Other elements of our dynamic system seek to gain insight into dynamic behavior by analyzing causal relationships within the system. The next two elements of the model (Equations 1-3 and 1-4) describe each of the causal relationships for energy efficiency and carbon intensity. They are major constraints in the decision-making process for transitioning to a low-carbon economy. Note that production activities first cause total energy use in Equation 1-3, and then only carbon-intensive energy consumption entails carbon emissions in Equation 1-4.

The final element of the model (Equation 1-5), the capital evolution function, shows the stocks and flows of

engineering, economics, management, and social sciences (Forrester 1971).

[2]The parametric specification and relevant assumptions used in the mathematical analysis are presented in Appendix I.

[3]This internalizationcan be achieved in a carbon tax and/or cap-and-trade system.A discussion of how to accomplish this is beyond the scope of this paper's analysis and is left as a future research question.

[4]The two factor (capital, labor) CES production function was initially introduced by Solow (1956) and made popular by Arrow et al. (1961).

the dynamic system. The capital stock is related to both investment (inflows into the capital stock) and depreciation (outflows from the capital stock). The capital evolution function is also characterized by time delays in our dynamic system because it takes into account the time difference between when capital is accumulated and when it is used in production. These components also constitute a feedback loop, an interaction mechanism that affects the behavior of the dynamic system.[5]In this way, our dynamic system contains non-linear relationships where changes in one component do not affect other components proportionally.

Overall, these functions identify interconnections and feedback between different components of the system. The predicted behavior of the system under different scenarios depends on the causal relationships between these components (production, energy, emissions, and capital change). Thus, our dynamic system can be used as a powerful toolset for understanding, simulating, and managing the complex interactions between production, energy use, carbon emissions, and capital accumulation. This can contribute to more effective decision-making and climate policy design to fulfill NDCs.

3.3. Optimization

As stated earlier, the purpose of this paper is to identify the relationship between production, labor, capital, energy, and carbon emissions under standard profit maximization principles and to examine the implications for climate policy. To do this, the dynamic system presented in Equations 1-1 through 1-5 can be rephrased as the following:

$$Reve(Q_t) = r_Q Q_t \qquad (2-1)$$

$$Cost(Q_t) = r_L \hat{L}(Q_t) + r_K \widehat{K}(Q_t) + r_E\, g(Q_t) + r_C\, h\big(\omega_t\, g(Q_t)\big) \qquad (2-2)$$

$$MR(Q_t^*) = MC(Q_t^*) \qquad (2-3)$$

where Q_t^*represents the optimal production level that satisfies the first-order condition in Equation 2-3.

Equation 2-1 is a simple revenue function in linear form: quantity produced multiplied by price. Equation 2-2 shows a cost function with four terms for the relevant factors (labor, capital, energy, and emissions), each of which is a nonlinear function of output Q. The first two terms, $\hat{L}(Q_t)$ for labor and $\widehat{K}(Q_t)$ for capital, represents the demand for production factors to produce an output $Q_t$at a level that minimizes the cost of production, given a CES production function and a set of prices.[6] In the third term, $g(Q_t)$ shows how the energy demand for a given output Q is determined. In the last term, $h\big(\omega_t\, g(Q_t)\big)$ is a composite function that shows a continuous causal interconnection from output to energy and from energy to emissions. Equation 2-3 is the conventional first-order condition in which profit is maximized. Marginal revenue on the left-hand side is equal to the product price. In contrast, marginal cost on the right-hand side consists of the first-order derivatives of the four nonlinear functions in Equation 2-2.

Because the complex nonlinear relationships make it difficult to derive an analytical solution, we use numerical analysis to explore optimal production levels. This numerical analysis is performed in four steps, as follows.

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[5]As explained in Sterman (2001), a positive feedback loop amplifies the initial change and leads to exponential growth or decline in the system, whereas a negative feedback loop stabilizes the system, preventing it from going to extremes and maintaining equilibrium.Delays in feedback loops can lead to oscillations or even instability in the system.

[6]For the numerical simulations, we use the demand for production factors derived analytically from cost minimization, the results of which are presented in Appendix I.

- Step 1: The functions given in Equations 1-2 to 1-5 are estimated from observations on GDP, labor, capital, energy and emissions, and capital during the estimation period.
- Step 2: Assuming production took place under the optimization conditions given in Equation 2-3, we estimate prices using observations on the other variables and the functions estimated in Step 1. To estimate the set of prices (carbon, carbon-intensive energy, carbon-free energy, capital, labor, and output), we apply the assumption that profits were higher than zero during the estimation period (2000-2022).
- Step 3: Assuming that the parameters and prices estimated in Steps 1-2 remain the same throughout the forecast period, we find the optimal production level that satisfies Equation 2-3 for each year of the forecast period. Optimal output at each point in time cannot exceed the supply of production factors that exist then, with the working-age population acting as an upper bound on labor supply and the amount of capital accumulated up to that point as an upper bound on capital supply.
- Step 4: Once the optimal production is determined, the parameters estimated in Step 1 are used to determine the corresponding energy, emissions, and capital changes according to Equations 1-3 to 1-5.
- Step 5: The previous Steps 3-4, are repeated for each year of the forecasting period. The result is an optimal growth pathway to 2030, the NDC target year.

3.4. Scenarios

We use scenarios to place our analysis in the context of system dynamics to predict the interactions of various components. In our analysis, the baseline scenario is the pathway before the introduction of a carbon price, i.e., when carbon emissions are free of charge. In the baseline scenario (sc_ba), we compare carbon emissions projections with the NDC pathway. Because the feasibility of achieving NDC goals depends on technological progress, the results of the baseline scenario can provide clues to the interesting question of whether NDC goals are compatible with existing technology.

We explore an alternative scenario involving the energy mix between carbon-intensive energy and carbon-free energy. In the dynamic system, we assume a rippling path where production activities first cause total energy use in Equation 1-3, and then only carbon-intensive energy consumption entails carbon emissions in Equation 1-4. Therefore, for a given level of output, an increase in the share of carbon-free energy reduces carbon emissions even when the amount of energy required to produce that output is constant, that is when energy efficiency is constant. However, in situations where the price of carbon-free energy is higher than the price of carbon-intensive energy, the cost increases more. This scenario (sc_en) assumes a gradual increase in the share of carbon-free energy each year as climate policy progresses towards meeting the 2030 NDC target.

In the second alternative scenario, which introduces a carbon price, the cost of carbon emissions becomes to affect profits. In the scenario (sc_pr), climate policy aims to reduce carbon emissions, specifically through a carbon price that puts a price on carbon emissions to reflect the social cost of carbon. A carbon price sends market signals to market participants to encourage a shift to low-carbon goods and services.[7] In this scenario, the carbon price is assumed to increase gradually each year towards meeting the 2030 NDC target.

The dynamic model allows us to quantify the changes in the energy mix and carbon price needed to achieve the NDC targets. As a practical application of this framework, we adopt the NDC target pathway recently announced by the South Korean government. The target pathway is compared to the predicted pathway derived from the dynamic system. Once the gap between the two pathways is identified, we search for the required level of carbon-free energy and carbon price.

[7]Consumers may prefer products with a lower carbon footprint, and businesses that offer these products may gain a competitive advantage. Keep in mind that the extent to which carbon pricing affects profit maximization will depend on the stringency of the carbon pricing policy, the energy efficiency of the industry, and the availability of low-carbon alternatives.

4. Results

The numerical analysis involves the following steps: estimating causal parameters between components; estimating the implied price set; exploring optimal production levels based on the estimated parameters; calculating a baseline scenario for production, energy, and emissions; and solving for the share of carbon-free energy and carbon price needed to meet NDC targets.

Our dataset comprises population, GDP, energy, emission, capital stock, labor, and population. We obtained their annual data for 23 years(2000-2022)from the ECOS system of the Bank of Korea and the KOSIS system of Statistics Korea. For population, we use the long-term projections published in the KOSIS system.

4.1. Estimated causal relationships

Figure 1 shows the observed and fitted values for each component in equations 1-2 to 1-5: GDP, energy, emissions, and capital change. The trajectories of the three-dimensional graph are determined by the coefficients of the nonlinear regression, and the fitted trajectories indicate the causal relationship between the input and output components. These fitted trajectories are considered to be the expected paths of the components in the coming years until 2030, the target year of the NDC.

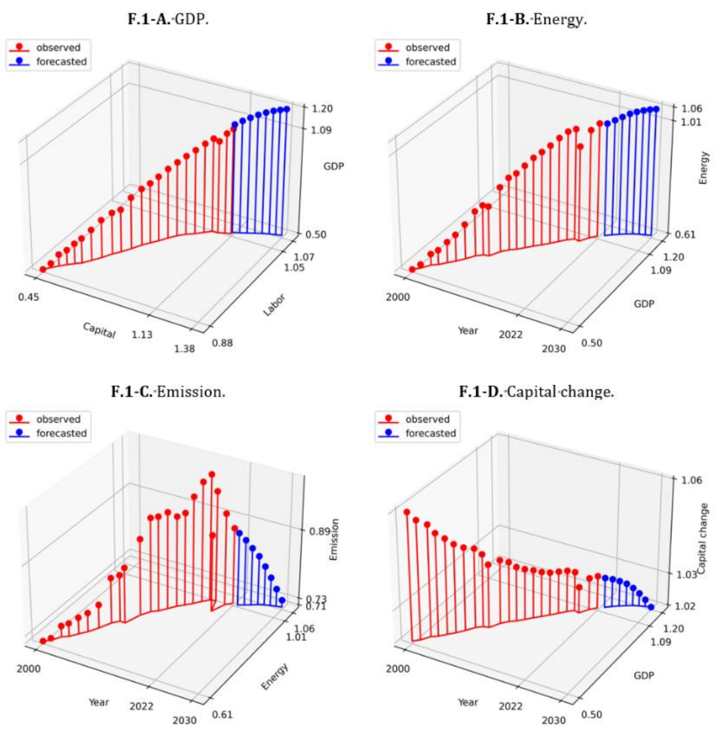


Figure 1. Observed and forecasted values.

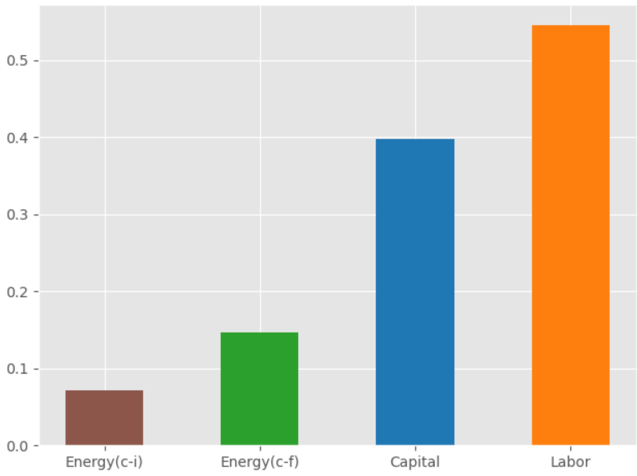
Notes: The figure connects the observed and forecast paths for each component in Equations 1-2 through 1-5: GDP, energy, emissions, and capital change. The red dot at the end of the red stem represents the observed path over the 23-year estimation period (2000-2022). The blue dots at the end of the blue stem represent the predicted path for each causal factor over the 8-year projection period (2023-2030). The x- and y-axes on the bottom represent the input factors associated with each function, and the vertical z-axis represents the corresponding output factors. Values on all axes are standardized to 2018 values, so a value of 1 for each variable means that the variable is at its 2018 level.

The trajectory of GDP, shown in F.1-A, has been a steady increase from a low level, with recent growth slowing as the impact of capital growth has been offset by the impact of a decline in labor. F.1-B shows an energy trajectory that continues to increase over time due to the impact of GDP growth, but we can see that the growth rate slows as we approach 2030. The emissions trajectory in F.1-C shows that South Korea's emissions peaked in 2018 and have been declining since then. The decline in emissions even as GDP and energy have increased suggests that decoupling has occurred. In contrast, the trajectory of capital change in F.1-D shows a steady decline over time, approaching low levels in recent years. The lower rate of capital growth, while GDP continues to grow, can be interpreted as a sign of weakening expectations for future growth.

4.2. Implied prices, revenue, and cost

Once we have estimated the parameters in Equations 1-2 through 1-5, we estimate the prices needed to utilize Equation 2-3. Since we are dealing with optimal choices at the country level, it is difficult to directly observe such information in practice. To bypass this difficulty, we assume that the output level is held at its optimal level. We then estimate the set of prices under the condition that Equation 2-3 is satisfied during the estimation period. Since our interest is in the set of relative prices, we normalize the price set so that the output price is equal to one. In addition, the carbon price is set to zero because a carbon tax has not yet been imposed and emission allowances are currently being allocated for free. Other prices were adjusted appropriately to ensure that revenues were not negative for the estimation period. F.2-A shows the estimated prices using data from South Korea over the last 23 years (2000-2022). Carbon-intensive energy had the lowest estimated price, followed by carbon-free energy, capital, and labor.

F.2-B shows the shape of the revenue and cost functions. The revenue function in Equation 2-1, which consists of the product of the output level and the output price, has a linear form concerning the output level. In contrast, the cost function concerning the output level in Equation 2-2 is a nonlinear curve and consists of four terms: labor cost, capital cost, energy cost, and carbon cost. The specific shape of the cost function (convexity and curvature) is determined by the parameter values in Equations 1-2 through 1-5 estimated in Step 1. With parameter estimates using data from South Korea over the last 23 years (2000 to 2022), the cost function is convex concerning output. Under these conditions, revenue increases linearly with the level of output, while the total cost of production (the sum of labor, capital, energy, and carbon costs) increases nonlinearly. As a result, F.2-B shows that the revenue function and the cost function intersect in 2022. It can be interpreted that the observed production in South Korea in 2022 is near the optimal level.



F.2-A. Implied relative price.

Notes: This figure shows the implied relative prices estimated using 23 years of observations over the estimation period (2000 to 2022). The relative prices are estimated using the observations and corresponding parameter estimates contained in Equations 1-2 through 1-5. The implied prices are estimated under the constraint that production levels during the estimation period have satisfied the profit optimization conditions in Equations 2-1 through 2-3. To normalize the relative prices, the production price is set to 1 and the carbon price to 0.

F.2-B. Revenue and cost function w.r.t. production level.

Notes: This figure shows the revenue and total cost curves for different levels of production. It uses the parameter estimates for Equations 1-2 through 1-5 estimated in Step 1, implied relative prices estimated in Step 2, and production levels set in the range 0.5 to 1.5.

Figure 2. Implied prices, revenue, and cost.

4.3. Required changes in energy mix and carbon price

We conduct scenario analysis to investigate the size of changes in the energy mix and carbon price required to meet NDC goals. To do this, we set up a comparison scenario where the initial conditions in 2022 are the same as in the baseline scenario, but the energy mix or carbon price gradually increases through 2030, and perform dynamic system analysis. In a system dynamics framework, as a factor changes, other factors also change and take different paths over the next eight years, depending on the estimated interconnections between the components specified in Equations 1-2 through 1-5, and on estimated relative prices.

F.3-A shows the assumptions for the proportion of carbon-free energy used in the alternative scenario. This scenario assumes a pathway that starts at the level observed in 2022 and increases linearly at the same rate each year until it reaches the level needed to meet the NDC target (40% emissions reduction from the 2018 peak) in 2030. F.3-B compares the pathways obtained in the alternative scenario to those in the baseline scenario. In the alternative scenario, we see that GDP and energy converge to lower levels in 2030 as emissions reach the NDC target. The relative pricing scheme estimated in Step 2 shows that the price of carbon-free energy is higher than the price of direct carbon energy. Assuming that this price regime remains unchanged over the projection period, the production level that satisfies the optimization conditions presented in Equation 2-3 is lower than in the reference case. Furthermore, assuming that the parameter estimates of Equation 1-4 estimated in Step 1 remain unchanged, the energy level is also lower. As a result, the production and energy levels are progressively lower as the share of carbon-free energy in the alternative scenarios gradually increases.

F.3-C shows the assumptions about carbon prices used in the alternative scenarios. The carbon price is assumed to be zero in 2022 and to rise linearly at the same rate each year to a level that corresponds to achieving the NDC target in 2030. F.3-D shows that both GDP and energy will be lower in 2030 than those in the baseline scenario as the carbon price gradually increases. Referring to the cost function in Equation 2-2 and the curve shown in F.2-B, the optimal level of production is lower because the cost curve shifts upward as the carbon price increases, holding other conditions constant. If the link between production and energy identified in Equation 1-4 remains unchanged over the forecast period, the energy level will also be lower.

It is worth noting that the response of production and energy in the carbon price adjustment scenario is relatively large compared to the results in the energy mix adjustment scenario. These results are based on the 2022 observations, the estimates of the estimated linkages between the components presented in Equations 1-2 through 1-5, and the estimates of relative prices.

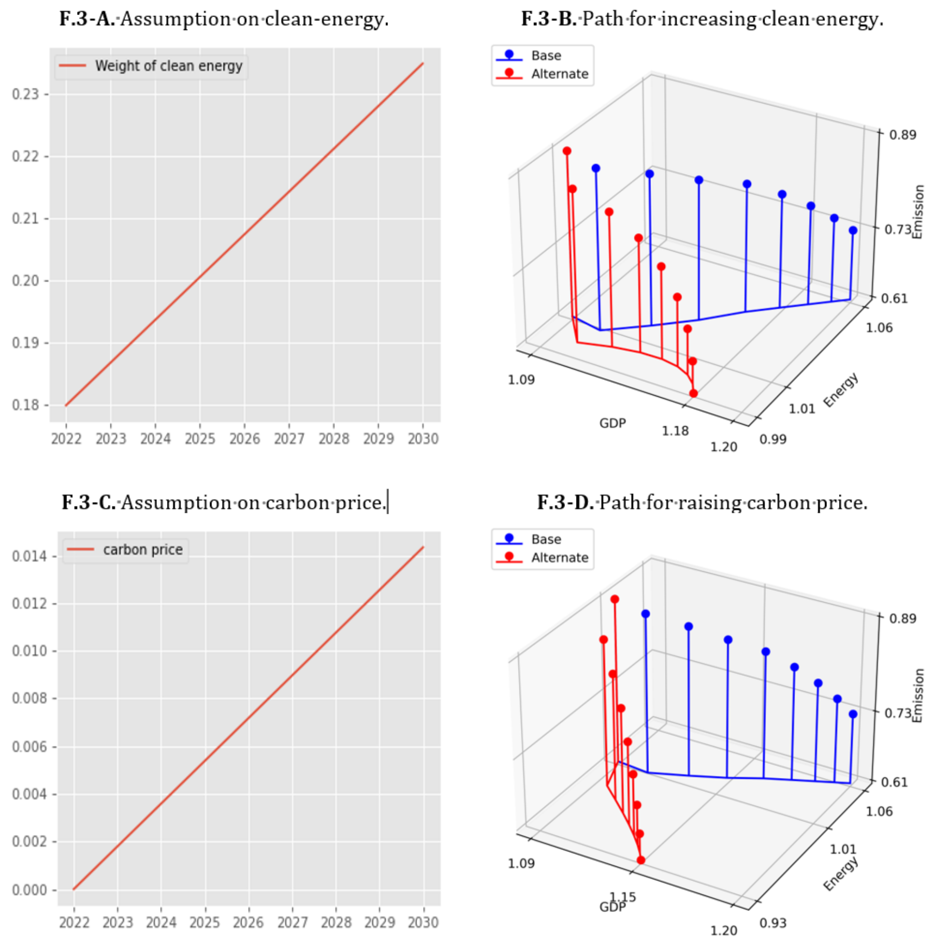


Figure 3. Scenario comparison.

Notes: Figures F.3-A and F.3-C show the assumptions of the alternative scenarios for achieving the 2030 NDC target. Over the eight-year forecast period (2023-2030), the share of clean energy continues to increase linearly in F.3-A, while the price of carbon continues to rise linearly in F.3-C. Figures F.3-B and F.3-D compare the forecast paths under the baseline and alternative scenarios. The blue dot at the end of the blue stem represents the path under the baseline scenario and the red dot at the end of the red stem represents the path under the alternative scenario. The x- and y-axes at the bottom represent GDP and energy, and the z-axis represents emissions. The values on all axes are standardized to 2018 values, so a value of 1 for each variable means that the variable is at its 2018 level.

5. Discussion

5.1. Feasibility of NDC

The emission pathway in the baseline scenario presented in F.1-C shows that the Republic of Korea faces a significant risk of being short of the NDC target. This finding is consistent with previous studies. Using the methods of trend extrapolation and back propagation neural networks, Dong et al. (2018) show that there will be a shortfall in achieving targets in South Korea. According to the evaluation results on whether G20 members are on track to meet their NDCs, the Republic of Korea's policy trajectory based on the information available until 2018 is more than 15% above the unconditional NDC target (den Elzen et al., 2019).[8]

Assessing the feasibility of NDC targets should be read with caution, as noted by den Elzen et al. (2019). First, it does not necessarily imply that countries that are not yet on track to meet their NDCs are taking fewer mitigation actions than countries that are currently on track. First and foremost, NDCs are inherently heterogeneous because they are determined on a country-by-country basis. In addition, the level of ambition, along with the strength of current policies, affects the level of effort to fulfill NDCs. Our model is flexible enough that it can be modified to incorporate relevant factors to directly assess ambition levels.

Second, the projected pathways are subject to a range of uncertainties related to the interconnected causalities in equations 1-2 through 1-5, the implied prices used in equations 2-1 through 2-2, and policy impacts that could cause changes in the estimated parameters over the forecast period. There are also uncertainties about the implementation gap associated with the policy scenarios used. Furthermore, because South Korea has recently made higher-level commitments than it has achieved, it will take several years to close the gap by strengthening the implementation of redesigned policies.

Our framework would contribute to transforming from a symbolic act of environmental activism to a practical means of changing climate policy. After the 2015 Paris accord, almost 200 countries submitted their NDC targets, some aiming to reach net zero by 2050. However, there are growing cases that achieving the goal may require immense effort. For example, a McKinsey report estimates the cost of achieving carbon neutrality for governments around the world over the next 30 years at $275 trillion.[9] An article in the Financial Times, the unexpectedly high cost of achieving carbon neutrality has politicians around the world scrambling to win over voters.[3] For instance, the Swedish government has acknowledged the difficulty of achieving carbon neutrality on time, saying that it would miss its 2030 interim goal, as well as its 2045 target.[10] In Germany, the fragile governing coalition is almost broken by proposals to ban domestic boilers run on oil and gas. EU center-right politicians point to the bureaucratic burden of the Green Deal climate law ahead of the 2024 European Parliament elections. In the US, there is controversy over a $369 billion green subsidy through the Inflation Reduction Act (IRA). So far, IRAs have relied on providing subsidies and rebates instead of imposing direct costs on voters. Judgments about the cost of fulfilling NDC targets can vary depending on perceptions of economic conditions, and there is considerable disagreement among stakeholders. These differences of opinion can lead to climate litigation. According to a report of the Grantham Institute for Climate Change and the Environment, 190 lawsuits were filed globally in the past year (June 2022-May 2013).[11] If the climate agenda continues to be politically polarized, the social costs of transitioning to a low-carbon economy could increase further. In these situations, our approach can contribute to more efficient consensus building among disagreeing stakeholders by providing science-based, value-neutral information.

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[8]The results of the analysis predicted that South Korea's carbon emissions will continue to increase until 2030. However, using the 2021 revised NDC and the latest information on energy policy after 2022, our analysis shows that South Korea's carbon emissions are expected to follow a steadily declining path through 2030, with a slightly faster rate of decline.

[9] The net-zero transition: What it would cost, what it could bring, https://www.mckinsey.com/capabilities/sustainability/our-insights/the-net-zero-transition-what-it-would-cost-what-it-could-bring

[10] How net zero became an election issue around the globe, https://www.ft.com/content/f6667506-d38f-43c2-8e75-b39c72112a41

[11] Global trends in climate change litigation: 2022 snapshot, https://www.lse.ac.uk/granthaminstitute/publication/global-trends-in-climate-change-litigation-2022/

5.2. Marginal contribution of the framework

The marginal contribution of our framework can be summarised in a few aspects. Most importantly, while previous studies have mainly analyzed the impact of economic growth or energy consumption on carbon emissions, our study focuses on the impact that emission reduction policies represented by NDCs can have on economic growth and energy consumption. Our approach allows us to analyze the bidirectional causality between the two, rather than the unidirectional causality from economic growth to carbon emissions. In particular, the identification of spill-over pathways from carbon policy to economic growth based on output optimization principles is a novel attempt that has not been explicitly addressed in other approaches.

Next, our methodology allows for a more systematic analysis of the interconnections between the main factors that determine carbon emissions. Conventional methodologies (IPAT, ImPACT, and STIRPAT) assume that the main determinants move independently of each other. CO-STIRPAT attempts to account for interconnections between determinants but has the limitation of not including direct interconnections between determinants beyond the correlations between estimated residuals. In contrast, our approach (CO-STIRPAT system dynamics) has the flexibility to include non-linear causal relationships between key drivers in the analysis.

Next, our framework can be used to develop a cost-effective climate policy mix that is a backbone for the right combination of carbon pricing, energy efficiency, and carbon intensity. In the long term, climate policy is mutually influential with climate technology regarding carbon intensity and energy efficiency. Given this dynamic interconnectedness, it is important to identify the policy priorities that control the direction of technology development and adoption. For instance, Jin (2023) points out the short-term inverse correlation between energy efficiency and carbon intensity, two proxy indicators of climate technology. Although not fully explored in this study, the scale of climate finance can unlock synergies between energy efficiency and carbon intensity. It is helpful to scale up private climate finance as large as possible. ESG investments can naturally flow into climate finance because systemic ESG risks encompass climate risks.[12] Our framework may policymakers to modify the climate policy mix as our scientific understanding of the relative costs of energy efficiency and carbon intensity evolves.

Next, our approach can provide a practical tool to assess NDC targets with respect to ambition gaps, implementation gaps, and feasibility. Baseline results, such as those shown in Figure 1, can help countries assess how ambitious their targets are by examining whether they are in line with their economic circumstances. Overly ambitious targets may be set based on strategic or opportunistic motives.[13] Access to transparent tools that objectively disclose progress toward achieving NDC targets can encourage countries to close implementation gaps. Our framework, along with a robust reporting and monitoring system, can help countries update their NDC targets at a more feasible level.

Finally, this approach allows us to evaluate the effectiveness of climate policies by explicitly quantifying how much change is needed in the clean energy mix and carbon price given economic conditions. Scenario comparisons, such as Figure 3, show how much effort is needed to achieve NDC goals through different climate policies. Modifying the alternative scenarios reveals the effect of each measure, such as energy efficiency and carbon intensity, as shown in Figure 4. In this way, policymakers can be informed about the effectiveness of new climate policies by investigating how aggressively they can be modified to increase the likelihood of meeting NDC

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12 For the detailed discussion on systematic ESG risk, strategic screening strategy, how it is related to passive investing, and extended criteria for optimal portfolio, please refer to Jin (2018, 2022a, 2022b, 2022c) and Kim, Son, and Jin (2022).

13In this sense, a high probability of failing the NDC target may indicate that a form of green washing has occurred.If this is the case, efforts to increase accountability and transparency will be needed to curb the occurrence of green washing.

targets. The numerical evidence from the South Korean data emphasizes that an optimal mix of policies is essential to achieve the 2030 NDC target without burdening economic growth. In this respect, our numerical analysis tools can help policymakers design a more cost-effective and inclusive policy mix.

6. Conclusion and Policy Implications

This paper proposes an operational framework that emphasizes the importance of considering the co-evolution of multiple factors when addressing climate change mitigation. The framework combines the CO-STIRPAT approach with dynamical systems through optimization principles. The framework can help countries optimally achieve their NDC goals by designing comprehensive policies that synchronize emission reductions, economic growth, and capital accumulation with clean energy mixes, carbon pricing, energy efficiency, and carbon intensity. This methodology can also help assess the feasibility of NDC targets based on the assumption that the causal relationships between components and implied relative prices will remain stable in the future. In the case of South Korea's observational data, the predicted baseline pathway under current economic conditions is likely to be higher than the NDC target pathway. The result indicates that policy implementation may need to be improved over the projection period to 2030 to achieve the NDC target. Or it may be necessary to appropriately slow down the pace of NDC target increases to a level consistent with economic conditions.

There are several directions for future research. First, an underlying assumption of this analysis is that the components of IPAT, ImPACT, STIRPAT, and CO-SITRPAT accurately capture the main factors driving carbon emissions. Future research could examine the impact of including other factors to validate this assumption. Next, the analysis estimates a set of implied relative prices that satisfy the optimal conditions justified by current economic conditions and assumes that they will remain stable over the forecast period. Future research could formulate a model that captures unstable price changes over a longer forecast period. Finally, our dynamic system is based on simple causal relationships between components by allowing for feedback loops as well as time lags only through capital accumulation. Future research could attempt more sophisticated feedback loops, such as a direct feedback loop between carbon emissions and economic growth following the spirit of green growth strategy.

Our analysis provides a rigorous description and intuitive interpretation of the feasibility of NDC targets and the effectiveness of climate policies. The framework can be used as a flexible operational tool to better understand country-specific circumstances and design comprehensive climate policy mixes. We hope that this framework can be a step forward in advancing our understanding of how to effectively and efficiently close existing gaps in NDC targets.

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Conflict of interest

The author claims that the manuscript is completely original. The author also declares no conflict of interest.

Appendix

A1. Parametric specification of dynamic system.

The CES (constant elasticity of substitution) production function is expressed as follows:

$$Q_t = f(K_{t-1}, L_t) = A[\alpha\,(K_{t-1})^{\rho} + (1-\alpha)(L_t)^{\rho}]^{\frac{v}{\rho}}\eta_t \qquad (A-1)$$

$$ln(\eta_t) \sim N(\mu_Q, \sigma_Q^2)$$

where Q_t is the total output produced, K_{t-1} and L_t represent the capital and labor inputs as factors of production. A is the efficiency metric to capture the portion of the growth in output not explained by growth in inputs of capital and labor used in production. α is the weight representing the share of capital in the production process. ρ is the elasticity of substitution between two inputs, and it determines the curvature of the production function. There are three special cases of the CES production function, depending on the value ofρ: Cobb-Douglas production function when$\rho \to 0$, perfect substitutes when $\rho \to 1$, and perfect complements (Leontief production function) when $\rho \to -\infty$. v represents the degree of homogeneity of the production function showing the returns to scale. The CES production function exhibits a decreasing return to scale for $v < 1$, a constant return to scale for $v = 1$, and an increasing return to scale for $v > 1$, respectively. The residual term of the production causal relationship, η_t, is assumed to follow a log-normal distribution. For the tractability of analysis and reliability of results, we use the following assumptions for these parameters.

$$A > 0; 0 < \alpha < 1; \rho < 1; 0 < v \le 1$$

The causal relationship functions for other components have the following forms:

$$Y_{i,t} = \beta_{i,0}/\left(1 + \exp[-\beta_{i,1}(t - \beta_{i,2})]\right) + \beta_{i,3}X_{i,t} + \beta_{i,4}X_{i,t}^{\ 2} + \varepsilon_{i,t} \qquad (A-2)$$

$$\varepsilon_{i,t} \sim N(\mu_i, \sigma_i^2)$$

where Y_i is an output component and $X_{i,t}$ is an input component for an i-th causal link in our dynamic system.t is a time variable (year), and the logistic time trend of the function maps a real-valued number to a value between 0 and$\beta_{i,0}$, the upper asymptote. $\beta_{i,1}$ represents the slope around the inflection point, controlling the growth behavior. If $\beta_{i,1} < 0$, then $X_{i,t}$increases over time and if $\beta_{i,1} > 0$then $X_{i,t}$decreases over time.$\beta_{i,2}$controls the location of the inflection point (relative to t), and thus the function has an S-shaped curve with an inflection point at $t = \beta_{i,2}$. These characteristics of the logistic function allow us to predict the time-varying level in each output component. Then we combine the logistic time trend with a quadratic function to predict the future path of each output component. The residual term of the i-th causal relationship, $\varepsilon_{i,t}$, is assumed to follow a normal distribution.

Using the CES production function in Equation A-1, we can derive the levels of capital and labor that minimize production costs given the prices of the factors and then derive the minimized cost by multiplying those factor quantities by the corresponding factor prices. For a given production level Q_t, the optimal cost $\Theta(Q_t)$ can be expressed as a function of cost-minimizing capital $\widehat{K}(Q_t)$, cost-minimizing labor $\widehat{L}(Q_t)$, and relevant prices:

$$\Theta(Q_t) = r_L\widehat{L}(Q_t) + r_K\widehat{K}(Q_t) = \left(r_F A^{-\frac{1}{v}}\right) Q_t^{\frac{1}{v}} \qquad (A-3)$$

$$r_F = \left[\alpha^{\sigma} r_K^{(1-\sigma)} + (1-\alpha)^{\sigma} r_L^{(1-\sigma)}\right]^{\frac{1}{(1-\sigma)}}$$

where $\sigma = 1/(1-\rho)$. In Equation A-3, the optimal cost is linearly related to the weighted average of the factor prices r_F and nonlinearly related to the level of production Q_t. In Equation A-1, if the parameter representing returns to scale v is less than 1 (decreasing returns to scale), the optimal cost function in Equation A-3 is convex concerning the production level Q_t. In other words, the slope of the factor cost function gets larger and larger as the production level increases. This feature contributes to the convex shape of the total cost function presented in Figure 2-B.

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