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RESEARCH ARTICLE

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Emission Prediction, Global Stocktake, and NDC Update: CO-STIRPAT Dynamic System

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Abstract: This analysis proposes a prediction framework for estimating the probability of fulfilling nationally determined contributions (NDC). The framework using conventional empirical methodology (CO-STIRPAT, bootstrapping sampling, and system dynamics) is employed to project the paths of carbon emissions up to 2030. Applying this approach to data from the Republic of Korea (ROK) shows that increasing the share of green energy alone may not be enough to meet NDC targets by 2030. Additional efforts are required to adopt advanced climate technologies related to carbon intensity and energy efficiency, given the predicted economic conditions until 2030. Alternatively, it may be appropriate for ROK to slow down the pace at which it raises its NDC. Our prediction framework can provide information that can motivate countries to reevaluate whether the ambition level of its target is compatible with the projected economic conditions and to set more reasonable goals in their subsequent NDCs.

Keywords: bootstrapping sampling, carbon emission, energy mix, Global Stocktake, NDC, STIRPAT, system dynamics

1. Introduction

The parties have committed to nationally determined contribution (NDC) targets in a concerted effort to reduce greenhouse gas emissions. The countries' failure to achieve their targets will undermine the credibility of their commitments to limit global warming. If countries keep reducing emissions at the same speed after meeting their NDCs until 2030, the odds of maintaining warming below 2°C increase from 5% to 26% [1]. Thus, assessing the feasibility of NDC targets is a key element in charting a carbon-neutral pathway to sustainable development. Achievability can be influenced by the implementation gap, the ambition gap, and the current state of emissions. According to Perino et al. [2], a country's targeted pathway may differ from the expected pathway achieved through current instruments of climate policy. As addressed in Friedlingstein et al. [3], the 1.5° corridor of the Paris Agreement implies the carbon budget which relates to the ambition gap. Carbon emissions are strongly influenced by the level of economic activity and the energy demand it generates, so the likelihood of achieving the NDCs depends on the medium-term economic outlook to 2030.

This research aims to suggest an operational framework for assessing the NDC targets' achievability. Our paper goes like this. First, we introduce the related literature and describe the framework used for the analysis. Next, we design the empirical model and show the data. We then apply the framework to Republic of Korea (ROK) data and its NDC target, presenting the empirical results. Lastly, we present future research directions while concluding the paper.

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2. Literature Review

This study is deeply related to four research streams: NDC target attainability, drivers of carbon emissions, system dynamics, and the nexus between GDP, energy, and emissions. Table 1 briefly summarizes the main findings of each research stream that are closely related to this paper. In Panel A, some papers have investigated if parties are progressing toward their NDCs. There is a concern that countries with high CO_2 emissions will not be able to achieve their promised contributions simply by implementing current policies. In Panel B, many studies have analyzed the major drivers of carbon emissions by using the IPAT, the Kaya identity (or the ImPACT), and the STIRPAT framework. Many papers identify drivers of carbon emissions by analyzing factors of the Kaya identity. In Panel C, some works have applied system dynamics to address how climate policy impacts the economy. Panel D shows some papers in which the causal links between carbon emissions, GDP, and energy consumption are analyzed. Those studies concentrate on whether energy consumption or GDP affects carbon emissions. Conversely, our analysis tries to verify the way NDCs make an impact on energy consumption or GDP through carbon emission reductions.

3. Analytical Framework

3.1. CO-STIRPAT

The models used in this analysis are consistent with those that assess the impact of economic activity on carbon emissions: STIRPAT, ImPACT, and IPAT. For IPAT, the environmental impact (I) is expressed as the product of three components (population P; affluence, A; technology, T), as addressed in Commoner [22] and Ehrlich and Holdren [23]. In this approach, environmental

Table 1
Key findings of relevant research

Paper	Finding
Panel A. Committed NDCs and feasibility	
Paper	Finding
den Elzen et al. [4]	Some of the G20 economies are off track to fulfill their NDCs.
Dong et al. [5]	Among the top ten CO2 emitters, seven countries will shortfall in meeting targets.
Liobikienė and Butkus [6]	The EU countries are required to attempt more to raise the share of RES and to reduce energy consumption.
Liu and Raftery [1]	The probabilities of achieving their NDCs for the largest emitters are low.
Roelfsema et al. [7]	For the countries under evaluation, there may be an implementation gap to achieve their NDCs.
Panel B. Carbon emissions drivers	
Paper	Finding
Ang and Zhang [8]	The impact on the intensity and the total carbon emissions are analyzed within the Kaya identity.
Hwang et al. [9]	The decomposed variables in the Kaya identity have significant indirect effects on carbon emissions.
Wang et al. [10]	For 198 countries between 1990 and 2018, the robust U-shaped EKC was confirmed from the STIRPAT perspective.
York et al. [11]	In STIRPAT, a more exact specification is allowed for the environmental impact sensitivity to the driving forces.
Panel C. Climate policy and system dynamics	
Paper	Analysis
Ahmad et al. [12]	A model for Malaysia is constructed to investigate the effect of feed-in tariffs till 2050.
Al-Refaie and Abdelrahim [13]	A system dynamics model is used to analyze the effect of green logistics on the total transportation cost.
Daneshgar and Zahedi [14]	A dynamic production profitability model is developed to analyze a hydro reservoir system in Iran.
Nair et al. [15]	A model for Malaysia is used to examine the role of renewable energy in the energy mix.
Smit et al. [16]	Issues about energy bias, energy fuel choice, and energy switching are investigated through system dynamics.
Panel D. Nexus of climate policy, emission, NDC, energy, and GDP	
Paper	Analysis
Gyimah et al. [17]	Carbon emissions in Ghana are affected not by economic growth but by renewable energy and fossil fuel.
Khan et al. [18]	The causality between carbon emission and GDP growth, along with the bidirectional causality between energy use and economic growth are identified.
Raihan et al. [19]	In Malaysia, environmental quality is deteriorated by economic growth, whereas carbon emissions are reduced by technological innovation and renewable energy.
Sohag et al. [20]	TFP in the production process is spurred by the use of renewable energy in the long run under various macroeconomic channels.
Wen et al. [21]	In South Asia, economic growth leads to environmental pollution at the early stages of development, confirming the EKC hypothesis.

degradation is explained by increasing affluence patterns, technological advancements, and population growth. ImPACT is an extended version of IPAT [24] that includes consumption (C) as an additional factor, emphasizing the interconnections between consumption patterns and other components (technological choices, economic development, and population dynamics). STIRPAT is a statistical approach to IPAT [25, 26], and it estimates the impacts of PAT components on the environment through regression technique. As a modified STIRPAT [27], CO-STIRPAT incorporates a stochastic component in the dynamic path for each component of the Kaya identity (or ImPACT). The approaches aim to capture the relationship between environmental impacts and human activities while they incorporate different variables.

3.2. System dynamics

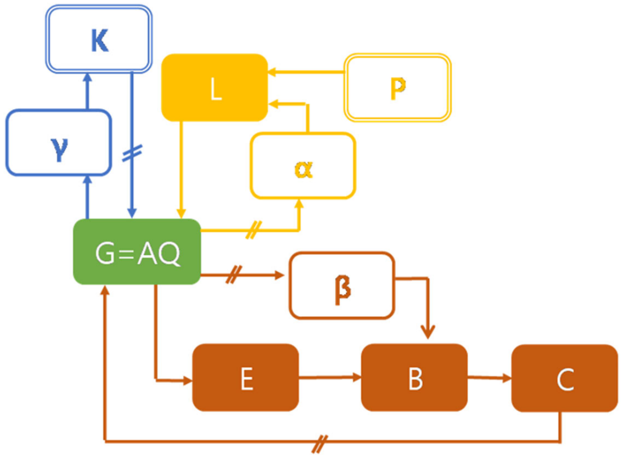
We utilize the CO-STIRPAT dynamic system to analyze the feedback loops and interconnections to gain insights into its dynamic behavior. Table 2 shows the notation, definition, and type of components included in the system. Each element represents the key angles that describe the national economy. Two components (K, P) are stock variables. Seven components (A, B, C, E, G, L, Q) are flow variables. The remainder (α, β, γ) are ratio variables calculated by other components.

Table 2
Components of dynamic system

Notation	Definition	Type
A	Total factor productivity	Flow
B	Brown energy consumption	Flow
C	Carbon emission	Flow
E	Energy consumption	Flow
G	Real GDP	Flow
K	Real capital stock	Stock
L	Labor	Flow
P	Population	Stock
Q	Production	Flow
α	Economic activity participation rate	Ratio
β	Brown energy weight	Ratio
γ	Capital growth rate	Ratio

Figure 1 shows a causal loop diagram of the CO-STIRPAT dynamic system with 12 components. The diagram includes three

Figure 1
Causal loop diagram



Note: Color-coded squares are flow variables, white squares with double borders are stock variables, and white squares with single borders are ratio variables. The population is set as an exogenous variable and uses projections from the KOSIS system of Statistics Korea. Arrows indicate causal relationships between factors, and arrows with two short slashes indicate causal relationships with a time lag.

feedback loops (yellow, blue, and brown). The yellow loop describes the dynamic evolution of labor supply. For an exogenously given population P_t, the economic activity participation rate α_t is affected by the previous level of TFP A_{t-1}. Labor supply L_t is determined by multiplying the population P_t by the economic activity participation rate α_t. Labor then enters the production function as in traditional economic growth theory. The blue loop shows the dynamic evolution of capital accumulation. Once the current TFP level A_t is determined, along with the level of production, this, in turn, affects the growth rate of capital γ_t. The current level of capital K_t is then the result of the growth rate γ_t multiplied by the previous level of capital K_{t-1}. Capital is another input to the production function. The brown loop identifies key causal relations related to carbon emissions: production, energy consumption, carbon emissions, and productivity. Production activities Q_t first drive total energy consumption E_t, then only brown energy consumption B_t entails carbon emissions C_t. The share of brown energy consumption in total energy consumption β_t is affected by TFP levels A_{t-1}.

The CO-STIRPAT dynamic system contains several nonlinear causal relationships, represented in the equations below: BL1-2, BR1-4, LO1-2, PR1-3, and YE1-2. The main relationship is associated with traditional inputs (labor and capital) in production function. The constant elasticity of substitution (CES) is assumed for the production between the two inputs. Deviating from a typical CES function, we set productivity as a nonlinear function that varies with time and carbon emissions, as shown in Equation (PR3). Causality in the yellow and blue feedback loops is related to the economic cycle of inputs to production (capital and labor): Equations (BL1-2, PR1-3, and YE1-2). The brown loop corresponds to causal relationships in ImPACT: Equation (BR1-4). For example, these causal links reflect energy efficiency (Equation BR3) and carbon intensity (Equation BR2), which are key indicators of the extent of the transition to a low-carbon economy.

$$G_t = A_t Q_t \qquad \text{(PR1)}$$

$$Q_t = \{\omega L_t^{\rho} + (1-\omega)K_{t-1}^{\rho}\}^{1/\rho} + \varepsilon_{Q,t} \qquad \text{(PR2)}$$

$$A_t = 0.5\pi(\mathrm{t}) + 0.5\pi(C_{t-1}) + \varepsilon_{A,t} \qquad \text{(PR3)}$$

$$K_t = \gamma_t K_{t-1} \qquad \text{(BL1)}$$

$$\gamma_t = 0.5\pi(\mathrm{t}) + 0.5\pi(A_t) + \varepsilon_{\gamma,t} \qquad \text{(BL2)}$$

$$L_t = \alpha_t P_t \qquad \text{(YE1)}$$

$$\alpha_t = 0.5\pi(\mathrm{t}) + 0.5\pi(A_{t-1}) + \varepsilon_{\alpha,t} \qquad \text{(YE2)}$$

$$B_t = \beta_t E_t \qquad \text{(BR1)}$$

$$C_t = 0.5\pi(\mathrm{t}) + 0.5\pi(B_t) + \varepsilon_{C,t} \qquad \text{(BR2)}$$

$$E_t = 0.5\pi(\mathrm{t}) + 0.5\pi(G_t) + \varepsilon_{E,t} \qquad \text{(BR3)}$$

$$\beta_t = 0.5\pi(\mathrm{t}) + 0.5\pi(A_{t-1}) + \varepsilon_{\beta,t} \qquad \text{(BR4)}$$

$$\pi(z_i) = \frac{\theta_{i,0}}{1 + \exp\left[-\theta_{i,1}\left(z_i - \theta_{i,2}\right)\right]} \qquad \text{(LO1)}$$

$$\varepsilon_i \sim N(\mu_i, \sigma_i^2) \qquad \text{(LO2)}$$

We also introduce time lags in some causal links. In Figure 1, straight lines with two short slashes represent those causal links with time lags. In the brown loop, we assume that the previous year's carbon emissions have a staggered effect on the current year's TFP in Equation (PR3). A relationship in which productivity decreases as carbon emissions increase implies that green growth is possible, and our empirical analysis confirms this relationship. Similarly, the previous year's TFP has a staggered effect on the current year's share of brown energy consumption in Equation (BR4). Other influences can be found in the yellow and blue rings. The capital evolution function considers the lag between when capital is used for production (Equation PR2) and when it is accumulated (Equation BL1). Similarly, TFP in the previous year has a staggered impact on the labor force participation rate in the current year in Equation (YE2).

3.3. Scenarios

The pathway without the effect of implementing climate policies is the baseline scenario Path[A]. An alternative scenario is the pathway with a changing energy mix (brown vs. green). For a given output, an increasing share of green energy reduces carbon emissions, which leads to a gradual decrease in carbon intensity while energy efficiency is constant. This scenario Path[B] assumes meeting the 2030 NDC target through climate policy compatible with a gradually increasing share of green energy. Carbon emissions projections in Path[B] are compared with the NDC pathway. The result of the baseline scenario can provide clues to whether NDC goals are compatible with implemented policies. We compare the NDC target pathway announced by the ROK with the projected pathway derived from the dynamic system.

3.4. Prediction interval

We use Monte Carlo methods to derive the distribution of projected carbon emissions. The prediction interval shows the range of values that are likely to contain the true value of future carbon emissions based on the CO-STIRPAT dynamic system. The derivation of the prediction interval proceeds as follows. After obtaining residuals from training the CO-STIRPAT dynamic system, we generate randomized noise data by bootstrapping technique for each year from 2023 to 2030. Once you have estimates for the parameters and initial values in 2022, you can predict the trajectory of the component's path from year to year until 2030. Repeat this step tens of thousands of times. The next step is to calculate the prediction interval by calculating the intervals of the selected confidence levels, 95%. From the distribution of paths, we calculate the probability of achieving the NDC goal. This can help identify ambition gaps and implementation gaps for current NDC targets.

4. Empirical Analysis

4.1. Data and estimation

We first estimate the relationship between components of the CO-STIRPAT dynamic system. Our dataset comprises capital, carbon emission, (brown and total) energy consumption, GDP, labor (economic activity population), and population. We obtain their annual data from the KOSIS system of Statistics Korea and the Bank of Korea ECOS system, for 43 years (1980–2022). As for value-based indicators such as GDP and capital, we use real variables rather than nominal variables to control the effects of inflation. By standardizing each variable as a ratio of its level at base year 2018, the empirical analysis is conducted on variables that are scale- and unit-independent. Note that the carbon emissions in Korea peaked around the year 2018. In our empirical analysis, we also use years divided by 1,000 to adjust for scaling differences with other variables. The population is set as an exogenous variable and uses projections from the KOSIS system of Statistics Korea.

We estimate six causal relationships based on the nonlinear function given in Equations (BL1-2, BR1-4, LO1-2, PR1-3, and YE1-2): the relationship between inputs (labor, capital) and output (GDP), GDP and energy demand, energy demand and carbon emissions, productivity and employment, productivity and carbon energy share, and capital growth and productivity. We assume a nonlinear relationship between the components of each causal relationship, and we use nonlinear regression techniques to account for this nonlinearity. Compared with traditional linear regression, which assumes linearity of causality, nonlinear regression has more flexibility to capture various forms of nonlinear relationships between factors, like in the equations: BL1-2, BR1-4, LO1-2, PR1-3, and YE1-2. Table 3 shows estimates for the coefficients of the functions that make up the dynamic system.

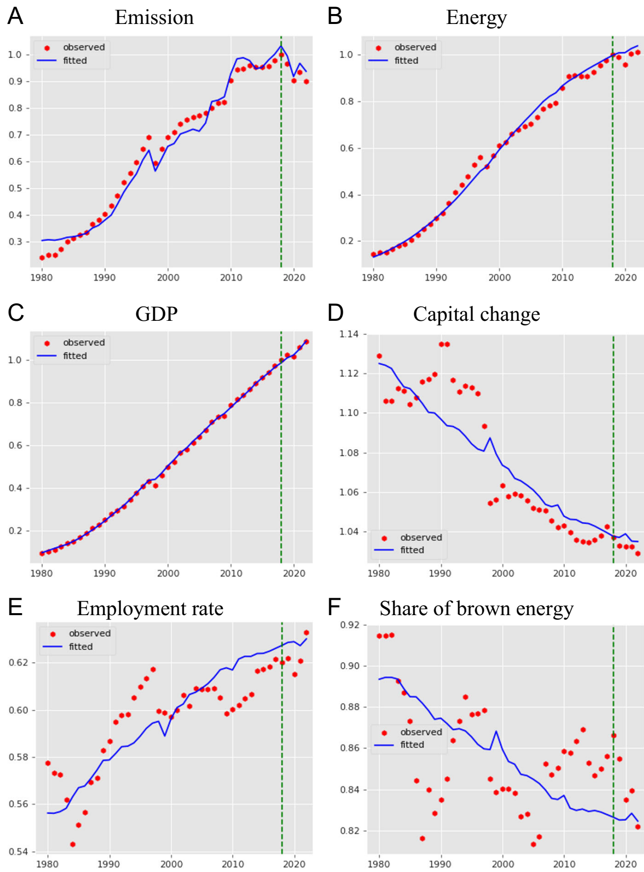
Table 3
Estimated parameters

	$\pi(t)$		$\pi(z_i)$	
Equation	θ_0	θ_1	θ_0	θ_1
BL2	2.08	0.22	2.08	0.56
BR2	2.49	35.83	2.48	−4.47
BR3	1.44	−162.13	1.44	−1.37
BR4	1.62	−3.97	1.62	0.88
PR3	1.52	−97.29	1.53	0.25
YE2	1.26	0.77	1.26	−0.76
	ρ	ω		
PR2	−0.08	0.31		

Note: These parameters are estimated under the condition that $\theta_2 = 2$ in $\pi(t)$ and $\theta_{i,2} = 1$ in $\pi(z_i)$.

Figure 2 shows fitted values along with observed values for six components of the CO-STIRPAT dynamic system. The curve is shaped by the nonlinear regression coefficients, and the causal relationship between components is represented through the fitted line in Figure 1. These estimated lines are used to predict the trajectory of the elements until the target year of NDC, 2030. Note that the carbon emissions in Korea peaked around the year 2018. Given this, we perform an empirical analysis of the yearly levels of the variable in proportion to 2018 levels and set $\theta_{i,2} = 1$ in $\pi(z_i)$ (corresponding to the value at the peak year 2018). Also, we set $\theta_2 = 2$ in $\pi(t)$ (corresponding to the year 2,000). The assumption is to consider that the Korean economy experienced structural changes before and after the 1997–98 East Asian financial crisis. In Figure 2, the green vertical dotted line represents the year 2018.

Figure 2
Observed value vs. fitted value



4.2. Distribution of residuals

Next, we check the distribution of estimated residuals. Table 4 shows descriptive statistics for residuals of six components of the CO-STIRPAT dynamic system. The table shows the Jarque and Bera normality statistics along with other descriptive statistics. Under the null hypothesis of normality, the p-value means the probability of obtaining the estimated test statistic. The test results show that residuals for ratio components (α, β, γ) are log-normally distributed, whereas residuals for level components (C, E, G) are not log-normally distributed. This shows that it is appropriate for

Table 4
Normality test of residuals

Vari.	Mean	SD	Skew	Kurt	JB	*p*-val.
C	0.000	0.075	−1.405	1.818	20.06	0.000
E	0.000	0.048	1.092	0.224	8.63	0.013
G	0.000	0.025	−1.617	5.018	63.85	0.000
α	0.000	0.021	0.242	−0.914	1.92	0.383
β	0.000	0.015	0.795	0.216	4.61	0.100
γ	0.000	0.030	−0.531	−0.544	2.55	0.279

us to use the bootstrapping technique to derive the prediction interval.

4.3. Probability to fulfill NDC

Figure 3 compares the predicted pathway with the NDC target pathway until 2030. Carbon emissions increased through 2018, dropped during the pandemic, and recovered after the pandemic. Our analysis shows that the NDC target pathway remains below the estimated pathway until 2030. ROK may not fulfill its NDC target unless it significantly improves policy implementation through that point, since the NDC target path deviates from the 95% prediction band before 2030.

Figure 3
Predicted pathway vs. NDC target pathway

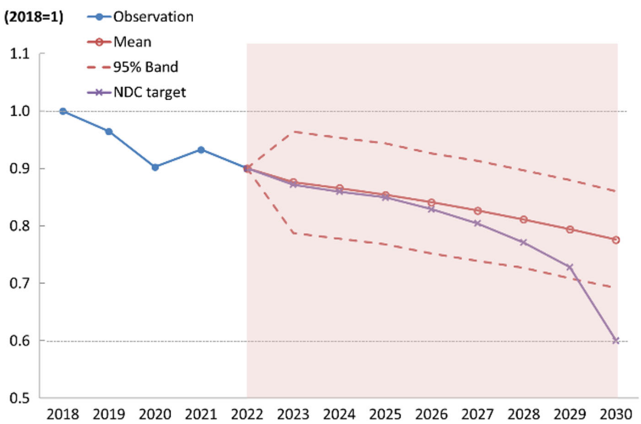
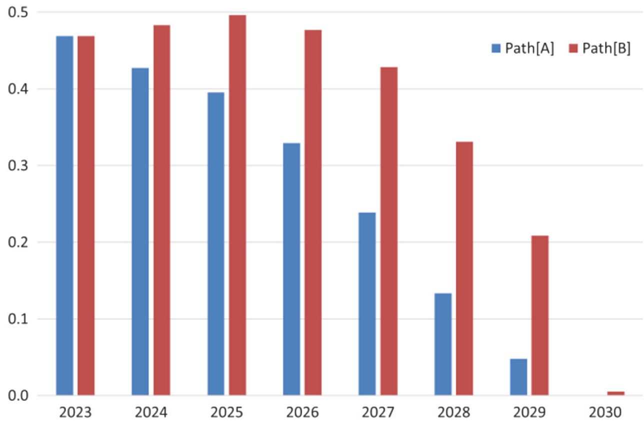


Figure 4 presents the trajectory of the probability of going along with the NDC target pathway during the coming eight years (2023 to 2030). Using the baseline pathway [A], the probability of achieving the NDC target by 2030 is less than 0.1%. The continuous decline over time indicates that the effectiveness of current climate policies may not be sufficient to achieve the final NDC target in 2030. In pathway [B], policies that change the energy mix may be somewhat effective in increasing the probability of achieving the NDC target pathway. However, the probability of meeting the NDC target is still less than half under the assumption that the existing patterns among the components of the CO-STIRPAT dynamic system up to 2022 continue through 2030. This means that the effect of increasing the share of green energy alone may not be enough to achieve the NDC target by 2030.

Figure 4
Probability of meeting the NDC target



5. Discussion

5.1. Main results

The model predicts that South Korea faces material risks of being short of its NDC goals. Prior research shows similar results. According to Dong et al. [5], South Korea is expected to fall short of its NDC targets. According to den Elzen et al. [4], South Korea appears to need to do more to meet its targets. However, readers should consider these results carefully, as den Elzen et al. [4] provide the following caveats: First, uncertainty exists in all projected pathways related to exogenous factors such as population growth, technological advances, and policy impacts. Pathway [B] can take into account recent information through 2022, but there is uncertainty about the implementation gap. Second, countries that are far from their NDCs may be able to take more effective mitigation actions than countries that are currently close to their NDCs. The level of ambition could affect the level of effort to fulfill NDCs along with the strength of current policies.

5.2. Implication for NDC update

Measuring the achievability of NDC targets provides significant insights for Global Stocktake (GST) and regular NDC updates. GST serves as a reality check on countries' collective efforts to fulfill their NDCs. GST identifies the gap between current emissions trajectories and the emissions reductions demanded to stay within desired temperature limits. It highlights areas where countries' NDCs may fall short in terms of ambition and implementation. Höhne et al. [28] suggest that it is particularly important to assess the ambition of national climate proposals because periodic reviews of national contributions are called in the Paris Agreement. Our analysis can provide information that can motivate countries to reevaluate whether the ambition level of its target is aligned with the latest economic conditions and to set more reasonable goals in their subsequent NDCs. Our analysis can also inform countries about areas of implementation where they need to improve their efforts. It may be required for a country to adopt more effective policies for raising the probability of fulfilling its target. Measures for carbon intensity and energy efficiency are included in such policies. In addition, high odds of being short of the NDCs indicate that opportunistic or strategic motivations might result in overly ambitious targets. In such a case, efforts to improve transparency and accountability will be required to ensure robust reporting and monitoring systems.

5.3. Research contribution and limitation

Our analysis is so flexible that it can be modified easily to compute the probability of meeting the NDC target of individual countries by accommodating uncertain factors. Any projection includes the uncertainty associated with several components. According to Rogelj et al. [29], the likelihood of limiting warming below 2 °C can be affected critically by this uncertainty. When we need to incorporate additional components, our model can be easily revised to add error terms relevant to those components. Liu and Raftery [1] suggest a large-scale statistical framework using a joint Bayesian hierarchical model. Although the large-scale model concentrates on global carbon emissions, we propose a small-scale model to design a concise tool to predict each country's emissions. It would be more manageable to accommodate the specificities of individual countries in our small-scale model. Also, it would be easier to identify properties of the whole that are difficult to find among the elements' properties. In particular, the co-movement in major drivers of carbon emissions can be assessed systematically in our approach. In STIRPAT (similarly, ImPACT or IPAT), the components are assumed to change individually. Although CO-STIRPAT tries to incorporate interconnections, it is done through indirect relationships (the correlations between shocks). By comparison, our approach includes direct interconnections between main components. For instance, COP28 assessed the level of implementation of NDCs by Parties to the UNFCCC through the first GST and adopted the UAE Consensus as a decision document.[1] The consensus recognizes the need for deep, rapid, and sustained reductions in emissions by tripling renewable energy capacity globally, doubling the global average annual rate of energy efficiency improvements, and accelerating zero- and low-emission technologies by 2030. Our methodology can contribute to analyzing the economic effects of these changes. In such a context, it may be useful to try machine learning models (extreme learning machines, support vector machines, random forests, LSTM neural networks, and backpropagation neural networks) reviewed by Zhao et al. [30]. Lastly, the size of climate finance can affect the feasibility of the NDCs. It is critical to scale up private climate finance, which can be addressed by linking it to ESG investments. Since climate risk is regarded as a systemic ESG risk, our methodology can integrate ESG investment which coevolves with climate finance.[2]

6. Conclusion

This paper suggests a framework to estimate carbon emissions through the CO-STIRPAT dynamic system. The approach assumes that the inter-connectedness of the components will remain unchanged for the prediction period and measures the probability of fulfilling the NDC targets. The analysis results show that advances in energy mix are critical to making achieving the 2030 NDC target more feasible without hampering economic growth, given exogenous population growth. The information on the probability provides essential implications for the NDC updates. Empirical evidence implies that ROK faces a quite challenge to fulfill its 2030 NDC target. More efforts are required to be made to promptly adopt emerging climate technologies regarding carbon intensity and energy efficiency, given the predicted economic conditions until 2030. Alternatively, it may be appropriate for the ROK to slow down the pace at which it raises its NDC.

We make some suggestions for the following research. Our framework's premise is that the CO-STIRPAT dynamic system correctly captures the major components determining carbon emissions. Follow-up studies may examine the effect of incorporating additional components to uncover richer associations. Next, our investigation is conducted under the hypothesis that the inter-connectedness of components remains stable over time. If future research needs to modify the model to serve as an appropriate benchmark for a particular country, the model can be improved to accommodate the structural breaks observed in that country's economy. Last, our analysis provides an intuitive description of evaluating the probability of achieving NDC targets. Our conveniently modifiable tool would be utilized to explore policy strategy about how the observed gaps against NDC targets can be managed. We hope the framework enables us to improve climate policy implementation.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by the author.

Conflicts of Interest

The author declares that he has no conflicts of interest to this work.

Data Availability Statement

Data sharing not applicable – no new data generated.

Author Contribution Statement

Ick Jin: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resouces, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration.

References

[1] Liu, P. R., & Raftery, A. E. (2021). Country-based rate of emissions reductions should increase by 80% beyond nationally determined contributions to meet the 2 °C target. *Communications Earth & Environment*, *2*(1), 29. https://doi.org/10.1038/s43247-021-00097-8

[2] Perino, G., Jarke-Neuert, J., Schenuit, F., Wickel, M., & Zengerling, C. (2022). Closing the implementation gap: Obstacles in reaching net-zero pledges in the EU and Germany. *Politics and Governance*, *10*(3), 213–225. https://doi.org/10.17645/pag.v10i3.5326

[3] Friedlingstein, P., Jones, M. W., O'Sullivan, M., Andrew, R. M., Bakker, D. C., Hauck, J., . . . , & Zeng, J. (2022). Global carbon budget 2021. *Earth System Science Data*, *14*(4), 1917–2005. https://doi.org/10.5194/essd-14-1917-2022

[4] den Elzen, M., Kuramochi, T., Höhne, N., Cantzler, J., Esmeijer, K., Fekete, H., . . . , & Vandyck, T. (2019). Are the G20 economies making enough progress to meet their NDC targets? *Energy Policy*, *126*, 238–250. https://doi.org/10.1016/j.enpol.2018.11.027

[5] Dong, C., Dong, X., Jiang, Q., Dong, K., & Liu, G. (2018). What is the probability of achieving the carbon dioxide

[1] Matters relating to the global stocktake under the Paris Agreement. https://unfccc.int/documents/636584

[2] For a 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 [31, 32].

emission targets of the Paris agreement? Evidence from the top ten emitters. *Science of the Total Environment*, *622–623*, 1294–1303. https://doi.org/10.1016/j.scitotenv.2017.12.093

[6] Liobikienė, G., & Butkus, M. (2017). The European Union possibilities to achieve targets of Europe 2020 and Paris agreement climate policy. *Renewable Energy*, *106*, 298–309. https://doi.org/10.1016/j.renene.2017.01.036

[7] Roelfsema, M., van Soest, H. L., Harmsen, M., van Vuuren, D. P., Bertram, C., den Elzen, M., . . . , & Vishwanathan, S. S. (2020). Taking stock of national climate policies to evaluate implementation of the Paris agreement. *Nature Communications*, *11*(1), 2096. https://doi.org/10.1038/s41467-020-15414-6

[8] Ang, B. W., & Zhang, F. Q. (2000). A survey of index decomposition analysis in energy and environmental studies. *Energy*, *25*(12), 1149–1176. https://doi.org/10.1016/S0360-5442(00)00039-6

[9] Hwang, Y., Um, J. S., Hwang, J., & Schlüter, S. (2020). Evaluating the causal relations between the Kaya identity index and ODIAC-based fossil fuel CO_2 flux. *Energies*, *13*(22), 6009. https://doi.org/10.3390/en13226009

[10] Wang, M., Arshed, N., Munir, M., Rasool, S. F., & Lin, W. (2021). Investigation of the STIRPAT model of environmental quality: A case of nonlinear quantile panel data analysis. *Environment, Development and Sustainability*, *23*, 12217–12232. https://doi.org/10.1007/s10668-020-01165-3

[11] York, R., Rosa, E. A., & Dietz, T. (2003). STIRPAT, IPAT and ImPACT: Analytic tools for unpacking the driving forces of environmental impacts. *Ecological Economics*, *46*(3), 351–365. https://doi.org/10.1016/S0921-8009(03)00188-5

[12] Ahmad, S., Tahar, R. M., Muhammad-Sukki, F., Munir, A. B., & Rahim, R. A. (2015). Role of feed-in tariff policy in promoting solar photovoltaic investments in Malaysia: A system dynamics approach. *Energy*, *84*, 808–815. https://doi.org/10.1016/j.energy.2015.03.047

[13] Al-Refaie, A., & Abdelrahim, D. A. Y. (2021). A system dynamics model for green logistics in a supply chain of multiple suppliers, retailers and markets. *International Journal of Business Performance and Supply Chain Modelling*, *12*(3), 259–281. https://doi.org/10.1504/IJBPSCM.2021.117905

[14] Daneshgar, S., & Zahedi, R. (2022). Investigating the hydropower plants production and profitability using system dynamics approach. *Journal of Energy Storage*, *46*, 103919. https://doi.org/10.1016/j.est.2021.103919

[15] Nair, K., Shadman, S., Chin, C. M., Sakundarini, N., Yap, E. H., & Koyande, A. (2021). Developing a system dynamics model to study the impact of renewable energy in the short- and long-term energy security. *Materials Science for Energy Technologies*, *4*, 391–397. https://doi.org/10.1016/j.mset.2021.09.001

[16] Smit, S., Musango, J. K., & Brent, A. C. (2019). Understanding electricity legitimacy dynamics in an urban informal settlement in South Africa: A community based system dynamics approach. *Energy for Sustainable Development*, *49*, 39–52. https://doi.org/10.1016/j.esd.2019.01.004

[17] Gyimah, J., Hayford, I. S., Nwigwe, U. A., & Opoku, E. O. (2023). The role of energy and economic growth towards sustainable environment through carbon emissions mitigation. *PLOS Climate*, *2*(3), e0000116. https://doi.org/10.1371/journal.pclm.0000116

[18] Khan, M. B., Saleem, H., Shabbir, M. S., & Xie, H. (2022). The effects of globalization, energy consumption and economic growth on carbon dioxide emissions in South Asian countries. *Energy & Environment*, *33*(1), 107–134. https://doi.org/10.1177/0958305X20986896

[19] Raihan, A., Begum, R. A., Said, M. N. M., & Pereira, J. J. (2022). Relationship between economic growth, renewable energy use, technological innovation, and carbon emission toward achieving Malaysia’s Paris agreement. *Environment Systems and Decisions*, *42*(4), 586–607. https://doi.org/10.1007/s10669-022-09848-0

[20] Sohag, K., Chukavina, K., & Samargandi, N. (2021). Renewable energy and total factor productivity in OECD member countries. *Journal of Cleaner Production*, *296*, 126499. https://doi.org/10.1016/j.jclepro.2021.126499

[21] Wen, J., Mughal, N., Zhao, J., Shabbir, M. S., Niedbała, G., Jain, V., & Anwar, A. (2021). Does globalization matter for environmental degradation? Nexus among energy consumption, economic growth, and carbon dioxide emission. *Energy Policy*, *153*, 112230. https://doi.org/10.1016/j.enpol.2021.112230

[22] Commoner, B. (2020). *The closing circle: Nature, man, and technology*. USA: Dover Publications.

[23] Ehrlich, P. R., & Holdren, J. P. (1972). Critique. *Bulletin of the Atomic Scientists*, *28*(5), 16–27. https://doi.org/10.1080/00963402.1972.11457930

[24] Waggoner, P. E., & Ausubel, J. H. (2002). A framework for sustainability science: A renovated IPAT identity. *Proceedings of the National Academy of Sciences*, *99*(12), 7860–7865. https://doi.org/10.1073/pnas.122235999

[25] Dietz, T., & Rosa, E. A. (1994). Rethinking the environmental impacts of population, affluence and technology. *Human Ecology Review*, *1*(2), 277–300.

[26] Rosa, E. A., & Dietz, T. (1998). Climate change and society: Speculation, construction and scientific investigation. *International Sociology*, *13*(4). 421–455. https://doi.org/10.1177/026858098013004002

[27] Jin, I. (2023). Probability of achieving NDC and implications for climate policy: CO-STIRPAT approach. *Journal of Economic Analysis*, *2*(4), 82–97. https://doi.org/10.58567/jea02040005

[28] Höhne, N., Fekete, H., den Elzen, M. G., Hof, A. F., & Kuramochi, T. (2018). Assessing the ambition of post-2020 climate targets: A comprehensive framework. *Climate Policy*, *18*(4), 425–441. https://doi.org/10.1080/14693062.2017.1294046

[29] Rogelj, J., den Elzen, M., Höhne, N., Fransen, T., Fekete, H., Winkler, H., . . . , & Meinshausen, M. (2016). Paris Agreement climate proposals need a boost to keep warming well below 2 °C. *Nature*, *534*(7609), 631–639. https://doi.org/10.1038/nature18307

[30] Zhao, Y., Liu, R., Liu, Z., Liu, L., Wang, J., & Liu, W. (2023). A Review of macroscopic carbon emission prediction model based on machine learning. *Sustainability*, *15*(8), 6876. https://doi.org/10.3390/su15086876

[31] Jin, I. (2022). Systematic ESG risk and passive ESG investing. *The Journal of Portfolio Management*, *48*(5), 71–86. https://doi.org/10.3905/jpm.2022.1.344

[32] Jin, I. (2022). Systematic ESG risk and decision criteria for optimal portfolio selection. *The Journal of Portfolio Management*, *48*(10), 206–225. https://doi.org/10.3905/jpm.2022.1.418

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