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### Abstract

This paper examines the effectiveness of China's indigenous R&D investment and technological innovation to curb its carbon emissions. The mechanism of endogenous technical change (TC) is incorporated an intertemporal computable general equilibrium (CGE) model. R&D investments and knowledge creations are modeled as the endogenous behaviors of private firms. The accumulated stocks of knowledge are applied in the production process to affect the rate and bias of TC. Simulation results show that: 1) While China's indigenous R&D efforts play a significant role to curb carbon emissions, sole dependence on R&D may be far from sufficient to achieve China's pledged Copenhagen climate target with complementary policies being required to reinforce existing climate actions; 2) Innovation policies including public R&D subsidy and stringent patenting system can help strengthen economy-wide R&D investment and further reduce emissions, but this complementary effect is still minor and insufficient to meet the stipulated emission cuts target; 3) Carbon taxation can create significant carbon-saving benefits and fulfill climate target, but this achievement is at the cost of economic losses. The induced technical improvement, however, can partially mitigate the deadweight loss incurred by carbon tax distortion.

## **Keywords**

CGE model; Induced technical change; R&D; Climate policy; China

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# Can Technological Innovation Help China Take on Its Climate Responsibility? A Computable General Equilibrium Analysis<sup>\*</sup>

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**Abstract:** This paper examines the effectiveness of China's indigenous R&D investment and technological innovation to curb its carbon emissions. The mechanism of endogenous technical change (TC) is incorporated an intertemporal computable general equilibrium (CGE) model. R&D investments and knowledge creations are modeled as the endogenous behaviors of private firms. The accumulated stocks of knowledge are applied in the production process to affect the rate and bias of TC. Simulation results show that: 1) While China's indigenous R&D efforts play a significant role to curb carbon emissions, sole dependence on R&D may be far from sufficient to achieve China's pledged Copenhagen climate target with complementary policies being required to reinforce existing climate actions; 2) Innovation policies including public R&D subsidy and stringent patenting system can help strengthen economy-wide R&D investment and further reduce emissions, but this complementary effect is still minor and insufficient to meet the stipulated emission cuts target; 3) Carbon taxation can create significant carbon-saving benefits and fulfill climate target, but this achievement is at the cost of economic losses. The induced technical improvement, however, can partially mitigate the deadweight loss incurred by carbon tax distortion.

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## 1 Introduction

Since launching the “open-door” policy in the late 1970s, China has experienced a profound transformation from a rural agricultural-based to an urban industrial-focused society. As one of the fastest growing economies, China is expected to continue its growth trend and overtake the U.S. to become the world’s largest economy by 2030 ([World Bank, 2011](#)). While China’s rapid growth has created tremendous wealth and prosperity, its development path – with enormous resource depletion and environmental degradation – is becoming unsustainable, putting China at the center of international debates on energy governance and climate mitigation ([IEA, 2010](#); [EIA, 2010](#)).

While a country’s economic size generally reflects its energy demand and carbon emission, China’s appetite for energy and emission is unsurprisingly mammoth. During the period 1990-2005, China’s total primary energy demand grew by 4.7% annually from 874 to 1742 Mtoe, and its CO<sub>2</sub> emissions grew by 5.6% per year from 2244 to 5101 Mt ([IEA, 2007](#)). In a global context, China had overtaken the U.S. in 2010 to become the world’s largest carbon emitter, and its emissions will continue to rise rapidly in line with its industrialization and urbanization. Reportedly, China has accounted for nearly three quarters of world emission growth in recent years, and its emission levels are projected to rise to about 28% of the world’s total in 2020 ([IEA, 2010](#); [BP, 2011](#)). Without regulations, this growth trend is likely to offset climate mitigation elsewhere. In the global efforts of tackling climate change, there is no disagreement that China needs to take on a growing responsibility of carbon abatement.

To stabilize the rising emission trend, China would have set a daunting challenge of cutting its carbon intensity given a large demographic base and rapidly rising consumption levels ([Kaya, 1990](#); [IPCC, 2000](#)). In the minds of the leadership in Beijing, the key to handling this challenge is to decouple carbon emissions from economic growth through technological innovation. This is true for China where the growth story, beyond the role of global manufacturing engine, is increasingly about innovation. In the course of building a “harmonious society” through “scientific development”, Beijing has begun to raise awareness of the pivotal role that scientific development and innovation play in sustaining long-term quality growth and addressing major social challenges.<sup>1</sup>

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<sup>1</sup> This is reflected by a commitment to create an “innovation-oriented” society made by Chinese

In a changing landscape of global innovation, the emergence of innovation hubs in China is underpinned by the strong growth of R&D investments in indigenous innovation. While the U.S. and Japan remain leaders in science and technology innovation, they face increasing competition from emerging markets, notably China - the world's third leading R&D investor at \$100 billion in 2010 (OECD, 2010). R&D spending in China grew by about 20% per year over the last decade. Average R&D investments in G7 markets, by comparison, have grown by 3.2% annually during the same period. R&D intensity remained flat across G7 markets over the past decade at 2.1%. In China it has double as a share of GDP since 1999, reaching 1.5%, leaving room for potential improvement by international standards (OECD, 2008, 2010). In a transition to the innovation-oriented society, Beijing is expected to boost future investments in indigenous innovation. This is reflected by the government's spending target of 2.5% of GDP on R&D by 2020, translating into a tripling of China's R&D investment over the next decade to \$300 billion (MOST, 2006b).

In a context where climate mitigation and technological innovation are closely interconnected, it is vital to investigate the effectiveness of China's R&D efforts to achieve its carbon reduction commitment. I thus aim to address the following four issues: 1) How substantially can R&D-induced TC drive China's carbon emissions below projected baseline levels; 2) Can emission cuts driven by R&D efforts guarantee the achievement of Beijing's pledged climate target; 3) Do public R&D intervention with the aim of correcting for innovation market failure provide significant aid to cut emissions; 4) Is it needed to introduce carbon tax to complement technology policy in order to achieve the climate target.

To handle these issues, I incorporate the endogenous mechanism of R&D-induced TC into a multi-sector computable general equilibrium (CGE) model for climate policy analysis. The theory of R&D-induced TC has its origins in the second-generation endogenous growth literature, which highlights the key role of R&D and knowledge stock in shaping economic growth (Romer, 1990; Aghion and Howitt, 1998; Acemoglu, 2009a). In this direction, most climate policy studies represent the R&D-induced TC by adopting knowledge substitution for physical inputs, with an *innovation possibility frontier (IPF)* specifying the process of knowledge accumulation (Nordhaus, 2002; Popp, 2004; Sue Wing, 2006; Bosetti et al., 2008;

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President Hu at the National Science and Technology Conference in January 2006, an occasion which also saw the unveiling of the 2006-2020 Medium to Long-term Plan for the Development of Science and Technology (MOST, 2006b).

[Acemoglu et al., 2009b](#)). As a feature, the representation of disaggregated sectors in a CGE model provides a useful platform to explore general equilibrium effect of intersectoral knowledge interactions, which facilitates examining the externality of knowledge (e.g., spillover, crowding-out) and its impacts on the timing and costs of carbon emissions reduction ([Löschel, 2002](#); [Popp, 2006](#); [Clarke et al., 2006, 2008](#); [Gillingham, 2008](#)).

To our knowledge, few CGE studies with the R&D-induced TC have appeared in climate policy analysis literature. [Goulder and Schneider \(1999\)](#) investigate the attractiveness of the U.S. climate policies in the presence of induced TC. [Sue Wing \(2003\)](#) explores the impact of induced TC on the U.S. macroeconomic cost of carbon taxation. [Wang et al. \(2009\)](#) examine the role that TC could play in designing China's climate mitigation targets. [Bye and Jacobsen \(2011\)](#) scrutinize the welfare effects of differentiated R&D subsidies across general and carbon-saving TC on the Norwegian economic cost of carbon tax. Investigations of R&D-induced TC also include the studies on the cost effectiveness of climate policies that combine R&D subsidies with carbon constraints in the presence of technological externality by [Otto et al. \(2007\)](#), [Otto et al. \(2008\)](#), [Otto and Reilly \(2008\)](#) and [Löschel and Otto \(2009\)](#).

As a needed complement to the existing literature, this paper contributes to advancing methods of climate policy modeling in the following ways: 1) Instead of using recursive-dynamic modeling, I develop an intertemporal optimization framework to capture the time path of adjustment associated with particular climate policy shocks;<sup>2</sup> 2) To represent the endogenous process of innovation, I incorporate the mechanism of R&D-induced TC into a CGE framework, with special treatments on innovation externalities including R&D crowding-out, intersectoral knowledge spillovers and the dual role of R&D in knowledge absorption.

The paper is organized as follows: [Section 2](#) provides a detailed description of modeling framework. [Section 3](#) discusses model implementation, with an emphasis on how to undertake knowledge accounting for model calibration. Simulation results and discussion under various scenarios are presented in [Section 4](#). [Section.5](#) concludes.

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<sup>2</sup> This differs from the traditional recursive-dynamic model that solves for a sequence of static equilibrium in a Slow-Swan formulation, where capital stock accumulation is based on an exogenous saving rate with myopic expectations. In contrast, optimization models endogenize the intertemporal behavior of economic agents, with current decisions depending on expectation about future economic prospect ([Jorgenson and Wilcoxon, 1990](#); [Bovenberg and Goulder, 1996](#); [McKibbin and Wilcoxon, 1999](#); [Dixon et al., 2005](#)).

## 2 Model Description

Fossil energy is an indispensable input into every industry in the energy-intensive Chinese economy. A model encompassing multiple industries and commodities is thus required to capture the full general equilibrium effect of climate policies.<sup>3</sup> In our modeling framework, the Chinese economy is represented by multiple economic agents, including: Twelve production sectors, an investment (physical capital producing sector), a R&D sector (producing R&D goods), a representative household, and a government. To be relevant to climate policy analysis, the twelve production sectors consists of five energy sectors and seven non-energy sectors.<sup>4</sup> Carbon emissions are calculated based on carbon intensities of fossil fuels inputs (coal, oil and natural gas) in intermediate production and final use.

In the spirit of the G-Cubed model (McKibbin and Wilcoxon, 1999),<sup>5</sup> our modeling framework describes economic behaviors of multiple agents within a general equilibrium structure which outlines the input-output (IO) circular flows of multiple commodities and primary factors within an economy (see Fig. 1). There are 12 commodities and corresponding production sectors, indexed by the row subscript  $j$  ( $j=1,2,\dots,12$ ) and the column subscript  $i$  ( $i=1,2,\dots,12$ ); 3 types of primary factors (labor, physical capital, knowledge capital), indexed by the subscript  $f$  ( $f=L,K,H$ ); 5 types of final uses (consumption, investment, R&D, government and export), indexed by the subscript  $d$  ( $d=C,I,R,G,X$ ). Intersectoral transaction in intermediate production are represented by the  $j \times i$  matrix  $\mathbf{X}$ ; the inputs of primary factors into production are indicated by the  $f \times i$  matrix  $\mathbf{V}$ ; the final use of produced commodities are represented by the  $j \times d$  matrix  $\mathbf{G}$ .

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<sup>3</sup> The multi-sector specification differs from Ramsey growth model where the supply side of an economy is represented as a single producer of unique final goods. The economic dynamics are captured by a social planner choosing the optimal level of inputs into an aggregate production function, e.g., R&DICE (Nordhaus, 2002), ENTICE (Popp, 2004), and WITCH (Bosetti et al., 2008).

<sup>4</sup> For model sectoral classification and mapping by reference to the GTAP, see Appendix A.

<sup>5</sup> The G-Cubed model incorporates more macroeconomic elements into the micro-founded CGE framework. The macroeconomic features include: a full specification of the interactions between real and financial sides; intertemporal dynamics of physical asset; the neoclassical optimizing and liquidity-constrained behavior of consumers; imperfect capital mobility and adjustment costs; intertemporal equilibrium with rational expectation.

Figure 1: The input-output circular flows of commodities and primary factors within an economy, with an explicit representation of R&D investment (R) and knowledge inputs (H)

	Industries i						Final Demand d					Total Output	
Commodities j		1	.	.	i	.	12	C	I	G	R	X	
	1	$x_{1,1}$	.	.	$x_{1,i}$	.	$x_{1,12}$	$C_1$	$I_1$	$G_1$	$R_1$	$X_1$	$Y_1$
	.	.	.	.	.	.	.	.	.	.	.	.	.
	.	.	.	.	.	.	.	.	.	.	.	.	.
	j	$x_{j,1}$	.	.	$x_{j,i}$	.	$x_{j,12}$	$C_j$	$I_j$	$G_j$	$R_j$	$X_j$	$Y_j$
	.	.	.	.	.	.	.	.	.	.	.	.	.
	.	.	.	.	.	.	.	.	.	.	.	.	.
12	$x_{12,1}$	.	.	$x_{12,i}$	.	$x_{12,12}$	$C_{12}$	$I_{12}$	$G_{12}$	$R_{12}$	$X_{12}$	$Y_{12}$	
Primary Factor f	K	$K_1$	.	.	$K_i$	.	$K_{12}$						
	L	$L_1$	.	.	$L_i$	.	$L_{12}$						
	H	$H_1$	.	.	$H_i$	.	$H_{12}$						
Imports	M	$M_1$	.	.	$M_i$	.	$M_{12}$						
Total Outlays		$Y_1$	.	.	$Y_i$	.	$Y_{12}$						

From this IO schematic framework to a numerical CGE model, I need to describe the optimization problems facing these representative agents and characterize their economic behaviors in a decentralized equilibrium. This will be articulated in following sections.<sup>6</sup>

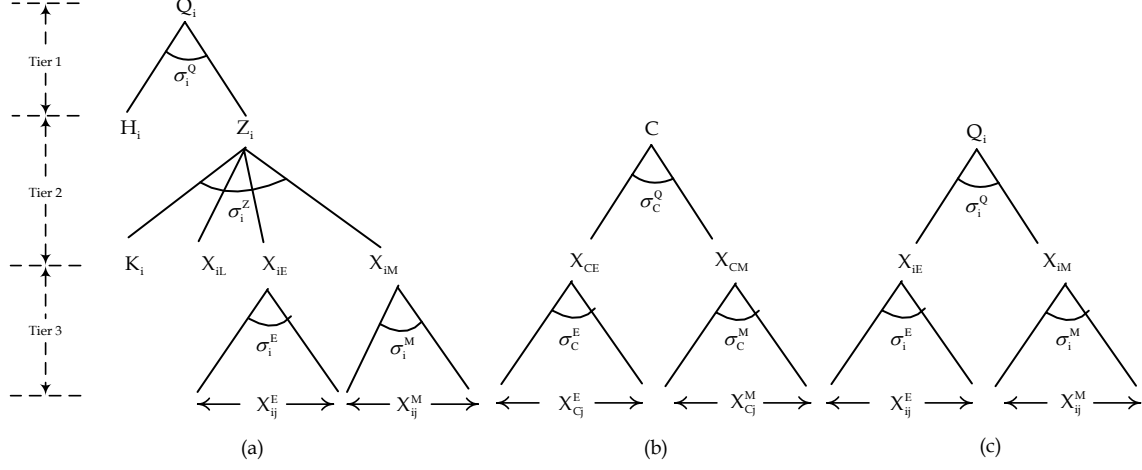
## 2.1 Production

As Fig. 2(a) shows, the representative firm in each production sector has the same generic technology – a separable KLEM-H nested CES function. For any given sector  $i$  producing output  $Q_i$ , knowledge capital  $H_i$  substitutes for a composite of physical inputs  $Z_i$ , which is in turn made up of primary factor inputs of physical capital  $K_i$  and labor  $X_{iL}$ , and intermediate inputs of energy bundle  $X_{iE}$  and material bundle  $X_{iM}$ .  $X_{iE}$  comprises five energy goods  $X_{ij}^E$ , and  $X_{iM}$  is composed of seven non-energy goods  $X_{ij}^M$ . Given this production technology, the producer problem in production sector  $i$  is formulated as:

<sup>6</sup> A detailed description of the specification and characterization of the problem faced by each economic agent are provided in [Appendix B](#).



Figure 2: Nested CES production and consumption structure



Note: (a) KLEM-H three-tier nested CES technology of twelve production sectors; (b) two-tier nested CES structure of household consumption; (c) two-tier nested CES production technology of investment and R&D sectors.

$$\max V_i(t) = \int_t^\infty \exp\left[-\int_t^s r(s') \cdot ds'\right] \cdot \Pi_i(s) \cdot ds \quad (1)$$

$$\text{s.t. } \Pi_i(t) = (1 - \tau_Q) \cdot [P_i(t) \cdot Q_i(t) - P_{iL}(t) \cdot X_{iL}(t) - (1 + \tau_C) \cdot P_{iE}(t) \cdot X_{iE}(t) - P_{iM}(t) \cdot X_{iM}(t)] \\ - (1 - \tau_I) \cdot P_{iI}(t) \cdot I_i(t) - (1 - \tau_R) \cdot P_{iR}(t) \cdot R_i(t) \quad (2)$$

$$\dot{K}_i(t) = J_i(t) - \delta_K \cdot K_i(t) \quad I_i(t) = \varphi_i(J_i(t), K_i(t)) = J_i(t) + \frac{\psi}{2} \cdot \frac{J_i(t)^2}{K_i(t)} \quad (3)$$

$$\dot{H}_i(t) = \eta \cdot R_i(t)^\alpha \cdot H_i(t)^\beta + \frac{R_i(t)}{\sum_j R_j(t)} \cdot \left[ \theta \cdot \sum_j R_j(t) - R_i(t) \right] - \delta_H \cdot H_i(t) \quad (4)$$

where the firm's objective is to optimally choose the inputs of labor  $X_{iL}$ , energy  $X_{iE}$ , material  $X_{iM}$ , physical investment  $I_i$  and R&D investment  $R_i$  to maximize an intertemporal profit streams  $V_i$ , subject to the technology constraints. In Eq. (1),  $V_i$  is expressed as a discounted present value of future profit streams from time  $t$  to an infinite future, with real interest rate  $r$  as the discounting factor. In Eq. (2), current profit flow  $\Pi_i$  equals output revenues minus inputs costs, with  $\tau_Q, \tau_C, \tau_I, \tau_R$  being corporate profit tax, carbon tax on fossil fuel input, investment tax credit and R&D tax credit, respectively.

Eq. (3) specifies the law of motion for physical capital  $K_i$ , which depends on fixed capital formation  $J_i$  and capital depreciation rate  $\delta_K$ .<sup>7</sup> Eq. (4) describes the *IPF* as an representation of knowledge creation process, where the accumulation of sector-specific knowledge stock  $\dot{H}_i$  depends on R&D investment  $R_i$ , existing knowledge stock  $H_i$  and intersectoral R&D spillovers  $(R_i/\sum_j R_j) \cdot (\theta \cdot \sum_j R_j - R_i)$ .<sup>8</sup>  $\eta$  denotes the efficiency of knowledge creation.  $\delta_H$  is the depreciation rate of knowledge obsolescence. The condition  $0 < \alpha + \beta < 1$  implies diminishing returns to R&D in innovation (Romer, 1990; Rivera-Batiz and Romer, 1991; Jones, 1995; Popp, 2004; Bosetti et al., 2008).

Drawing on the seminal work of Schmookler (1966), Terleckyj (1974), Scherer (1982) and Griliches (1992), our model highlights knowledge externality generated by the inter-industry spillovers.<sup>9</sup> Due to the imperfect appropriability of knowledge, physical goods produced by each individual sector could partially embody intangible knowledge created by its purposeful R&D investments. Other sectors, in the multi-sector economic transaction, can hereby enjoy the benefits of these external R&D efforts through forward and backward sectoral linkages along the supply chains – the so-called intersectoral R&D spillovers (Clark et al., 2006, 2008).

To specify it, our multi-sector model postulates that each individual sector is exposed to a public pool of intersectoral R&D and absorbs a fraction of this public good for creating its own sector-specific knowledge. For any given sector  $i$ , the accessible R&D pool is the gap between its own sector-specific R&D and the economy-wide one:  $\theta \cdot \sum_j R_j - R_i$ .  $\theta$  denotes the externality of intersectoral R&D spillovers that occur in imperfect innovation markets, of which the value is determined by exogenous factors such as patent policy.<sup>10</sup> I also assume

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<sup>7</sup> We also consider imperfect capital mobility and investment adjustment cost. The investment process is subject to rising marginal costs of physical capital installation. The adjustment cost function  $\varphi(J, K)$  is homogenous of degree one in its two arguments, with  $\varphi_J > 0, \varphi_{JJ} > 0, \varphi_K < 0$  (Lucas, 1967; Treadway, 1969; Goulder and Schneider, 1999; McKibbin and Wilcoxon, 1999).

<sup>8</sup> In the formulation of *IPF*, the additive specification between sector-specific R&D and intersectoral spillovers are building on the work by Cohen and Levinthal (1989). For an alternative of multiplicative specification, see Bosetti et al. (2008).

<sup>9</sup> Innovations are less the product of individual sector than of a clustering of assembled resources, knowledge, capacities and inputs from all sectors. It is the organizational clustering of knowledge and information that facilitates knowledge-sharing and cross-fertilization of ideas.

<sup>10</sup> A value of one means that the benefits of research can fully spill over to a public R&D pool that is potentially available to all other sectors. A value of zero means that the benefits of research are exclusively appropriated by the sector undertaking research.

that the capacity of a sector to absorb externally generated knowledge depends on its own R&D effort, with the ratio of sector-specific R&D to economy-wide one representing knowledge absorptive capacity  $R_i / \sum_j R_j$ . Therefore, R&D not only directly generate in-house technical know-how, but also enhance the firm's ability to absorb knowledge developed elsewhere – the dual faces of R&D in knowledge creation (Nelson and Phelps 1966; Cohen and Levinthal, 1989; Keller, 1996).

Note that, the specification of *IPF* underlines three key factors of sector-specific knowledge creation: 1) purposeful R&D investment – the “no free lunch” assumption (to gain the economic benefits of innovation firms should commit to undertake own R&D efforts and not free ride on external knowledge spillovers); 2) current stock of knowledge – the “standing on the shoulders of predecessors” assumption (the more existing stocks of knowledge a firm has, the easier it is to create new knowledge); 3) intersectoral R&D spillovers – the “public good sharing” assumption (any sector can benefit from the positive externality of knowledge spillovers resulting from other sector's innovation).

So far R&D investment and knowledge creation are modeled as the endogenous behaviors of private firms. To affect the rate and bias of TC, the accumulated knowledge assets are applied in the production process to facilitate a reconfiguration of production inputs for higher productivity (the rate of production TC). At the same time, the use of knowledge inputs leads to a substitution for physical inputs such as labor, energy and materials (the bias of production TC).

Solving the dynamic optimization problem outlined in Eqs. (1)-(4) yields the producer demand for each variable input (labor, energy and materials), physical investment and R&D. The optimal level of R&D investment can be characterized as:

$$(1 - \tau_R) \cdot P_{iR}(t) = \lambda_{iH}(t) \cdot \left[ a \cdot \eta \cdot R_i(t)^{a-1} \cdot H_i(t)^\beta + \theta - \frac{2R_i(t)}{\sum_j R_j(t)} \right] \quad (5)$$

$$\frac{\dot{\lambda}_{iH}(t) + (1 - \tau_Q) \cdot P_i(t) \cdot \frac{\partial Q_i(t)}{\partial H_i(t)} + \lambda_{iH}(t) \cdot \eta \cdot \beta \cdot R_i(t)^a \cdot H_i(t)^{\beta-1}}{\lambda_{iH}(t)} = r(t) + \delta_H \quad (6)$$

where Eq. (5) is the static optimality conditions for R&D investment  $R_i$  that instruct the

firm to equate marginal cost (LHS) to marginal benefit (RHS). The marginal cost comes from expenditures on purchasing an extra unit of R&D goods. The marginal benefit is the product of innovation possibility gain and the shadow price of knowledge capital  $\lambda_{IH}$ .<sup>11</sup> In particular, the innovation possibility gains are harvested from two sources: R&D investments not only create in-house new knowledge, but also enhance the firm's capacity to assimilate and exploit external R&D spillovers (the dual face of R&D).

The intertemporal part of this problem is to optimally choose the dynamic path of the shadow price as Eq. (6) shows, which provides the implicit arbitrage condition of knowledge accumulation. The RHS is a sum of real interest rate and knowledge depreciation rate as the opportunity cost. The LHS represents the rate of return from knowledge accumulation, including: an increase in the shadow price of knowledge asset, a rise in the marginal product of knowledge input, and innovation possibility gain from higher existing knowledge stocks.

## 2.2 Consumption

As Fig. 2(b) shows, the representative household values her aggregate consumption in the form of a two-tier nested CES structure. The aggregate consumption  $C$  is a CES composite of energy bundle  $X_E$  and materials bundle  $X_M$ .  $X_E$  comprises five energy goods  $X_{E_i}^E$ , and  $X_M$  is made up of seven non-energy goods  $X_{M_i}^M$ . This household is infinitely lived with perfect foresight, with an objective of maximizing an intertemporal utility subject to a static budget constraint and transversality condition as:

$$\max U(t) = \int_t^\infty \ln C(s) \cdot \exp[-\rho \cdot (s-t)] \cdot ds \quad (7)$$

$$\begin{aligned} \text{s.t. } & P_C(s) \cdot C(s) + \dot{A}(s) = r(s) \cdot A(s) + w(s) \cdot L(s) \\ & \lim_{s \rightarrow \infty} A(s) \cdot \exp\left[-\int_t^s r(s') \cdot ds'\right] = 0 \end{aligned} \quad (8)$$

where the household values aggregate consumption in a logarithmic form, exhibiting positive but diminishing marginal utility.  $\rho$  is the pure rate of time preference. Integrating static budget constraint over infinite time horizon, I derive the following lifetime budget

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<sup>11</sup> This is the so-called "Tobin's-q" theory: the shadow price of a particular type of capital is a forward-looking variable determined by the agent's rational expectation about future economic conditions. This shadow price denotes the increment to the stock-market value of the firm from adding an extra unit of investment (Tobin, 1969; Summers, 1981; Hayashi, 1982).

constraint where discounted present values of future consumption expenditures are financed by a sum of human and financial wealth:

$$\int_t^\infty P_C(s) \cdot C(s) \cdot \exp\left[-\int_t^s r(s') \cdot ds'\right] \cdot ds = H_C(t) + A_C(t)$$

with

$$H_C(t) = \int_t^\infty (1 - \tau_w) \cdot w(s) \cdot L(s) \cdot \exp\left[-\int_t^s r(s') \cdot ds'\right] \cdot ds$$

$$A_C(t) = \sum_i [\lambda_{iK}(t) \cdot K_i(t) + \lambda_{iH}(t) \cdot H_i(t)]$$
(9)

where  $C, P_C$  are aggregate consumption level and consumer price index, respectively.  $H_C$  is the human wealth that is expressed as the discounted present value of future income streams. Labor income is made up of after-tax wage earnings  $(1 - \tau_w) \cdot w(s) \cdot L(s)$ . Financial wealth  $A_C(t)$  includes the equity values held by the household, equaling to the stock-market values of physical asset  $\lambda_K \cdot K$  plus knowledge asset  $\lambda_H \cdot H$ .

Solving the problem of intertemporal utility maximization yields an equation that characterizes the consumption behavior of households as:

$$P_C(t) \cdot C(t) = \omega \cdot \rho \cdot [H_C(t) + A_C(t)] + (1 - \omega) \cdot \kappa \cdot w(s) \cdot L(s)$$
(10)

where aggregate consumption expenditure  $P_C \cdot C$  is a weighted average of neoclassical optimizing behavior and liquidity-constrained behavior. A portion  $\omega$  of households are fully leveraged whose consumption expenditure equal to a constant proportion  $\rho$  of the sum of human and financial wealth, in accordance with the permanent income hypothesis (Modigliani, 1976; Hall, 1978; Flavin, 1981; McKibbin and Wilcoxon, 1999). The remaining liquidity-constrained households are only able to consume a fraction of their current incomes, given by exogenous marginal propensity to consume  $\kappa$ . Using two-tier nested CES consumption structure, the aggregate consumption expenditures are further allocated to consumer demand for each individual energy and material good.

## 2.3 Investment and R&D

So far I have determined the producer demand for investment and R&D goods in [Section 2.1](#). This section will model the supply side of investment and R&D goods that are available for accumulating physical and knowledge assets. With such a specification of demand-supply interactions, I can capture R&D crowding-out effect that may occur in imperfect innovation

market. That is, due to the limited supplies of R&D resources, climate policies that induce energy-saving R&D may reduce the availability of R&D resources for innovation in other sectors, potentially driving down the aggregate economic output (Goolsbee, 1998; Nordhaus, 2002; Popp, 2004; Sue Wing, 2006; Gillingham et al., 2008).

As Fig. 2(c) shows, investment and R&D sectors are constructed to produce and supply raw investment and R&D goods respectively. Both sectors have a two-tier nested CES production technology that produces outputs by combining the inputs of energy and materials goods. In both sectors,  $i=I,R$ , the respective producer solves problems as follows:

$$\max \Pi_i(t) = P_i(t) \cdot Q_i(t) - P_{iE}(t) \cdot X_{iE}(t) - P_{iM}(t) \cdot X_{iM}(t) \quad (11)$$

where the firm's objective is to optimally choose the inputs of energy bundle  $X_{iE}$  and materials bundle  $X_{iM}$  to maximize current profit flows  $\Pi_i$ , subject to the technology constraints. Solving this static optimization problem yields demands for the inputs of energy and material bundles. Subsequently, the demand for each bundle is optimally allocated to each individual energy and material goods.

## 2.4 Government and International Trade

Government behavior is normally constrained by a specific budgetary regime, which is represented by a certain well-defined fiscal target. The target of the Chinese government is to ensure a balanced budget with public revenue neutrality (NBS, 2010). Thus, our model specifies the government behavior as follows: it collects the revenue of tax imposed on corporate profit, household income and fossil energy use to finance public expenditure and subsidies on private investment and R&D:

$$G(t) = T_Q(t) + T_W(t) + T_C(t) - T_I(t) - T_R(t) \quad (12)$$

where  $G$  is aggregate government expenditure for the current use of goods and services. This aggregate spending is then allocated among individual energy and material commodities according to historical spending shares. Tax revenues are collected from corporate profit tax  $T_Q$ , household income tax  $T_W$  and carbon tax  $T_C$ .  $T_I, T_R$  denote government spending on subsidizing private investment and R&D, respectively. The government budget constraint is hereby determined by endogenous economic activities of

private agents and exogenous tax rates setting.

I model international trade flows in line with the Armington structure: a commodity produced domestically is an imperfect substitute for the imported goods ([Armington, 1969](#)). For any given good, the domestically-produced output is combined with the imports to create a CES Armington composite of that commodity. Total supplies of that Armington commodity are used to clear the demands by intermediate production and final use. The export is modeled by allocating each Armington commodity between domestic and export markets via a constant elasticity of transformation (CET) assumption.

## 2.5 Equilibrium Characterization

In an intertemporal optimization model, the full characterization of equilibrium condition involves both intraperiod and intertemporal equilibrium. Since decisions on consumption, investment and R&D are based on rational expectations of forward-looking agents, our model derives a set of intertemporal equations (e.g., [Eq. \(6\)](#)) to characterize economic variables at different time points in equilibrium.

For each energy and material goods, the supplies of that Armington commodity are used to satisfy the demands by intermediate and final use, with market clearing condition pinning down the equilibrium price of that commodity. Similarly, production outputs of the investment and R&D sectors are used to clear the demands by production sectors for physical and knowledge capital accumulation, which determine the equilibrium prices of raw investment and R&D goods. In the competitive labor market, the representative household derives no felicity from leisure and inelastically supplies its labor endowment at a constant exponential rate of growth. The demand side is determined by labor employment in production sectors. Equilibrium closure requires full employment and labor market clearing, which pins down the equilibrium labor wage.

## 3 Model Implementation

To implement the modeling structure in a numerical simulation, I construct a consistent benchmark dataset for model calibration. First, the year 2004 IO table of China is collected

from the GTAP 7 Data Base (Narayanan and Walmsley, 2008).<sup>12</sup> Second, I aggregate the GTAP 57 sectors into the 12 sectoral groupings used in our model. The 5 value-added inputs are aggregated into 2 primary factors (labor and physical capital). Finally, the 2004 IO table is scaled to approximate the Chinese economy in the year 2005 (base year of simulation) using the 2005 growth rate of real GDP (9.1 percent).

These aforementioned steps produce a stylized IO table of China, which records the input flows of multiple commodities and primary factors into production and final use. However, as a departure from traditional calibration, this IO table is not well suited to calibrate a CGE model with R&D-induced TC, because it does not record economic flows associated with R&D investment and knowledge inputs. To transform the conventional IO data into a structure like Fig. 1, I undertake knowledge accounting to capture intangible knowledge flows. To this I now turn.

### 3.1 Knowledge Accounting

In the *System of National Accounts*, the conventional IO table treats corporate expenditures on R&D as current cost of production along with intermediate inputs, implying that only a portion of each intermediate transaction reflects the value of pure physical flows, with the remainder being the value of intangible knowledge flows embodied in that transaction (BEA, 2007; SNA, 2008). In line with this principle, knowledge accounting can be conceptualized as follows: in a stylized IO table, the intangible knowledge flows matrix  $\Omega = [\omega_{ji}]_{j=1, \dots, n; i=1, \dots, n}$  is embodied in the intermediate transactions matrix  $X = [x_{ji}]_{j=1, \dots, n; i=1, \dots, n}$ . The row sums of  $\Omega$  represent the sector-specific R&D investments,  $R_j = \sum_i \omega_{ji}$ , and the column sums of  $\Omega$  denote the remuneration of knowledge capital as primary factor inputs into production,  $H_i = \sum_j \omega_{ji}$ .

Based on the embodied technology hypothesis, I estimate the intangible knowledge flows embodied in the intermediate transaction as:<sup>13</sup>

<sup>12</sup> This original IO table records the economic flows associated with 57-by-57 production sectors intermediate transactions, 5 categories of value-added inputs, and 4 components of final use.

<sup>13</sup> Embodied technology hypothesis claims that intangible knowledge inputs must be embodied in specific tangible physical materials in order to manifest economically useful characteristics. The knowledge accounting technique used in our work builds on the seminal work of Terleckyj



$$\underbrace{\frac{\omega_{j1}}{x_{j1}} = \dots = \frac{\omega_{ji}}{x_{ji}} = \dots = \frac{\omega_{jn}}{x_{jn}}}_{\text{Embodied technology hypothesis}} = \frac{\sum_i \omega_{ji}}{\sum_i x_{ji}} = \frac{R_j}{X_j} \Rightarrow \omega_{ji} = \frac{x_{ji}}{X_j} \cdot R_j \quad (13)$$

where  $x_{ji}$  is the (j,i) cell of the intermediate transaction matrix  $\mathbf{X}$  in the stylized IO table, representing the intersectoral transaction of intermediate inputs from sector j to i.  $\omega_{ji}$  is the intangible knowledge flows embodied in that transaction.  $R_j, X_j$  denote R&D investment and intermediate production specific to sector j, respectively. The embodied technology hypothesis claims that, for any given commodity j, the knowledge embodiment ratio  $\omega_{ji}/x_{ji}$  is invariant across sectors in intermediate production.

Given the available data on sector-specific R&D expenditure  $R_j$  and the shares of product sales to other sectors in intermediate transaction  $x_{ji}/X_j$ ,<sup>14</sup> I use Eq. (13) to estimate intangible knowledge flows  $\omega_{ji}$  embodied in the intermediate transaction  $x_{ji}$ , and hence capture the entries in knowledge flows matrix. Then, I vertically aggregate this knowledge flows matrix to create an additional row of knowledge inputs in the primary factors matrix  $\mathbf{V}$ , with each element being the value of knowledge input into production sector. Finally, the knowledge flows matrix is horizontally aggregated to generate an additional column of R&D investments in the final use matrix  $\mathbf{G}$ , with each element being the value of sector-specific R&D investment. This procedure hereby constructs a modified IO dataset with an explicit representation of R&D investments and knowledge inputs (see Fig. 1), based on which our CGE model with R&D-induced TC is calibrated.

### 3.2 Parameterization and Solver

The software GEMPACK is used to solve the intertemporal optimization model.<sup>15</sup> The solver requires an initial baseline equilibrium for computing economic response to a policy shock.

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(1974), Scherer (1982) and Griliches and Lichtenberg (1984), which used IO-based technology flow matrices to measure the intersectoral technology flows in an economic system.

<sup>14</sup> The sector-level R&D data are collected from *China Statistical Yearbook on Science and Technology 2006* (MOST, 2006a). The product sale shares are calculated from intermediate transaction matrix in the stylized IO table.

<sup>15</sup> GEMPACK is a suite of general-purpose economic modeling software designed for solving large-scale CGE models, which is capable of solving intertemporal models. For an introduction, see Harrison and Pearson (1996). For solving intertemporal optimization CGE models, see Codsì et al. (1992), Malakellis (1994) and Wendner (1999).

For an intertemporal dynamic model, this benchmark equilibrium is required to record the values of variables at each time point over the simulation periods, which is a time-series IO dataset (one for each time point) consistent with both intratemporal and intertemporal equations (e.g., [Eq. \(6\)](#)) in the model.

To obtain such a full intertemporal dataset, I take the available initial period dataset (base year 2005 IO table) and replicate it in all future years over the period 2005-2030, which satisfies all the intratemporal equations but not the intertemporal ones in the model. Next, I add a Homotopy term to each intertemporal equation and carry out a simulation where the Homotopy variables are shocked. This experiment then generates a time-series IO data that satisfies every equations of the intertemporal model. Based on this consistent time-series benchmark dataset and model parameters listed in [Tab. 1](#), the entire system of equations in the model can be numerically solved by GEMPACK.

## 4 Results and Discussions

### 4.1 Alternative Scenario Settings

Recall that, I aim to examine the effectiveness of China's R&D efforts and technological innovation to curb its carbon emissions. To achieve that goal, I attempt to simulate and compare emissions paths under two different scenarios, including: 1) Reference scenario: the incentives of innovation are not factored into private agent decisions, with R&D investments and knowledge inputs are set to null in simulations. Without the process of knowledge creation, this scenario represents the baseline growth trajectory; 2) R&D scenario: the mechanism of R&D-induced TC is introduced into producer problem, where R&D investment and knowledge creation are modeled as endogenous response of profit-seeking firms to input price changes. Its comparison with the reference scenario reflects the effect of R&D-induced TC. In [Sections 4.3-4.4](#), additional policy scenarios will be developed to investigate the effectiveness of technology and climate policies to cut carbon emissions.

Table 1: Substitution elasticity and parameters

	$\sigma^Q$	$\sigma^Z$	$\sigma^E$	$\sigma^M$	$\sigma^A$	$\sigma^T$
Production sectors						
Electric utility	1.0	0.8	0.2	1.0	2.8	1.0
Gas utilities	1.0	0.8	0.9	0.2	2.8	1.0
Petro refining	1.0	0.5	0.2	0.2	2.1	1.0
Coal mining	1.0	1.7	0.2	0.5	3.0	1.0
Crude oil & gas	1.0	0.5	0.1	0.2	5.0	1.0
Agriculture	1.0	1.0	1.1	2.8	0.9	1.0
Forestry	1.0	1.3	0.6	1.7	2.5	1.0
Mineral mining	1.0	0.9	0.9	0.2	2.5	1.0
Durable	1.0	0.4	0.8	0.2	3.0	1.0
Non-durable	1.0	1.0	1.0	0.1	3.0	1.0
Transportation	1.0	0.5	0.2	0.2	1.9	1.0
Services	1.0	0.3	0.3	3.0	1.9	1.0
$\tau_Q$	Corporate short-run profit tax rate					0.1
$\tau_I$	Investment tax credit					0
$\tau_R$	R&D tax credit					0
$\tau_C$	Carbon tax imposed on fossil fuel input					0
$\alpha$	Elasticity of knowledge creation to R&D investment					0.2
$\beta$	Elasticity of knowledge creation to existing knowledge stock					0.55
$\eta$	Sector-wide efficiency of knowledge creation					1
$r$	Real interest rate					0.05
$\delta_K$	Depreciation rate of physical capital					0.05
$\delta_H$	Depreciation rate of knowledge capital					0.1
$\Psi$	Investment adjustment cost coefficient					4
$\theta$	Externality of intersectoral R&D spillovers					1

$\sigma^Q$ : Elasticity of substitution between knowledge capitals and physical input composite

$\sigma^Z$ : Elasticity of substitution among capital, labor, energy, material (KLEM) physical inputs.

$\sigma^E$ : Elasticity of substitution among intermediate energy goods.

$\sigma^M$ : Elasticity of substitution among intermediate material goods.

$\sigma^A$ : Armington elasticity of substitution between domestical and imported varieties.

$\sigma^T$ : Elasticity of output transformation between domestic and exported varieties.

Notes: For the parameters of substitution elasticity, twelve production sectors have sector-differentiated parameter values. For other parameters, the twelve production sectors are assumed to have the same parameter values in baseline simulation.

Source: McKibbin and Wilcoxon (1999); Goulder and Schneider (1999); Popp (2004); Sue Wing (2006); Bosetti et al. (2008); Wang et al. (2009); Narayanan and Walmsley (2008); Otto et al. (2008).

## 4.2 Impacts of R&D-induced TC

Given the scenario settings in [Section 4.1](#) and the model's parameter assumptions in [Tab. 1](#), I simulate the economic and emission growth paths under the two aforementioned scenarios, so that the impact of R&D-induced TC can be captured. As shown in [Fig. 3\(a\)](#), GDP in the reference scenario is projected to grow by 6.3% annually from \$2327 to \$9650 billion dollars between 2005 and 2030. In contrast, GDP in the R&D scenario rises by almost 5 folds from \$2327 to \$11182 billion dollars during the same period, generating an annual average growth rate of 7.6%.<sup>16</sup> This suggests a stronger GDP growth with the stimulus of R&D investments and technical innovation.

Climate repercussions resulting from the R&D-induced TC are shown in [Fig. 3\(b\)](#). The reference scenario exhibits a rising trajectory of carbon emissions that grow by 4.2% annually from 5100 to 13800 Mt. In comparison, carbon emissions in the R&D scenario are set to rise from 5100 to 12300 Mt between 2005-2030 - an average annual growth rate of 3.5%. Measured in terms of percentage change, R&D efforts are seen to drive China's absolute emissions below its projected baseline levels by 8.5% in 2020 and 11.2% in 2030. As a result, cumulative emission cuts relative to the reference level are estimated to reach 22 gigatons over the period 2005-2030, indicating that R&D-induced TC has a notable effect to curb baseline emissions. Simulation also shows that the reference scenario projects a trajectory where China's carbon intensity is likely to fall from its 2005 level of 2.2 to a 2030 level of 1.4 tons per thousand dollars.<sup>17</sup> In contrast, that intensity in the R&D scenario will be cut deeper to 1.1 tons per thousand dollars at the end of simulation.

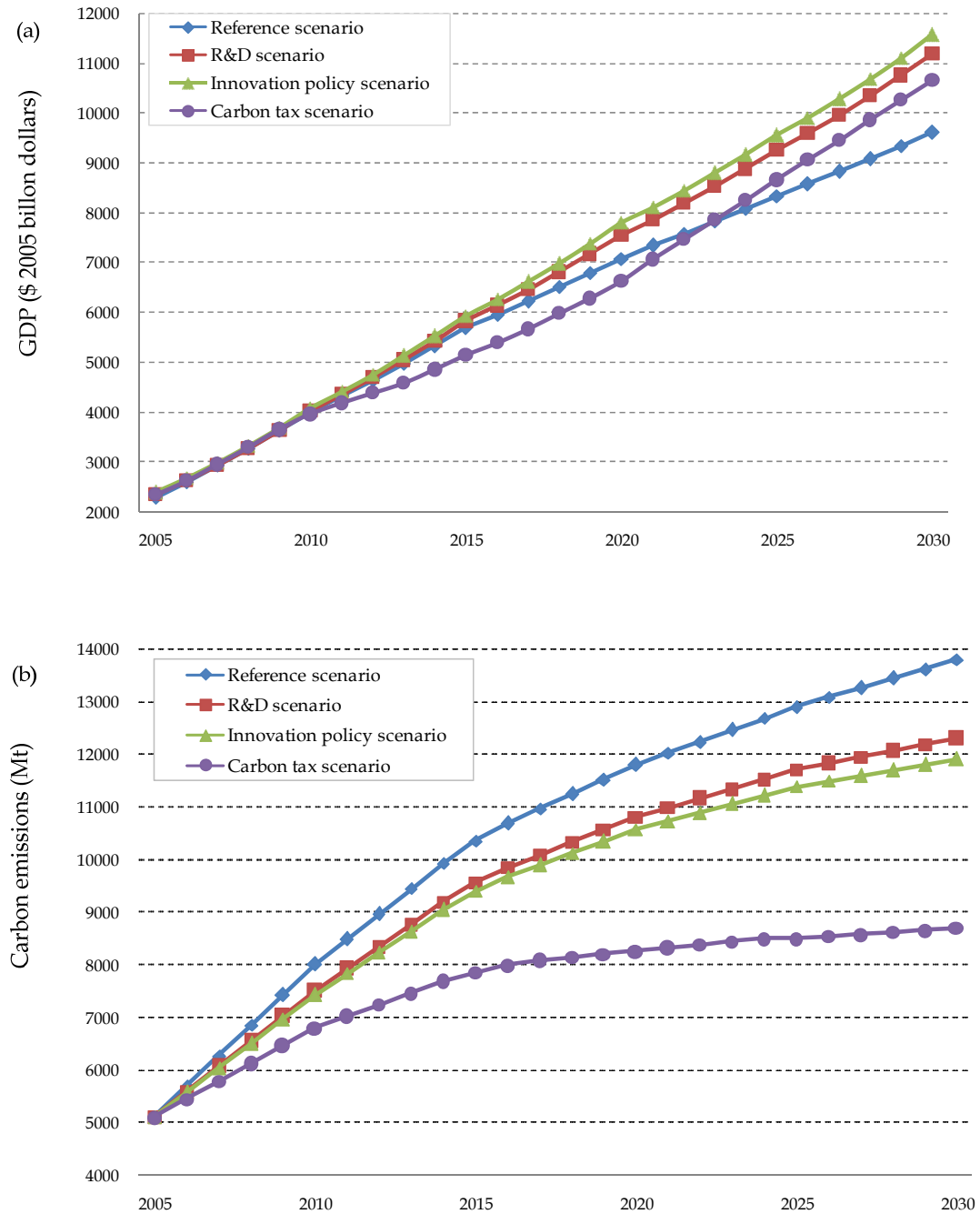
Furthermore, the multi-sector CGE framework is used to examine the effect of R&D-induced TC on emission abatement potential at the sector level. This is done by examining the sector-specific cumulative emission cuts relative to the reference levels. As [Fig. 4\(a\)](#) shows, the sectors of durable manufacturing, electricity and transport accommodate the highest abatement potential from innovation and TC. This is primarily because current production recipes of these sectors heavily rely on fossil fuel inputs. Once R&D funds are in

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<sup>16</sup> In our study, all measurements of output values are real GDP (constant price estimate) in unit of 2005 U.S. dollars (year 2005 is the base period). Differences in real GDP reflect changes in output volume.

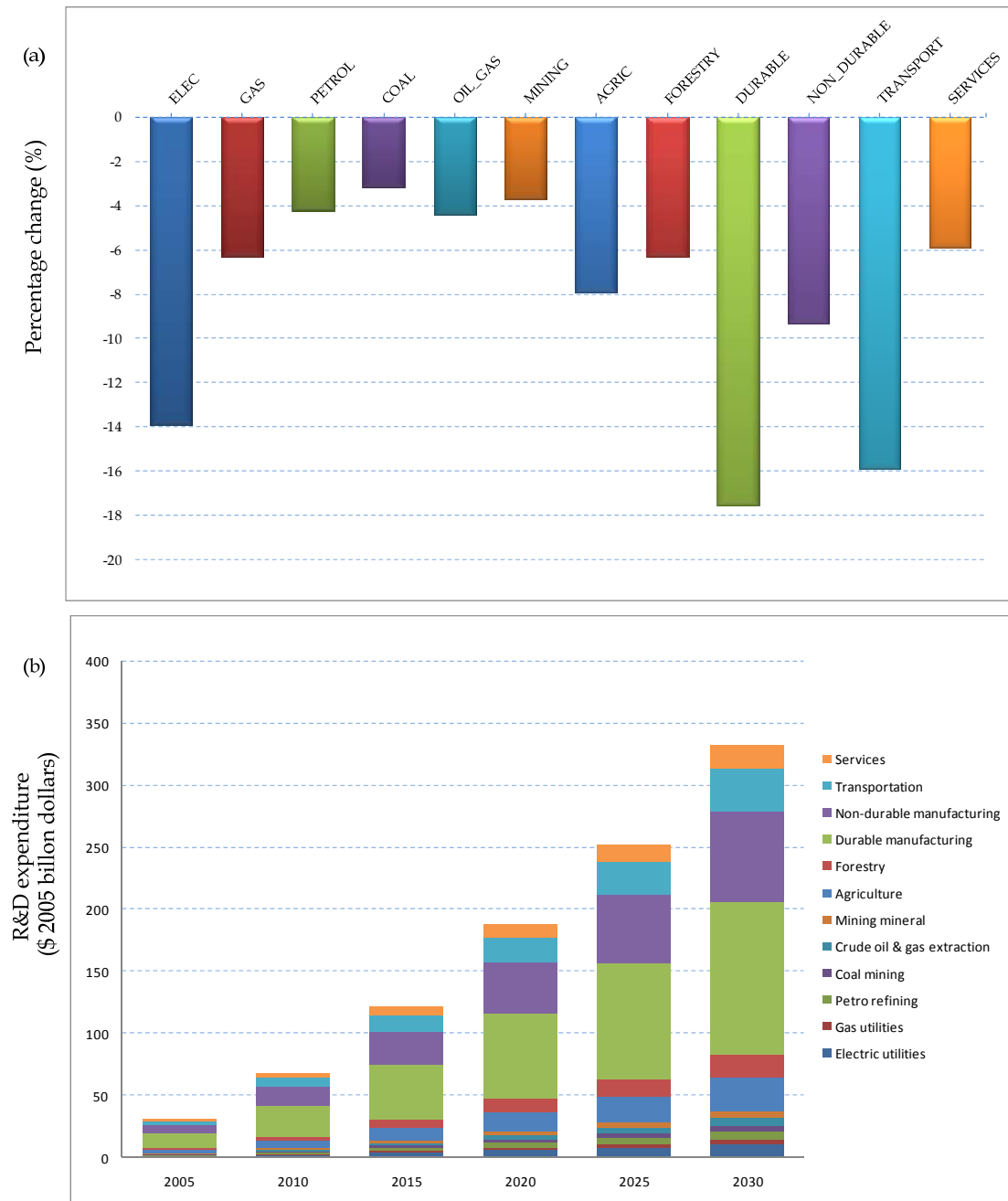
<sup>17</sup> Our analysis focuses on the time path of carbon intensity because China is normally using the intensity targets to bind its climate responsibility of carbon emission cuts.

Figure 3: GDP and carbon emission growth trajectory



Note: (a) GDP growth path under four scenarios (reference, R&D-induced, innovation policy, carbon tax); (b) Carbon emissions growth path under four scenarios (reference, R&D-induced, innovation policy, carbon tax).

Figure 4: Growth trend of R&D investment expenditure and the effect on carbon emission abatement



Note: (a) Effect of R&D-induced TC on sector-level cumulative emission cuts relative to the reference emission levels; (b) Intertemporal trends of economy-wide R&D investment expenditure and its sectoral composition.

place for innovation, these sectors have a large room of developing clean production technologies. For example, R&D investment in electric utility sector can foster development of low-carbon energy technology and produce “green” electric power, satisfying electricity demand without increasing carbon emissions.

As the driving force to the aforementioned changes, the dynamic profile of R&D investment is shown in Fig. 4(b). Between 2005 and 2030, the economy-wide R&D investments are expected to grow by 12% annually from \$31 to \$335 billion dollars. The strong growth in R&D is spread across industrial sectors, with manufacturing, agriculture, electric utility and transportation making up the bulk (almost 80%) of aggregate R&D.<sup>18</sup> As a result, R&D intensity is projected to rise from 1.3% to 3.2% as a share of GDP, which basically coincides with China’s R&D intensity target by 2020 (2.5% of GDP) in its transit towards a knowledge-based economy (MOST, 2006b).

To elucidate the process of R&D-induced TC, I can think the following mechanism. The stimulus of R&D investment improves innovative capacity and creates a stock of knowledge assets (e.g., technique know-how, managerial skills). Once applied to the production process, the knowledge assets facilitate a reconfiguration of production factor inputs for higher productivity – an explanation for the stronger output growths in the R&D scenario. At the same time, owing to knowledge substitution for physical inputs, production technology experiences a decline in the cost share of each physical input and a rise for the knowledge input. The bias of production TC thus gives rise to a reduction in the intensity of fossil energy input - an explanation for the lower carbon intensity in the R&D scenario.

While the emission cuts achieved by R&D are notable, global climate concerns are calling for China’s commitment on deeper carbon intensity cuts (or even hard emission caps). This then raises two issues: 1) On the basis of absolute emission levels, does the R&D-induced TC generate a significant carbon-saving effect; 2) In terms of relative carbon intensity, do technological innovations guarantee the achievement of climate target that is officially set out.

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<sup>18</sup> R&D efforts in these sectors can create higher levels of marginal benefits due to higher innovation efficiency and marginal products of knowledge input. Given a certain level of marginal cost of R&D, the producers in these sectors would hence rationalize their economic behaviors by undertaking more R&D investments.

Firstly, as [Fig. 3\(b\)](#) shows, China's carbon emissions are still on a climbing trajectory, even if its carbon intensity has been driven down by R&D efforts. While knowledge substitution for fossil energy inputs brings about a reduction in carbon intensity, fuelling China's rapidly expanding economy still entails mammoth inputs of factor endowments. This unsurprisingly leads to a continuous increase in the absolute levels of fossil energy use and carbon emissions, without a significant carbon-saving effect.<sup>19</sup> Secondly, at the 2009 Copenhagen climate summit, China unilaterally pledged to cut its carbon intensity by 40-45% below its 2005 levels by 2020. This climate target is likely to aim for a 60-65% carbon intensity cut by 2030 relative to its 2005 levels. However, simulations show that China's R&D efforts will drive down its 2005 carbon intensity level by 35% by 2020 and 50% by 2030, which is well below the pledged climate target. Moreover, if the risky nature of innovation is taken into account, massive R&D investment can't translate into new knowledge creation and its substitution for fossil energy input, China's carbon intensity will still remain a high level and fail to fulfill the climate target.<sup>20</sup> In this regard, there is a growing need for China to call for additional intensity cuts on top of the existing achievement by R&D efforts.

In this context, China's R&D strategy is likely to be far from sufficient to realize "green" innovations and the pledged climate target. The underlying reasons are twofold. First, from the perspective of microeconomic foundation of innovation ([Binswanger, 1974](#)), R&D investment is an inventive response of private firms to input price changes in the pursuit of economic profitability, without particular concerns about climate mitigation; Second, China's national innovation blueprints appear to focus on pushing domestic industries upstream in global value chains through improvements in productivity and competitiveness, without the motivation to capture the niche market of climate-friendly technologies. This innovation pattern is basically "normal" with carbon neutrality, as opposed to a carbon-saving "green" innovation ([Nordhaus, 2011](#)).<sup>21</sup>

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<sup>19</sup> This may reflect why Beijing has repeatedly rejected the calls to commit to an emission peak year. Its fast expanding economy consistently reinforce the increases in its emissions ([IEA, 2007](#)).

<sup>20</sup> For a detailed discussion about climate policy uncertainty, see [McKibbin and Wilcoxon \(2009\)](#).

<sup>21</sup> While China is gaining speed as a world leader in producing renewable energy technology, the bulk of these capacities are used for exports instead of domestic deployment ([Kahrl et al., 2011](#); [de la Tour et al., 2011](#)). China still maintains its focus on key research areas and enabling general-purpose technologies like biotechnology, nanotechnology, pharmaceuticals, large-scale IC manufacturing, broadband telecommunication ([MOST, 2006b](#)).



### 4.3 Innovation Policy Scenario

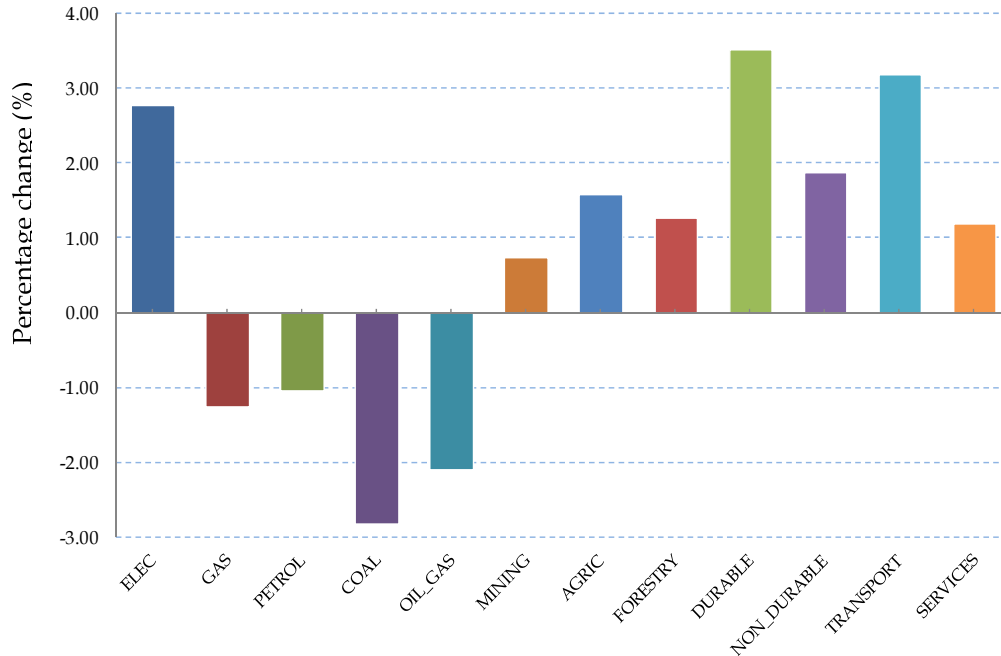
The R&D scenario reveals that, while China is becoming increasingly committed to R&D, the nation still confronts a gap between achieved emissions cuts and expected climate targets. To bridge this gap, Beijing needs to implement complementary policies to create additional intensity reductions. In this section, I examine the effect of innovation policies that aim for public R&D subsidies and stringent patent protection. The climate policy of carbon taxation will be examined in next section.

Recall that, in the R&D scenario the private firm in each sector fully finances R&D spending from own output sale revenues, but broader R&D investments can be attained if public R&D support is in place. As a key form of public R&D intervention, government can use tax revenue to subsidize private R&D and hence encourage more innovation. Moreover, public R&D support should be biased towards innovative activities of non-fossil fuel sectors (clean sectors), so that their reliance on fossil fuel inputs can be reduced. To represent this particular type of innovation policy, I impose the policy shock on R&D subsidy rate  $\tau_R = 0.3$  for all non-fossil fuel sectors (include the electric utility sector and seven non-energy sectors). That is, 30% of R&D spending is financed by government fiscal revenues (OECD, 2008).

As Fig. 3 shows, in the presence of public subsidy, R&D investments continue to rise to 385 billion dollars in 2030 – a level that is 14% higher than that without the subsidy. As a result, GDP is projected to grow by 7.7% annually from \$2327 to \$11381 billion dollars between 2005 and 2030 – a stronger growth than that in the R&D scenario. Meanwhile, carbon emissions are likely to rise from 5100 to 12019 Mt, with a growth rate of 3.4% that is slightly below the rate in the R&D scenario (3.5%). That's because public R&D subsidies provide private firms stronger incentives of knowledge creation. Once these knowledge assets are applied in the production, more physical inputs will be substituted out, further lowering fossil fuel use and carbon emissions.

In addition to the economy-wide changes, I further examine the effect of this biased R&D subsidy on cumulative output at the sectoral level. As shown in Fig. 5, in the presence of public R&D intervention, fossil fuel sectors are likely to suffer from output losses, while outputs in other sectors will continue to grow. The reasons are twofold. Firstly, with public R&D subsidies biased towards the non-fossil fuel sectors, the expansion of R&D resources in

Figure 5: Effect of biased R&D subsidy on cumulative production output changes at the sectoral level



these sectors will reduce that is available in fossil fuel sectors. Knowledge creation and productivity growth are hereby inhibited in fossil fuel sectors, generating the crowding-out effect in the R&D pool. Secondly, the biased R&D subsidies tend to encourage non-fossil fuel sectors to innovate and apply new knowledge in production, substituting for the use of fossil fuel inputs. To clear the market, the declining demand for fossil fuel inputs will drive down the output supply of fossil fuel sectors, with the output falls of fossil fuel sectors representing the opportunity cost of this particular type of R&D policy. However, as public R&D subsidies bring about significant productivity growth in non-fossil fuel sectors, this effectively offsets the output declines in fossil fuel sectors without a potential GDP loss. Put another way, R&D subsidies biased towards non-fossil fuel sectors diminish the contribution of fossil fuel industries to GDP, without limiting the output growth. This is an appealing strategy for China to restructure its carbon-intensive economy into a low-carbon one.

I now turn to the other type of innovation policy, intellectual property rights (IPR). In principle, due to the positive externality of knowledge spillovers, innovators do not fully appropriate the benefits of innovation with private returns to R&D usually below the social

returns, leading to less R&D investments than the socially optimal levels (Nordhaus, 1969; Mansfield, 1996; Popp, 2006). Accordingly, innovation policy that aims for stringent IPR can correct for imperfect innovation market, creating an improved excludability of innovation and knowledge creation.

To represent this stringent patent policy, the model scales down the values of  $\theta$  by half  $\theta=0.5$ . Simulation results show that, under a stringent IPR system, enhanced R&D efforts push the growth of GDP to 11509 billion dollars by 2030 - an additional 1.1% increase on top of the outputs achieved by R&D subsidies. Carbon emissions are likely to drop further to 11892 Mt by 2030 - an additional 0.8% emission cut on top of that achieved by R&D subsidies. The reason for this improvement is that, stringent IPR serves to eliminate the externality of intersectoral knowledge spillovers that occurs in the imperfect innovation market. Therefore, the benefits of knowledge creation are largely appropriated by the private sector undertaking R&D, with smaller amount of knowledge spillover as a public good. To gain the benefits of innovation, private firms need to undertake more purposeful R&D, with a weak incentive of free riding on intersectoral R&D spillovers. Given more R&D efforts at the sectoral level, economy-wide knowledge accumulated and its substitution for fossil fuel in production is accordingly strengthened.

In summary, innovation policies that aim for R&D subsidies and stringent IPR enable China to lower emission intensity further, but the effect is relatively minor, generating only 1-2% additional cuts on top of the intensity level achieved in R&D scenario. Consequently, the joint effect of private R&D efforts and public R&D intervention is to cut China's carbon intensity by 38% by 2020 (1.36 tons per thousand dollars) and 53% by 2030 (1.03 tons per thousand dollars) relative to its 2005 levels. Such a cut may still fall short of the pledged climate target (40-45% cuts by 2020 and 60-65% cuts by 2030). Doubts still remain about the effectiveness of innovation policies as the sole strategy, because continued growth in public R&D subsidies may become uncertain due to diminishing return to R&D.<sup>22</sup> Also stringent IPR only serves to improve innovation excludability *ex post*, which is ancillary to *ex ante* incentive of R&D investments (the response of profit-seeking firms to input price changes).

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<sup>22</sup> Worries also exist at the central leadership level about whether massive public R&D can bear productive and sustainable innovations. Reportedly, many Chinese R&D activities have been plagued by research fund waste, haste and shoddy workmanship, and low quality standards. A political culture of corruption, prestige projects and top-down obedience could hinder the efficient use of public R&D funds (e.g., Shi and Rao, 2010).

## 4.4 Climate Policy Scenario

As shown above, the emission cuts achieved by private R&D efforts and public R&D intervention fall short of the pledged climate target. To bridge this gap, a carbon price signal should be thought of as indispensable. On the one hand, as China's current administrative measures on emission abatement are becoming increasingly costly and challenging to reach medium-term climate target, carbon taxation may serve as a pivotal market-based supplement to cutting emissions.<sup>23</sup> On the other hand, by fulfilling carbon intensity target via carbon taxation, China can pave the way to introduce an emission trading scheme to hard cap its long-run absolute emissions.<sup>24</sup>

I thus introduce a carbon tax of \$20 dollars per ton of carbon dioxide from 2012, growing at a rate of 5% to \$50 dollars per ton by 2030.<sup>25</sup> As shown in [Fig. 3\(b\)](#), the carbon tax generates a noticeable effect to stabilize emissions path, with the emission levels down by 25% to 8702 Mt by 2030. Carbon intensity is likely to fall by 47% in 2020 and by 65% in 2030 relative to the 2005 levels, reaching a level of 0.78 tons per thousand dollars at the end of time frame. Put differently, on top of private R&D and public innovation policies, carbon tax can yield additional carbon intensity cuts of 9% in 2020 and 12% in 2030. This translates into additional absolute emissions cuts of 24% in 2020 and 28% in 2030. Over the period 2005-2030, carbon taxation yields an additional cumulative abatement of about 50 gigatons of carbon emissions, of which the sectoral composition is given in [Fig. 6\(a\)](#). Coal sectors have the highest abatement of cumulative emissions (50-60%), followed by oil and natural gas sectors (20-30%), with a modest level of abatement (10-20%) occurring in non-energy sectors.

As [Fig. 3\(a\)](#) reveals, it comes as no surprise that the environmental benefit of deeper emission cuts achieved by carbon tax is at the compliance cost of output losses. Putting a

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<sup>23</sup> This is reflected by China's difficulty in achieving its energy saving target during the 11<sup>th</sup> five year cycle. Local governments conducted forceful administrative measures, such as power plant shutdown, electricity and vehicle use control. As abatement levels become more stringent, such measures will become costly to achieve climate targets ([Zhang, 2011](#)).

<sup>24</sup> China's share of historical cumulative emissions between 1900-2030 is expected to rise to 16%, approaching that of the U.S. (25%) and the E.U. (18%). China's per capita emission in 2030 is projected to approach that of OECD Europe. Provided that developed countries have made concrete efforts of absolute emissions cuts, China will lose its ground not to take on hard emission caps, even if it remains on a climbing trajectory ([IEA, 2010](#)).

<sup>25</sup> The timing and level of carbon tax are set according to the shadow carbon prices calculated by [IEA \(2010\)](#), which represents a hypothetical policy experiment.

carbon price on the economy incurs a growth slowdown in the near term (2012-2020). After this transition period, the economy absorbs fossil fuel price shock and continues its normal growth path without compromising long-run growth prospect. This simulation trend is consistent with the findings in other modelling studies (e.g., [McKibbin, 2008](#); [McKibbin and Wilcoxon, 2004, 2009](#)). Results show that, GDP is likely to grow by 6.8% annually to \$11153 billion dollars in 2030 (2.1% fall relative to the GDP levels without carbon tax). This translates into present-value cumulative GDP losses of \$2981 billion dollars, of which the sectoral composition is displayed in [Fig. 6\(b\)](#). Most non-energy sectors experience cumulative output losses of about 5%. The carbon-intensive fossil fuel sectors suffer precipitous output declines of roughly 30%.

While carbon tax enables China to achieve the stringent climate target, the compliance costs may raise worries in the nation that such a policy may give rise to growth slowdown and job losses. However, Beijing's nerves can potentially be eased if induced TC as another benefit of climate policy (in addition to the direct benefit of emission cuts) is taken into account. Provided that private firms tend to innovate as their responses to input price changes, putting a price on carbon can induce firms to undertake R&D and knowledge creation, so that cost burden of higher fossil fuel prices can be avoided. This phenomenon is demonstrated in [Fig. 6\(c\)](#), although the reductions in private output incurred by carbon tax would diminish sale revenues and hence the absolute levels of spending in R&D, the relative ratio of R&D to output (R&D-output ratio or R&D intensity) does not necessarily drop across sectors. Decline in cumulative R&D spending exceeds the fall in cumulative output in fossil fuel sectors, but falls short of those in other sectors. Consequently, the R&D-output ratio increases slightly across a range of less carbon-intensive industries including manufacturing, transport and electric utilities, indicating that R&D is induced by carbon tax in these sectors.

The inducement of R&D investment appears to coincide with the changes in knowledge-output ratio (knowledge inputs as a share of output). As depicted in [Fig. 6\(d\)](#), knowledge-output ratio falls sharply in fossil fuel sectors but rise slightly in others sectors, suggesting that inputs of productive knowledge are reallocated from the output-constrained fossil fuel sectors to the input-constrained non-fossil fuel sectors that accommodate higher potential of knowledge substitution for fossil fuel inputs. The result confirms findings on the induced innovation hypothesis, suggesting that a change in the relative price of a production input is in itself a spur to innovations that economize the use of that relatively expensive

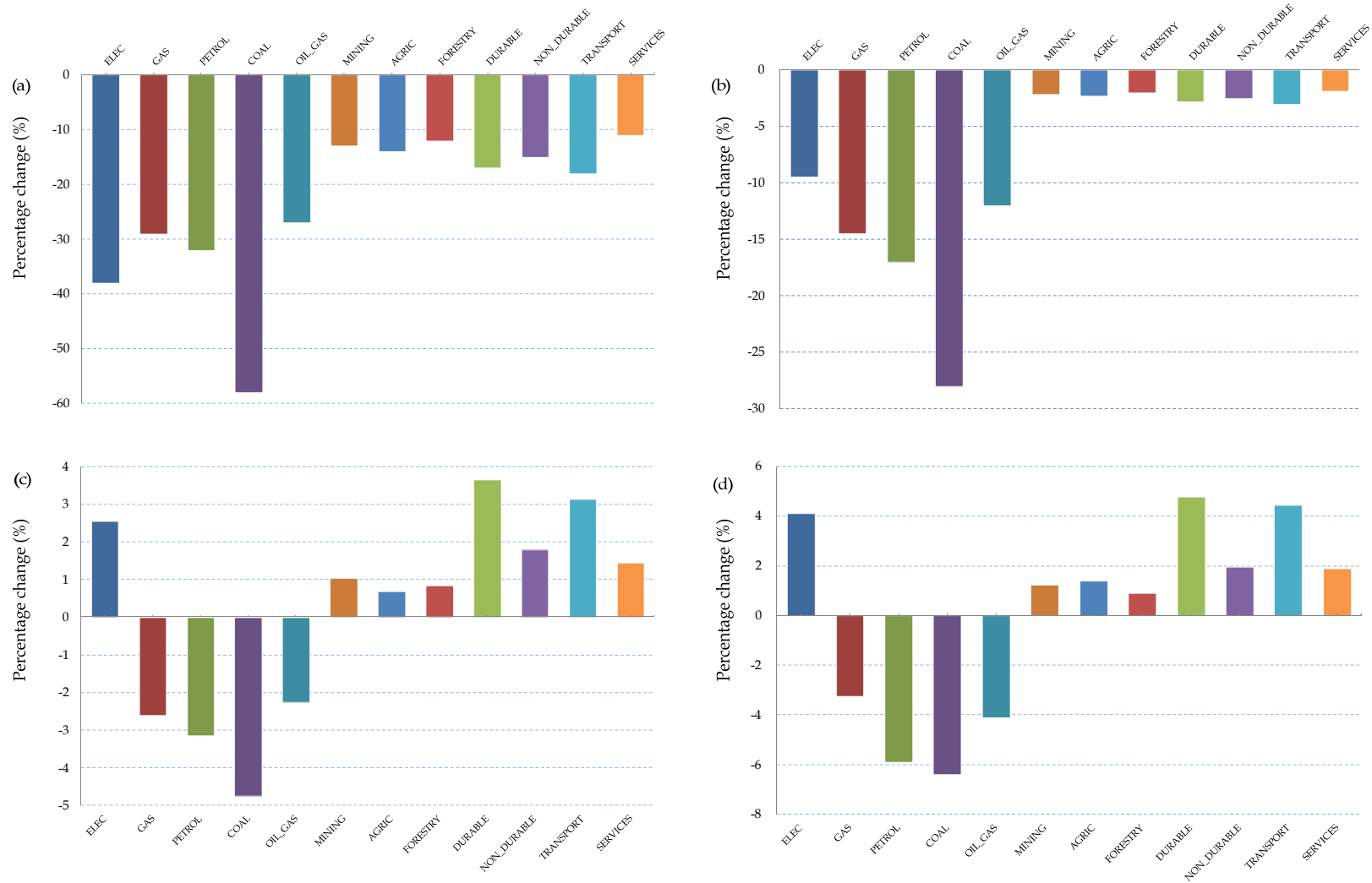
factor ([Hicks, 1932](#)).<sup>26</sup>

In summary, putting a carbon price on the economy may incur growth slowdown, but additional R&D investment and knowledge creation induced by carbon tax can partially mitigate the deadweight loss of such distortion, making the long-run growth performance still better than the reference trajectory. In other words, if a carbon tax is set to correct for emission externality, the price signal will induce private agents to undertake carbon-saving “green” innovation, which is an important complement to existing carbon-neutral “normal” innovation.

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<sup>26</sup> For theoretical expositions of the induced innovation hypothesis, see [Kennedy \(1964\)](#), [Kamien and Schwartz \(1968\)](#), [Goulder and Schneider \(1999\)](#) and [Sue Wing \(2006\)](#). For empirical evidences, see [Newell et al. \(1999\)](#) and [Popp \(2002\)](#).

Figure 6: Environmental and economic effects of carbon taxation and the induced innovation



Note: (a) The effect of carbon tax on the sector-level cumulative emission cuts ; (b) The effect of carbon tax on the sector-level cumulative output losses; (c) The effect of carbon tax on the sector-level R&D-output ratio; (d) The effect of carbon tax on the sector-level knowledge-output ratio. All measured in terms of percentage changes relative to the corresponding case without carbon taxation.

## 4.5 Sensitivity Analysis

Tab. 2 provides the results of sensitivity analysis (SA) for technology parameters in our CGE model. The SA is implemented by lowering and raising these exogenous parameters by 25% relative to their original values (see Tab. 1). I then compare new simulation results (parameters take new values) with regular simulation results (parameters take original values), and report the SA results as percentage change between them.

The general SA results (as shown the column of carbon intensity cuts in Tab. 2) suggest that the findings reached from Sections 4.1-4.4 are basically robust to changes in exogenous technology parameters. That is, sole dependence on R&D efforts is not sufficient to achieve pledged carbon intensity cut target, and a carbon price signal is indispensable to fulfill the climate target.

Turning to the specific technology parameters, in the case of lowering  $\sigma^Q$  by 25%, a smaller substitution possibility translates into lower incentives of private firms to undertake innovation due to a lower possibility of knowledge substitution. As less knowledge assets are created and applied in production process, it becomes less likely to stimulate productivity growth and substitute out fossil energy for carbon saving. Accordingly, GDP and R&D investment falls, and emissions rise in all scenarios. The opposite holds if the parameter  $\sigma^Q$  is raised by 25%.

Lowering the parameter  $\delta_H$  by 25% translates into a higher level of accumulated knowledge stock. Its application in production is more likely to enhance output growth and substitute out fossil energy inputs. Accordingly, GDP and R&D investments rise, and emissions fall in all scenario. The opposite holds if the parameter  $\delta_H$  is raised by 25%.

For the *IPF* parameters  $\alpha$ ,  $\beta$ ,  $\eta$ , lowering their values by 25% translates into a lower possibility of knowledge creation in innovation. Given lower returns of R&D in innovation, private agents have less incentive of undertaking R&D and knowledge accumulation. A smaller amount of knowledge, once applied in production, is less likely to boost productivity growth and substitute for fossil energy. Accordingly, GDP and R&D fall, and emissions rise in all scenario. The opposite holds when these parameters are raised by 25%.



Table 2: Results of sensitivity analysis

Scenario <sup>e</sup>		GDP <sup>a</sup>			Carbon Emissions <sup>b</sup>			R&D Investment <sup>c</sup>			Carbon Intensity Cuts <sup>d</sup>		
		1	2	3	1	2	3	1	2	3	1	2	3
$\sigma^Q$	Low <sup>f</sup>	-0.72%	-0.53%	-1.31%	1.94%	1.62%	2.51%	-3.48%	-3.15%	-4.51%	45.6%	48.2%	60.8%
	High	0.54%	0.27%	1.75%	-1.73%	-1.27%	-2.65%	3.81%	3.52%	4.76%	54.7%	57.5%	68.5%
$\delta_H$	Low	0.43%	0.32%	0.79%	-1.16%	-0.97%	-1.51%	2.09%	1.89%	2.71%	52.1%	55.3%	67.3%
	High	-0.32%	-0.16%	-1.05%	1.04%	0.76%	1.59%	-2.29%	-2.11%	-2.86%	47.2%	50.8%	62.8%
$\alpha$	Low	-0.29%	-0.21%	-0.52%	0.78%	0.65%	1.00%	-1.39%	-1.26%	-1.80%	48.5%	52.2%	63.7%
	High	0.22%	0.11%	0.70%	-0.69%	-0.51%	-1.06%	1.52%	1.41%	1.90%	50.9%	53.9%	65.2%
$\beta$	Low	-0.36%	-0.27%	-0.66%	0.97%	0.81%	1.26%	-1.74%	-1.58%	-2.26%	47.2%	51.5%	62.8%
	High	0.27%	0.14%	0.88%	-0.87%	-0.64%	-1.33%	1.91%	1.76%	2.38%	51.7%	54.2%	66.5%
$\eta$	Low	-0.50%	-0.37%	-0.92%	1.36%	1.13%	1.76%	-2.44%	-2.21%	-3.16%	46.9%	49.6%	62.7%
	High	0.38%	0.19%	1.23%	-1.21%	-0.89%	-1.86%	2.67%	2.46%	3.33%	52.6%	55.2%	67.7%

<sup>a</sup> Percentage change of cumulative GDP in new simulation relative to that in regular simulation.

<sup>b</sup> Percentage change of cumulative carbon emissions in new simulation relative to that in regular simulation.

<sup>c</sup> Percentage change of cumulative R&D investment in new simulation relative to that in regular simulation.

<sup>d</sup> Year 2030 carbon intensity cuts relative to the year 2005 carbon intensity level.

<sup>e</sup> Scenario 1,2,3 refer to R&D-induced TC scenario, innovation policy scenario, and carbon tax scenario, respectively.

<sup>f</sup> Low and High refer to lowering and raising exogenous parameters by 25% relative to their central case values, respectively.

$\sigma^Q$ : Elasticity of substitution between knowledge and physical input

$\delta_H$ : Depreciation rate of knowledge capital

$\alpha$ : Elasticity of knowledge creation to R&D investment

$\beta$ : Elasticity of knowledge creation to existing knowledge stock

$\eta$ : Efficiency of knowledge creation

## .5 Concluding Remarks

This paper develops an intertemporal CGE model that incorporates the endogenous mechanism of R&D-induced TC. The model is used to analyze the effectiveness of China's indigenous R&D investments and technological innovation to curb its carbon emissions. The results provide various policy implications for China's strategy to address climate mitigation: 1) R&D-induced TC has a notable effect on curbing China's baseline carbon emissions levels, with the sectors of durable manufacturing, electric utility and transport accommodate the highest abatement potential from innovation; 2) While indigenous R&D plays a significant role in emissions cut, sole dependence on R&D may be far from sufficient to achieve the pledged climate target. That's because China's pursued innovation pattern is fundamentally "normal" with a focus on productivity improvements rather than carbon saving; 3) As complementary actions to existing R&D efforts, innovation policies (public R&D subsidy and stringent IPR) can strengthen R&D investment and cut emissions further, but the effect is still minor and insufficient to meet the stipulated emission cuts target; 4) A carbon price signal through carbon taxation should be thought of as indispensable in order to fulfill the climate target, but the achievement of carbon-saving benefits is at the cost of sizable economic losses; 5) The induced technical improvement can partially mitigate the deadweight loss incurred by carbon tax distortion, because additional R&D investment and knowledge application would be induced by carbon tax in a pattern of carbon-saving "green" innovation, without compromising the long-run economic growth prospect.

Needless to say, a number of refinements and model extensions are required for future work. In particular, our current modeling frameworks only focus on indigenous innovation within a single economy, with no attention paid to cross-country technology interaction and knowledge diffusion. As China is increasingly integrated into a globalized world economy through trade, FDI and human capital mobility, international knowledge diffusion may serve as a key complement to indigenous R&D in facilitating climate innovation and emissions reduction. There is hence a growing need for future research to incorporate the mechanism of international technology interaction into a multi-region global framework and explore the role of international knowledge diffusion in low-carbon innovation and climate mitigation.

## Appendix A. Model Sectoral Classification and Mapping

Sector Number	Sector Name	GTAP Sector Numbers
1	Electric utilities	43
2	Gas utilities	44
3	Petroleum refining	32
4	Coal mining	15
5	Crude oil & gas extraction	16-17
6	Mineral mining	18
7	Agriculture	01-12, 14
8	Forestry & wood products	13, 30
9	Durable manufacturing	34-42
10	Nondurable manufacturing	19-29, 31, 33
11	Transportation	48-50
12	Services	45-47, 51-57

## Appendix B. Specification of Model Structure

### B.1 Production

#### 1) Production technology

The representative firm in each production sector has a separable KLEM-H nested CES function, with the following production technology:

$$\begin{aligned}
 Q_i &= A_i^Q \cdot \left[ \left( \delta_{iz}^Q \right)^{\frac{1}{\sigma_i^Q}} \cdot Z_i^{\frac{\sigma_i^Q - 1}{\sigma_i^Q}} + \left( \delta_{ih}^Q \right)^{\frac{1}{\sigma_i^Q}} \cdot H_i^{\frac{\sigma_i^Q - 1}{\sigma_i^Q}} \right]^{\frac{\sigma_i^Q}{\sigma_i^Q - 1}} \\
 Z_i &= A_i^Z \cdot \left\{ \left[ \sum_{j=L,E,M} \left( \delta_{ij}^Z \right)^{\frac{1}{\sigma_i^Z}} \cdot X_{ij}^{\frac{\sigma_i^Z - 1}{\sigma_i^Z}} \right] + \left( \delta_{ik}^Z \right)^{\frac{1}{\sigma_i^Z}} \cdot K_i^{\frac{\sigma_i^Z - 1}{\sigma_i^Z}} \right\}^{\frac{\sigma_i^Z}{\sigma_i^Z - 1}} \\
 X_{iE} &= A_i^E \cdot \left[ \sum_{j=1,\dots,5} \left( \delta_{ij}^E \right)^{\frac{1}{\sigma_i^E}} \cdot \left( X_{ij}^E \right)^{\frac{\sigma_i^E - 1}{\sigma_i^E}} \right]^{\frac{\sigma_i^E}{\sigma_i^E - 1}} \\
 X_{iM} &= A_i^M \cdot \left[ \sum_{j=6,\dots,12} \left( \delta_{ij}^M \right)^{\frac{1}{\sigma_i^M}} \cdot \left( X_{ij}^M \right)^{\frac{\sigma_i^M - 1}{\sigma_i^M}} \right]^{\frac{\sigma_i^M}{\sigma_i^M - 1}}
 \end{aligned}$$

By the principle of duality, the dual cost functions corresponding to each quantity variable are derived as follows:

$$\begin{aligned}
 P_i &= (A_i^Q)^{-1} \cdot \left[ \delta_{iz}^Q \cdot (P_{iz})^{1-\sigma_i^Q} + \delta_{ih}^Q \cdot (P_{ih})^{1-\sigma_i^Q} \right]^{\frac{1}{1-\sigma_i^Q}} \\
 P_{iz} &= (A_i^Z)^{-1} \cdot \left\{ \left[ \sum_{j=L,E,M} \delta_{ij}^Z \cdot (P_{ij})^{1-\sigma_i^Z} \right] + \delta_{ik}^Z \cdot (P_{ik})^{1-\sigma_i^Z} \right\}^{\frac{1}{1-\sigma_i^Z}} \\
 P_{iE} &= (A_i^E)^{-1} \cdot \left[ \sum_{j=1,\dots,5} \delta_{ij}^E \cdot (P_{ij}^E)^{1-\sigma_i^E} \right]^{\frac{1}{1-\sigma_i^E}} \\
 P_{iM} &= (A_i^M)^{-1} \cdot \left[ \sum_{j=6,\dots,12} \delta_{ij}^M \cdot (P_{ij}^M)^{1-\sigma_i^M} \right]^{\frac{1}{1-\sigma_i^M}}
 \end{aligned}$$

where  $Q_i, P_i$  are the quantity and price of domestically-produced good,  $Z_i, P_{iz}$  are the quantity and price of physical inputs composite,  $X_i = [X_{iL}, X_{iE}, X_{iM}, K_i, H_i]$ ,  $P_i = [P_{iL}, P_{iE}, P_{iM}, P_{iK}, P_{iH}]$  are quantity and price of labor, energy bundle, materials bundle, physical capital and knowledge capital.  $X_{ij}^E, P_{ij}^E$  are the quantity and price of intermediate energy commodities,  $X_{ij}^M, P_{ij}^M$  are the quantity and price of intermediate material commodities.

#### 2) Solving Producer Problem

For each production sector  $i$ , the problem of a representative producer is specified as .

$$\begin{aligned}
\max \quad & V_i(t) = \int_t^\infty \exp\left[-\int_t^s r(s') \cdot ds'\right] \cdot \Pi_i(s) \cdot ds \\
\text{s.t.} \quad & \Pi_i(t) = (1 - \tau_Q) \cdot [P_i(t) \cdot Q_i(t) - P_{iL}(t) \cdot X_{iL}(t) - P_{iE}(t) \cdot X_{iE}(t) - P_{iM}(t) \cdot X_{iM}(t)] \\
& \quad - (1 - \tau_I) \cdot P_{iI}(t) \cdot I_i(t) - (1 - \tau_R) \cdot P_{iR}(t) \cdot R_i(t) \\
& \dot{K}_i(t) = J_i(t) - \delta_K \cdot K_i(t) \\
& I_i(t) = \varphi_i(J_i(t), K_i(t)) = J_i(t) + \frac{\psi}{2} \cdot \frac{J_i(t)^2}{K_i(t)} \\
& \dot{H}_i(t) = \eta \cdot R_i(t)^\alpha \cdot H_i(t)^\beta + \frac{R_i(t)}{\sum_j R_j(t)} \cdot \left[ \theta \cdot \sum_j R_j(t) - R_i(t) \right] - \delta_H \cdot H_i(t)
\end{aligned}$$

The dynamic optimization problem is solved by using the current-value Hamiltonian formulas:

$$\begin{aligned}
\Gamma_i(t) = & (1 - \tau_Q) \cdot [P_i(t) \cdot Q_i(t) - P_{iL}(t) \cdot X_{iL}(t) - P_{iE}(t) \cdot X_{iE}(t) - P_{iM}(t) \cdot X_{iM}(t)] \\
& - (1 - \tau_I) \cdot P_{iI}(t) \cdot \left[ J_i(t) + \frac{\psi}{2} \cdot \frac{J_i(t)^2}{K_i(t)} \right] + \lambda_{iK}(t) \cdot [J_i(t) - \delta_K \cdot K_i(t)] \\
& - (1 - \tau_R) \cdot P_{iR}(t) \cdot R_i(t) + \lambda_{iH}(t) \cdot \left\{ \eta \cdot R_i(t)^\alpha \cdot H_i(t)^\beta + \frac{R_i(t)}{\sum_j R_j(t)} \cdot \left[ \theta \cdot \sum_j R_j(t) - R_i(t) \right] - \delta_H \cdot H_i(t) \right\}
\end{aligned}$$

We first optimally solve for the demand for labor  $X_{iL}(t)$ , energy bundle  $X_{iE}(t)$  and materials bundle  $X_{iM}(t)$  from the F.O.C. with respect to  $X_{ij}(t)$  for  $j = L, E, M$ .

$$\begin{aligned}
\frac{\partial \Gamma_i(t)}{\partial X_{ij}(t)} &= P_i(t) \cdot \frac{\partial Q_i(t)}{\partial X_{ij}(t)} - P_{ij}(t) = 0 \\
\Rightarrow \quad \frac{P_{ij}(t)}{P_i(t)} &= \frac{\partial Q_i(t)}{\partial X_{ij}(t)} = \frac{\partial Q_i(t)}{\partial Z_i(t)} \cdot \frac{\partial Z_i(t)}{\partial X_{ij}(t)} = \left[ \delta_{iZ}^Q \cdot (A_i^Q)^{\sigma_i^Q - 1} \cdot \frac{Q_i(t)}{Z_i(t)} \right]^{\frac{1}{\sigma_i^Q}} \cdot \left[ \delta_{ij}^Z \cdot (A_i^Z)^{\sigma_i^Z - 1} \cdot \frac{Z_i(t)}{X_{ij}(t)} \right]^{\frac{1}{\sigma_i^Z}}
\end{aligned}$$

We further use the optimality condition at tier one in the nested CES structure - the value of marginal product of physical input composite  $Z_i(t)$  should equal its cost, and obtain the optimal level of demand for physical input composite as follows:

$$P_i(t) \cdot \frac{\partial Q_i(t)}{\partial Z_i(t)} - P_{iZ}(t) = 0 \quad \Rightarrow \quad Z_i(t) = (A_i^Q)^{\sigma_i^Q - 1} \cdot \delta_{iZ}^Q \cdot \left( \frac{P_i(t)}{P_{iZ}(t)} \right)^{\sigma_i^Q} \cdot Q_i(t)$$

By substituting out  $Z_i(t)$ , we express the optimal level of demand for  $X_{ij}(t)$  as function of  $Q_i(t)$ :

$$X_{ij}(t) = \left[ \delta_{ij}^Z \cdot (A_i^Z)^{\sigma_i^Z - 1} \cdot \left( \frac{P_{iZ}(t)}{P_{ij}(t)} \right)^{\sigma_i^Z} \right] \cdot \left[ \delta_{iZ}^Z \cdot (A_i^Z)^{\sigma_i^Z - 1} \cdot \left( \frac{P_i(t)}{P_{iZ}(t)} \right)^{\sigma_i^Z} \right] \cdot Q_i(t)$$

In the second step, we solve for the optimal level of demand for raw investment goods  $J_i(t)$  and

R&D goods  $R_i(t)$ , and obtain the following static optimality conditions for investment and R&D:

$$\begin{aligned}\frac{\partial \Gamma_i(t)}{\partial J_i(t)} &= -(1-\tau_i) \cdot P_{il}(t) \cdot \left(1 + \psi \cdot \frac{J_i(t)}{K_i(t)}\right) + \lambda_{ik}(t) = 0 \\ \Rightarrow J_i(t) &= \left[ \frac{\lambda_{ik}(t)}{(1-\tau_i) \cdot P_{il}(t)} - 1 \right] \cdot \frac{K_i(t)}{\psi} \\ \frac{\partial \Gamma_i(t)}{\partial R_i(t)} &= -(1-\tau_R) \cdot P_{il}(t) + \lambda_{ih}(t) \cdot \left[ a \cdot \eta \cdot R_i(t)^{a-1} \cdot H_i(t)^\beta + \theta - \frac{2R_i(t)}{\sum_j R_j(t)} \right] \\ \Rightarrow (1-\tau_R) \cdot P_{il}(t) &= \lambda_{ih}(t) \cdot \left[ a \cdot \eta \cdot R_i(t)^{a-1} \cdot H_i(t)^\beta + \theta - \frac{2R_i(t)}{\sum_j R_j(t)} \right]\end{aligned}$$

The above equations are static form of optimality conditions, the truly intertemporal part of this problem is solved by optimally choosing the dynamic paths for the shadow price of physical and knowledge capital  $\lambda_{ik} \lambda_{ih}$ :

$$\begin{aligned}\dot{\lambda}_{ik}(t) - r(t) \cdot \lambda_{ik}(t) &= -\frac{\partial \Gamma_i(t)}{\partial K_i(t)} = -(1-\tau_Q) \cdot P_i(t) \cdot \frac{\partial Q_i(t)}{\partial K_i(t)} - (1-\tau_i) \cdot P_{il}(t) \cdot \frac{\psi}{2} \cdot \left( \frac{J_i(t)}{K_i(t)} \right)^2 + \delta_K \cdot \lambda_{ik}(t) \\ \Rightarrow \frac{\dot{\lambda}_{ik}(t) + (1-\tau_Q) \cdot P_i(t) \cdot \frac{\partial Q_i(t)}{\partial K_i(t)} + (1-\tau_i) \cdot P_{il}(t) \cdot \frac{\psi}{2} \cdot \left( \frac{J_i(t)}{K_i(t)} \right)^2}{\lambda_{ik}(t)} &= r(t) + \delta_K\end{aligned}$$

Where the expression represents the implicit arbitrage condition for physical capital investment: LHS denotes the shadow rate of return from an extra unit of investment in physical capital, including: the increase in the shadow price of physical capital, marginal product of physical capital, and the adjustment cost saving. RHS represents the cost of physical capital investment, including the market interest rate and the capital depreciation rate. Hence, in determining the optimal path of  $\lambda_{ik}$ , the firm is guided by this implicit arbitrage equation. In a similar way, we can solve for the optimal dynamic path for the shadow price of knowledge asset  $\lambda_{ih}$ .

$$\begin{aligned}\dot{\lambda}_{ih}(t) - r(t) \cdot \lambda_{ih}(t) &= -\frac{\partial \Gamma_i(t)}{\partial H_i(t)} \\ \Rightarrow \frac{\dot{\lambda}_{ih}(t) + (1-\tau_Q) \cdot P_i(t) \cdot \frac{\partial Q_i(t)}{\partial H_i(t)} + \lambda_{ih}(t) \cdot \eta \cdot \beta \cdot R_i(t)^a \cdot H_i(t)^{\beta-1}}{\lambda_{ih}(t)} &= r(t) + \delta_H\end{aligned}$$

### 3) Characterization of Producer Problem

- For any production sector  $i$  ( $i=1, \dots, 12$ ), the optimal level of demand for labor, energy bundle and materials bundle are characterized as follows:

$$\begin{aligned}
X_{iL}(t) &= \left[ \delta_{iL}^Z \cdot (A_i^Z)^{\sigma_i^Z-1} \cdot \left( \frac{P_{iZ}(t)}{P_{iL}(t)} \right)^{\sigma_i^Z} \right] \cdot \left[ \delta_{iZ}^Q \cdot (A_i^Q)^{\sigma_i^Q-1} \cdot \left( \frac{P_i(t)}{P_{iZ}(t)} \right)^{\sigma_i^Q} \right] \cdot Q_i(t) \\
X_{iE}(t) &= \left[ \delta_{iE}^Z \cdot (A_i^Z)^{\sigma_i^Z-1} \cdot \left( \frac{P_{iZ}(t)}{P_{iE}(t)} \right)^{\sigma_i^Z} \right] \cdot \left[ \delta_{iZ}^Q \cdot (A_i^Q)^{\sigma_i^Q-1} \cdot \left( \frac{P_i(t)}{P_{iZ}(t)} \right)^{\sigma_i^Q} \right] \cdot Q_i(t) \\
X_{iM}(t) &= \left[ \delta_{iM}^Z \cdot (A_i^Z)^{\sigma_i^Z-1} \cdot \left( \frac{P_{iZ}(t)}{P_{iM}(t)} \right)^{\sigma_i^Z} \right] \cdot \left[ \delta_{iZ}^Q \cdot (A_i^Q)^{\sigma_i^Q-1} \cdot \left( \frac{P_i(t)}{P_{iZ}(t)} \right)^{\sigma_i^Q} \right] \cdot Q_i(t)
\end{aligned}$$

where the optimal demands for energy bundle  $X_{iE}(t)$  and materials bundle  $X_{iM}(t)$  are further disaggregated into demand for each energy commodities  $X_{ij}^E(t)$  for  $j=1,...,5$  and material commodities  $X_{ij}^M(t)$  for  $j=6,...,12$  as follows:

$$\begin{aligned}
X_{ij}^E(t) &= \left[ \delta_{ij}^E \cdot (A_i^E)^{\sigma_i^E-1} \cdot \left( \frac{P_{iE}(t)}{P_{ij}^E(t)} \right)^{\sigma_i^E} \right] \cdot X_{iE}(t) \\
X_{ij}^M(t) &= \left[ \delta_{ij}^M \cdot (A_i^M)^{\sigma_i^M-1} \cdot \left( \frac{P_{iM}(t)}{P_{ij}^M(t)} \right)^{\sigma_i^M} \right] \cdot X_{iM}(t)
\end{aligned}$$

- Investment behavior of producer is characterized by the following conditions:

$$\begin{aligned}
J_i(t) &= \left[ \frac{\lambda_{iK}(t)}{(1-\tau_I) \cdot P_{iL}(t)} - 1 \right] \cdot \frac{K_i(t)}{\psi} \\
\frac{\dot{\lambda}_{iK}(t) + (1-\tau_Q) \cdot P_i(t) \cdot \frac{\partial Q_i(t)}{\partial K_i(t)} + (1-\tau_I) \cdot P_{iL}(t) \cdot \frac{\psi}{2} \cdot \left( \frac{J_i(t)}{K_i(t)} \right)^2}{\lambda_{iK}(t)} &= r(t) + \delta_K \\
I_i(t) &= J_i(t) + \frac{\psi}{2} \cdot \frac{J_i(t)^2}{K_i(t)} \\
\dot{K}_i(t) &= J_i(t) - \delta_K \cdot K_i(t)
\end{aligned}$$

where the first term is the static optimality conditions for investment determined by the shadow price of physical capital. The second is the implicit arbitrage condition that determines the time path of the shadow price of physical capital. The third denotes the actual purchases of investment goods with adjustment cost function. The fourth is the law of motion for physical capital stock.

- R&D behavior of producer is characterized by the following conditions:

$$\begin{aligned}
(1-\tau_R) \cdot P_{iR}(t) &= \lambda_{iH}(t) \cdot \left[ a \cdot \eta \cdot R_i(t)^{a-1} \cdot H_i(t)^\beta + \theta - \frac{2R_i(t)}{\sum_j R_j(t)} \right] \\
\frac{\dot{\lambda}_{iH}(t) + (1-\tau_Q) \cdot P_i(t) \cdot \frac{\partial Q_i(t)}{\partial H_i(t)} + \lambda_{iH}(t) \cdot \eta \cdot \beta \cdot R_i(t)^a \cdot H_i(t)^{\beta-1}}{\lambda_{iH}(t)} &= r(t) + \delta_H \\
\dot{H}_i(t) &= \eta \cdot R_i(t)^a \cdot H_i(t)^\beta + \frac{R_i(t)}{\sum_j R_j(t)} \cdot \left[ \theta \cdot \sum_j R_j(t) - R_i(t) \right] - \delta_H \cdot H_i(t)
\end{aligned}$$

where the first term is the static optimality conditions for R&D investment determined by the shadow price of knowledge stock. The second is the implicit arbitrage condition that determines

the time path for the shadow price of knowledge asset. The third denotes the *innovation possibility frontier* for knowledge creation.

### 3.B.2. Consumption

#### 1) Structure of Consumption

In each economy, we assume a representative household owns all factors of production and all shares in firms, and determine the consumption which is a CES aggregate of individual consumption goods:

$$C = \left[ \sum_{j=E,M} (\delta_{Cj}^O)^{\frac{1}{\sigma_C^O}} \cdot (X_{Cj})^{\frac{\sigma_C^O-1}{\sigma_C^O}} \right]^{\frac{\sigma_C^O}{\sigma_C^O-1}}$$

$$X_{CE} = \left[ \sum_{j=1,...,5} (\delta_{Cj}^E)^{\frac{1}{\sigma_C^E}} \cdot (X_{Cj}^E)^{\frac{\sigma_C^E-1}{\sigma_C^E}} \right]^{\frac{\sigma_C^E}{\sigma_C^E-1}}$$

$$X_{CM} = \left[ \sum_{j=6,...,12} (\delta_{Cj}^M)^{\frac{1}{\sigma_C^M}} \cdot (X_{Cj}^M)^{\frac{\sigma_C^M-1}{\sigma_C^M}} \right]^{\frac{\sigma_C^M}{\sigma_C^M-1}}$$

The dual cost functions corresponding to each above variable are as follows

$$P_C = \left[ \sum_{j=E,M} \delta_{Cj}^O \cdot (P_{Cj})^{1-\sigma_C^O} \right]^{\frac{1}{1-\sigma_C^O}}$$

$$P_{CE} = \left[ \sum_{j=1,...,5} \delta_{Cj}^E \cdot (P_{Cj}^E)^{1-\sigma_C^E} \right]^{\frac{1}{1-\sigma_C^E}}$$

$$P_{CM} = \left[ \sum_{j=6,...,12} \delta_{Cj}^M \cdot (P_{Cj}^M)^{1-\sigma_C^M} \right]^{\frac{1}{1-\sigma_C^M}}$$

where  $C, P_C$  are aggregate consumption and consumer price index,  $X_C = [X_{CE}, X_{CM}]$ ,  $P_C = [P_{CE}, P_{CM}]$  are the consumed quantity and consumer price of energy bundle and materials bundle.  $X_{Cj}^E, P_{Cj}^E$  are the consumed quantity and consumer price of energy commodities,  $X_{Cj}^M, P_{Cj}^M$  are the consumed quantity and consumer price of material commodities.

#### 2) Consumer Problem

The consumer problem is to maximize an intertemporal utility subject to the budget constraint and transversality condition:

$$\max U(t) = \int_t^\infty \ln C(s) \cdot \exp[-\rho \cdot (s-t)] \cdot ds$$

$$\text{s.t. } P_C(s) \cdot C(s) + \dot{A}(s) = r(s) \cdot A(s) + w(s) \cdot L(s)$$

$$\lim_{s \rightarrow \infty} A(s) \cdot \exp \left[ -\int_t^s r(s') \cdot ds' \right] = 0$$



By integrating the static budget constraint over an infinite time horizon, we can derive a lifetime budget constraint where the discounted present value of future consumption expenditure is financed by the sum of human wealth and financial wealth:

$$\int_t^\infty P_C(s) \cdot C(s) \cdot \exp\left[-\int_t^s r(s') \cdot ds'\right] \cdot ds = H_C(t) + A_C(t)$$

with  $H_C(t) = \int_t^\infty (1 - \tau_w) \cdot w(s) \cdot L(s) \cdot \exp\left[-\int_t^s r(s') \cdot ds'\right] \cdot ds$

$$A_C(t) = \sum_i [\lambda_{iK}(t) \cdot K_i(t) + \lambda_{iH}(t) \cdot H_i(t)]$$

where  $C, P_C$  are aggregate consumption level and consumer price index, respectively.  $H_C$  denotes the human wealth as the discounted present value of future income stream. The labor income is made up of after-tax wage earnings  $(1 - \tau_w) \cdot w(s) \cdot L(s)$ . The financial wealth  $A_C(t)$  involves the equity values hold by the representative household, equaling the stock market value of physical assets  $\lambda_K \cdot K$  and knowledge assets  $\lambda_H \cdot H$ .

The problem of intertemporal utility maximization is solved by constructing the Lagrangian:

$$L(t) = \int_t^\infty \ln C(s) \cdot \exp[-\rho \cdot (s - t)] \cdot ds + \lambda(t) \cdot \left( H_C(t) + A_C(t) - \int_t^\infty P_C(s) \cdot C(s) \cdot \exp\left[-\int_t^s r(s') \cdot ds'\right] \cdot ds \right)$$

F.O.C. with respect to  $C(s)$  yields:

$$\frac{1}{C(s)} \cdot \exp[-\rho \cdot (s - t)] - \lambda(t) \cdot \left( P_C(s) \cdot \exp\left[-\int_t^s r(s') \cdot ds'\right] \right) = 0 \Rightarrow P_C(s) \cdot C(s) = \frac{1}{\lambda(t)} \cdot \exp[-\rho \cdot (s - t)] \cdot \exp\left[-\int_t^s r(s') \cdot ds'\right]$$

Plug back into the lifetime budget constraint yields:

$$\begin{aligned} H_C(t) + A_C(t) &= \int_t^\infty P_C(s) \cdot C(s) \cdot \exp\left[-\int_t^s r(s') \cdot ds'\right] \cdot ds \\ &= \int_t^\infty \frac{1}{\lambda(t)} \cdot \exp[-\rho \cdot (s - t)] \cdot \exp\left[-\int_t^s r(s') \cdot ds'\right] \cdot \exp\left[-\int_t^s r(s') \cdot ds'\right] \cdot ds \\ &= \int_t^\infty \frac{1}{\lambda(t)} \cdot \exp[-\rho \cdot (s - t)] \cdot ds = \frac{1}{\lambda(t)} \cdot \frac{1}{\rho} \\ \Rightarrow \rho \cdot (H_C(t) + A_C(t)) &= \frac{1}{\lambda(t)} \\ \Rightarrow P_C(s) \cdot C(s) &= \rho \cdot (H_C(t) + A_C(t)) \cdot \exp[-\rho \cdot (s - t)] \cdot \exp\left[-\int_t^s r(s') \cdot ds'\right] \end{aligned}$$

Given the human and financial wealth at time  $t$ , the household will choose her optimal consumption path over time  $s = [t, t+1, \dots, \infty]$  according to the above equation. Let  $s = t$  and derive the optimal consumption level at current period:

$$P_C(s) \cdot C(s) = \rho \cdot (H_C(t) + A_C(t))$$

This formula represents the consumption behavior of household according to permanent income hypothesis – household's consumption expenditure equals to a constant proportion of the aggregated human and financial wealth. However, some group of household are liquidity-constrained with myopic expectations about her future income, and are only able to consume a fraction of their after-tax income, thus the aggregate consumption expenditure is expressed as follows:

$$P_C(t) \cdot C(t) = \theta \cdot \rho \cdot [H_C(t) + A_C(t)] + (1 - \theta) \cdot \sigma \cdot w(s) \cdot L(s)$$

Based on the two-tier nested CES structure of consumption, the aggregate consumption expenditure can be allocated to each goods and services component:

$$\begin{aligned} P_G(t) \cdot X_G(t) &= \left[ \delta_G^O \cdot \left( \frac{P_C(t)}{P_G(t)} \right)^{\sigma_C^O - 1} \right] \cdot P_C(t) \cdot C(t) & j = E, M \\ P_G^E(t) \cdot X_G^E(t) &= \left[ \delta_G^E \cdot \left( \frac{P_{CE}(t)}{P_G^E(t)} \right)^{\sigma_C^E - 1} \right] \cdot P_{CE}(t) \cdot X_{CE}(t) & j = 1, \dots, 5 \\ P_G^M(t) \cdot X_G^M(t) &= \left[ \delta_G^M \cdot \left( \frac{P_{CM}(t)}{P_G^M(t)} \right)^{\sigma_C^M - 1} \right] \cdot P_{CM}(t) \cdot X_{CM}(t) & j = 6, \dots, 12 \end{aligned}$$

where  $P_G(t) \cdot X_G(t) = [P_{CE}(t) \cdot X_{CE}(t), P_{CM}(t) \cdot X_{CM}(t)]$  are the consumption expenditure on energy and material bundles.  $P_G^E(t) \cdot X_G^E(t)$  are the consumption expenditure on energy commodities,  $P_G^M(t) \cdot X_G^M(t)$  are the consumption expenditure on material commodities

### 3) Characterization of Consumer Problem

- From labor endowment, human and financial wealth, aggregate consumption expenditures are determined:

$$P_C(t) \cdot C(t) = \theta \cdot \rho \cdot [H_C(t) + A_C(t)] + (1 - \theta) \cdot \sigma \cdot w(s) \cdot L(s)$$

$$H_C(t) = \int_t^\infty (1 - \tau_w) \cdot w(s) \cdot L(s) \cdot \exp \left[ - \int_t^s r(s') \cdot ds' \right] \cdot ds$$

$$A_C(t) = \sum_{i=1, \dots, 12} [\lambda_{iK}(t) \cdot K_i(t) + \lambda_{iH}(t) \cdot H_i(t)]$$

- Aggregate consumption expenditure is allocated into individual E/M commodities as:

$$X_{CE}(t) = \left[ \delta_{CE}^O \cdot \left( \frac{P_C(t)}{P_{CE}(t)} \right)^{\sigma_C^O} \right] \cdot C(t)$$

$$X_{CM}(t) = \left[ \delta_{CM}^O \cdot \left( \frac{P_C(t)}{P_{CM}(t)} \right)^{\sigma_C^O} \right] \cdot C(t)$$

where the demand for energy bundle  $X_{CE}(t)$  and materials bundle  $X_{CM}(t)$  is further allocated into each energy commodities  $X_{Gj}^E(t)$   $j = 1, \dots, 5$  and material commodities  $X_{Gj}^M(t)$   $j = 6, \dots, 12$ :

$$X_{Gj}^E(t) = \left[ \delta_{Gj}^E \cdot \left( \frac{P_{CE}(t)}{P_{Gj}^E(t)} \right)^{\sigma_{Gj}^E} \right] \cdot X_{CE}(t)$$

$$X_{Gj}^M(t) = \left[ \delta_{Gj}^M \cdot \left( \frac{P_{CM}(t)}{P_{Gj}^M(t)} \right)^{\sigma_{Gj}^M} \right] \cdot X_{CM}(t)$$

### 3.B.3 Capital good producing sector

The investment sector produces new investment goods by combining energy and materials according to a two-tier nested CES production technology:

$$Q_I = A_I^Q \cdot \left[ \sum_{j=E,M} (\delta_{Ij}^Q)^{\frac{1}{\sigma_I^Q}} \cdot (X_{Ij})^{\frac{\sigma_I^Q-1}{\sigma_I^Q}} \right]^{\frac{\sigma_I^Q}{\sigma_I^Q-1}}$$

$$X_{IE} = A_I^E \cdot \left[ \sum_{j=1,\dots,5} (\delta_{Ij}^E)^{\frac{1}{\sigma_I^E}} \cdot (X_{Ij}^E)^{\frac{\sigma_I^E-1}{\sigma_I^E}} \right]^{\frac{\sigma_I^E}{\sigma_I^E-1}}$$

$$X_{IM} = A_I^M \cdot \left[ \sum_{j=6,\dots,12} (\delta_{Ij}^M)^{\frac{1}{\sigma_I^M}} \cdot (X_{Ij}^M)^{\frac{\sigma_I^M-1}{\sigma_I^M}} \right]^{\frac{\sigma_I^M}{\sigma_I^M-1}}$$

The dual cost function corresponding to each variable is as follows:

$$P_I = (A_I^Q)^{-1} \cdot \left[ \sum_{j=E,M} \delta_{Ij}^Q \cdot (P_{Ij})^{1-\sigma_I^Q} \right]^{\frac{1}{1-\sigma_I^Q}}$$

$$P_{IE} = (A_I^E)^{-1} \cdot \left[ \sum_{j=1,\dots,5} \delta_{Ij}^E \cdot (P_{Ij}^E)^{1-\sigma_I^E} \right]^{\frac{1}{1-\sigma_I^E}}$$

$$P_{IM} = (A_I^M)^{-1} \cdot \left[ \sum_{j=6,\dots,12} \delta_{Ij}^M \cdot (P_{Ij}^M)^{1-\sigma_I^M} \right]^{\frac{1}{1-\sigma_I^M}}$$

where  $Q_I, P_I$  are the quantity and price of investment good,  $X_I = [X_{IE}, X_{IM}]$ ,  $P_I = [P_{IE}, P_{IM}]$  are quantity and price of E/M bundle used in financial sector.  $X_{Ij}^E, P_{Ij}^E$  are the quantity and price of energy commodities,  $X_{Ij}^M, P_{Ij}^M$  are the quantity and price of material commodities.

For the investment sectors, the producer problem is specified as:

$$\max \Pi_I(t) = P_I(t) \cdot Q_I(t) - P_{IE}(t) \cdot X_{IE}(t) - P_{IM}(t) \cdot X_{IM}(t)$$

where the firm's objective is to optimally choose the inputs of energy bundle  $X_{IE}$  and materials bundle  $X_{IM}$  for maximizing its current profit flows  $\Pi_I$ . Solving this top-tier static maximization problem can determine the demands for the inputs of energy and materials bundles. We further

solve a cost minimization problem at energy and material tier, and characterize the demand for each individual energy and material commodities.

The optimal level of demand for energy bundles and materials bundles are characterized as:

$$X_{IE}(t) = \delta_{IE}^Q \cdot (A_I^Q)^{\sigma_I^Q - 1} \cdot \left( \frac{P_I(t)}{P_{IE}(t)} \right)^{\sigma_I^Q} \cdot Q_I(t)$$

$$X_{IM}(t) = \delta_{IM}^Q \cdot (A_I^Q)^{\sigma_I^Q - 1} \cdot \left( \frac{P_I(t)}{P_{IM}(t)} \right)^{\sigma_I^Q} \cdot Q_I(t)$$

where the demand for energy bundle  $X_{IE}(t)$  and materials bundle  $X_{IM}(t)$  is further disaggregated into each energy commodities  $X_{ij}^E(t)$   $j=1,...,5$  and material commodities  $X_{ij}^M(t)$   $j=6,...,12$ :

$$X_{ij}^E(t) = \delta_{ij}^E \cdot (A_I^E)^{\sigma_I^E - 1} \cdot \left( \frac{P_{IE}(t)}{P_{ij}^E(t)} \right)^{\sigma_I^E} \cdot X_{IE}(t)$$

$$X_{ij}^M(t) = \delta_{ij}^M \cdot (A_I^M)^{\sigma_I^M - 1} \cdot \left( \frac{P_{IM}(t)}{P_{ij}^M(t)} \right)^{\sigma_I^M} \cdot X_{IM}(t)$$

### 3.B.4 R&D good producing sector

The structure of production technology in R&D sector is to produce R&D goods by combining energy and material bundles according to a two-tier nested CES function.

$$Q_R = A_R^Q \cdot \left[ \sum_{j=E,M} (\delta_{Rj}^Q)^{\frac{1}{\sigma_R^Q}} \cdot (X_{Rj})^{\frac{\sigma_R^Q - 1}{\sigma_R^Q}} \right]^{\frac{\sigma_R^Q}{\sigma_R^Q - 1}}$$

$$X_{RE} = A_R^E \cdot \left[ \sum_{j=1,...,5} (\delta_{Rj}^E)^{\frac{1}{\sigma_R^E}} \cdot (X_{Rj}^E)^{\frac{\sigma_R^E - 1}{\sigma_R^E}} \right]^{\frac{\sigma_R^E}{\sigma_R^E - 1}}$$

$$X_{RM} = A_R^M \cdot \left[ \sum_{j=6,...,12} (\delta_{Rj}^M)^{\frac{1}{\sigma_R^M}} \cdot (X_{Rj}^M)^{\frac{\sigma_R^M - 1}{\sigma_R^M}} \right]^{\frac{\sigma_R^M}{\sigma_R^M - 1}}$$

By the principle of duality, the dual cost function can be expressed as follows:

$$P_R = (A_R^Q)^{-1} \cdot \left[ \sum_{j=E,M} \delta_{Rj}^Q \cdot (P_{Rj})^{1 - \sigma_R^Q} \right]^{\frac{1}{1 - \sigma_R^Q}}$$

$$P_{RE} = (A_R^E)^{-1} \cdot \left[ \sum_{j=1,...,5} \delta_{Rj}^E \cdot (P_{Rj}^E)^{1 - \sigma_R^E} \right]^{\frac{1}{1 - \sigma_R^E}}$$

$$P_{RM} = (A_R^M)^{-1} \cdot \left[ \sum_{j=6,...,12} \delta_{Rj}^M \cdot (P_{Rj}^M)^{1 - \sigma_R^M} \right]^{\frac{1}{1 - \sigma_R^M}}$$

where  $Q_R, P_R$  are the quantity and price of produced R&D good,  $\mathbf{X}_R = [X_{IE}, X_{IM}]$ ,  $\mathbf{P}_R = [P_{IE}, P_{IM}]$  are quantity and price of capital service, labor, energy and materials used in R&D sector.  $X_{Rj}^E, P_{Rj}^E$  are the quantity and price of energy commodities,  $X_{Rj}^M, P_{Rj}^M$  are the quantity and price of material commodities.

For R&D sectors, the producer problem is specified as follows:

$$\max \Pi_R(t) = P_R(t) \cdot Q_R(t) - P_{RE}(t) \cdot X_{RE}(t) - P_{RM}(t) \cdot X_{RM}(t)$$

where the firm's objective is to optimally choose the inputs of energy bundle  $X_{RE}$  and materials bundle  $X_{RM}$  for maximizing its current profit flows  $\Pi_R$ . Solving this top-tier static maximization problem can determine the demands for the inputs of energy and materials bundles. We further solve a cost minimization problem at energy and material tier, and characterize the demand for each individual energy and material commodities. The optimal level of demand for energy bundles and materials bundles are characterized as :

$$X_{RE}(t) = \delta_{RE}^Q \cdot (A_R^Q)^{\sigma_R^Q - 1} \cdot \left( \frac{P_R(t)}{P_{RE}(t)} \right)^{\sigma_R^Q} \cdot Q_R(t)$$

$$X_{RM}(t) = \delta_{RM}^Q \cdot (A_R^Q)^{\sigma_R^Q - 1} \cdot \left( \frac{P_R(t)}{P_{RM}(t)} \right)^{\sigma_R^Q} \cdot Q_R(t)$$

where the demand for energy  $X_{RE}(t)$  and materials bundle  $X_{RM}(t)$  is disaggregated into each energy good  $X_{Rj}^E$   $j = 1, \dots, 5$  and material good  $X_{Rj}^M$   $j = 6, \dots, 12$ :

$$X_{Rj}^E(t) = \delta_{Rj}^E \cdot (A_R^E)^{\sigma_R^E - 1} \cdot \left( \frac{P_{RE}(t)}{P_{Rj}^E(t)} \right)^{\sigma_R^E} \cdot X_{RE}(t)$$

$$X_{Rj}^M(t) = \delta_{Rj}^M \cdot (A_R^M)^{\sigma_R^M - 1} \cdot \left( \frac{P_{RM}(t)}{P_{Rj}^M(t)} \right)^{\sigma_R^M} \cdot X_{RM}(t)$$

### 3.B.5 Government

Government behavior is normally constrained by a specific budgetary regime, which is represented by a certain well-defined fiscal target. The target of the Chinese government is to ensure a balanced budget with public revenue neutrality (NBS, 2010). Thus, our model specifies the government behavior as follows: it collects the revenue of tax imposed on corporate profit, household income and fossil energy use to finance public expenditure and subsidies on private investment and R&D:

$$G(t) = T_Q(t) + T_W(t) + T_C(t) - T_I(t) - T_R(t)$$

where  $G$  is aggregate government expenditure for the current use of goods and services. This aggregate spending is then allocated among individual energy and material goods according to historical spending shares. Tax revenue is collected from corporate profit  $T_Q$ , household income  $T_W$  and carbon emissions  $T_C$ .  $T_I, T_R$  denote government spending on subsidizing private investment and R&D, respectively. The government budget constraint is hereby determined by endogenous economic activities of private agents and exogenous tax rates setting.

According to historical spending shares, aggregate government expenditure is allocated among individual commodities, and yield government demands for each energy good  $X_{Gj}^E(t)$   $j=1,...,5$  and material good  $X_{Gj}^M(t)$   $j=6,...,12$ :

$$\begin{aligned} X_{Gj}^E(t) &= \frac{G_j^E(0)}{G(0)} \cdot G(t) \quad j=1,...,5 \\ X_{Gj}^M(t) &= \frac{G_j^M(0)}{G(0)} \cdot G(t) \quad j=6,...,12 \end{aligned}$$

where  $G(0), G_j^E(0), G_j^M(0)$  denote the initial period government aggregate spending, spending on energy goods and spending on material goods, respectively.

### 3.B.6 International Trade

We model international trade flows in line with the Armington structure: a commodity produced domestically is an imperfect substitute for the imported goods. For any given good, the domestically-produced output is combined with the imports to create a CES Armington composite of that commodity.

$$Y_i(t) = \left[ Q_i(t)^{\frac{\sigma_i^Y - 1}{\sigma_i^Y}} + M_i(t)^{\frac{\sigma_i^Y - 1}{\sigma_i^Y}} \right]^{\frac{\sigma_i^Y}{\sigma_i^Y - 1}}$$

where  $Y_i$  denote the total supply of Armington composite good  $i$  as a CES aggregate of domestically-produced output  $Q_i$  and import  $M_i$  that is set exogenously. Total supplies of that Armington commodity are used to clear the demands by intermediate production and final use. The export is modeled by allocating each Armington commodity between domestic and export markets via a constant elasticity of transformation (CET) assumption.

$$X_{Xi}(t) = \left( P_i(t) \right)^{\sigma^{CET}} \cdot Y_i(t)$$

where the export  $X_{Xi}$  is modeled by allocating Armington composite  $Y_i$  to export market

according to its product price  $P_i$  and CET parameter  $\sigma^{\text{CET}}$ .

### 3.B.7 Market clearing condition

- Market clear condition for each individual commodity  $j$  ( $j=1,\dots,12$ )

$$Y_j(t) = \sum_i X_{ij}(t) + X_{Cj}(t) + X_{Ij}(t) + X_{Rj}(t) + X_{Gj}(t) + X_{Xj}(t)$$

where the LHS denotes the total supply of Armington goods  $j$  ( $j=1,\dots,12$ ), which is used to satisfy the RHS demand by production, consumption, investment, R&D, government and export. This market clearing condition thus pins down an equilibrium price of commodity  $j$ .

- Market clear condition for raw investment good

$$Q_I(t) = \sum_i I_i(t)$$

where the LHS denotes the total supply of raw investment good (the output produced by investment sector), which is used to satisfy the capital good demand by production sectors in the RHS. This market clearing condition pins down an equilibrium price of raw investment good.

- Market clear condition for raw R&D good

$$Q_R(t) = \sum_i R_i(t)$$

where the LHS denotes the total supply of raw R&D good (the output produced by R&D sector), which is used to satisfy the R&D good demand by production sectors in the RHS. This market clearing condition thus pins down an equilibrium price of raw R&D good.

- Market clear condition for labor

$$L^S(0) \cdot \exp(n_L \cdot t) = \sum_i X_{iL}(t)$$

where the representative household derives no felicity from leisure and inelastically supplies its labor endowment at a constant exponential rate of growth  $n_L$ , with initial period labor endowment  $L^S(0)$ . The demand side is determined by labor employment in production sectors. Equilibrium closure requires full employment and labor market clearing, which pins down the equilibrium labor wage.

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