The Role of RD for Climate Change Mitigation in China: a Dynamic General Equilibrium Analysis

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The Role of R&D for Climate Change Mitigation in China: a Dynamic General Equilibrium Analysis

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This paper develops a dynamic general equilibrium integrated assessment model (DGE-IAM) with endogenous technological changes to explore strategies for China to optimize social welfare, mitigate climate change, and transition to green development. We analyze three solutions and provide corresponding projections of their outcomes: market solution (no intervention), carbon tax solution (carbon taxes and rebates), and green technology solution (induced R&D investment in green knowledge). While the temperature rise will reach $4.2°C$ in market solution by the next century, it is reduced to $4.0°C$ in the carbon tax solution with social welfare gains. In the green technology solution, economic growth pattern is almost intact with welfare gains while carbon emission approaches net-zero and climate change is curbed and even repairs consistently lower than $1°C$ in centuries. Our results highlight the potential of R&D investment in green knowledge, e.g., the modern new energy sector, as crucial for China's green transition in the long run with possibly welfare gains. We emphasize the need for immediate and intensive actions and offer valuable insights for policymakers addressing climate change and promoting a sustainable future for China.

JEL: E27, O33, O44, Q54

Keywords: Climate Change, Endogenous Technological Changes, Induced R&D, China

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1. Introduction

Climate change has emerged as a critical global issue, with profound implications for economies and societies worldwide. As a rapidly developing economy, China is confronted with the daunting challenge of balancing its economic growth, which necessitates substantial energy consumption and potentially increased carbon emissions, against the urgent need to mitigate the impacts of climate change (Liu et al., 2022). Despite the implementation of emission trading schemes (ETS) to marketize carbon emissions in China, R&D investment in the modern new energy sector remains insufficient like the development of carbon capture, utilization and storage (CCUS) (Jiang et al., 2020), as evidenced by the relatively small margin allocated to non-fossil energies, despite China's the world's largest government spending on energy research and development (International Energy Agency, 2023).

In this paper, we address these challenges by exploring various strategies, including carbon tax interventions and induced technological advancements, to help China achieve climate change mitigation and transition to green development. For this purpose, we build a dynamic general equilibrium (DGE) model with climate change and endogenous technological changes, calibrate the model with data from multiple sources, and obtain projections of the optimal equilibrium paths for three solutions, i.e., market solution, carbon tax solution and green technology solution. Our findings underscore the importance of proper R&D investment in green knowledge (i.e., the modern new energy sector) as a key driver for China's transition to green development with more sustainable future. Furthermore, the optimal equilibrium path with induced green technological advances indicates that too small or large induced R&D may both deteriorate welfare, because the former can not curb ongoing climate change and the latter speeds up the green transition too fast with substantial consumption

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losses.

Our paper contributes to two primary areas of literature. First, it adds to the growing body of studies that seeks to understand the relationship among climate change, economic activities and technological advancements by building a dynamic general equilibrium integrated assessment model (IAM). Second, it enriches the extensive literature on policy implications, future policy impact projection and implementation details for transitioning to green development, with a particular focus on China. By offering these insights, our study not only expands the existing knowledge base but also serves as a valuable resource for policymakers and stakeholders involved in China's sustainable development efforts.

Our paper's first contribution lies in examining the relationship between climate change and economic activities, with a focus on the induced technological changes.

Nordhaus' pioneering DICE and RICE models connect economic activities with global warming through macroeconomic dynamic growth models (Nordhaus, 1994; Nordhaus and Yang, 1996). With multiple updates, the DICE and RICE models become the most influential dynamic IAMs revealing the social cost of carbon and proposing insightful policy implications to the international societies [1]. While many relevant extensions follow the insights of DICE model assuming that climate change undermines productivity, some consider the damage of climate change directly on utility (Acemoglu et al., 2012). Our model adopts the latter perspective, with climate change as a discount factor in the utility function. It explains that the well-beings by consumption and its quality are affected by the severity of climate change. By internalizing climate change's negative impacts on the economy, we can identify the optimal trade-offs between economic development and climate change mitigation in the long term.

[1]The review of Nordhaus (2018) describes the evolution of DICE models and the recent work by Barrage and Nordhaus (2024) encompasses the results of the latest version. And Yang (2023) developed the latest version of RICE-2022.

With particular interests in projections, most models discuss climate-economy system with exogenous technological changes. However, an increasing number of studies consider endogenous technological changes to reduce carbon emissions, addressing the impacts of economic activity and policy on technologies. Such changes typically stem from accumulated investment in research and development (R&D)[2]. As an extension to the DICE model, the R&DICE model by Nordhaus (2010) incorporates R&D and knowledge lowering carbon intensities. The ENTICE model (Popp, 2004) assumes the role of knowledge as technological advances that substitute for fossil fuels, with the accumulation of knowledge stock allowing for more substitution and resulting in fewer carbon emissions. Additionally, R&D investment and low-carbon knowledge exhibit benefits in increasing revenues in models with abatement costs (Goulder and Schneider, 1999).

Building on the concept of R&D-based technological changes, we incorporate R&D in our model that accumulates as public green knowledge stock, generating green technologies to perfectly substitute fossil energies with non-fossil alternatives[3]. Given the absence of market incentives for R&D investment due to technology spillovers, the economy exhibits total imperfection, necessitating policy interventions to support induced technological improvements. In doing so, our paper provides a comprehensive analysis of the interplay among climate change, economic activities, and endogenous technological advancements, further contributing to this area of research. Although our model is calibrated particularly for China, it can be extended to other specific region/country with updates of calibration and results in different projections and implications.

Second, our paper contributes to the extensive literature focused on policy implications and implementations for reducing carbon emissions in China.

Despite significant achievements in alleviating emissions through various chan-

[2]In models discussing endogenous growth, R&D and learning-by-doing are usually applied. However, learning-by-doing may overstate the benefits of technological changes in lowering carbon intensity (Buonanno et al., 2003), as pointed out by Popp (2004).

[3]For more discussions, Popp (2019) is a comprehensive review of recent studies encompassing innovation in the energy sector, which contributes to climate change mitigation.

nels (Liu et al., 2022), such as the emission trading scheme (Liu et al., 2015; Huang et al., 2022), there is a need for further investigation into policy implications, implementation details, and future impact projections. Empirical work in this area has been sufficient in demonstrating China's achievements thus far. However, for long-term goals, it is essential to have future projections that can guide policy decisions and evaluate current process. Existing projections in the literature employ different methodologies and arrive at varying conclusions about China's carbon emission peak and its Nationally Determined Contribution (NDC). For instance, Mi et al. (2017) suggest that China's carbon emission may peak earlier in 2026, while Fang et al. (2019) indicate a peak between 2028 and 2040. On the other hand, den Elzen et al. (2016) argue that current policies are unlikely to achieve a carbon peak by 2030 and call for enhanced policy measures.

While these studies provide valuable insights, most discuss the world economy and climate as a whole. There is a knowledge gap in the literature when discussing the policy interventions and projections for one specific country/region using structural climate-economy models with endogenous technological changes. Our research fills this gap by such a structural model and providing future projections aimed at maximizing social welfare in the long run for the largest carbon emitter, China. Specifically, we conduct meticulous calibration for all parameters of our model to suit Chinese situation, allowing for different magnitudes of government interventions, and obtain projections of future policy impacts.

These projections enable us to suggest policy implications for different contexts, analyze the effects of different policy interventions, and provide policy implementation details. Our paper's main conclusions are threefold: (1) optimal carbon tax policy aimed at social welfare yields welfare gains, emission reductions, and climate change mitigation; (2) China needs proper induced R&D investment in green knowledge for welfare improvement, and too small or large R&D deteriorates welfare; (3) the transition towards green development and decoupling carbon emissions is significantly effective in long term, taking decades and centuries if maintaining welfare improvement; and (4) existing goals of climate change mitigation are too ambitious and highly possible to reduce social welfare despite R&D and endogenous technological changes if China fights alone.

By drawing these conclusions, our paper adds value to the existing literature and contributes to the ongoing efforts to understand and address the challenges of carbon emissions and climate change in China. This research emphasizes the importance of timely policy interventions and consistent R&D at proper rates in green knowledge for climate change mitigation and welfare improvement, highlighting the potential for a more sustainable and prosperous future for China.

In the subsequent of this paper, Section 2 describes the model with equations and finds the policy implications. Section 3 presents the calibration strategies and results of the model. Section 4 present the results and projections with comparisons to existing findings and Section 5 supplements discussions. Section 6 summarizes the main finding and contribution of our research.

2. Model

In this section, we provide a comprehensive description of the models that links climate change and economic activities. The models encompass various scenarios aimed at identifying potential solutions for China to achieve green development, as well as quantifying the effects of these solutions. These solutions include (1) the market solution (i.e., the benchmark model): a "laissez-faire" economy without any interventions or "business as usual" in some contexts, (2) the carbon tax solution (i.e., the emission reduction model): implementation of carbon tax and lump-sum rebates, and (3) the green technology solution (i.e., the induced R&D model): economic development induces R&D investment in the modern new energy to accumulate green knowledge to reduce carbon emissions.

Descriptively for the benchmark model, households' utility is determined by the impacts of climate change and their consumption levels. The households own the physical capital stock and make forward-looking decisions to maximize their discounted aggregate utility by deciding on consumption and future physical capital stock. Carbon emissions are produced through production in each period and contribute to the atmospheric carbon concentration, which serves as a state variable in the model. An increase in atmospheric carbon concentration leads to temperature rises and a decline in households' utility. As the benchmark model does not have markets for carbon emissions or parent for green knowledge, it characterizes apparent negative and positive externality for them, respectively.

We investigate two extensions to the benchmark model to find implementation details and effects for the carbon tax and induced R&D. The main disparities among the three models can be summarized as follows. (1) In the market solution, households are not aware of the role of carbon emissions and green knowledge, and they only consider optimal consumption and investment choices. This lack of awareness constitutes a market failure caused by the negative externality of carbon emissions and green knowledge. (2) In the emission reduction model, a social planner is responsible to allocate resources and internalize the impacts of carbon emissions and climate change. As the carbon tax solution, the optimal path suggests a taxation to reduce the marginal return on physical capital and a lump-sum rebate as usage of the tax revenue. (3) In the induced R&D model, economic growth induces R&D investment in green knowledge that can reduce carbon emissions through green technology, while households act the same as in the benchmark model. Different cases of the induced R&D are investigated to find the optimal one with the largest social welfare.

2.1. Economic Growth and Climate Change

The production sector utilizes physical capital stock (K_t) and labor (L_t) the function of $F(\cdot)$ with a Cobb-Douglas specification at each period

$$Y_t = F(A_t, K_t, L_t) = A_t K_t^{\alpha} L_t^{1-\alpha}, \tag{1}$$

where A_t, L_t are factor productivity and labor (or population) and α is the capital share.

Non-negative carbon emissions (E_t) are generated through the production process

$$E_t = \max\{0, \xi_t Y_t - \omega H_t\}, \tag{2}$$

where ξ_t is exogenous emission factor, and ωH_t represents the negative emissions due to the green technology as a linear specification over the green knowledge H_t with coefficient ω. As a conservative assumption, A_t, L_t and L_t change over time and converge to certain levels, denoted as A^*, ξ^* and L^*, respectively.

Atmospheric carbon concentration (Q_t) is a state variable of the model and changes along with carbon emissions through the law of motion

$$Q_{t+1} - 280 = (1 - \delta_Q)(Q_t - 280) + \eta f^G(E_t), \tag{3}$$

where δ_Q represents the natural absorption rate of carbon dioxide, $f^G(\cdot)$ stands for the global emission w.r.t Chinese emissions, and η controls the transformation of global carbon emission that condense in the atmosphere.

Due to atmosphere movements, the concentration for China belongs to the global system and is affected by global emissions instead of its own. The excessive carbon concentration beyond the pre-industrial level is represented as $Q - 280$ (the pre-industrial level of atmospheric carbon concentration is 280 parts per million), and a constant parameter This law of motion narrates that future excessive carbon concentration equals the remaining of existing concentration after the natural absorption plus the condense of carbon emissions.

As for the specification of the relation between global carbon emission and China's emission $f^G(\cdot)$, we adopt the piece-wise function

$$f^G(E_t) = \max\{E_{\text{const}} + E_{\text{coef}} \cdot E_t, E/0.30\}, \tag{4}$$

where $E_{\text{coef}} < 1/0.3$ with transition point as $\hat{E} = \frac{E_{\text{const}}}{1/0.3 - E_{\text{coef}}}$. When China's emission is relatively small ($E_t \leq \hat{E}$), the global emission exhibits almost linear relationship. And when the economy grows and emission increases ($E_t > \hat{E}$), the carbon emission gradually becomes a fixed share of the globe (i.e., 30%, slightly larger than observations in recent years). Such a specification guarantees that (1) global emission is increasing in E_t, (2) global emissions are positive even though China has zero emission, and (3) the carbon emission share of China can not grow too much, exceeding 30%. As for how existing observations justify this specification, please refer to the calibration sector.

Climate change happens with excessive atmospheric carbon concentration that leads to temperature rise above the pre-industrial level (Δ_t). The relationship between temperature rise and atmospheric carbon concentration is described by $T(\cdot)$ such that

$$\Delta_t = T(Q_t) = T_{\text{const}} + T_{\text{coef}} \cdot \log_2(\frac{Q_t}{280}). \tag{5}$$

In line with the IPCC report and many relevant works (e.g., DICE model and Acemoglu et al. (2012)), this relationship builds upon that the doubling of atmospheric carbon concentration beyond the pre-industrial level brings a fixed temperature rise, which is defined as climate sensitivity.

Following the insights of Acemoglu et al. (2012), climate change affects the economy by decreasing utility as a discounter to consumption. The climate change discounter ($\Phi_t \in [0,1]$) is decreasing in temperature rise as the function $\psi(\cdot)$ such that

$$\Phi_t = \psi(\Delta_t) = \begin{cases} \frac{(D-\Delta_t)^\lambda - \lambda(D-\Delta_t)D^{\lambda-1}}{(1-\lambda)D^\lambda} & , 0 \leq \Delta_t \leq D \\ 0 & , \Delta_t > D \end{cases}, \tag{6}$$

where D represents the dangerous temperature rise in which consumption is not beneficial ($\Phi = 0$) and $0 < \lambda < 1$ controls the concavity.

With a compound function $\phi = \psi \circ T$ that directly links climate change discounter and atmospheric carbon concentration ($\Phi_t = \phi(Q_t)$), higher Q serves a climate change factor on consumption (c) to deteriorate households' utility

$$u_t = U(Q_t, c_t) = \frac{(\phi(Q_t) \cdot c_t)^{1-\sigma}}{1-\sigma}, \tag{7}$$

which exhibits constant elasticity of substitution between inter-temporal discounted consumption ($\Phi_t c_t$) as $\frac{1}{\sigma}$.

We normalize the number of households to one, the population level corresponds household sizes (L_t). As physical capital stock is owned by households consisting of homogeneous people and all markets are complete and perfectly competitive, the constraint exhibits both the law of motion for physical capital and the budget constraint at the market equilibrium

$$c_t L_t + K_{t+1} \leq (1 - \delta_K) K_t + Y_t - Z_t, \tag{8}$$

where c_t stands for consumption per capita, Z_t refers to induced R&D investment in the modern new energy (Z_t), and δ_K is the depreciation rate of physical capital.

Our work includes endogenous technological changes to reduce carbon emission by the introduction of green knowledge (H_t). R&D investment contributes to the accumulation of green knowledge through the law of motion

$$H_{t+1} = H_t + Z_t^{\theta}, \tag{9}$$

where depreciation does not exist in green knowledge such that it does not get obsolete and $0 < \theta < 1$ sets decreasing return to scale. Thus, the green knowledge is a public stock because it is non-rival, non-excludable, and can be accumulated.

2.2. The Market Solution

In the benchmark model, households are not aware of the impacts of their decision on climate change and there is no R&D investment in green knowledge. They only make decisions on consumption and future physical capital. In the meanwhile, atmospheric carbon concentration Q_t is regarded as given and affects their inter-temporal behaviors. Henceforth, households are aimed to maximize aggregate discounted utility with infinite-time horizon subject to the budget constraint

$$\max_{c_t, K_{t+1}} \sum_{t=0}^{\infty} L_t U(Q_t, c_t) \tag{10}$$

$$\text{s.t. } \forall t \quad \text{budget constraint (equation 8)} \tag{11}$$

$$\{A_t, L_t, Q_t\}, Z_t = 0, H_0, K_0 \text{ as given.} \tag{12}$$

By rearrangement and substitution in first order conditions, we derive the Euler equation

$$\frac{\partial U}{\partial c}\Big|_t = \beta \frac{\partial U}{\partial c}\Big|_{t+1} \left(\frac{\partial F}{\partial K}\Big|_{t+1} + 1 - \delta_K\right), \tag{13}$$

which implies that the marginal utility of consumption equals the discounted marginal utility of physical capital. It is indeed a common Euler equation in the neoclassical dynamic general equilibrium (DGE) model.

The equilibrium path is defined such that given the sequences of $\{Q_t\}$, the results of $\{c_t, K_t\}$ clear budget, satisfy Euler equation, and the law of motion for Q_{t+1}. As all exogenous variables are convergent after T_{ss}, there exists a steady state such that an equilibrium is constituted and all variables are fixed. Forward shooting method is adopted to obtain the numerical optimal equilibrium path that approaches to the steady state over a large amount of periods (T), which serves the projection for the outcomes of the market solution.

Due to the negative externality nature of carbon emissions and the public goods characteristics of green knowledge, the market solution proves inadequacy in addressing climate change and harnessing the potential of green knowledge due to the absence of appropriate incentives. Climate change continues along with market equilibrium and it is determined by the exogenous factors like carbon intensity ξ_t and total factor productivity A_t. Hence, the market solution fails to deal with climate change at all.

2.3. *The Carbon Tax Solution*

The results of emission reduction model yield the carbon tax solution, in which households are aware of climate change dynamics and determine $\{c_t, K_{t+1}\}$ to find the optimal path. Conclusively, the optimization problem is

$$\max_{c_t, K_{t+1}} \sum_{t=0}^{\infty} L_t U(Q_t, c_t) \tag{14}$$

$$\text{s.t. } \forall t \quad \text{budget constraint (equation 8)} \tag{15}$$

$$\text{law of motion for } Q_{t+1} \text{ (equation 2, 3 and 4)} \tag{16}$$

$$\{A_t, L_t, \xi_t\}, Z_t = 0, H_0, K_0 \text{ as given,} \tag{17}$$

where $Z_t = 0$ because green technology is not profitable in our model. Denote the Lagrangian multiplier for the law of motion for Q_{t+1} as ζ^Q. Corresponding Lagrangian constraint is $\zeta_t^Q[(1-\delta_Q)(Q_t - 280) + \eta f^G(E_t) - (Q_{t+1} - 280)]$. The solution to the optimization problem should satisfy first order conditions

$$\frac{\partial U}{\partial c}\Big|_t = \beta \frac{\partial U}{\partial c}\Big|_{t+1} \left(\frac{\partial F}{\partial K}\Big|_{t+1} + 1 - \delta_K\right) + \beta \zeta_{t+1}^Q \eta x_{t+1} \xi_{t+1} \frac{\partial F}{\partial K}\Big|_{t+1} \tag{18}$$

$$\text{where } x_{t+1} = \begin{cases} E_{\text{coef}} & \text{when } f^G(E_t) > \frac{E_t}{0.3} \\ \frac{1}{0.3} & \text{elsewhere} \end{cases} \tag{19}$$

$$\zeta_t^Q = \beta L_{t+1} \frac{\partial U}{\partial Q}\Big|_{t+1} + \beta \zeta_{t+1}^Q (1 - \delta_Q). \tag{20}$$

Thanks to the concavity and Inada condition of the damage function, the Lagrangian multiplier is strictly non-zero and the transversality condition is automatically satisfied in such an infinite time optimization problem. Comparing it to Euler equation in the benchmark model, we find policy implications of carbon taxes

$$\tau_{t+1} = -\eta x_{t+1} \frac{\zeta^{Q}_{t+1}}{\frac{\partial U}{\partial c}\big|_{t+1}}, \tag{21}$$

where τ_{t+1} ($\tau_0 = 0$) is the tax for each unit of carbon emission. And the tax revenue is used as lump-sum rebates to households, resulting in fiscal balance at each period. Thus, the budget constraint for households at the market equilibrium becomes

$$c_t L_t + K_{t+1} - (1 - \delta_K) K_t = Y_t - \tau_t \xi_t Y_t + T_t, \tag{22}$$

where $\tau_t \xi_t Y_t$ is total carbon tax paid and lump-sum rebates ($T_t = \tau_t \xi_t Y_t$) are exogenous to households. Please notice that when $\tau_{t+1} > 0$, carbon taxes and lump-sum rebates to households are imposed, but they become carbon subsidy and lump-sum taxes from households when $\tau_{t+1} < 0$.

In this emission reduction model, a general equilibrium is defined such that all variables satisfy the first order conditions (Euler equation), budget is clear and the law motion motion for Q_{t+1} holds true. The equilibrium path toward the steady state constitutes the optimal equilibrium path. We apply both the backward and forward shooting method to find the path that can resemble the optimal.

2.4. *The Green Technology Solution*

To obtain the details and outcomes of the green technology solution, we extend the benchmark model to include induced R&D investment (Z_t) in green knowledge (H_t) as a policy implementation. We assume the amount of induced

R&D as a fraction of real output that depends on current emission level such that $Z_t = R(E_t)Y_t$. For simplicity, the specification of $R(\cdot)$ takes the piece-wise function

$$R(E_t) = \begin{cases} r & \text{when } E_t > 0 \\ 0 & \text{when } E_t = 0, \end{cases} \tag{23}$$

where a constant share of real output is induced as R&D investment in green knowledge once these is carbon emission and there is no R&D if emission becomes zero. Such a R&D investment that is induced from endogenous variables is a common practice in models that include many multiple variables (e.g., R&DICE (Nordhaus, 2010)). It is indeed a compromise from allowing Z_t as an endogenous control variable for households or a social planner because of the difficulty for finding the optimal equilibrium path for models with multiple complex state variables. The specification is simply controlled by one constant but still enables us to discuss different scenarios of how fast green knowledge accumulates.

As the same as the benchmark model, households only face trade-offs between consumption and future physical capital stock, regarding climate change, R&D expenses and tax payment as given (i.e., Q_t, $Z_t = R(E_t)$, $T_t = 0$). Therefore, the household optimization problem can be written as

$$\max_{c_t, K_{t+1}} \sum_{t=0}^{\infty} L_t U(Q_t, c_t) \tag{24}$$

$$\text{s.t. } \forall t \quad \text{budget constraint (equation 8)} \tag{25}$$

$$\{A_t, L_t, Q_t, Z_t\} Y_t, H_0, K_0 \text{as given,} \tag{26}$$

where the amount of induced R&D Z_t is determined exogenously. Euler equation for this optimization problem is the same as equation 13 because households regard both Q_t and Z_t as given.

However, different from the previous models, emission must be zero ($E^* = 0$)

at the steady state otherwise green knowledge will grow, violating the definition of steady state. Therefore, the green knowledge stock must satisfy that $\omega H^* \geq \xi^* Y^*$ to guarantee the zero emission. In the meanwhile, because global emission is still positive when China has zero emission ($f^G(0) = E_{\text{const}}$), China's atmospheric carbon concentration can not decrease to the pre-industrial level (i.e., 280 p.p.m) but remains at Q^* such that $\delta_Q(Q^* - 280) = \eta E_{\text{const}}$.

In the induced R&D model, a equilibrium is defined as given a sequence of $\{Q_t, Z_t\}$, a sequence of $\{c_t, K_t\}$ satisfies Euler equation, clears budget, and the law of motion for Q_{t+1} and $Z_t = R(E_t)Y_t$ both hold true. Given a value for the constant r, the equilibrium path that all variables approach to the steady state serves the optimal equilibrium path to the optimization problem. And the corresponding results are the outcomes of the green technology solution. Intuitively, smaller r makes green knowledge accumulate slowly and mitigation in climate change is limited. And larger r reduces households' budget for consumption and future physical capital, though green knowledge should grow faster to remove more carbon emissions. These two completing forces shape the relationship between r and welfare as a reverse-U, which implies an optimal r exists to pursue the maximum social welfare.

3. Calibration

3.1. *Determination of Exogenous Variables and Parameters*

The principle of calibration for exogenous parameters and variables (the parameters ω and θ are estimated in the next section) is to improve the performance of the benchmark model to match real-world observations. As the market solution does not account for carbon emissions and climate change, we determine the parameters of the economic development and climate change parts independently.

To calibrate for the economic development of the benchmark model, we collect variables of Chinese national accounts from 1978 to 2019 at constant 2017 prices in U.S. dollars from the Penn World Table (PWT) (Feenstra et al., 2015). Thus, real-term variables are measured in USD at the 2017 fixed prices from now on, or simply as 2017 USD. The variables include GDP, consumption, domestic absorption, labor share and depreciation rate. For fixed parameters, we set δ_K and $1-\alpha$ to the average values from the PWT and discount rate $\beta = 0.995$. Such a discount rate makes the discounted utility die out slowly in the long run as the time span of the model lasts for centuries.

As our model excludes stochastic shocks, we use the HP filter to identify the trends of log-GDP differences, the fraction between consumption and domestic absorption, and investment. Using these variables together with population L_t, we compute the corresponding observations for $Y_t, c_t L_t$ and I_t and obtain K_t using perpetual inventory method ($t = 0$ represents year 1978). Hence, we have the initial physical capital stock as $K_0 = 3821.7$. With these variables, we compute the values of observed TFP using Y_t, K_t, L_t and α, denoted as TFP_t.

Prior to the period $t_{ss} = 122$ (year 2100), exogenous variables $\{A_t, L_t, \xi_t\}$ change over time and converge to constants A^*, L^*, ξ^* at the period t_{ss}. The results for L_t take the function

$$L_t = f^L(t) = \begin{cases} \text{PWT Population}_t & 0 \leq t \leq 41 \\ \text{UNWPP}_t & 41 < t \leq t_{ss} \\ \text{UNWPP}_{t_{ss}} & t > t_{ss}, \end{cases} \tag{27}$$

where L_t takes the population for observed years in the PWT (denoted as PWT Population_t), future L_t takes the population from the United Nation World Population Prospects for China (United Nations, Department of Economic and Social Affairs, Population Division, 2022), denoted as UNWPP_t.

For total factor productivity A_t, its logarithm values are parameterized with two phases

$$\log A_t = f^A(t) = \begin{cases} \ln \mathrm{TFP}_t & 0 \le t \le T_A \\ TFP_{T_A} + \sum_{n=0}^{n=t} (A_{\text{const}} + A_{\text{coef}}) \cdot n & T_A < t \le 89 \\ TFP_{T_A} + \sum_{n=0}^{89} (A_{\text{const}} + A_{\text{coef}}) \cdot n & t > 89. \end{cases} \tag{28}$$

In the first phase ($t \le T_A$) when A_t grows increasingly, $\log A_t$ takes the values of $\ln \mathrm{TFP}_t$ computed using trend of variables after HP filter for annual time series. In the phase two ($t > T_A$) when marginal A_t diminishes, the differences in the logarithm exhibits positive linearity such that $\ln A_{t+1} - \ln A_t = \max\{0, A_{\text{const}} + A_{\text{coef}} \cdot t\}$ where $A_{\text{coef}} < 0$. As the results of $\ln \mathrm{TFP}_t$ from $t = 0$ to $t = 41$ show, $T_A = 27$ when the differences start to decrease almost in linearity. Using $\ln \mathrm{TFP}_t$ with $t \in [27, 41]$, OLS estimation provides $A_{\text{const}} = 0.0495$ and $A_{\text{coef}} = -5.509 \times 10^{-4}$ with 0.977 r-squared [4]. Such parameters yield a zero increase in A_t when $t > 89$, so A_t already converges prior to t_{ss}.

For ξ_t, its iteration follows a convergent relationship $\xi_{t+1} - \xi_{\text{const}} = \xi_{\text{base}} \cdot (\xi_t - \xi_{\text{const}})$ with ξ_{base}, which derives the parameterized general function

$$\xi_t \times 10^6 = f^\xi(t) = \begin{cases} \xi_{\text{const}} + \xi_{\text{coef}} \cdot (\xi_{\text{base}})^t & 0 \le t \le t_{ss} \\ \xi_{\text{const}} + \xi_{\text{coef}} \cdot (\xi_{\text{base}})^{t_{ss}} & t > t_{ss}, \end{cases} \tag{29}$$

where ξ_t is measured in $G.t$ per billion USD. We collect the national fossil fuel carbon emissions from 1902 to 2019 provided by the Global Carbon Project (GCP) as the data for E_t. From 1978 to 2019, using Y_t we calculate the observed emission intensity, denoted as EI_t measured in gram per USD. The parameterized $f^\xi(t)$ is supposed to generate the least squared differences between $\xi(t) \times 10^6$ and EI_t. As results, $\xi_{\text{const}} = 292.4$, $\xi_{\text{coef}} = 576.7$ and $\xi_{\text{base}} = 0.979$. Fig. **A.2.** in the appendix illustrates the performance of $f^\xi(t)$ in predicting observed emission

[4]For details, Fig. **A.1.** in the appendix exhibits the pattern of $\Delta \ln \mathrm{TFP}_t$ and the linear estimation.

intensity.

It should be noted that we set H_0 to zero based on the notion that the observed emission intensity already include the information of existing and in-trend R&D investment in the modern new energy sector. With $H_0 = 0$, we explain Z_t as additional or out-of-trend R&D. Hence, the negative emission ωH_t represents the reduction of carbon emissions induced by the out-of-trend green knowledge.

For the calibration of some climate change parameters, we refer to the results of Lin and Xie (2024) because the integration of climate change with economic system in our model follows the same intuition and structure. In conclusion, we have $\lambda = 0.3027$, $T_{\text{const}} = -0.247$, $T_{\text{coef}} = 2.444$ for equations 6 and 5. And we compute the corresponding atmospheric carbon concentration for the dangerous temperature (i.e., $\bar{Q} = 1646.7$). For other parameters in equations 4 and 3, we determine their values in this research independently because regional disparity is not considered here.

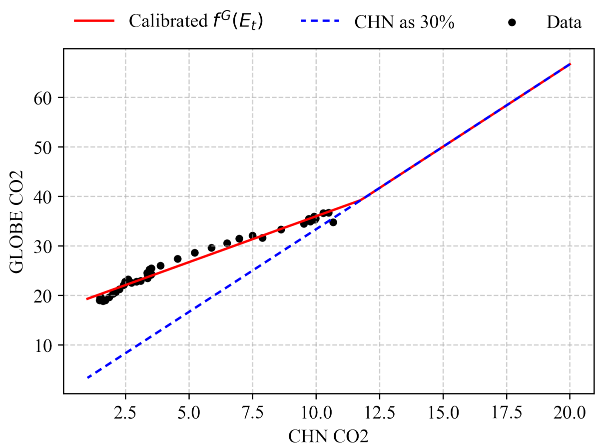

Fig. 1. Carbon Emissions in $G.t$ and Calibration for $f^G(E_t)$

In addition to China's emissions, we also collect global emissions from the GCP database from 1978 to 2019 to estimate the parameters in equation 4. Using the observed data, the OLS estimation yields $E_{\text{const}} = 17.462$ and $E_{\text{coef}} = 1.850$. And Fig. **1.** presents the relation of $f^G(E_t)$ to demonstrate the good fitness.

To estimate the law of motion for Q_{t+1} from the global scale, we need to collect the atmospheric carbon concentration data representative for China. Specifically, we collect the monthly atmospheric carbon concentration observations from the Waliguan atmosphere background station located in Qinghai province, China, published by the World Data Center for Greenhouse Gases (WDCGG) affiliated with the World Meteorological Organization (WMO). The annual averages of these observations are obtained from 1994 to 2019. However, it is not enough for our calibration period from year 1978 to 2019. To obtain indicator for Q_t from 0 to 41, we collect the global average carbon concentration (Q_t^G) at the same time span as Lin and Xie (2024), and estimate China's levels based on a linear relation $Q_t - 280 = Q_{\text{coef}}(Q_t^G - 280)$ ($t \in [0, 41]$) such that the excessive concentration in China is a constant fraction to the global average. The result shows $Q_{\text{coef}} = 1.027$ and the fitness is very good ($R^2 = 0.9997$). Thus, we obtain Q_t data based on the global average observations with $Q_0 = 333.1$.

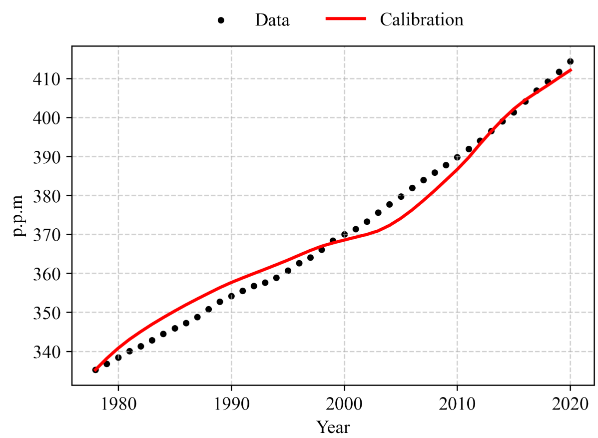

Fig. 2. Atmospheric Carbon Concentration: Data and Calibration

Note: $t = 0$ represents the year 1978. The model prediction of Q_t is obtained based on Q_0 and the law of motion using carbon emissions from the model results.

Then, we run the non-linear generalized in-model calibration using data of Q_0 and E_t into the law of motion for Q_{t+1} (equation 3) to find the parameters that yield the least squared differences between the model result Q_t and data. We have $\delta_Q = 0.1150$ and $\eta = 0.4579$ as the results. Fig. **2.** shows the atmospheric carbon concentration of the calibrated law of motion and data.

Given all parameters above, K_0, H_0, Q_0 and $\{A_t, L_t, \xi_t\}$, we can use the forward shooting method[5] to find the optimal equilibrium path of the benchmark model as long as we set σ in the utility function. Among all attempts of σ from 0.2 to 4 with 0.2 step ($\sigma = 1$ yields logarithm utility function), $\sigma = 3$ generates the optimal equilibrium path in which the results of (Y_t, c_t, E_t, Q_t) from 0 to 41 best simulate the observations[6].

3.2. Estimation of the Effects of Green Knowledge

Recall that the green knowledge lowers carbon emissions (equation 2) and R&D increases the level of green knowledge, the parameter ω is of great significance for quantitative results. As our model assumes that emission factors are exogenous and change along with time despite of the green knowledge, the estimation of ω should exclude the exogenous change of emission factors. However, there is little empirical studies trying to quantify the effects of R&D in lowering carbon intensities while assuming that emission factors change along with time. We need to collect relevant data and estimate the effects on our own.

The International Energy Agency (IEA) releases the R&D investment ratio (R&D per GDP) in the modern new energy sector of its members[7]. After combining the data set with the GCP and PWT, we obtain a balanced panel data set[8] with variables of real GDP ($Y_{i,t}$), R&D investment ($Z_{i,t}$) and carbon emissions ($E_{i,t}$) where i labels country and t stands for time. Then, we need to obtain the level of green knowledge for each country. Because log-R&D ($\ln Z_{i,t}$) exhibits polynomial patterns of high degrees, we adopt the polynomial interpolation for $\ln Z_{i,t}$ of degree-k_i such that the interpolation is consistently increasing in t prior

[5]Specifically, the forward shooting must last for at least $T = 272$, and (c_T, K_T, Q_T) are all within the 0.4% distances approaching the steady state levels.
[6]From the results of the optimal equilibrium path in Fig. **A.3.** in the appendix, it is evident of the good fitness of the calibrated benchmark model.
[7]China is not included because it is association country other than member.
[8]There are 31 countries with IEA membership. Some of them pay much attention to carbon emission reduction and achieve carbon neutrality like Norway and Sweden.

to observations. Combining the interpolation and data of $Z_{i,t}$, we compute green knowledge $H_{i,t}$ using the perpetual inventory method till year 1946 (Post-WW2) given the value of θ.

To estimate the effects of green knowledge, we propose the structure form that $E_{i,t} = f_i(t)Y_{i,t} - f_{\text{new}}(H_{i,t})$, where $f_i(t)$ indicates the carbon emissions from fossil energy needed by each GDP and $f_{\text{new}}(H_{i,t})$ measures how many emissions are substituted by the modern new energy (zero emission) brought by the green knowledge. We adopt the simple specifications of quadratic $f_i()$ and linear $f_{\text{new}}()$ for the estimation. Hence, we can derive the formulation of observed carbon intensities

$$\frac{E_{i,t}}{Y_{i,t}} = \beta_{i,0} + \beta_{i,1}t + \beta_{i,2}t^2 - \omega\frac{H_{i,t}}{Y_{i,t}}. \tag{30}$$

Given the value of θ, parameters $\beta_{i,0}, \beta_{i,1}, \beta_{i,2}$ and ω are estimated to minimize the squared differences of equation 30. Thus, OLS regression is feasible to solve the problem. And θ is determined such that the OLS regression has the highest R-squared. As results, $\theta = 0.4763$ and $\omega = 0.00876$ for $E_{i,t}$ in gigaton and $H_{i,t}$ in billion 2017 USD[9]. The estimation means that one unit of green knowledge reduces carbon emission by 8.76 million tons while x billion 2017 USD of R&D contributes to future green knowledge by $x^{0.4732}$ units.

3.3. *Summary of Calibration*

In summary, the calibration results of all relevant parameters are summarized in Table **1**.

[9]Fig. **A.4.** in the appendix compares carbon intensities between observations and model predictions and shows good fitness.

Table 1
Summary of the Calibration Results

Total Factor Productivity (equation 28)					
A_{const}	A_{coef}	T_A			
0.0495	-5.509×10^{-4}	27			
Emission Intensity (equation 29) and **Global Emission (equation 4)**					
ξ_{const}	ξ_{coef}	ξ_{base}	E_{const}	E_{coef}	
292.4	576.7	0.979	17.462	1.850	
Green Knowledge (equation 2, 9)			**Initial Status**		
θ	ω		K_0	Q_0	H_0
0.4763	8.76×10^{-3}		3821.7	333.1	0
Other Parameters for Calibration					
β	α	δ_K	δ_Q	η	σ
0.995	0.418	0.054	0.1150	0.4579	3.0
Parameters Borrowed from Chapter 2					
Equation 5		Equation 6		Corresponding $\bar{Q}$	
$T_{\text{const}} = -0.247$	$T_{\text{coef}} = 2.444$	$\lambda = 0.3027$	$D = 6$	$\bar{Q} = 1646.7$	

4. Results and Implications

Based on both forward and backward shooting methods, we find the simulation for optimal equilibrium results of the three models with infinite time horizon from periods 0 to T. After the period T when the system becomes very close and still approaches to the steady state, linear interpolation is applied for variables (K_t, c_t, Q_t, H_t) for a long period to reach the steady state, denoted as $T_{\text{Steady State}}$. In fact, the real optimal equilibrium path will never reach the steady state but only get close to it infinitely. Our practice combining a shooting method and interpolation is designed to simulate the path that resembles the real optimal one with negligible subtle differences. In the meanwhile, the optimal equilibrium paths also serve the outcomes for the three solutions, i.e., the market solution, the carbon solution, and the green technology solution.

4.1. Comparisons Among Three Solutions

For the market solution and carbon tax solution, at $T = 272$ and $T = 152$ respectively, variables (K_t, Q_t, c_t) have already been within the 0.5% proximity to the steady state. The linear interpolations for them start at T and end at $T_{\text{Steady State}} = 400$. The combined results are thus very representative for the optimal equilibrium path. For the green technology solution, the constant share of output as induced R&D is $r = 0.05 \times 10^{-3}$ such that 1 billion USD of GDP will induce 50 thousand R&D investment in green knowledge. As discussed previously, too small and too large r should result in worse-off welfare than the benchmark model. This share yields better social welfare than the other two solutions. The accumulation of green knowledge and repair of climate change takes longer time that our shooting method can not reach, although economic variables have approached steady-state levels closely (i.e., Y_t, K_t and c_t). In order to obtain a reliable simulation to the real optimal path, the shooting ends at $T = 522$ and the interpolation lasts for a very long time span until $T_{\text{Steady State}} = 2483$ as smooth as possible which is calculated based on the convergent rate of Q toward Q^* between $[480, 522]$.

As an overview for the comparison among solutions, Fig. **3.** exhibits the time patterns of important variables of the three solutions, including real GDP (Y_t), consumption per capita (c_t) until year 2200, and carbon emissions (E_t) and temperature rises (Δ_t) for centuries. As the economic variables are convergent and almost fixed until 2200 among solutions, we do not show longer periods for simplicity of the graphs. However, as the courses of green knowledge accumulation and climate change repair take longer time, the graphs for E_t and Δ_t show centuries for comparison among solutions. The market solution suggests a temperature rise by $4.2°C$ in the coming century for China, which is higher than the national average temperature rise around $4.0°C$ projected by the benchmark scenario SSP5-8.5 in the latest IPCCAR6. Afterwards, carbon tax solution can reduce carbon emission consistently over time (up to $7.85G.t$ or 12.7%) and mitigate temperature rise (from $4.5°C$ to $4.13°C$) along with declines in real GDP (up to 23.3 trillion 2017 USD, or 12.7%), compared to the market solution. However, carbon taxes make a difference by simply lowering real GDP and physical

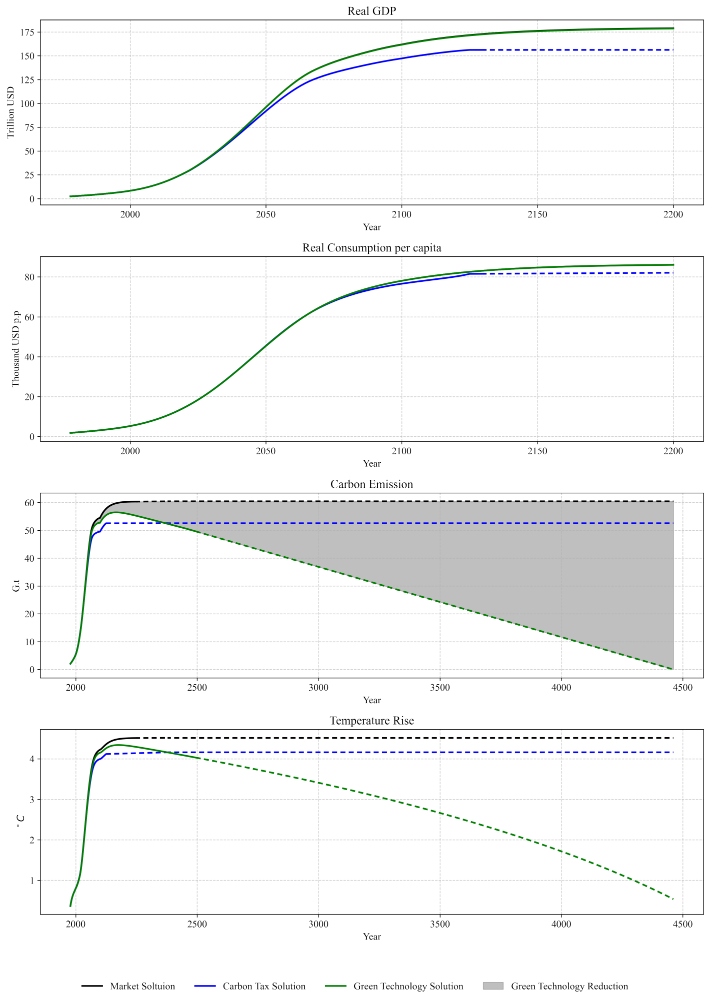

Fig. 3. Time Patterns of Important Variables in the Three Solutions

Note: For each solution, solid lines are results while dashed lines are interpolation toward the levels at steady states for a long time. As the accumulation of green knowledge and repair of climate change do take a long time, the interpolation for the green technology solution toward the steady state lasts for centuries into the $44th$, while the economic variables are already very close to their steady-state levels.

capital accumulation, posing the trade-off between economic growth and climate change mitigation.

However, it can not cut in carbon emission substantially to further decrease atmospheric carbon concentration and mitigate temperature rise. Among the three solutions, only the green technology solution makes it possible to reduce carbon emission consistently with little impacts on economic growth. The induced R&D almost has no negative effects on the path of real GDP because only

0.05 per thousand is used as R&D. However, we demonstrate that due to slow course of green knowledge accumulation and the natural absorption as the only channel to lower Q_t, the induced R&D investment rate of 0.05 per thousand GDP takes centuries to solve the challenge of climate change and decoupling fossil fuels.

Due to the law of motion for Q_{t+1} and H_{t+1}, the time series analyses suggest substantial but delayed improvement in climate conditions. From the perspective of variable relations, Fig. 4. presents consumption per capita (c) and atmospheric carbon concentration (Q) with respect to physical capital per capita ($k \equiv \frac{K}{L}$). While the economic growth shrinks in the carbon tax solution, the rise in consumption share and lower Q both compensate and result in social welfare improvement. For the green technology solution, the induced R&D investment does not shift the economic development path but to slow it down a little as a small fraction of output serves investment in green knowledge. Meanwhile, as the economy approaches the steady state ($k \to k^*$), larger declines are witnessed even toward a very low level (Q^*) due to the accumulation of green knowledge using just a small fraction of output.

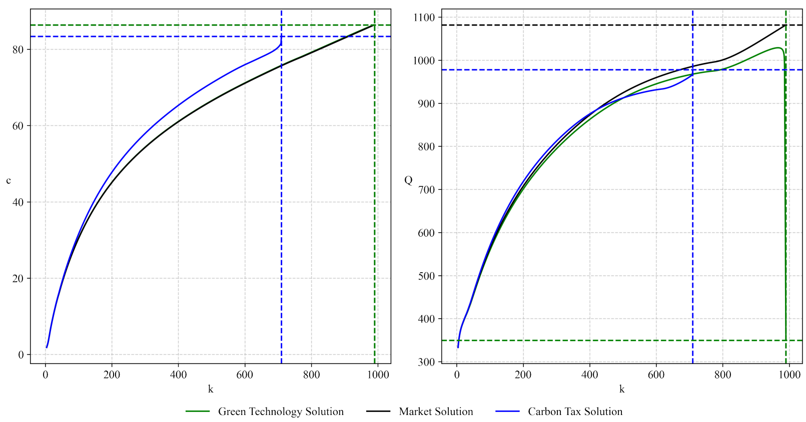

Fig. 4. Diagrams of (k, c) and (k, Q) in Three Solutions

In terms of social welfare, we defined it as the aggregate discounted utility of all households. Because of the nature of ordinal measurements of social welfare (equation 31), we can not claim to what extent one solution is better than another in improving welfare. Hence, we develop the constant equivalent consumption $\bar{c}$ in equation 32 such that the discounted social utility remains the same replacing c_t with $\bar{c}$ under pleasant climate condition (i.e, replacing all Φ_t with 1).

$$\mathbf{V} = \sum_{t=0}^{T_{\text{Steady State}}} \beta^t L_t u(Q_t, c_t) + \beta^{1+T_{\text{Steady State}}} \frac{L^* u(Q^*, c^*)}{1-\beta} \tag{31}$$

$$\frac{(\bar{c})^{1-\sigma}}{1-\sigma} \left\{ \sum_{t=0}^{T_{ss}} \beta^t L_t + \beta^{1+T_{ss}} \frac{L^*}{1-\beta} \right\} = \mathbf{V} \tag{32}$$

It is for sure that the carbon tax solution yields large constant equivalent consumption than the market solution because of the internalization of carbon emissions and climate change. However, it remains uncertain for the green technology solution because of R&D investment is induced other than chosen by the households. As mentioned, green knowledge almost makes no difference with small induced R&D investment rates but economic growth will be impeded significant with large rates of induced R&D. Fig. **5.** presents the constant equivalent consumption with different r in the green technology solution and compares them to the performances of other two solutions. When $r = 0$, the green technology

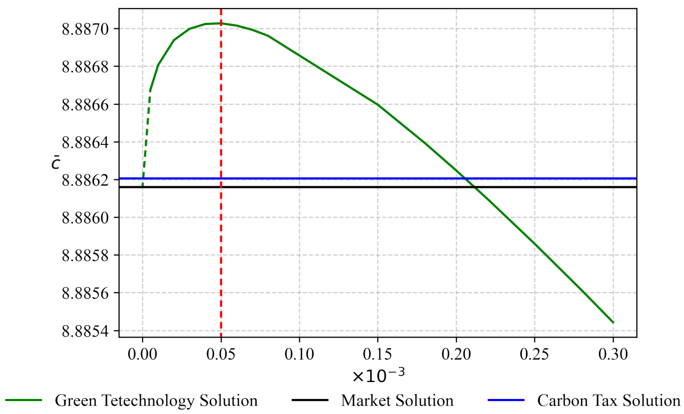

Fig. 5. Constant Equivalent Consumption with Different r

Note: The vertical line represents $r = 0.05 \times 10^{-3}$ selected as example in this section. Due to computational capacity, we use interpolation toward the market solution at $r = 0$ in dashed line.

solution has no differences from the market solution. As r increases, the constant equivalent consumption rises and declines as an outcome of the two competing forces, i.e., less real GDP and fast accumulation of green knowledge. In this section, we choose $r = 0.05 \times 10^{-3}$ in which the social welfare outweighs both the market solution and the carbon tax solution. Please notice that the welfare gains should be more substantial if R&D investment is endogenous as control variables instead of being induced as a fixed share of output. For instance, it should be more beneficial for R&D investment rates to gradually grow considering the decreasing marginal utility of consumption and growing marginal cost of emissions onver time. Nonetheless, it is of importance to consider situations with such a simple induced R&D investment to investigate the potential of green knowledge in lowering carbon emissions, curbing climate change and improving social welfare.

While the market solution requires nothing to react and a simple share of real GDP is induced as R&D investment in green knowledge to pursue the green technology solution, it remains unclear how to take the path in the carbon tax solution. Fig. **6.** exhibits the carbon taxes implied by the emission reduction model in equation 21 to achieve the carbon tax solution.

Compared to the increasing carbon taxes recommended by Timilsina et al. (2018), which uses a CGE analysis to achieve China's Nationally Determined Contribution (NDC) with exogenous technology and saving rates, our study suggests slightly higher tax levels for optimal social welfare. Specifically, they proposed carbon taxes of approximately 1.5, 15, and 22 USD/tCO2 at 2015 prices for 2015, 2025, and 2030, respectively. The carbon tax solution in our work, however, implies higher and faster increasing carbon taxes at 6.6, 29.5, and 45.2 USE/ton at 2017 prices for these years, respectively. Although the policy intervention is more intensive, the goal of NDC is still because we assume a convergent and conservative emission intensity as exogenous variables (equation 29). Consequently, the emission reduction model predicts a carbon plateau (still

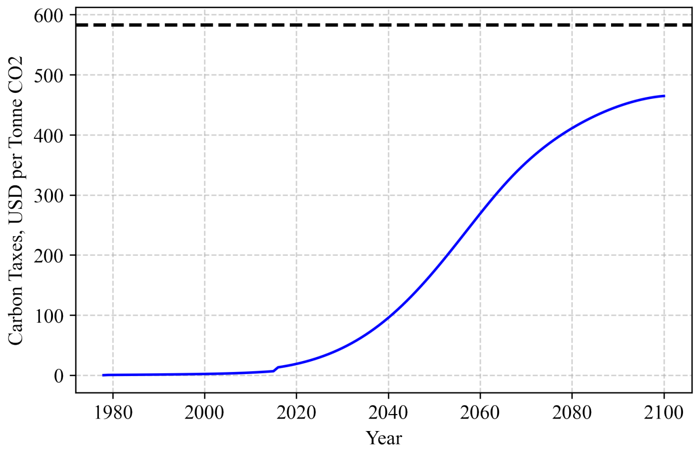

Fig. 6. Implied Carbon Taxes until 2100

Note: The dashed horizontal line represents the carbon tax needed at the steady state, to which the carbon taxes are convergent. The sudden jump in the path between year 2015 and 2016 is the changing of x from E_{coef} to $\frac{1}{0.3}$ such that the emission reaches high enough to make the global share of China fixed at 30%.

increasing but very limited) around 2060 rather than the target of 2030.

Despite the advise of $40 - 80$ USD/tCO2 in 2020 by the Paris Agreement to meet the goal of $2°C$ temperature rise limit, the carbon tax solution suggests a much lower value at around 18.8 USD/tCO2 in this year (2017 prices should not differ too much from 2020). As the reasoning, carbon taxes in our model are intended to pursue optimal social welfare instead of adherence to the Paris Agreement goal and any other goals of carbon emission reduction including the NDC. Consequently, our analysis highlights the potential for significant welfare losses if China attempts to limit carbon emissions to meet these goals without prioritizing R&D investment and green technologies.

4.2. Different Patterns of Induced R&D

While the previous part compares the three solutions in stratified perspectives, this part focuses on the green technology solution with different r to discuss the green development transition for China. Fig. **7.** presents carbon emissions, intensities and temperature rises to show the green development transition path for China under different r in the long run until the year 2300. From the results,

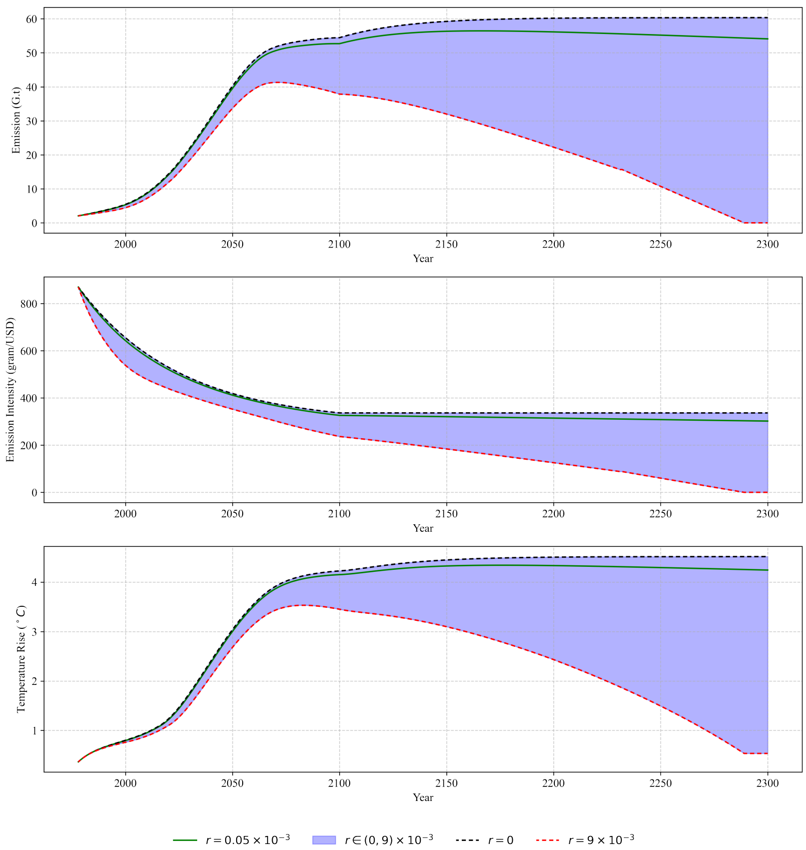

Fig. 7. Key Variables of Green Development Transition under Different Green Knowledge R&D Path

Note: We do not present the project with larger r because the time pattern of them are able to foresee based on existing results: earlier peak and faster decrease in emission and temperature rise and more substantial declines in the intensity.

carbon emissions increase consistently up to more than 50 G.t within the century and keep growing in the non-green development path ($r = 0$). As more resources are induced as R&D in green knowledge to pursue faster transition to green development for China, carbon emissions increase slower, peak comes earlier, and decrease afterwards due to the emission removal by green technology. While the path with 0.05 R&D investment per thousand GDP yields welfare improvement, the peak comes around the middle of next century and carbon emission decline to zero over centuries, which may not meet the existing climate change mitigation goal like the NDC or Paris Agreement. This study investigates a maximum $r = 9.0 \times 10^{-3}$ where the reduction in carbon emission is substantial, the constant equivalent consumption reduces by 1.1%.

In terms of carbon emission intensity, larger r leads to more reduction. Concerning the NDC that the carbon intensity should fall by 65% from 2005 to 2030, larger R&D investment is needed as the maximum reduction reaches 34% in the graph. As presented by the temperature rise, climate change mitigation is more intensive with larger r. And the relation is similar to carbon emission such that the maximum temperature rise comes earlier and climate conditions repair over time to even lower than $1°C$ with more efforts attributed to green knowledge.

In conclusion, if China wished to achieve any goals of climate change mitigation (e.g., carbon peak prior to 2030, carbon neutrality before 2060, the NDC or Paris Agreement), more R&D investment must be applied to fasten the accumulation of green knowledge and lower carbon emissions earlier in large scale. More importantly, instead of using a fixed share of GDP as induced R&D (equation 23), a more strategic pattern is supposed to better deal with any of these ambitious goals[10]. However, more R&D means less accumulation in physical capital and consumption. As the consequence, social welfare would deteriorate and become less than the market solution as Fig. **5.** shows. Such a concern is also put forward by many studies, e.g., losses in household welfare by achieving the NDC (Timilsina et al., 2018), although some studies believe the welfare optimization coincides with timely carbon peak (Mi et al., 2017). And the scenario analysis by Chen and Nie (2016) found possibly positive or negative effects of carbon taxes in welfare.

5. Discussion

To effectively examine the optimal green development path for China, our model must be properly parsimonious. While a model covering multiple aspects

[10]In fact, a case with 15% GDP induced as R&D ($r = 0.15$) yields a path where temperature rise is limited to $2°C$ by 2060 and decline to $\Delta^* = 0.53$ by 2100. But $\bar{c}$ reduces substantially by 19% consequently. No further discussion or implications are provided based on this projection because the peak of $2°C$ and repair to pre-industrial level is off the interest of any groups, and such a decline in welfare is not acceptable.

can capture more facts, it can lower computational efficiency and feasibility with little gain. Thus, it is crucial to discuss such trade-off in our study, how these assumptions affect the main findings of the research, and call for future efforts.

5.1. *Transitional Difficulty to Green Development*

In this model, the transition to green development is achieved through induced R&D, independent of household decision-making. A notable limitation of our approach is its inability to fully reflect the transitional challenges associated with R&D in green knowledge. While our results demonstrate the long-term benefits of R&D in the modern new energy sector, they also highlight the short-term trade-offs in terms of reduced current consumption and income levels. The model assumes households make decisions with an infinite time horizon, and this visionary behavior enhances social welfare. However, this assumption may not adequately reflect the real-world difficulties of R&D implementation.

In practice, the transition to green development faces significant hurdles: (1) The societal payoff from green knowledge R&D often materializes only after decades or even centuries, introducing substantial risk and making it challenging to garner tangible support; and (2) It necessitates sacrificing the interests of the current generation for the benefit of future ones. Consequently, this transitional complexity demands policymakers with enhanced implementation capabilities to effectively allocate resources towards green knowledge. Particularly, the new energy innovation in China is quite primitive and non-profitable, calling for more policy support (Acemoglu et al., 2012).

Nevertheless, the transitional difficulties can be mitigated by the presence of short-term financial incentives, such as reduced carbon emission abatement costs, tax exemption policies and green bond. For instance, numerous climate-economy models incorporating endogenous technological change consider the dual benefits of lowering carbon emissions: both through temperature rise mitigation and decreased abatement costs. Examples of such models include the R&DICE and

ENTICE models, which provide a more comprehensive framework for assessing the short- and long-term impacts of green R&D investments. And the study by Sartzetakis (2021) illustrates why green bonds contribute to low carbon transitions from multiple perspective and demonstrates its importance and necessity.

5.2. *Closed Economy with Global Warming*

Our model focuses on the economic development of a closed economy. It is indeed a necessary simplification of the real world because the model is intended to discuss the optimal path and relevant policy instruments interior to China. An endogenous international trade increases the model complexity and difficulty in calibration and finding the optimal equilibrium path. In fact, the calibration of TFP has captured the information of net exports consistently accounting for an important component to China's economic growth for decades (Song et al., 2011). If the model was modified to account for international trades, the benefits of green knowledge would increase because net exports contribute to GDP with less negative impacts as green knowledge accumulates. Despite the potential overestimation of GDP losses, the assumption of a closed economy does not contradict our main findings regarding the great potential of green knowledge in climate change mitigation with social welfare gains. We also call for future research extending the model to discuss the role of international trade.

In the meanwhile, our model includes climate change as a global issue by building the relation of carbon emission and atmospheric carbon concentration between China and the globe. Such a practice fully accepts the fact that carbon emissions and climate change are global issues due to global atmosphere movement. However, the linearity relation simply based on historical observations may ignore the complicated relationship between China and the globe. While we acknowledge the compromise, considering all these details about the global atmosphere would make the model less focused on climate-economy development.

5.3. Induced R&D Investment

In the green technology solution, R&D investment is induced as a fixed fraction of GDP, exogenous to households who determine consumption and investment for the optimal welfare. For models considering both physical capital and carbon concentration as state variables which are determined through optimization, the inclusion of knowledge as another state variable faces the great challenges of solving the model, e.g., the R&DICE model (Nordhaus, 2010) and its extensions. Therefore, the assumption of induced R&D is mainly for the sake of computational availability. If R&D was modified as endogenous in our model, the green technology solution should perform better in terms of social welfare gains because it accounts for the trade-off among consumption, physical capital accumulation, and green knowledge innovation to generate the optimal solution.

There are studies investigating endogenous R&D in the literature with different focus. For instance, the ENTICE model (Popp, 2004) discusses the effects of endogenous or exogenous technological changes on the projection of climate-economic growth, particularly addressing the crowd-out of investment by R&D. It is computational feasible because temperature rises are determined by general equilibrium of cumulative GHG emissions instead of optimization. Given different focuses of models, disparity in assumptions about state variables and the dynamic optimization problem explains the availability of R&D as induced or endogenous decision.

5.4. Combination of Carbon Taxes and Green Technology

The model is applied to investigate scenarios involving carbon taxes and induced R&D separately, prioritizing computational efficiency over a combined approach. Theoretically, a comprehensive scenario that integrates both elements is feasible and could significantly enrich policy insights aimed at identifying the optimal pathway for green development. However, the technical challenges are considerable. Finding the optimal equilibrium path toward a steady state with an infinite time horizon is already complex, particularly in a model with two state variables—capital stock and atmospheric carbon concentration—whose dynamic changes are governed by the optimization process. Introducing a third state variable, such as green knowledge, would complicate the model further, making it nearly impossible to derive solutions using existing methodologies.

Given these challenges, it is a pragmatic compromise to separate the analysis into two distinct scenarios. This approach allows for a clearer examination of the relative benefits of green technology solutions compared to carbon tax solutions in terms of social welfare and climate change mitigation. Intuitively, one would expect that the combination of carbon taxes and R&D would yield superior outcomes for addressing climate change while promoting economic growth. Nonetheless, we recognize the limitations of our current model and remain optimistic about the potential of emerging techniques, such as deep learning methods, to tackle these challenges. These advanced methodologies could enable us to extend the model and explore the effectiveness of combined policy instruments, ultimately contributing to a more robust understanding of how to achieve sustainable development goals.

6. Conclusion

In this paper, we develop a dynamic general equilibrium model that incorporates climate change and endogenous technological improvements to investigate various strategies for China to achieve social welfare, climate change mitigation, and transition to green development. We consider the negative externality of carbon emissions, which contribute to climate change and deteriorate utility as a discount factor, and the positive externality of green knowledge, which is a public knowledge stock that accumulates with R&D investment and improves green technologies to reduce carbon emissions directly. Optimizing social welfare necessitates government interventions to address these externalities effectively. To explore effective strategies to tackle the challenge, we propose three solutions, each with corresponding policy implications:

Market Solution A "Laissez-faire" economy without any interventions.

Carbon Tax Solution Implementation of policies such as carbon taxes on the production sector and lump-sum rebates to households.

Green Technology Solution A part of real GDP is induced as R&D investment in green knowledge, which reduces carbon emissions through green technology.

After carefully calibrating the model, we obtain projections for the optimal equilibrium path as outcomes of each solution. Our findings indicate that, compared to the market solution, the carbon tax solution lead to (1) gains in social welfare; (2) mitigation in temperature rises from $4.2°C$ to $4.0°C$ by 2100 and from $4.5°C$ to $4.1°C$ in afterward centuries, (3) gradually rising reduction in carbon emissions associated with losses in real GDP by 4.3%, 9.1% and 12.7% in years 2050, 2100 and centuries afterwards.

In the green technology solution with $r = 0.05 \times 10^{-3}$ share of real GDP induced as R&D investment in green knowledge specifically, the results show (1) welfare improvement beyond the other two solutions, (2) temperature rise reaches $4.15°C$ and $4.3°C$ in 2100 and 2200 respectively, which exhibits reduction from the market solution, and then gradually declines to $0.53°C$ over centuries of natural climate condition repair, (3) carbon emissions are lower than the market solution consistently and the economy achieves carbon decoupling or net zero emission as green knowledge gradually accumulates over time and (4) almost no differences in real GDP and consumption from the market solution.

Furthermore, we provide detailed policy implementation for each solution, including or carbon taxes for the carbon tax solution and the R&D investment pattern for the green technology solution. These insights offer valuable information for policymakers seeking to expand their toolkit to balance social welfare while combating climate change.

Our most significant implication emphasizes the immense potential of R&D investment in green knowledge (specifically, the modern new energy sector) as a solution for China to mitigate climate change and transition to green development. Without green knowledge and technological interventions, pure policies to internalize the social costs of carbon emissions, such as carbon taxes, can achieve only limited welfare gains and climate change mitigation. In addition, we also emphasize a smart pattern of R&D investment is needed otherwise social welfare faces potential losses if China is aimed to achieve ambitious goals of climate change mitigation (e.g., Paris Agreement or carbon peak by 2030).

7. Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT in order to improve the readability and language of the manuscript. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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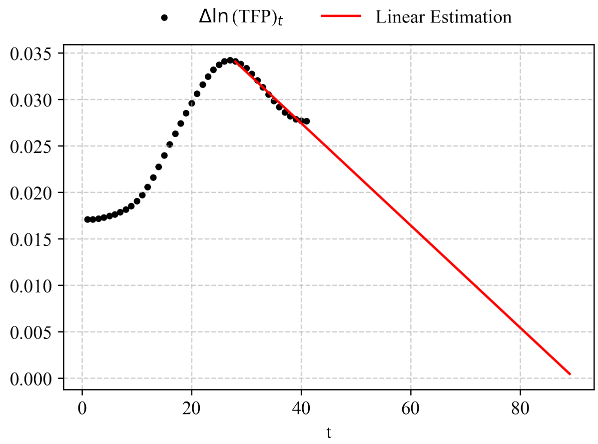

Fig. A.1. Differences in ln(TFP) and the Linear Estimation

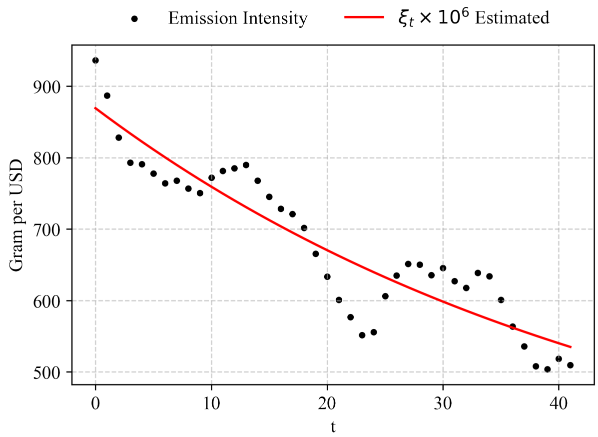

Fig. A.2. Observed Emission Intensity and Estimation by $f^{\xi}(t)$

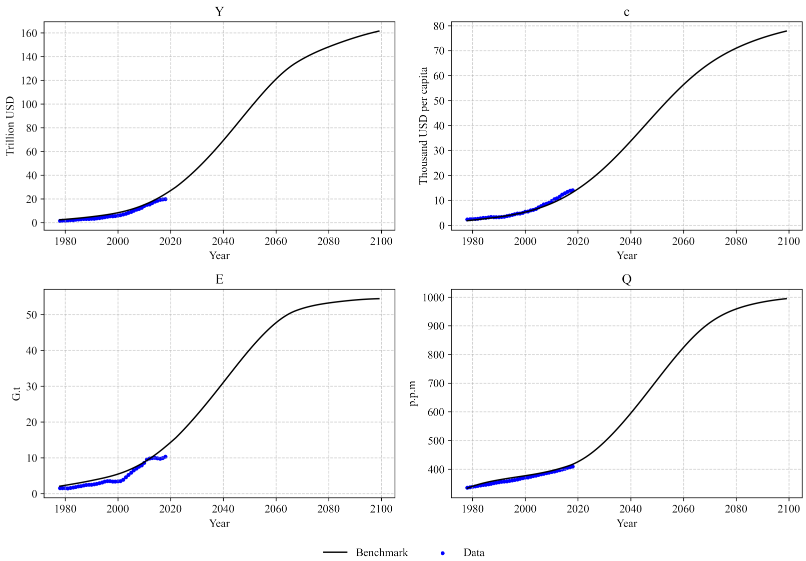

Fig. A.3. Optimal Equilibrium Path in the Benchmark Model and Data

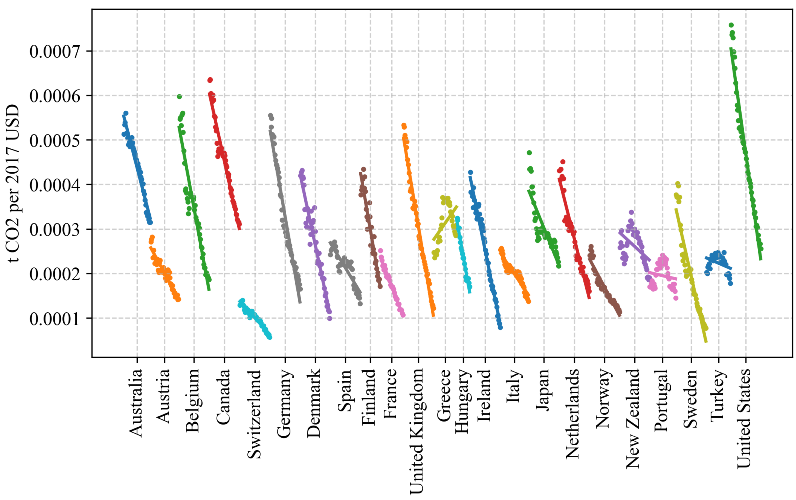

Fig. A.4. Carbon emission intensities, observations in dots and model predictions in lines