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Research Paper

Carbon Neutrality Analysis by Linking Top-down CGE and Power Sector Models for Korea

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상하향 통합모형을 활용한 한국의 탄소중립 분석

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요약 : 본 연구는 한국의 2050 탄소중립 목표 달성이 가져올 경제적 영향을 분석하기 위해 상향식(bottom-up) 전력부문 모형과 하향식(top-down) 일반균형경제(CGE) 모형을 통합한 통합평가 접근법을 개발하였다. 이러한 통합은 탄소중립 실현에 핵심적인 전력부문의 기술적 제약과 세부 특성을 정밀하게 반영함과 동시에, 산업·가계·정부 등 다른 부문과의 상호작용을 통해 거시경제적 파급효과를 종합적으로 분석할 수 있게 한다. 특히 본 연구에서는 기존 상·하향 통합 방법론을 보완하여 수렴 안정성과 계산 효율성을 제고한 새로운 연계 알고리즘을 적용하였다. 기술 시나리오 분석 결과, 저탄소 기술의 가용성 확대가 재생에너지 기반 전력 경제성을 개선하고 전력화를 촉진함으로써 탄소중립 달성에 따른 경제적 비용을 완화하는 것으로 나타났다. 이를 통해 적극적인 재생에너지 기술개발 및 시장 확산의 중요성을 확인하였다.

주요어 : **에너지전환, 거시경제분석, 전력시스템분석, 모형 연계**

Abstract : This study develops an integrated assessment framework that links a bottom-up power system capacity expansion model (UNICON-K-Power) with a top-down Computable General Equilibrium model (UNICON-K-CGE) to analyze the economic impacts of Korea's 2050 carbon neutrality pathways. The linkage enables detailed representation of technological and operational constraints in the power sector while capturing macroeconomic feedback across industries, households, and the government. A new linking algorithm is introduced to enhance convergence stability and computational efficiency compared to conventional hybrid modeling approaches. Scenario analysis shows that greater availability of low-carbon technologies accelerates renewable-based electrification, thereby mitigating the economic cost of achieving carbon neutrality. The results highlight the pivotal role of the power sector in providing

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affordable, clean electricity and underscore the importance of accelerating deep emission reduction technology development and market deployment to reduce the overall economic burden of decarbonization.

Keywords : Energy Transitions, Macroeconomic Analysis, Power System Analysis, Modeling Integration

I. Introduction

With limited domestic energy resources, a high dependence on imported fossil fuels, and a power sector historically dominated by coal and nuclear generation, Korea faces various challenges including energy security, decarbonization, and economic competitiveness. To achieve Korea's nationally determined contribution (NDC) and the 2050 carbon neutrality target, the country has announced to expand renewable energy deployment, enhance energy efficiency, and introduce market mechanisms such as emissions trading(Kim et al., 2022). However, the scale and speed of the transformation required raise questions about the economic costs, distributional effects, and system-level feasibility of policy pathways.

Model-based analysis has been widely used to assess energy transition at both country and global levels. Bottom-up power system optimization models capture the technical and economic trade-offs of generation capacity expansion, grid integration, and emissions reduction potentials. Top-down computable general equilibrium (CGE) models, in contrast, provide a comprehensive view of macroeconomic implications by representing interactions across energy, industry, and household sectors. Each framework has its own strength and limitations: power system models often ignore feedback effects on the wider economy, while CGE models lack the technological detail needed to assess power sector transitions in a realistic way(Nasirov et al., 2020).

This study is among the few that employ and further advance integrated modeling approaches to assess Korea's carbon neutrality pathways. We extend existing bottom-up–top-down integration methodologies to achieve a more consistent representation of electricity system dynamics and its feedback with the CGE model. While bottom-up model assesses more realistic technology mixes in power sector under system level constraints, the linking approach enables economy-wide factors such as demand growth, trade, and policy shocks to feed back into electricity-sector outcomes. By enhancing the integration mechanism between the two modeling frameworks with diverse deep emission reduction technologies such as Direct Air Capture (DAC), hydrogen, Carbon Capture and Sequestration (CCS) etc., this study provides more robust and holistic insights into the costs, trade-offs, and systemic interactions underlying Korea's decarbonization strategies.

From a policy perspective, the integrated framework highlights the importance of assessing energy transition measures within a broader economic context. By quantifying how power sector policies such as renewable deployment and technology incentives affect overall economic performance, and how macroeconomic conditions in turn shape electricity system outcomes, the framework enables a more balanced design of Korea's carbon neutrality roadmap. Ultimately, this approach provides an analytical foundation for coordinating sectoral and economy-wide policies under a coherent and sustainable decarbonization strategy.

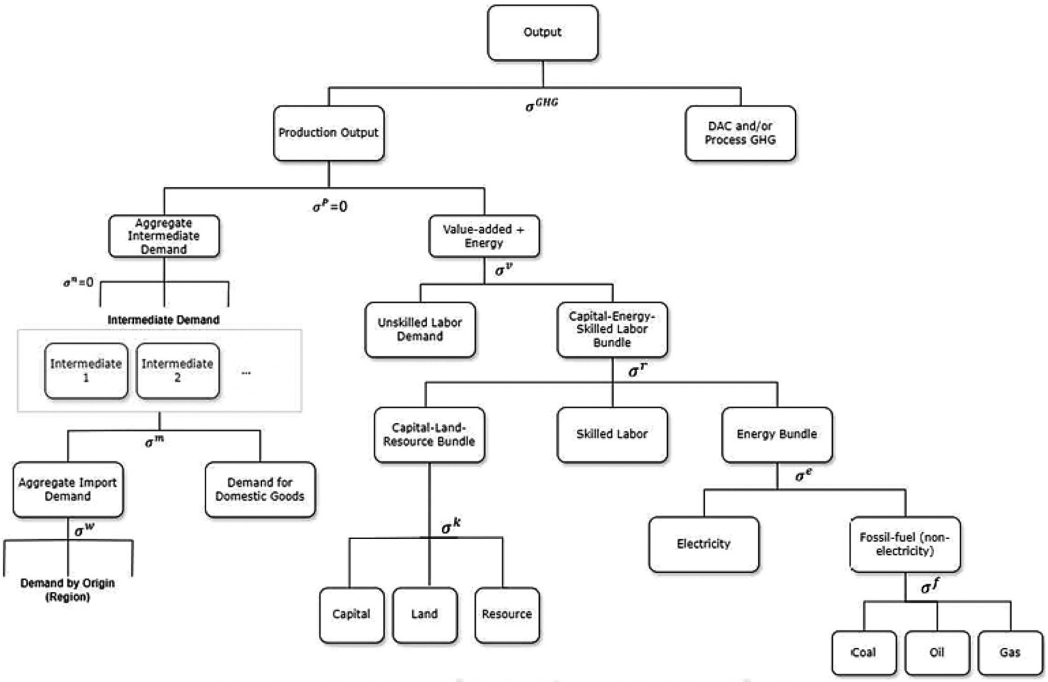
The remainder of this paper is organized as follows. Section 2 introduces the modeling framework and the linking methodology with scenario settings. Section 3 discusses the results, focusing on technology mixes, carbon prices, and macroeconomic indicators under alternative transition pathways. Section 4 concludes with policy implications for Korea's energy transition.

II. Material and methods

1. Framework

We deploy the UNIfied Climate Options Nexus (UNICON) framework, specifically the UNICON-K-Power and UNICON-K-CGE for assessing macro-economic impact of carbon neutrality of Korea. The analysis specifically focuses on the integration of the CGE model with the power sector optimization model for Korea. The linking process is executed using a decomposition algorithm, following the method proposed by Bohringer & Rutherford (2009). A crucial step in this process is the transformation of the bottom-up optimization model's objective function from cost minimization (Linear Programming, LP) to social surplus maximization (Quadratic Programming, QP). To enhance consistency between the TD and BU models and improve convergence, a new algorithm was developed. This revised approach allows for the simultaneous reproduction of GDP and power sector forecasts. The foundation of the economic model relies on a Hybrid Social Accounting Matrix (SAM), which combines the Korean Input-Output Table (IOT) and the Power Database (KPX) after a reconciliation procedure.

The CGE model is formalized as a simultaneous equation system. It covers standard general equilibrium components, including supply-demand balance, the zero-profit condition, budget constraints (household, government), current account balance, and the capital stock dynamics equation(Wing, 2004). Production technologies are modeled using Constant Elasticity of Substitution (CES) functions, while final demands use more various assumptions such as Linear Expenditure System (LES), Constant Difference Elasticity (CDE), and An Implicitly Directly Additive Demand System (AIDADS), and exports are modeled using the Armington model. Specialized technologies are incorporated, such as DAC, which is modeled via an additional nest on the top, following Hyman et al. (2003) The model also includes a learning curve to project cost reductions,



Source: Kim et al. (2023)

Figure 1. Nesting structure of UNICON–K-CGE

where the Investment cost decreases as cumulative capacity increases(Nemet, 2006; Abdelkhalek et al. 2020).

A nested CES framework allows for flexible substitution across inputs at different levels of aggregation. For our study we develop a nesting structure as in Figure 1. At the top level, total output is composed of aggregate production and, in the extended model, direct air capture (DAC) and process-based GHG removal. On the production side, output is derived from a CES composite of intermediate inputs and a value-added–energy bundle. Intermediate demand is split between domestic and imported goods, while the value-added–energy bundle is further disaggregated into unskilled labor and a capital–energy–skilled labor composite. Within this nest, capital, land, and natural resources form one branch, while the energy bundle is separated into electricity and non-electric fossil fuels, the latter further divided into coal, oil, and gas. This hierarchical structure provides a consistent representation of production technology and substitution possibilities across factors and energy carriers.

To capture negative emissions, DAC is explicitly introduced as an additional nest at the top level of the production structure. DAC inputs and outputs are integrated such that captured CO_2 and associated sequestration are represented as a joint product alongside conventional goods, calibrated to baseline scenarios to ensure consistency with reference pathways. The inclusion of DAC enables substitution between conventional production and carbon removal technologies depending on carbon prices, policy instruments, and technology costs. In the electricity sector, the bottom-up model explicitly represents DAC in combination with natural gas CCS, ensuring alignment between sector-specific detail. This extension allows the hybrid framework to evaluate the role of DAC in achieving stringent climate targets, while maintaining internal consistency between technological detail and economy-wide equilibrium.

The power sector is modeled as a Capacity Expansion Model formulated as a Linear Program, (Eq.1) The model incorporates over 250 generators, which cover 20 technologies including coal, gas with and without CCS, oil, nuclear, solar, onshore/offshore wind, pumped hydro, waste, ocean energy, DAC, hydrogen (fuel cell, electrolysis, turbine), etc. The objective minimizes the net present value of total system costs over time, including Investment costs ($INV_{k,t}$) and Fixed O&M costs ($FOM_{k,t}$) for installed capacity $N_{k,v,t}$, Variable O&M ($VOM_{k,t}$) and fuel costs ($FC_{k,t}$), and Carbon costs ($Tax_{gas} \cdot EmiCoef_{gas,k,t}$) applied to power generation $P_{k,t,r}$.

$$\min \sum_{t=0}^{t} df^{t} [\sum_{k} \sum_{v=t-L_k}^{t} (INV_{k,t} + FOM_{k,t}) N_{k,v,t}] + \sum_{r,k} (VOM_{k,t} + FC_{k,t} + \sum_{gas} Tax_{gas} EmiCoef_{gas,k,t}) P_{k,t,r}] \quad (1)$$

where k: technology, s: storage technology, v: vintage year, t: period, L_k: lifetime, r: load region, df: discount factor.

Key constraints include capacity constraints, demand constraints, reserve margin constraints, storage constraints, emission constraints, and specific renewable capacity constraints used for modeling piece-wise linear costs. Each technology's generation $P_{k,t,r}$ is limited by the available installed capacity $N_{k,v,t}$, adjusted for capacity credit CR_k and utilization factors, $UR_{k,t,r}$ (eq.2). Total generation (net of self-consumption F_k) and storage discharge $S_{s,t,r}$ must meet electricity demand at each time and region (eq.3).

$$P_{k,t,r} \le UR_{k,t,r} \cdot \sum_{v=t-LK}^{t} CR_k N_{k,v,t} \quad \forall k,t,r \quad (2)$$

$$\sum_{k} (1 - F_k) P_{k,t,r} - S_{s,t,r} \ge Demand_{t,r} \quad \forall t,r \quad (3)$$

To ensure reliability, total available capacity must exceed demand by a specified reserve margin $Buffer_r$ during peak periods.(eq.4) Total emissions from all technologies and fuels must not exceed the emission cap $EmiCap_{gas,t}$, set by policy or scenario conditions. (eq.5) Storage constraints eq. 6 and 7 ensure power supply using storage technology do not exceed the amount of stored energy We model that renewable capacity shares meet or exceed renewable policy targets such as RPS or RE100.

$$\sum_{k} CR_k \sum_{v=t-LK}^{t} N_{k,v,t} \geq Demand_{t,r} + Buffer_r \quad \forall\, t, r_{peak} \tag{4}$$

$$\sum_{k}\sum_{r} EmiCoef_{gas,k,t}\, P_{k,t,r} \leq EmiCap_{gas,t} \quad \forall\, t, gas \tag{5}$$

$$\sum_{r\in l}\sum_{s} P_{s,t,r} \leq \sum_{r\in l}\sum_{s} (1-SL_s) S_{s,t,r} \quad \forall\, s, l \tag{6}$$

$$\sum_{r'\leq r}\sum_{s} P_{s,t,r'} \leq \sum_{r'\leq r}\sum_{s} (1-SL_s) S_{s,t,r} \quad \forall\, s, r \tag{7}$$

where SL_s: storage loss, $S_{s,t,r}$ stored power, L_k: lifetime, l storage block. CR: capacity credit.

2. Integration process

Linking the models involves several steps. First, a hybrid Social Accounting Matrix (SAM) is constructed to scale TD and BU outputs and to exchange outputs of the two models to feed each other. The linking algorithm connects the bottom-up (BU) and top-down (TD) models through an iterative exchange of results until convergence is achieved. Key linking components—including fuel use (coal, gas, oil, nuclear, hydrogen), capital investment in power infrastructure, and employment associated with operation and maintenance—are dynamically adjusted during the iteration process in response to evolving price and demand signals.

We adopted the decomposition algorithm proposed by Böhringer and Rutherford (2009). The decomposition algorithm is to reformulate the cost minimizing LP problem of the bottom-up model into a welfare maximizing quadratic programming QP problem (eq. 8). The objective function now

$$\begin{aligned} \text{“}minimize\text{”} \sum_{t=0}^{T} df^t \Big[\sum_{k} \sum_{v=t-L_K}^{t} \big(& \overline{P_k^t} INV_{k,t} + \overline{P_l^t} FOM_{k,t} N_{k,v,t} \\ & + \sum_{v,r} \overline{P_{ser}^t} VOM_{k,t} + \sum_{f} \overline{P_f^t} FC_{k,t} \\ & + \sum_{gas} Tax_{gas}\, EmiCoef_{gas,k,t} P_{k,t,r} \big) \\ & - \overline{P_e^t} Q_e^t \left\{ 1 - \frac{Q_e^t - 2\overline{Q_e^t}}{2\varepsilon \overline{Q_e^t}} \right\} + \mu^t Q_e^t \Big] \end{aligned} \tag{8}$$

where the electricity market term,

$$\overline{P^{t_e}} Q_e^t \left\{ 1 - \frac{Q_e^t - 2\overline{Q^{t_e}}}{2\varepsilon \overline{Q_e^t}} \right\} = \int P_e^t(Q_e^t)\, dQ_e^t \tag{9}$$

is derived from the inverse demand function:

$$Q_e^t(P_e^t) = \overline{Q_e^t} \left[1 - \varepsilon \left(\frac{P_e^t}{\overline{P_e^t}} - 1 \right) \right] \tag{10}$$

The term $Q_e^t[1 - (Q_e^t - 2) / (2\varepsilon)]$ represents the consumer surplus integral. $\mu^t Q_e^t$ acts as a Lagrange multiplier that ensures the total electricity demand matches the projection used in the system expansion plan, stabilizing convergence between supply and demand modules. Linking variables P now reflects prices of each cost component (capital, labor, service, fuel) calculated from the CGE model and are fed back into BU objective function to adjust BU outputs.

Eq. 11 constraint ensures that the total net generation (after self-consumption and storage losses) satisfies the electricity demand in each region, proportionally scaled by the aggregate demand share. It maintains regional demand balance while allowing for endogenous adjustments in total electricity consumption Q_e^t.

$$\sum_{k} (1-F_k) P_{k,t,r} - \sum_{s} S_{s,t,r} \geq \left[\frac{Q_e^t}{\sum_{r'} Demand_{t,r'}} \right] Demand_{t,r} \quad \forall\, t, r \tag{11}$$

Figure 2 and 3 provide an overview of the linking framework between the BU power system model and the TD CGE model and the information exchanged between

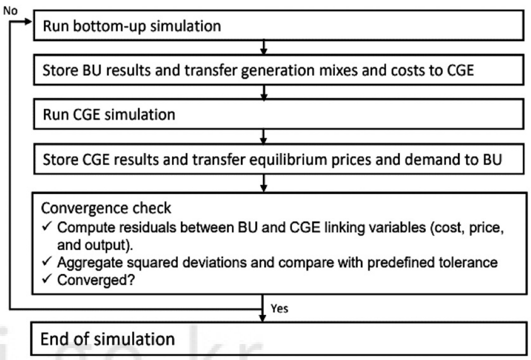


Figure 2. Flow chart of linking algorithm

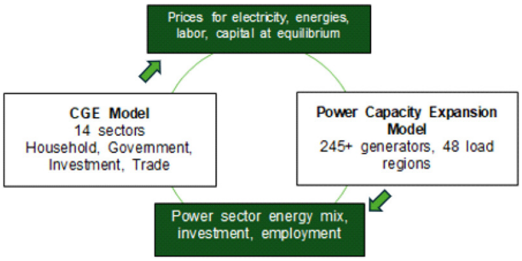


Figure 3. Exchange of information between CGE and Power models

them for integration. The process begins with standalone simulations for each model for base simulation, followed by the exchange of key parameters such as electricity demand, fuel prices, labor, and capital. The flowchart summarizes the main steps of this linkage from independent calibration to iterative feedback ensuring that each model operates within its analytical strength while maintaining consistency in shared variables.

In each iteration, the bottom-up optimization model provides detailed outcomes such as annual fuel consumption, generation mix, investment, and employment levels to the top-down CGE model (Figure 3). The top-down model then simulates the economy-wide equilibrium and returns feedback in the form of electricity prices by fuel type, carbon prices, and aggregate demand levels. These results are used to update price coefficients in the bottom-up model, ensuring that shifts in carbon and energy prices are reflected in generation decisions. The bottom-up model subsequently recalculates the optimal generation and fuel mix under the given demand elasticity. This iterative process continues until the differences between the two models in prices and quantities fall below a defined convergence threshold, ensuring consistency between technological detail in the bottom-up model and macroeconomic equilibrium in the top-down system.

We developed an adjustment mechanism to prevent deviations from the base-year equilibrium during model integration. Although both models independently reproduce the calibration year equilibrium, coupling through decomposition often shifts the solution. To address this, we introduced a linear correction term into the bottom-up model's objective function, penalizing deviations from exogenously specified annual electricity demand. The correction coefficients were iteratively updated, ensuring that electricity demand trajectories and GDP benchmarks remained consistent across the linked framework.

While the decomposition method effectively ensures convergence under exogenous carbon price policies, it often fails under quantitative caps because endogenous carbon price determination generates oscillations between models. To resolve this issue, we incorporated emissions constraints directly into the bottom-up model and designed a subroutine to harmonize carbon prices between models. Specifically, when discrepancies arose, the emissions cap in the bottom-up model was adjusted iteratively until convergence of carbon prices was achieved.

Finally, we addressed the treatment of non-zero profits in the bottom-up model. While general equilibrium frameworks typically impose zero-profit conditions, bottom-up optimization can yield positive or negative profits. How these profits are interpreted and integrated has significant implications for simulation outcomes and reflects the structural characteristics of the electricity sector.

3. Scenarios

To assess the implications of Korea's decarbonization pathways, we develop two net-zero (NZ) scenarios that differ in their assumptions regarding technology availability, each paired with a corresponding reference (baseline) scenario (Table 1). This design enables isolation of the effects of stringent emission constraints while accounting for variations in technological progress.

The Business-as-Usual (BAU) scenario builds upon the assumptions of Korea's 2050 Carbon Neutrality Strategy formulated by the Presidential Committee on Carbon Neutrality and Green Growth. Population and GDP trajectories follow the official long-term low-emission

Table 1. Scenario settings

Scenario	Emission constraint	Technology assumptions
BAU	No emission constraint	Relatively low availability of low carbon technologies
BAU_adv		High availability of advanced technologies
NZ_cons	Net zero by 2050 (A linear decrease from 2025 to 2050)	Relatively low availability of low carbon technologies
NZ_adv		High availability of advanced technologies

Note: Authors elaboration. Detailed technology assumptions are dIscussed/referenced in the scenario section.

development strategy (LEDS) projections, which anticipate an average annual population change of +0.1% during 2020–2040 and −0.5% during 2040–2050, alongside real GDP growth rates of 2.0% and 1.0% for the same periods, respectively. Labor productivity is calibrated to reproduce the projected GDP path. Electricity demand is projected to reach 1,054.5 TWh by 2050, excluding hydrogen-based generation. Within the model framework, industrial structure, energy consumption, and CO_2 emissions are determined endogenously.

In contrast, the NZ scenarios impose a linear reduction in total emissions from the base-year level toward net-zero by 2050, consistent with Korea's mid-century carbon neutrality target. Within the CGE framework, the Lagrange multiplier associated with the emission constraint represents the shadow price of carbon, interpreted as the endogenous carbon tax. The revenues from this tax are treated as government income and fully recycled through a uniform reduction in labor taxation, thereby mitigating potential distortionary effects of carbon pricing on the broader economy(Klenert et al., 2018; Costantini & Sfornn 2020; Korea Energy Economics Institute 2020; Roach 2021). While alternative revenue recycling options—such as direct support for low-carbon technology development, transfers to vulnerable households, are also relevant in real policy contexts, the labor-tax recycling assumption serves as a analytical benchmark to identify the pure efficiency effects of carbon taxation, by isolating them from broader fiscal expansion impacts.

While technological advancement and availability are key to achieving deep decarbonization, substantial uncertainties remain regarding their future progress. These uncertainties are explicitly addressed in our scenario analyses of alternative emission pathways. The scenario assumptions are grounded in data sources such as technology cost projections from NREL (2022) and CSIRO (2024), as well as domestic resource potential assessments from KEEI (2020). These settings reflect both technical feasibility and policy direction, with renewable, hydrogen, and CCS constraints aligned with national energy roadmaps and storage capacity evaluations. By incorporating uncertainties in technology progress and deployment, the scenarios provide a consistent framework for analyzing net-zero pathways.

Advanced scenarios (_adv) assume rapid technological innovation and broader deployment potential. Cost reductions follow the advanced pathway in NREL (2022). Renewable potentials reflect the higher technical availability reported by KEEI (2020), enabling significantly larger solar, wind, and biomass resources. Nuclear expansion is slightly higher at 34.7 GW with a 60-year lifetime. CCS/NETs potential doubles to 2 $GtCO_2$ with full availability after 2040. Hydrogen supply is expanded to 27 Mt H_2/yr by 2050 (77.5 Mtoe/yr), still allowing up to 80% imports, but with lower costs (3,000 KRW/kg by 2050).

The conservative scenarios (_cons) assume limited technological progress and resource deployment. Cost reductions follow the conservative pathway in National Renewable Energy Laboratory (NREL 2022). Renewable potentials are restricted to lower estimates from Korea Energy Economics Institute (KEEI 2020) with relatively small solar, wind, and biomass availability. Nuclear expansion is capped at 31.7 GW with a 60-year lifetime. CCS/NETs deployment is constrained by 1 $GtCO_2$ cumulative domestic storage potential, and NETs are only allowed after 2040. Hydrogen supply is limited to 50% of the advanced case, with a high reliance on imports (up to 80%) and higher costs (4,000 KRW/kg by 2050).

III. Results and Discussion

Our simulations indicate that GDP grows steadily in reference scenarios (BAU_con and BAU_adv), with an approximate 38% increase between the base year 2020 and 2050. Figure 4 illustrates the projected trajectories of real GDP across all scenarios relative to the baseline. Compared to the reference case, the net-zero (NZ) scenarios exhibit noticeable economic costs, with GDP declining by about 10% in NZ_con and 6% in NZ_adv by 2050. In NZ_con, GDP falls by nearly 10% relative to baseline by 2050, reflecting high carbon prices, reduced household consumption, and large distortions in energy-intensive sectors to be discussed later. NZ_adv shows a relatively smaller GDP loss of around 6%, as advanced technologies provide substitution opportunities that mitigate macroeconomic costs. Overall, the losses become more pronounced over time, as the emission reduction requirements tighten and technology constraints limit substitution possibilities. Overall, the widening gap between BAU and NZ scenarios underscores the macroeconomic burden of achieving deep decarbonization targets, particularly when advanced technologies are less available.

Figure 5 depicts the projected CO_2 emissions from 2020 to 2050 across all scenarios. Under the NZ scenarios, emissions are constrained by design and follow an identical reduction pathway that we imposed. The BAU scenarios, without explicit emission caps, show a noticeable divergence between the _con and _adv options. This indicates that improved technology availability and affordability can facilitate emission reductions even in the absence of emission/policy constraints. Overall, the divergence between BAU and NZ pathways widens substantially after 2030, reflecting the increasing stringency of the emission constraints and the growing importance of technology availability in meeting long-term climate goals.

In the CGE framework, the carbon tax emerges as the shadow price associated with the emission constraint, reflecting the marginal abatement cost of reducing one additional unit of CO_2. This approach ensures that the

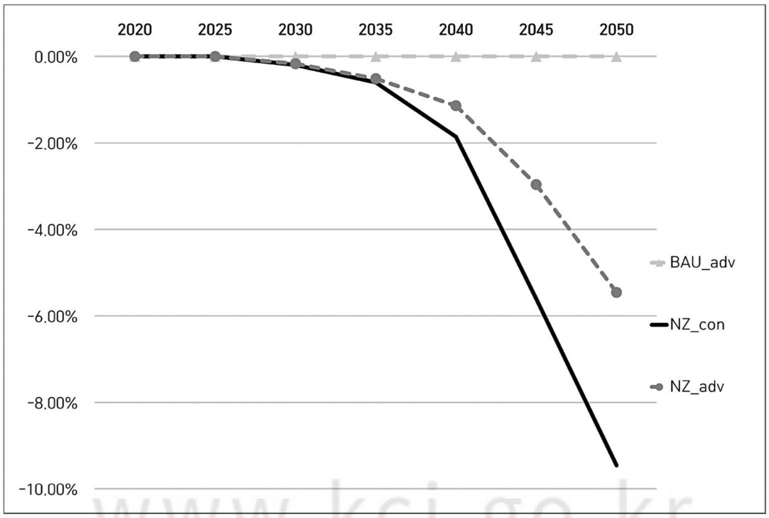


Figure 4. Real GDP projections up to 2050 compared to BAU_con (% difference)

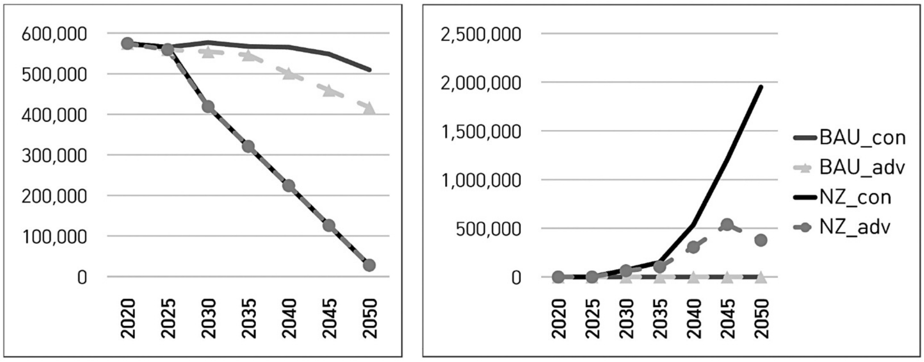


Figure 5. Emission pathway and endogenous carbon price by scenario (tCO_2, won)

carbon price is endogenously determined within the equilibrium system rather than imposed exogenously. As a result, carbon tax values rise over time, mirroring the tightening emission caps in the NZ scenarios. In particular, scenarios with limited technology availability display substantially higher carbon prices, reflecting the reduced flexibility in fuel switching and the heavier reliance on costly abatement options. The observed decline in the carbon price in 2050 compared with 2045 in NZ_adv is associated with assumptions regarding the DAC technologies. The _adv scenarios assume greater DAC deployment potential and its faster cost decline, which serve as an upper bound on the equilibrium carbon tax. These dynamics demonstrate how technology availability critically shapes the trajectory of mitigation costs.

Figure 6 shows the projected electricity price trends from 2020 to 2050. In the baseline scenarios (BAU_con and BAU_adv), electricity prices remain stable or gradually decline, reflecting efficiency gains and the absence of stringent carbon constraints. By contrast, electricity prices rise significantly under the net-zero scenarios. In NZ_con, where technological options are limited and costly, electricity prices increase sharply after 2035, more than doubling by 2050 relative to 2020 levels. In NZ_adv, the availability of advanced low-carbon

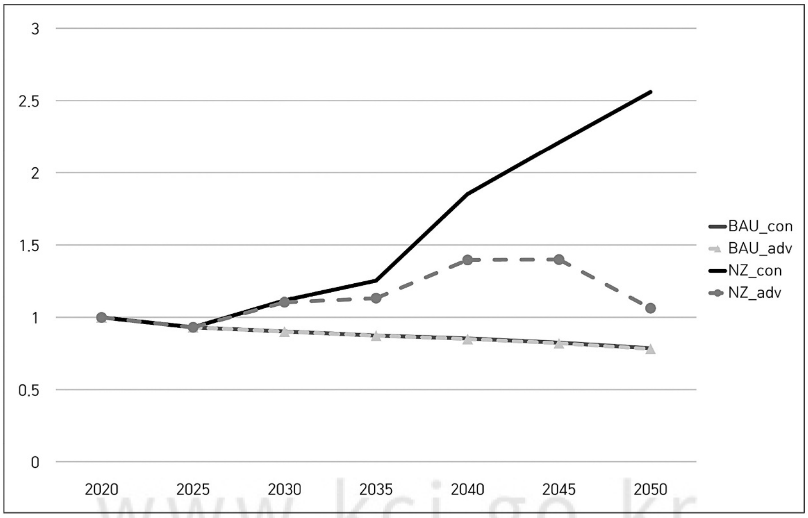


Figure 6. Price of electricity

technologies and DAC moderates price increases, with electricity prices peaking around 2045 before stabilizing and slightly declining toward 2050. These results highlight the crucial role of technology availability in containing electricity price shocks during the energy transition. Higher electricity prices under NZ scenarios also reflect the large-scale investment needs for clean generation and infrastructure, underscoring the economic trade-offs associated with achieving stringent decarbonization targets.

Figure 7 presents sectoral production changes in 2050 relative to the baseline. The results indicate strong heterogeneity across sectors under net-zero scenarios. On the production side, fossil fuel sectors decline in both NZ scenarios, but NZ_con experiences deeper contractions in energy-intensive industries due to higher energy costs. In NZ_adv, electricity expand more strongly, partially offsetting output losses elsewhere. The increase of electricity production also reflects accelerated deployment of low-carbon energy carriers to replace fossil fuels with electricity. In contrast, fossil-based energy sectors (coal, gas, petroleum) experience sharp declines, with production losses exceeding 80% in the most constrained NZ scenario (NZ_con). Energy-intensive manufacturing and transport also contract, though to a lesser extent, as higher carbon prices raise input costs and reduce competitiveness. Service and agriculture sectors show relatively marginal changes, indicating lower exposure to carbon pricing compared to energy-related industries.

Household consumption impacts across sectors, highlighting the demand-side effects of decarbonization. The results show that household demand for fossil fuel products (coal, gas, petroleum and coal products) drops, consistent with substitution away from carbon-intensive energy sources. In contrast, household demand for electricity and hydrogen increases, reflecting their role in supporting electrification and fuel switching in end-use sectors. Service consumption remains relatively stable, while transport demand shows noticeable declines in line with higher costs and structural changes in mobility patterns. Overall, the shift in household demand mirrors the broader production-side transition.

Also, Figure 8 presents the sectoral electricity supply in 2050 by scenario. Overall, electricity use expands across most sectors under both NZ scenarios, reflecting economy-wide electrification. However, in the NZ_con case, electricity supply to the manufacturing sector declines relative to the BAU pathways. This reduction indicates

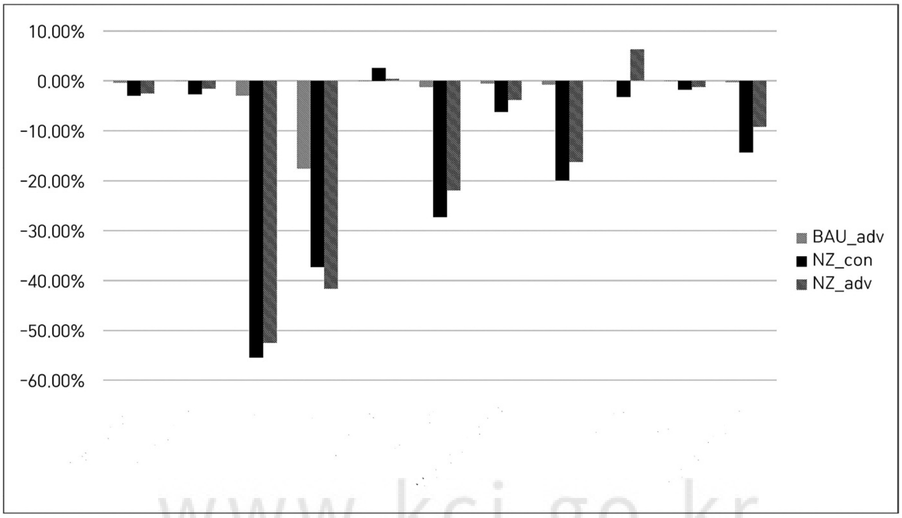


Figure 7. Sectoral production changes in 2050 in comparison to BAU_con (% difference)

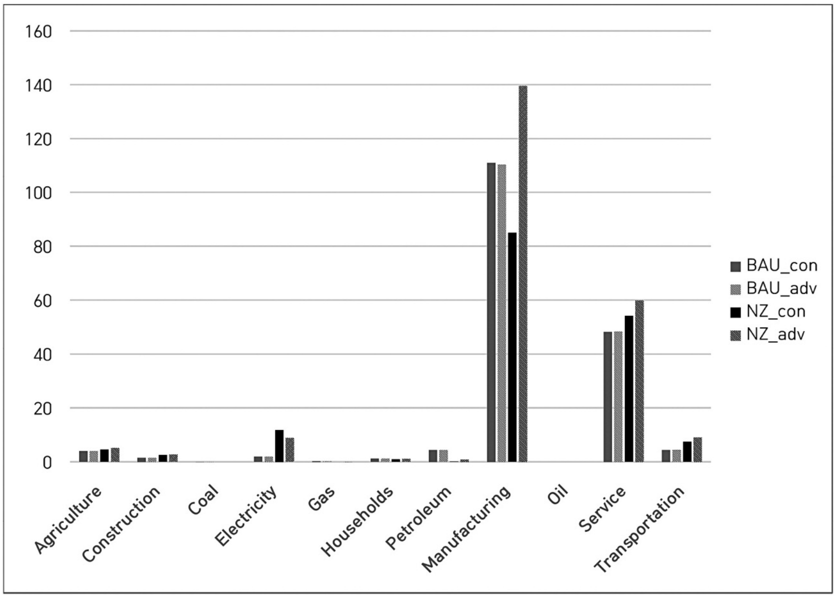


Figure 8. Sectoral electricity supply in 2050 by scenario

that limited technology availability and higher electricity prices constrain electrification in these sectors, leading to output contraction in energy-intensive manufacturing. In contrast, NZ_adv achieves higher electricity supply across nearly all sectors, supported by greater availability of low-carbon generation and storage technologies that enable cost-effective electrification. Particularly strong increases are observed in service sector and manufacturing, while agriculture and transport show moderate growth. These results highlight that technological progress is essential for sustaining industrial electrification and maintaining production while achieving economy-wide decarbonization.

Figure 9 and 10 illustrates the projected electricity generation mix, and capacity mix, respectively across scenarios. Under the BAU pathways, fossil fuels such as coal and LNG remain dominant, although renewables gradually expand, especially in the advanced technology case (BAU_adv). Nuclear generation remains stable, while oil and hydrogen contribute marginally. In contrast, the net-zero (NZ) scenarios show a clear structural shift: coal generation declines and almost disappears, while renewables and storage grow substantially, reflecting accelerated technological shift between high carbon and low carbon technologies.

The comparison between constrained (con) and advanced (adv) cases highlights the crucial role of technology availability in achieving deep decarbonization. In the NZ_adv scenario, renewable generation and storage capacity surge more dramatically compared to NZ_con, indicating that technological progress including cost reductions, efficiency improvements and greater availability can significantly reduce the economic burden of net-zero transitions. Results show toward 2050, hydrogen technologies shift from contributing to power generation (+) using fuel cells and hydrogen turbines to driving electricity consumption (−) for hydrogen production through electrolysis.

DAC technology is incorporated into the power sector model as a negative-emission option. Although DAC does not generate electricity, it consumes a certain amount of energy to remove CO_2, reducing the system's total net emissions. The learning curve for DAC is applied to investment costs, allowing unit costs to decline gradually

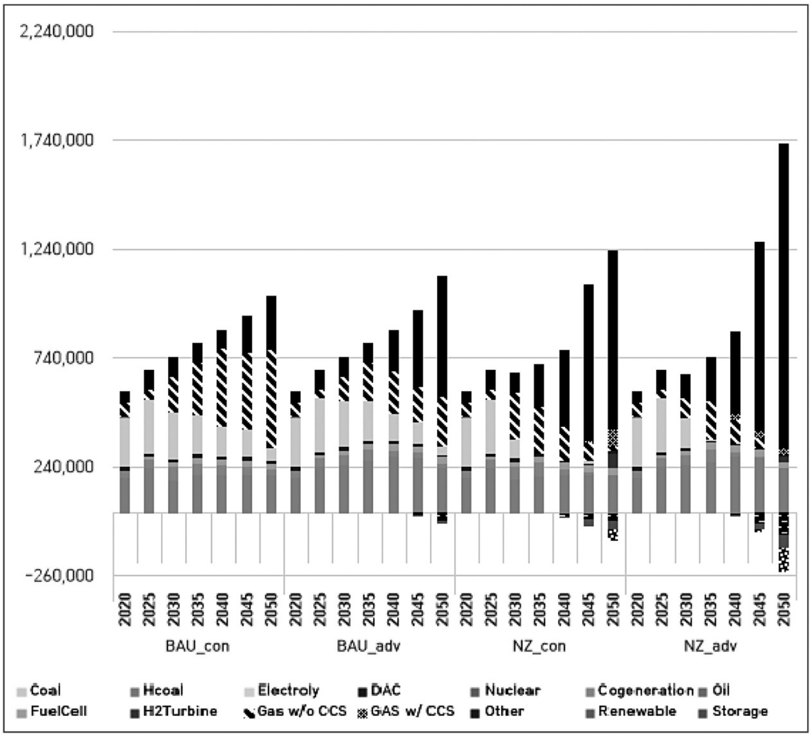


Figure 9. Least-cost generation mix over time by scenario (GWh) *Renewable includes solar, wind, hydro, hydro-Dam, hydro-River, Ocean, Waste, Landfill, Biomass energy.

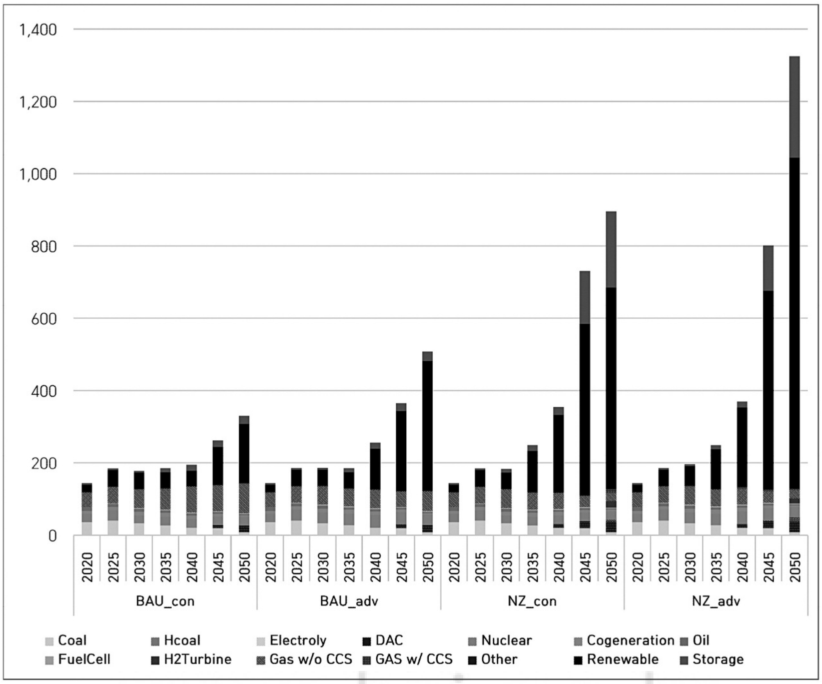


Figure 10. Capacity expansion over time by scenario (GW) *Renewable includes solar, wind, hydro, hydro-Dam, hydro-River, Ocean, Waste, Landfill, Biomass energy.

with cumulative installed capacity. As the learning effect strengthens, DAC becomes more economically viable, leading to a flatter marginal abatement cost curve and a downward adjustment of the endogenous carbon price. In the NZ_adv scenario, DAC is adopted earlier and scales up more rapidly, reaching about 11 GW of capacity by 2050, compared to 5 GW in NZ_con. Early adoption and faster learning-induced cost reductions in NZ_adv allow DAC to offset residual emissions sooner, lowering cumulative abatement costs and moderating carbon price growth.

Meanwhile, the limited technology case (NZ_con) exhibits slower renewable penetration and continued reliance on fossil fuels with CCS, suggesting higher abatement costs and lower system flexibility. Overall, power generation increases significantly under the advanced-technology cases, supporting the expanded electricity supply required for widespread electrification observed in the CGE results. While nuclear power generation remains stable across scenarios, enhanced technology availability enables more aggressive expansion of renewable capacity supported by energy storage systems.

IV. Conclusions

For the economic assessment of carbon neutrality using an integrated CGE–power sector modeling framework, this study developed an enhanced linking mechanism that ensures the consistency and stability between the bottom-up (power system) and top-down (CGE) models. A new iterative linking algorithm was designed to achieve smooth convergence between the two model layers through the dynamic adjustment of electricity demand scaling, carbon price feedback, and tolerance-based equilibrium criteria. The CGE model captures the macroeconomic feedbacks of energy demand and carbon pricing, while the power system model translates these signals into detailed technology-level responses in generation, capacity expansion, and emissions. The consistent exchange of information between the two models creates a mutually reinforcing feedback system in which macroeconomic and engineering-level results validate each other, thereby improving the robustness of the overall hybrid modeling framework.

Our results confirm that pursuing net-zero pathways imposes macroeconomic costs. Compared to the BAU trajectories, GDP declines by 6% in NZ_adv and 10% in NZ_con by 2050 under NZ scenarios, with the magnitude of impacts depending on technology availability. Production effects are uneven across sectors. Energy-intensive industries and transport contract significantly while services and agriculture remain relatively less affected. These patterns reflect both the direct burden of carbon pricing and the structural reallocation of resources from carbon-intensive sectors to low-carbon industries.

The results demonstrate that the economic and energy system impacts of achieving net-zero emissions are highly sensitive to the availability and timing of advanced technologies. Under NZ_con, where advanced options such as DAC, CCS, hydrogen, renewable energy, and large-scale storage are constrained, carbon prices rise to substantial levels, household consumption contracts sharply, and electricity prices more than double compared to NZ_adv. NZ_adv achieves the same emission reductions as NZ_con with substantially lower macroeconomic and welfare costs, reflecting greater flexibility in fuel substitution, faster expansion of renewables, and the integration of DAC and storage as balancing resources.

The divergent outcomes across NZ scenarios highlight the role of technology in shaping the affordability of net zero economy. In NZ_con, the endogenous carbon tax reaches substantial levels, underscoring importance of complementary innovation and deployment policies for advanced technologies. In NZ_adv, carbon prices rise more moderately, remaining within plausible policy ranges while reducing negative economic impact of the structural shift. These results confirm that accelerating technological development is not only an efficiency improvement but a prerequisite for making net-zero transitions economically and socially viable.

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