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### Abstract

This paper examines the effect of globalization, particularly international technology diffusion (TD), on China's domestic carbon savings. Building on a multi-region numerical model, this study considers both indigenous R&D and foreign TD as two sources of endogenous TC for domestic carbon savings. The model systematically describes foreign TD through three diffusion channels of trade, foreign direct investment (FDI) and disembodied spillovers, with an elaborate treatment on local knowledge absorptive capacity. Simulation results show that: (1) Foreign TD complements China's indigenous R&D to help reduce domestic carbon emissions, with the leading diffusion channel being disembodied spillovers in the short run and embodied diffusion (via import and FDI) in the long run; (2) Trade and FDI liberalization (economic globalization) facilitates economic integration and production growth, yet at the cost of higher emissions levels without carbon savings (scale effect); (3) Removal of foreign TD barriers (knowledge globalization) acquires the benefits of domestic carbon savings (technique effect); (4) Domestic climate regulation create the composition effect by inducing indigenous R&D and foreign TD to shift economic composition, hence helping partially mitigate climate compliance cost.

## **Keywords**

Globalization; International technology diffusion; Climate policy modelling

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# Can China Harness Globalization to Reap Carbon Savings? Modeling International Technology Diffusion in a Multi-region Framework\*

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**Abstract:** This paper examines the effect of globalization, particularly international technology diffusion (TD), on China's domestic carbon savings. Building on a multi-region numerical model, this study considers both indigenous R&D and foreign TD as two sources of endogenous TC for domestic carbon savings. The model systematically describes foreign TD through three diffusion channels of trade, foreign direct investment (FDI) and disembodied spillovers, with an elaborate treatment on local knowledge absorptive capacity. Simulation results show that: (1) Foreign TD complements China's indigenous R&D to help reduce domestic carbon emissions, with the leading diffusion channel being disembodied spillovers in the short run and embodied diffusion (via import and FDI) in the long run; (2) Trade and FDI liberalization (economic globalization) facilitates economic integration and production growth, yet at the cost of higher emissions levels without carbon savings (*scale effect*); (3) Removal of foreign TD barriers (knowledge globalization) acquires the benefits of domestic carbon savings (*technique effect*); (4) Domestic climate regulation create the *composition effect* by inducing indigenous R&D and foreign TD to shift economic composition, hence helping partially mitigate climate compliance cost.

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## 1. Introduction

In formulating prudent strategies to combat global warming, emissions from every corner of the world must be considered due to the global nature of climate stabilization (IEA, 2010; Stavins, 2011). Although most emission abatement obligations rest with the industrialized countries, it is likely that many low-cost mitigation opportunities exist in the developing world. In particular, the emerging economies call for international technology transfers to support indigenous efforts, so that the climate compliance cost can be mitigated (IPCC, 2000; World Bank, 2008; Popp, 2011).

While the traditional technology transfers paradigm (e.g., North-South Official Development Assistance programs) may be useful for climate negotiating agenda, it has become increasingly flawed due to a narrow conceptualization of the nature, size, scope and method of technology diffusion (TD). The paradigms emphasizing the role of government neglects the normal working of market force in the process of TD, which fundamentally brings about the current impasse of climate negotiations and slow progress of low-carbon technology transfers (Brewer, 2008; 2009).<sup>1</sup>

To break the impasse, there is a dire need for climate strategies to reorient the decentralized market and private sector as the key force to mobilize international TD. This pivot is particularly necessary in the current context of globalization. On the one hand, as the traditional aspect of globalization (production globalization), national economies are increasingly integrated into an interdependent world economy through multilateral trade and investment, the globalized network of production thus enables an extensive dissemination of technologies via cross-border transactions of material, capital, and products (UNCTAD, 2010a). On the other hand, as the modern aspect of globalization (innovation globalization), internationalization of R&D enhances a tendency for higher reliance of indigenous innovation on external knowledge sources, both developed and developing nations have leveraged the international heightened mobility of ideas for building domestic knowledge stock (OECD, 1997; UNCTAD, 2005).

Clearly, the globalization creates an opportunity of low-carbon TD and carbon savings for the world's largest carbon emitter - China. To decouple carbon emissions from economic growth, this nation has stepped up efforts to change its development pattern by boosting technological innovation (MOST, 2006). Albeit strong growths in indigenous R&D investment, China's indigenous innovation does not necessarily signal an abandonment of the "open door" policy.

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<sup>1</sup> Technology is at the hand of private sectors and can't be transferred at will by the government. As a result, the magnitudes of ODA programs remain quite small relative to private investments. FDI are on the order of hundreds of billions of dollars per year, as compared with total ODA flows on the order of hundreds of millions (World Bank, 2007; UNFCCC, 2007). Private financial contribution is essential for leveraging investments for a low-carbon economy, in view of huge public fiscal deficits worldwide (UNCTAD, 2010b).

Instead, China seeks to leverage the growing globalization to reinforce its innovative capacities. First, Beijing begins to attach the same importance to imports as exports in its foreign trade policy, with the purpose of importing foreign high-tech products and absorbing embodied technologies (WTO, 2010; IMF, 2011). Second, China's rapid expansion of higher education has reshaped global distribution of human capital, which fosters a transition of inward FDI into modern high-tech investment and hence a dispersion of technologies (UNCTAD, 2005). Thirdly, innovation globalization has created an international mobility of ideas through scientific papers, patent, technical conference, and academic networking. The worldwide spreads of disembodied pure knowledge thus favor technology learning and absorption by China (OECD, 1997).

Therefore, in such a context where China's integration into the globalized economy not only stimulates growth momentum but also provide an opportunity of knowledge diffusion, both of which have significant impacts on China's environmental performance. It is thus vital to explore the effect of globalization, particularly international TD, on China's carbon saving potential. In explicit, we aim to address the following issues: (1) what's the contribution of indigenous R&D and foreign TD to China's domestic carbon savings; (2) through which channels does China acquire foreign knowledge to complement indigenous innovation; (3) how knowledge absorptive capacity affect assimilation of foreign diffused technologies; (4) which policies can be designed to exploit the beneficial effect of globalization for domestic carbon savings; (5) can domestic climate regulations induce international knowledge inflows to help lower climate compliance costs.

To address these issues, we incorporate the mechanism of endogenous technical change (TC) into a multi-sector, multi-region CGE numerical model. The "stock of knowledge" approach is used to explicitly represent technology in the spirit of [Goulder and Schneider \(1999\)](#) and [Sue Wing \(2001\)](#).<sup>2</sup> To advance existing modeling literature that only consider indigenous innovation within a closed economy, we attempt to extend the single-country structure into a multi-region one, so that the mechanism of cross-nation knowledge diffusion can be explicitly examined. Such an effort is necessary, because with technology transfer placed high upon climate policy agenda, there is a pressing need for researchers to examine the potentials of international TD to facilitate low-carbon innovation. Modeling international TD thus becomes a fruitful avenue for future climate policy analysis ([Grubb et al., 2002](#); [Popp, 2006a](#); [Gillingham et al., 2008](#); [Popp et al., 2010b](#);

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<sup>2</sup> The explicit method of representing technology has theoretical origins in endogenous growth literature, which demonstrates the link between knowledge and technical progress ([Romer, 1990](#); [Aghion and Howitt, 1998](#); [Acemoglu, 2002, 2009](#)). Along this direction, this is a growing trend in climate policy analysis to model technology using the "stock of knowledge" approach (e.g., [Goulder and Schneider, 1999](#); [Nordhaus, 2002](#); [Buonanno et al., 2003](#); [Popp, 2004](#); [Sue Wing, 2006](#); [Löschel and Otto, 2009](#); [Acemoglu et al., 2009](#); [Jin, 2012](#)).

Hübler, 2011).<sup>3</sup>

To our knowledge, only a few studies exist that considers international TD in current climate policy modeling literature. Gerlagh and Kuik (2007) use the GTAP-E model to investigate a mechanism of technology spillovers through the transfers of price-induced energy-saving TC. Hübler (2011) develops a recursive-dynamic CGE model to examine a mechanism of international TD through FDI. Leimbach and Baumstark (2010) (also in Leimbach and Edenhofer (2007) and Leimbach and Eisenack (2009)) provides a multi-region framework to model TD embodied in foreign trade. Methodologically, these studies adopt the implicit (parametrical) approach to represent technology, where the mechanism of TD is described as productivity parameter growth as an outcome of underlying drivers (e.g., trade and FDI). In contrast, other studies choose the “stock of knowledge” approach to explicitly represent technology, where the mechanism of TD is described as the spillover of foreign knowledge into domestic knowledge stock. For example, Bosetti et al. (2008, 2011) explore the mechanism of disembodied knowledge spillovers that augments domestic knowledge assets. Buonanno et al. (2003) consider modeling a stock of global knowledge that generates international knowledge spillover into individual countries.

While providing insights into the TD mechanism, current modeling studies only capture one type of TD channel in isolation.<sup>4</sup> It is thus needed to develop a comprehensive framework that models various conduits of TD and their combined effect. To fill this gap, this paper contributes to climate policy modeling in the following ways: (1) An *innovation possibility frontier (IPF)* is specified to explicitly describe both indigenous R&D and international TD as the two sources of domestic knowledge creation; (2) A systematic framework is developed to capture international TD through the channels of trade, FDI and disembodied knowledge spillovers; (3) An elaborate treatment of knowledge absorptive capacity is provided to represent technology appropriateness (compatibility between foreign transferred technology and local technical condition).

The paper is organized as follows: Section 2 describes the modeling framework, with an emphasis on modeling international TD through various channels. Section 3 discusses model calibration and implementation. Simulation results and discussions are presented in Section 4. Section 5 concludes.

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<sup>3</sup> Most of existing literature focus on empirical evidences on environmentally friendly TD (e.g., Lanjouw and Mody, 1996; Popp, 2006b; Dechezleprêtre et al., 2008; Johnstone et al., 2010; Popp et al., 2010a; Lovely and Popp, 2011), but numerical modeling in this field are still not sufficient.

<sup>4</sup> As shown in empirical studies (e.g., Clerides et al., 1998; Keller, 2004), private firms do not merely conduct a single type of economic activity associated with TD, but perform several such activities simultaneously.

## 2. Model description

### 2.1 Basic framework

The basic framework is a multi-region, multi-sector intertemporal optimization CGE model.<sup>5</sup> It distinguishes six world countries/regions, including: China (CHN), USA, Japan (JPN), Western Europe (EUW), the rest of the industrialized countries (RIN), and the rest of the world (ROW).<sup>6</sup> Economic system in each region is represented by multiple agents, including: Twelve production sectors, an investment sector (producing physical capital goods), a R&D sector (producing R&D good), a representative household and a government. To be relevant to climate policy studies, the twelve production sectors consist of five energy sectors and seven non-energy sectors.<sup>7</sup> Carbon emissions are calculated based on carbon intensities of fossil fuel inputs (coal, oil and natural gas) used in intermediate production and final use.

In the spirit of the G-Cubed model (McKibbin and Wilcoxon, 1999),<sup>8</sup> our modeling framework describes economic behaviors of multiple agents within the general equilibrium structure, which outlines input-output (IO) circular flows of multiple commodities and primary factors within the economy (see Fig. 1). There are 12 produced commodities and corresponding production sectors, indexed by the row subscript  $j$  ( $j=1,2,\dots,12$ ) and the column subscript  $i$  ( $i=1,2,\dots,12$ ), respectively; 3 types of primary factors (labor, physical capital, knowledge capital), indexed by the subscript  $f$  ( $f=L,K,H$ ); 5 types of final use (consumption, investment, R&D, government, export), indexed by the subscript  $d$  ( $d=C,I,R,G,X$ ). Intersectoral transactions in intermediate productions are represented by the  $j \times i$  matrix; Inputs of primary factors in production are indicated by the  $f \times i$  matrix; Final uses of produced commodities are represented by the  $j \times d$  matrix.

From this IO framework to a CGE model, we describe decision problems facing these agents and characterize their economic behaviors and the decentralized equilibrium condition. To endogenously represent TC, our model broadens the traditional CGE framework by adding R&D

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<sup>5</sup> As compared to the recursive-dynamic models, intertemporal optimization CGE models endogenously determine the behavior of forward-looking agents, with their current decisions depending on expectation about future economic conditions (Jorgenson and Wilcoxon, 1990; Bovenberg and Goulder, 1996; McKibbin and Wilcoxon, 1998; Dixon et al., 2005).

<sup>6</sup> For the country composition of each world region, see Appendix A.

<sup>7</sup> For the model sectoral classification and mapping by reference to the GTAP, see Appendix B.

<sup>8</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; the neoclassical optimizing and liquidity-constrained behavior of consumers; imperfect capital mobility and structural adjustment costs; intertemporal equilibrium with rational expectation.

investment and knowledge input. This will be articulated in the following sections.

## 2.2 Endogenous technical change

In the spirit of [Goulder and Schneider \(1999\)](#) and [Sue Wing \(2001\)](#), our study adopts the “stock of knowledge” method to explicitly represent technology, because TC *per se* is a reconfiguration of production factors as a result of applying new knowledge (e.g., technique know-how, managerial skills) in production. A representation of knowledge as a production input can thus give insights into its effect on production TC. In explicit, knowledge is treated as an accumulated stock of economically useful asset which is augmented by indigenous R&D and foreign TD. The accumulated knowledge stocks are then applied in production to facilitate a reconfiguration of production inputs for productivity growth (the rate of production TC). Simultaneously, the use of intangible knowledge inputs leads to a substitution for physical inputs such as labor, energy and materials (the bias of production TC).

To model this mechanism, we represent the production technology as a separable KLEM-H nested CES function. As shown in [Fig. 2](#), for a given sector  $i$  producing output  $Q_i$ ,<sup>9</sup> knowledge capital  $H_i$  substitutes for the composite of physical inputs  $Z_i$ , which is in turn made up of primary factor inputs of physical capital  $K_i$  and labor  $X_{iL}$ , as well as 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 each individual sector  $i$  is formulated as:

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

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

$$\dot{K}_i(t) = J_i(t) - \delta_K \cdot K_i(t) \quad (3)$$

$$I_i(t) = \varphi_i [J_i(t), K_i(t)] = J_i(t) \cdot \left[1 + \frac{\psi}{2} \cdot \frac{J_i(t)}{K_i(t)}\right] \quad (4)$$

$$\dot{H}_i(t) = \hbar [R_i(t), H_i(t), R_i'(t)] \quad (5)$$

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

<sup>9</sup> To keep our notation simple as possible, we have not subscripted variables by country notation.



streams  $V_i$ , subject to the technology constraints. In Eq. (1),  $V_i$  is formulated as a discounted present value of future profit streams from time  $t$  to an infinite future, with real interest rate  $r$  as discounting factor. In Eq. (2), current profit flow  $\Pi_i$  equals output revenues minus input costs, with  $\tau_Q, \tau_C, \tau_I, \tau_R$  being corporate income tax, carbon tax on fossil energy inputs, investment tax credit and R&D tax credit, respectively.

Eq. (3) specifies the law of motion for physical capital stock  $K_i$ , its accumulation depends on fixed capital investment  $J_i$  and the rate of capital depreciation  $\delta_K$ . Eq. (4) models the capital investment process that is subject to imperfect capital mobility and investment adjustment cost (Goulder and Schneider, 1999; McKibbin and Wilcoxon, 1999).<sup>10</sup>

Eq. (5) is the *IPF* describing the process of knowledge creation, where the accumulation of domestic knowledge stock  $\dot{H}_i$  depends on indigenous R&D  $R_i$ , existing knowledge stocks  $H_i$  and international TD  $R_i^*$ . As illustrated in Fig. 3, in modeling the pattern of international TD we only consider unidirectional R&D spillovers from technologically advanced countries to China.<sup>11</sup> Accordingly, we assume that TC in each foreign country is driven by indigenous R&D, with the *IPF* degenerated as  $\dot{H}_i(t) = \hbar[R_i(t), H_i(t)]$  without international TD  $R_i^*$ .<sup>12</sup> In contrast, TC in China depends on both indigenous R&D and foreign TD, with its *IPF* remained as Eq. (5).<sup>13</sup> Before explicitly represent the *IPF* in Section 2.5, we will examine the two sources of endogenous TC - indigenous R&D (in Section 2.3) and international TD (in Section 2.4), to which we now turn.

### 2.3 Indigenous R&D investment

To capture indigenous innovation, we solve the producer problem outlined in Eqs. (1)-(5), and characterize the behavior of indigenous R&D investments as follows:

$$(1 - \tau_R) \cdot P_{iR}(t) = \lambda_{iH}(t) \cdot \frac{\partial \hbar[R_i(t), H_i(t), R_i^*(t)]}{\partial R_i(t)} \quad (6)$$

<sup>10</sup> In explicit, to install  $J_i$  unit of capital, a firm must buy a larger amount of raw investment goods  $I_i$  that depends on the rate of investment  $J_i/K_i$  and investment adjustment cost coefficient  $\psi$ .

<sup>11</sup> For the sake of model tractability, we surpass multidirectional knowledge spillovers and interaction which may involves computing a Nash Equilibrium. For example, see Leimbach and Baumstark (2010).

<sup>12</sup> This is according to the path dependence of innovation in technologically advanced nations, where technological progress tends to move along independent path with innovation pattern embedded in local specific socio-technological circumstances (Rosenberg, 1994; Bosetti et al., 2008; Acemoglu, 2009).

<sup>13</sup> Due to a backward position in global technology ladder, innovations in developing countries can largely benefit from their knowledge gap relative to technologically advanced countries and knowledge diffusion (Gerschenkron, 1962; Acemoglu, 2009).

$$\frac{\lambda_{iH}(t) + (1 - \tau_Q) \cdot P_i(t) \cdot \frac{\partial Q_i(t)}{\partial H_i(t)} + \frac{\partial h[R_i(t), H_i(t), R_i^*(t)]}{\partial H_i(t)}}{\lambda_{iH}(t)} = r(t) \quad (7)$$

where Eq. (6) is the optimality condition of indigenous R&D investment  $R_i$ , instructing R&D investment of private firms to reach an equilibrium level where marginal cost (LHS) is equal to marginal benefit (RHS). The marginal cost comes from expenditures on purchasing an extra unit of R&D goods. The marginal benefit involves the shadow price of knowledge capitals  $\lambda_{iH}$  and innovation possibility gain.<sup>14</sup> In particular, the innovation possibility gains from R&D investment can be harvested from two sources: Indigenous R&D not only create in-house knowledge, but also enhance indigenous capacity to assimilate international knowledge diffusion – the dual faces of R&D in innovation (Cohen and Levinthal, 1989; Keller, 1996; Griffith et al., 2000).

Similarly, Eq. (7) provides an intertemporal arbitrage condition of knowledge accumulation, which instructs marginal cost (RHS) to equal marginal benefit (LHS). The RHS is the real interest rate as an 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 more existing knowledge stocks.

## 2.4 International technology diffusion

Drawing on the insights of Griliches (1979) on two types of R&D spillovers, our model identifies two principal mechanisms of foreign TD: 1) Embodied knowledge diffusion through indirectly employing knowledge-embodied intermediate and capital goods; 2) Disembodied knowledge diffusion through directly learning disembodied knowledge spillover.

Embodied knowledge diffusion occurs when domestic firms indirectly benefit from external innovation by using knowledge-embodied foreign intermediate commodity (via import) or capital goods (via FDI). Embodied TD has its theoretical and empirical origins in the work by Coe and Helpman (1995), indicating that international TD should be embodied in the flows of physical commodity transactions through the channels of international trade and investment.

In parallel, disembodied knowledge diffusion involves direct learning and absorption of the disembodied forms of technologies (e.g., formulas, blueprints, patents), not necessarily linking to economic transactions of tangible physical goods. Disembodied TD is rooted in the seminal works by Rivera-Batiz and Romer (1991) that suggests the key role of disembodied knowledge

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<sup>14</sup> The shadow price of knowledge capital is determined according to the “Tobin’s-q” investment theory, with the shadow price denoting the increments to the equity value of the firm from investing an additional unit of capital (Tobin, 1969; Summers, 1981; Goulder and Schneider, 1999; McKibbin and Wilcoxon, 1999).

spillover externality in the process of international TD.

To describe both TD mechanisms, [Sections 2.4.1-2.4.3](#) provide a comprehensive framework to model three channels of TD, including: TD embodied in trade, TD embodied in FDI, and disembodied TD. Moreover, while knowledge can diffuse from abroad through these three channels, the efficiencies of assimilating diffused knowledge by the recipient countries are determined by local knowledge absorptive capacity, which will be considered in [Sections 2.4.4](#).

### 2.4.1 Technology diffusion embodied in trade

TD embodied in trade refers to the mechanism where domestic firms benefit from external knowledge by using knowledge-embodied foreign intermediate commodity via import.<sup>15</sup> In other words, if we think of commodity import as a vehicle of TD, then foreign knowledge is embodied in intermediate commodity imports, with the embodied knowledge being assimilated by the recipient country for knowledge accumulation. To describe this mechanism, we model China's import flows in line with the Armington structure, with the Armington composite of intermediate commodity being modeled as a CES aggregate of domestically-produced and imported component of that commodity as:

$$X_{i,j}(t) = \left[ X_{i,j}^D(t)^{\frac{\sigma_j^T - 1}{\sigma_j^T}} + X_{i,j}^T(t)^{\frac{\sigma_j^T - 1}{\sigma_j^T}} \right]^{\frac{\sigma_j^T}{\sigma_j^T - 1}} \quad (8)$$

where  $X_{i,j}$  is the composite of intermediate input commodity  $j$  used in China's sector  $i$ .  $X_{i,j}^D, X_{i,j}^T$  are domestically-produced and imported component of that intermediate goods, respectively. Substitution between domestic and import component is governed by the Armington elasticity  $\sigma_j^T$ . Within our multi-country model that distinguishes China's multiple trading partners, the imported component of that intermediate input is further modeled as a CES composite of imports from all foreign source countries as:

$$X_{i,j}^T(t) = \left[ \sum_r X_{i,j,r}^T(t)^{\frac{\sigma_j^{TT} - 1}{\sigma_j^{TT}}} \right]^{\frac{\sigma_j^{TT}}{\sigma_j^{TT} - 1}} \quad (9)$$

where  $X_{i,j,r}^T$  is the import of intermediate input commodity  $j$  into China's sector  $i$  from foreign

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<sup>15</sup> Empirical evidences of this TD pattern is recorded in the pioneering work by [Coe and Helpman \(1995\)](#) who found a statistically significant effect of bilateral trade on international TD. Other empirical studies also find the significant and positive link between a country's factor productivity and knowledge created by its trading partners (e.g., [Coe et al., 1997](#); [Keller, 1998](#); [Xu and Wang, 1999](#); [Pavcnik, 2002](#); [Madsen, 2007](#); [Eaton and Kortum, 2001, 2002](#); [Amiti and Konings, 2007](#); [Acharya and Keller, 2009](#)).

country  $r$ . Substitution among foreign countries is governed by the CES elasticity  $\sigma_j^{TT}$ .

By solving the producer problem, we can characterize China's import of intermediate input commodity from each foreign source country ( $X_{i,j,r}^T$ ) as:

$$X_{i,j,r}^T(t) = \left[ \frac{P_j^T(t)}{P_{j,r}(t) \cdot (1 + \tau_j^T)} \right]^{\sigma_j^{TT}} \cdot X_{i,j}^T(t) = \left[ \frac{P_j^T(t)}{P_{j,r}(t) \cdot (1 + \tau_j^T)} \right]^{\sigma_j^{TT}} \cdot \left[ \frac{P_j(t)}{P_j^T(t)} \right]^{\sigma_j^T} \cdot X_{i,j}(t) \quad (10)$$

where  $P_j$  is China's market price of intermediate goods composite  $j$ .  $P_j^T$  is ideal price index of imported component of intermediate goods  $j$ .  $P_{j,r}$  is the price of intermediate goods  $j$  supplied by foreign country  $r$ .  $\tau_j^T$  is the rate of import tariff imposed on commodity  $j$ .  $P_{j,r} \cdot (1 + \tau_j^T)$  is China's import price of commodity  $j$  from the foreign country  $r$ .

As mentioned above, both import flows and knowledge embodiment intensity determine the amount of knowledge diffused through trade. So far Eq. (10) has estimated the imports of intermediate input goods from foreign exporting countries into China. We further introduce the other factor: intensity of knowledge embodied in imports, which denotes the amount of knowledge that is embodied in each unit of import flows. In line with the embodied technology hypothesis, this intensity can be estimated as:<sup>16</sup>

$$RI_{j,r}^T(t) = \theta^T \cdot \frac{R_{j,r}(t)}{Y_{j,r}(t)} \quad (11)$$

where  $RI_{j,r}^T$  denotes the intensity of knowledge embodied in intermediate goods  $j$  imported from foreign country  $r$ . This intensity is measured as a ratio between R&D expenditure ( $R_{j,r}$ ) and production output ( $Y_{j,r}$ ) in foreign exporting country  $r$ .  $\theta^T$  is an exogenous parameter that indicates foreign barriers of exporting knowledge-intensive goods to China.<sup>17</sup>

Given the two determinants to TD through trade, we can model the diffusion of knowledge embodied in trade as a product of import flows ( $X_{i,j,r}^T$ ) and embodied knowledge intensity ( $RI_{j,r}^T$ ) as:

$$R_{i,j,r}^T(t) = X_{i,j,r}^T(t) \cdot RI_{j,r}^T(t) \quad (12)$$

<sup>16</sup> "Embodied technology hypothesis" claims that intangible knowledge has to be embodied in specific tangible physical products in order to embody their economically useful characteristics (Schmookler, 1966; Terleckyj, 1974; Scherer, 1982; Papaconstantinou et al., 1998; Hauknes and Knell, 2009).

<sup>17</sup> We introduce this parameter for the purpose of undertaking policy experiments (e.g., easing technology transfer restriction) in knowledge globalization scenario in Section 4, where policy shock raises the value of this exogenous parameter.

where  $R_{i,j,r}^T$  denotes knowledge embodied in import of intermediate commodity  $j$  from foreign country  $r$  into China's sector  $i$ . Next, we estimate the total amount of knowledge embodied in import flows as follows:

$$R_i^T(t) = \sum_j R_{i,j}^T(t) = \sum_j \sum_r R_{i,j,r}^T(t) \quad (13)$$

where, by summing over foreign countries  $r$  and intermediate input varieties  $j$ , we estimate the total amount of knowledge embodied in imports into China's sector  $i$  ( $R_i^T$ ). Once diffusing into the recipient country via the channel of import, the embodied knowledge  $R_i^T$  can be assimilated for domestic knowledge accumulation, which will be described by the *IPF* in [Section 2.5](#).

#### 2.4.2 Technology diffusion embodied in FDI

TD embodied in FDI refers to the mechanism where domestic firms benefit from external knowledge by using knowledge-embodied foreign capital goods via FDI. In this sense, if we think of FDI as a vehicle of TD, then foreign knowledge is embodied in foreign invested capital, with the embodied knowledge absorbed by the recipient country for knowledge accumulation.<sup>18</sup> To describe this mechanism, we assume that capitals installed by domestic and foreign investors are imperfect substitutes in physical capital formation ([Markusen, 2002](#); [Lejour et al., 2008](#)). The physical capitals invested in China are thus modeled as a CES aggregate of domestic and foreign components of that capital goods as:

$$I_i(t) = \left[ I_i^D(t)^{\frac{\sigma_i^F - 1}{\sigma_i^F}} + I_i^F(t)^{\frac{\sigma_i^F - 1}{\sigma_i^F}} \right]^{\frac{\sigma_i^F}{\sigma_i^F - 1}} \quad (14)$$

where  $I_i$  is the composite of capital goods invested in China's sector  $i$ .  $I_i^D, I_i^F$  are the domestic and foreign component of that capital good composite, respectively. Substitution between these two components is governed by the CES elasticity  $\sigma_i^F$ , indicating joint venture requirements on foreign investments entry. Within the multi-region model that distinguishes multiple FDI sources, the component of foreign-invested capital is further modeled as a CES composite of FDI from all foreign countries:

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<sup>18</sup> Empirical evidence for this kind of TD is recorded in the work by [Blomström and Persson \(1983\)](#) who found a statistically significant influence of FDI inflows on international TD. Other empirical studies also suggest that host countries benefit from knowledge diffused from MNC foreign affiliates, with FDI being a robust diffusion channel (e.g., [Haddad and Harrison, 1993](#); [Aitken and Harrison, 1999](#); [Keller and Yeaple, 2009](#); [Rodriguez-Clare, 1996](#); [Blomström and Kokko, 1998](#); [Javorcik, 2004](#); [Lin and Saggi, 2007](#); [Haskel et al., 2007](#); [Blalock and Gertler, 2008](#)).

$$I_i^F(t) = \left[ \sum_r I_{i,r}^F(t) \frac{\sigma_i^{FF}-1}{\sigma_i^{FF}} \right]^{\frac{\sigma_i^{FF}}{\sigma_i^{FF}-1}} \quad (15)$$

where  $I_{i,r}^F$  is the FDI inflows into China's sector  $i$  from foreign country  $r$ . Substitution between foreign countries is governed by the CES elasticity ( $\sigma_i^{FF}$ ).

By solving the producer problem, we can characterize the level of FDI by each foreign source country ( $I_{i,r}^F$ ) as: <sup>19</sup>

$$I_{i,r}^F(t) = \left[ \frac{P_i^F(t)}{P_{1,r}(t) \cdot (1 + \tau_1^F)} \right]^{\sigma_i^{FF}} \cdot I_i^F(t) = \left[ \frac{P_i^F(t)}{P_{1,r}(t) \cdot (1 + \tau_1^F)} \right]^{\sigma_i^{FF}} \cdot \left[ \frac{P_i(t)}{P_1^F(t)} \right]^{\sigma_i^F} \cdot I_i(t) \quad (16)$$

where  $P_i$  is China's market price of capital good composite.  $P_i^F$  is ideal price index of FDI composite.  $P_{1,r}$  is the price of capital goods invested by foreign country  $r$ .  $\tau_1^F$  is the rate of preferable tax (fiscal incentive) offered to MNC affiliates for FDI.  $P_{1,r}(t) \cdot (1 + \tau_1^F)$  is the after-tax price of capital goods invested by foreign country  $r$ .<sup>20</sup>

As mentioned previously, both the level of FDI and knowledge embodiment intensity determine the amount of knowledge diffusion through FDI. So far the level of inward FDI has been estimated by Eq. (16), we further model the knowledge intensity of FDI (the amount of knowledge embodied in each unit of FDI inflows) as follows:

$$RI_{i,r}^F(t) = \theta^F \cdot \frac{R_{i,r}(t)}{Y_{i,r}(t)} \quad (17)$$

where  $RI_{i,r}^F$  denotes the intensity of knowledge embodied in capital goods invested by foreign country  $r$ , measured as a ratio between R&D expenditure ( $R_{i,r}$ ) and production output ( $Y_{i,r}$ ) in foreign country  $r$ .  $\theta^F$  is an exogenous parameter, representing foreign barrier of FDI outflows.

Given the two determinants to TD through FDI, we can model the diffusion of knowledge embodied in FDI as a product of FDI inflows ( $I_{i,r}^F$ ) and embodied knowledge intensity ( $RI_{i,r}^F$ ) as:

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<sup>19</sup> The levels of capital investment are determined according to the Tobin's-q theory, where the levels of FDI are expressed as a function of output size of the sector where foreign capitals are installed. Such a specification reflects one of the incentives of FDI: market size and economic fundamentals in host country. It attracts market-seeking MNC to exploit the economics of scales (Blomström and Kokko, 2003; Blonigen, 2005).

<sup>20</sup> Such a specification reflects the other incentive of FDI: favorable FDI tax. It is set to lower the cost of installing foreign capital goods, thus facilitating physical capital formation in the recipient countries (Blomström and Kokko, 2003; UNCTAD, 2005).

$$R_{i,r}^F(t) = I_{i,r}^F(t) \cdot RI_{i,r}^F(t) \quad (18)$$

where  $R_{i,r}^F$  denotes knowledge embodied in FDI inflows into China's sector  $i$  from foreign country  $r$ . By summing over foreign countries  $r$ , we estimate knowledge embodied in FDI as:

$$R_i^F(t) = \sum_r R_{i,r}^F(t) \quad (19)$$

where  $R_i^F$  denotes the total amount of knowledge embodied in FDI inflow into China's sector  $i$ . Once diffusing into China via the channel of FDI, the embodied knowledge  $R_i^F$  can be absorbed for domestic knowledge accumulation, which will be described by the *IPF* in [Section 2.5](#).

### 2.4.3 Disembodied technology diffusion

Disembodied TD occurs when disembodied pure knowledge (as a public good) spill over from technology frontier countries to the laggards due to imperfect appropriability of knowledge, which does not necessarily link to the economic transactions of physical goods. Learning and absorption of disembodied knowledge thus favors innovation in places different from where originally created ([Romer, 1990](#); [Rivera-Batiz and Romer, 1991](#); [Jaffe and Trajtenberg, 1998](#); [Eaton and Kortum, 1999](#); [Lee, 2006](#)).

In this context, we draw on the insights of [Bosetti et al. \(2008\)](#), and postulates that China is exposed to an international knowledge pool created by technology frontier countries. On the one hand, due to heterogeneous nature of knowledge created by individual technologically advanced countries,<sup>21</sup> their aggregate knowledge constitutes the global pool of disembodied knowledge. On the other hand, because of a backward position in global technology ladder,<sup>22</sup> the knowledge gap of technologically backward country relative to advanced nations creates the disembodied knowledge pool that can be absorbed by China. Thus, the disembodied knowledge that may spill over to China can be modeled as

$$R_i^D(t) = \theta^D \cdot \sum_r R_{i,r}(t) - R_i(t) \quad (20)$$

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<sup>21</sup> This coincides with the path dependence of innovation. TC within technological advanced country tends to follow a specific path that is embedded in local socio-technological context, generating differentiated and heterogeneous technologies ([Nelson, 1993](#); [Rosenberg, 1994](#)). For example, U.S. has competitive advantage in coal gasification technology, E.U in renewable energy, Japan in energy efficiency equipments.

<sup>22</sup> This view was put forward by [Gerschenkron \(1962\)](#) in his seminal work *Economic Backwardness in Historical Perspective*, arguing that TC is a process where all countries move upwards along a technology ladder, with the innovator at the top and the laggards at the bottom. By adopting frontier technologies, the backward countries can catch up with the advanced countries at a relatively rapid pace ([Acemoglu, 2009](#)).

where  $\sum_r R_{i,r}$  is the aggregate of foreign R&D investment specific to sector  $i$ , summing over all foreign countries  $r$ .  $R_i$  is China's indigenous R&D investment in that sector. The R&D gap thus constitutes foreign disembodied knowledge that may spill over to China.  $\theta^D$  is an exogenous parameter indicating the externality of disembodied knowledge spillovers, of which the value is regulated by patent policy in foreign countries. Once spilling over to China, the disembodied knowledge  $R_i^D$  can be absorbed for domestic knowledge creation, which will be described by the *IPF* in [Section 2.5](#).

#### 2.4.4 Knowledge absorptive capacity

So far we have captured all three channels of international TD, the diffused knowledge, however, are not the "manna from heaven" that indiscriminately falls on the host country, only a fraction can be effectively absorbed according to local socio-technological circumstance.<sup>23</sup> The benefits of knowledge diffusion can be realized only if the recipient country builds indigenous capacity of knowledge absorption.

Accordingly, we distinguish two factors that influence knowledge absorptive capacity. 1) Indigenous R&D: host countries need to undertake R&D investment to enhance indigenous capacity to absorb foreign diffused technologies ([Cohen and Levinthal, 1989](#); [Keller, 2004](#); [Bosetti et al., 2008](#)); 2) Structural characteristics: host countries also need to improve structural characteristics (e.g., R&D intensity) of production technology, so that a match can be achieved between transferred technologies and local technical sophistication levels ([Atkinson and Stiglitz, 1969](#); [Basu and Weil, 1998](#); [Acemoglu, 2009](#)). To represent these two factors, we model the knowledge absorptive capacity as:

$$\gamma_i(t) = \gamma_i^{RD}(t) \cdot \gamma_i^{SS}(t) = \frac{R_i(t)}{\sum_r R_{i,r}(t)} \cdot \exp\left[-\left|\frac{d_i(t) - \bar{d}_i(t)}{d_i(0) - \bar{d}_i(0)}\right|\right] \quad (21)$$

where, for any given sector  $i$ , knowledge absorptive capacity  $\gamma_i$  is expressed as a product of indigenous R&D index  $\gamma_i^{RD}$  and structural characteristics index  $\gamma_i^{SS}$ , implying their complementary roles in affecting knowledge absorptive capacity.  $\gamma_i^{RD}$  is modeled as a ratio of China's indigenous R&D to foreign R&D totals, indicating China's technological distance relative

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<sup>23</sup> This "localness" is reflected by the mismatch between transferred technology and locality in developing countries. For an articulation on the inappropriateness of technologies and its effect on productivity difference across nations, see [Acemoglu \(2009\)](#).



to global technology frontier.<sup>24</sup> In specifying  $\gamma_i^{SS}$ , R&D intensity (R&D to output ratio) is used to indicate the structural characteristics of production technology.<sup>25</sup>  $d_i(t)$  is R&D intensity specific to China's sector  $i$  at period  $t$ , and  $\bar{d}_i(t)$  is the average of R&D intensity among foreign advanced countries  $\bar{d}_i(t) = (1/N) \cdot \sum_{r=1}^N d_{i,r}(t)$ .  $d_i(0) - \bar{d}_i(0)$  is structural difference in production technology between China and foreign countries at initial period. The exponential function scales the structural difference on a unit interval index.<sup>26</sup>

## 2.5 Synthesis of innovation possibility frontier

Having examined both indigenous innovation and international TD in [Sections 2.3-2.4](#), we now synthesize these two sources of endogenous TC and formulate the *IPF* (innovation process) as:

$$\dot{H}_i(t) = \underbrace{\eta \cdot R_i(t)^\alpha \cdot H_i(t)^\beta - \delta_H \cdot H_i(t)}_{\text{indigenous innovation}} + \underbrace{\gamma_i(t) \cdot [R_i^T(t) + R_i^F(t) + R_i^D(t)]}_{\text{international technology diffusion}} \quad (22)$$

where accumulations of China's domestic knowledge stocks  $\dot{H}_i$  are driven by two forces. 1) Indigenous innovation: Both indigenous R&D investment ( $R_i$ ) and existing knowledge stock ( $H_i$ ) contribute to the creation of in-house knowledge.  $\eta$  denotes the efficiency of knowledge creation.  $\delta_H$  is the depreciation rate of knowledge obsolescence. The conditions  $0 < \eta < 1$ ,  $0 < \alpha + \beta < 1$  implies diminishing returns to R&D in innovation ([Rivera-Batiz and Romer, 1991](#); [Popp, 2004](#); [Bosetti et al., 2008](#)); 2) International TD: Foreign knowledge diffusions occur through three channels: imports ( $R_i^T$ ), FDI ( $R_i^F$ ), and disembodied spillovers ( $R_i^D$ ). China assimilates a fraction of the diffused knowledge according to local knowledge absorption capacity ( $\gamma_i$ ).

Note that, this *IPF* specification highlights three determinants to China's knowledge creation: (1) Indigenous R&D investment – the “no free lunch” assumption (to benefit from innovation, domestic countries should commit to undertake indigenous R&D and not solely free ride on

<sup>24</sup> As mentioned in [Section 2.3](#) on the dual face of indigenous R&D, such a specification reflects the second face: indigenous R&D can reinforce domestic capacity to absorb and exploit foreign diffused knowledge ([Cohen and Lethvinal, 1989](#); [Keller, 1996](#)).

<sup>25</sup> Structural similarity index reflects the degree to which foreign-created knowledge is targeted to local structural characteristics of production techniques ([Acemoglu, 2009](#)). For example, German manufacturing sector has higher R&D intensity level as compared with China, implying that the technology of German produced products, once introduced into China, is less targeted to China's less sophisticated production recipe, so that the embodied knowledge can't be fully absorbed.

<sup>26</sup> At the initial period, the function takes a value of  $\exp(-1)=0.367$ , since China has the largest difference in R&D intensity relative to the advanced countries. As time goes by, indigenous R&D improves China's R&D intensity with its level steadily reaching advanced country levels. As a result, the function value increases to its maximal level  $\exp(0)=1$ . For a similar treatment, see [van Meijl and van Tongeren \(1999\)](#).

foreign knowledge diffusion); (2) Existing stocks of knowledge – the “standing on the shoulders of predecessors” assumption (the more current stocks of knowledge, the more likely to create new knowledge); (3) International knowledge diffusion – the “public good sharing” assumption (domestic countries benefit from the positive externality of international knowledge diffusion by absorbing foreign diffused knowledge).

### 3 Model calibration and implementation

#### 3.1 Input-output data and knowledge accounting

To implement the model in a numerical simulation, we construct a benchmark dataset for model calibration. First, the year 2004 IO tables are collected from the GTAP 7 Data Base ([Narayanan and Walmsley, 2008](#)). Second, we adapt the GTAP data to our model structure by aggregating the 113 world regions into 6, the 57 sectors into 12, and the 5 primary factors into labor and physical capital.<sup>27</sup> Finally, the 2004 IO tables are scaled to approximate each region’s economy in the year 2005 (base year of simulation) using 2005 growth rate of real GDP.

To calibrate China’s domestic and foreign varieties of intermediate input and capital goods, we refer to the GTAP database (it distinguishes intersectoral transaction flows between domestic and import sources) to calibrate substitution between domestic and imported components of intermediate input commodities as well as regional composition of China’s imports from foreign trading partners. For investment capital goods, we refer to the *China Statistical Yearbook 2010* for the data on domestic and foreign components of fixed capital investment as well as regional composition of foreign-invested capital (FDI among foreign source countries) ([NBS, 2011](#)).<sup>28</sup>

The aforementioned steps produce a stylized IO dataset that can calibrate a traditional CGE model. However, this dataset is not well suited to calibrate a CGE model featuring endogenous TC (explicitly represented by knowledge), because it does not separately record the economic flows associated with R&D investment and knowledge input. To transform this stylized IO data, we collect sector-level R&D expenditure data from the OECD ANBERD database, and perform

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<sup>27</sup> The GTAP dataset records 113 world regions’ economic IO flows associated with 57-by-57 sectors intermediate production transactions, 5 categories of primary factor inputs, and 4 components of final use. The FlexAgg program contained is used to perform data aggregation for model calibration.

<sup>28</sup> The GTAP dataset contains the sector-level data on physical capital investment, but not distinguishes domestic and foreign sources of such capital formations.

knowledge accounting to capture knowledge flows.<sup>29</sup> The knowledge accounting 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 that features endogenous TC can be calibrated.

### 3.3 Parameterization and solver

The GEMPACK is used to solve the intertemporal optimization model.<sup>30</sup> The solver requires an initial equilibrium data as the benchmark point to calibrate the model. For an intertemporal dynamic model, this benchmark equilibrium data is required to record the values of economic variables at each time point over simulation periods, which is a time-series IO dataset (one for each time point) consistent with both intratemporal and intertemporal equations in the model.

To obtain such a full time-series dataset, we collect the available initial period (base year 2005) dataset and replicate it in future years over the period 2005-2030. Next, the Homotopy treatment is used to generate a non-steady-state baseline equilibrium dataset for model calibration.<sup>31</sup> Based on this consistent time-series benchmark dataset and model parameters shown in [Tabs.1-2](#), the theoretical structure in our model can be numerically solved by the GEMPACK.

## 4 Results and discussions

### 4.1 Alternative scenario settings

Recall that, we are motivated to examine the effect of indigenous R&D and foreign TD (the two sources of endogenous TC) on China's knowledge creation and carbon savings. To do that, we

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<sup>29</sup> Knowledge accounting used in our study is building on the works of [Terleckyj \(1974\)](#), [Scherer \(1982\)](#), [Sue Wing \(2001; 2003\)](#), and [Jin \(2012\)](#), which used the IO-based knowledge flows matrices to measure inter-sectoral technology interactions in an economic system. For the details of R&D data preparation and knowledge accounting, see [Appendix C](#). For our model sectoral mapping by reference to the OECD ANBERD (ISIC Rev.3) sectoral classification, see [Appendix B](#).

<sup>30</sup> GEMPACK is a suite of general-purpose CGE modeling software, which is more efficient than GAMS to solve an intertemporal optimization model ([Codsi et al., 1992](#); [Harrison and Pearson, 1996](#); [Horridge and Pearson, 2011](#)). The GEMPACK codes for our model are available upon request from the authors.

<sup>31</sup> Normally, the initial period is not in a steady-state (SS) equilibrium, the dataset created by replicating initial period data into future periods thus can't be used as a baseline to calibrate intertemporal equations (e.g., [Eq. \(3\)](#), [Eq. \(5\)](#)). To remedy this problem, we add a Homotopy term into each intertemporal equation and carry out a simulation where the Homotopy variables are shocked. This simulation then generates a non-SS time-series dataset that can be used a baseline to calibrate both intra- and inter-temporal equations in our model. The Homotopy treatment is automated by the TABLO program in GEMPACK. For the details, see [Codsi et al. \(1992\)](#), and [Wendner \(1999\)](#).

design and simulate two alternative scenarios. One is endogenous TC scenario where indigenous R&D and foreign TD are explicitly considered, and the other is reference scenario where indigenous R&D and foreign TD are ignored.<sup>32</sup> In [Section 4.2](#), we compare both scenarios to give insights into the effect of endogenous TC. In [Section 4.3](#), we analyze the impact of policy interventions in the globalization context, where economic and knowledge globalization policies are explicitly considered. By doing that, we capture two important effects of globalization (scale and technique effect) on domestic carbon saving. In [Sections 4.4](#), we examine whether domestic climate policy can induce foreign knowledge inflows to help lower climate mitigation costs, from which the composition effect of globalization on domestic carbon savings can be considered.

## 4.2 Effects of endogenous TC

For insights into the effect of endogenous TC, we compare economic and emission growth paths under the two aforementioned scenarios. As shown in [Fig. 4\(a\)](#), GDP in the reference scenario is projected to grow by 6.4% annually from \$2327 to \$10779 billion dollars between 2005 and 2030.<sup>33</sup> In contrast, GDP in the endogenous TC scenario rises from \$2327 to \$14272 billion dollars during the same period, creating an annual average growth rate of 7.6%. Consider that, the effect of endogenous TC stems from both indigenous R&D and foreign TD. To distinguish them, we simulate the growth path solely driven by indigenous R&D. Results show that with the stand-alone effort of indigenous R&D, GDP rises from \$2327 to \$13078 billion dollars between 2005-2030, generating an annual average growth rate of 7.2% that is lower than the rate achieved by the joint efforts of indigenous R&D and foreign TD (7.6%). This suggests that, on top of indigenous R&D, international TD contributes to an additional growth rate of 0.36% annually over the time period.

Climate repercussions of endogenous TC are shown in [Fig. 4\(b\)](#). Carbon emissions in the reference scenario are set to rapidly rise from 5100 to 13980 Mt between 2005-2030 - an average annual growth rate of 4.2%. In comparison, the endogenous TC scenario exhibits a trajectory of carbon emissions that grow by a lesser 3.5% annually from 5100 to 11817 Mt during the same period. As a result, cumulative emission cuts by endogenous TC relative to the reference levels are estimated to reach 24.8 gigatons over the time frame, of which indigenous R&D and international TD contribute to 18.3 and 6.5 gigatons emission cuts respectively. Measured in

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<sup>32</sup> In explicit, by setting indigenous R&D and foreign TD null, simulation in the reference scenario can drop the mechanism of endogenous TC, e.g., the process of knowledge creation as specified in [Eq. \(5\)](#).

<sup>33</sup> In our analysis, all measurements of output values are real GDP in unit of 2005 constant price U.S. dollars (year 2005 is the base period). Differences in real GDP reflect changes in output volume.

terms of percentage deviation, endogenous TC are seen to drive China's cumulative emissions below its reference levels by 9.1%, of which indigenous R&D and international TD contribute to 6.7% and 2.4% respectively. This suggests that foreign TD plays an important role to complement indigenous R&D in helping cut China's carbon emissions.

In addition to the economy-wide effect, our multi-sector framework is used to examine the impact of endogenous TC on carbon abatement at sectoral level.<sup>34</sup> As Fig. 5 shows, the sectors of manufacturing, electricity and transport accommodate highest carbon abatement potential from endogenous TC, with 15-20% emission cuts relative to their sector-specific reference emission levels.<sup>35</sup> In particular, foreign TD contributes to about one fourth of these emission abatements, suggesting a notable benefit of carbon saving from foreign TD.

We now turn to the driving forces for the aforementioned economic and emission changes. As Fig. 6(a) shows, China's indigenous R&D investments are likely to grow by 12% annually from \$34.9 to \$484.3 billion dollars during the period 2005-2030. The strong growths in R&D are spread across sectors, with manufacturing, agriculture, electric utility and transport investing the bulk of aggregate R&D.<sup>36</sup> In terms of international TD (the other source of endogenous TC), Fig. 6(b) shows that international knowledge diffusions are estimated to rise by 9% annually from \$9.1 to \$87.2 billion dollars between 2005-2030. Foreign knowledge diffuses into China through three channels to favor domestic knowledge creation. In the short run (2005-2015), disembodied spillover serves as the leading channel of knowledge diffusion, because there is a huge international disembodied knowledge pool (created by China's knowledge gap relative to technology frontier countries) accessible to China for learning. In the long run (2015-2030), as China enhances indigenous R&D to catch up with global technology frontier, the knowledge pool would shrink. Hence the leading diffusion channel of disembodied spillovers will be replaced by import and FDI. On the one hand, China is anticipated to boost imports of knowledge-intensive high-tech goods, so that the knowledge embodied in imports can be absorbed for domestic technical upgrading.<sup>37</sup> On the other hand, China's continued growth is

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<sup>34</sup> This is done by firstly estimating sector-specific cumulative emission cuts by endogenous TC relative to the reference levels. Next, the cumulative emission cuts are decomposed into the abatement driven by indigenous R&D and international TD (the two sources of endogenous TC)

<sup>35</sup> The reason is that production technologies in these sectors heavily rely on the inputs of fossil fuels. Once indigenous R&D and foreign TD are induced to create new knowledge, these sectors have a large potential of applying knowledge to substitute for fossil energy inputs and hence carbon savings.

<sup>36</sup> The reason is that, these sectors have higher marginal benefits from R&D investments (due to higher innovation efficiency and marginal products of knowledge use). Given the same marginal cost of R&D, the sectors that accommodate higher marginal benefits would undertake more R&D investments.

<sup>37</sup> This technology acquisition strategy is reflected by China's recently announcement of boosting imports

expected to create a huge consumer market, which attracts market-seeking MNCs to undertake R&D-related FDI and hence induce transfer of foreign advanced technology.<sup>38</sup>

At the sector level, knowledge diffusions (cumulative amounts over time period 2005-2030) into each sector are displayed in Fig. 7, with the manufacturing sectors accommodating most of foreign diffused knowledge.<sup>39</sup> Within these sectors, diffusion through the channels of FDI and disembodied spillovers accounts for about 35% and 40% of the total amounts of foreign diffused knowledge respectively, suggesting their important roles in transferring tacit knowledge that has increasingly become an integral part of effective technology transfer.

Finally, we look at the trend of convergence in cross-country R&D commitment. As shown in Fig. 8(a), global R&D spending is projected to triple over the time period, reaching an absolute level of \$2.43 trillion dollars by 2030. This global picture, however, displays a shifting geography of R&D distribution. While foreign advanced countries like U.S. and Japan contribute to most of total R&D investments, their shares are anticipated to decline which is largely offset by China's share gains. As a result, the continued convergence in cross-country R&D growth trend suggests China's technology catch-up and an improvement of knowledge absorptive capacity.<sup>40</sup> This is demonstrated in Fig. 8(b) where individual sectors all feature an improvement in knowledge absorptive capacity. They begin with weak capacities of knowledge learning due to low levels of indigenous R&D and structural mismatch of production technology, and then steadily improve as China continues growth in indigenous R&D and restructure production technology over time.

We summarize this section by elucidating the endogenous TC mechanism, that is, the causal relation between knowledge creation (cause) and economic and emission growth (consequence). Indigenous R&D, combined with the complement of foreign TD, induce domestic knowledge accumulation. The augmented knowledge capitals are then applied in production to facilitate a reconfiguration of production factors for Hicks-neutral productivity growth (the rate of TC) – an explanation for stronger output growth in the endogenous TC scenario. At the same time, owing

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of hi-tech products, which gives priority to the imports of knowledge-intensive electronic and mechanical products that have gained growing shares in China's imports portfolio (UNCTAD, 2010a).

<sup>38</sup> R&D activities of MNCs are becoming increasingly internationalized, with the emerging economy continuing to be the most dynamic recipients. For example, the world's leading corporate R&D investors (e.g., Pfizer, Microsoft, Intel, and IBM) have their own R&D centers in China (UNCTAD, 2005).

<sup>39</sup> This is because most of knowledge-intensive intermediate goods imports (e.g., electronic components) and foreign-installed capital goods (e.g., equipment) concentrate in China's manufacturing sectors, making foreign TD more likely to occur in this sector. Meanwhile, the stronger knowledge absorptive capacity (due to more R&D investment) in China's manufacturing sector facilitates absorbing foreign diffused knowledge.

<sup>40</sup> Recall that, China's knowledge absorptive capacity is measured as the ratio of R&D investment between China and technologically advanced foreign countries.

to knowledge substitution for physical inputs, production technology experiences a decline in the share of physical input use and a rise for knowledge input (the bias of TC). This gives rise to a reduction in uses of fossil energy - an explanation for lower emissions levels in the endogenous TC scenario.

### 4.3 Globalization policy scenario

As mentioned in Section 4.1, globalization may provide the benefit of low-carbon TD and carbon saving, we thus design globalization policy scenario in this section, where the effects of economic and knowledge globalization policies are explicitly considered.<sup>41</sup>

To represent the economic globalization policy (trade and FDI liberalization), our model removes import and FDI barriers by imposing the policy shocks:  $\tau_j^T = 0$  for import tariffs and  $\tau_1^F = 0$  for FDI tax (see [Appendix D](#)). Simulation results show that as economic globalization policies stimulate further expansions of international trade and investment, GDP is projected to grow by 8.1% annually from \$2327 to \$15662 billion dollars between 2005-2030, generating stronger output growths than that in endogenous TC scenario (see [Fig. 4\(a\)](#)). In terms of climate repercussions, the dynamic growth pushes a further rise of carbon emissions from 5100 to 12705 Mt, with a growth rate of 3.8% that is above the rate in endogenous TC scenario (see [Fig. 4\(b\)](#)).

The results show that the economic effect of trade and FDI liberalization (as measured by GDP growth) is positive, but its environmental consequence (as measure by carbon savings) is negative. This is primarily because, as the global manufacturing engine, China is in a transition into a capital-abundant country specializing in manufacturing, of which the production pattern is both capital- and energy-intensive as compared to other sectors (e.g., services).<sup>42</sup> Therefore, in the presence of trade and FDI liberalization, manufacturing sectors will attract more foreign intermediate input and capital goods to expand production capacity, which entails more uses of fossil energy and carbon emission.

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<sup>41</sup> Globalization as a multi-faced process manifests itself in two basic ways. 1) Economic globalization: national economies are increasingly integrated into a globalized production system through trade and FDI liberalization; 2) Knowledge globalization: globalized innovation networks facilitate a geographically extensive diffusion of technology, making individual country actively involved in knowledge exchange and sharing ([Archibugi and Iammarino, 1999](#); [UNCTAD, 2005](#); [Freeman, 2010](#)).

<sup>42</sup> This is consistent with the “*factor endowment hypothesis*” testified by empirical studies: there is a strong correlation between emissions and capital intensity, with globalization leading to emission increases in the capital-abundant countries ([Antweiler et al. 2000](#); [Cole and Elliot, 2003](#); [Frankel, 2003](#)).

Generally, economic globalization policy creates the *scale effect* (Copeland and Taylor, 2003; 2004): It accelerates economic growth momentum through the stimulus of international trade and investment, but without improving the intensity of knowledge embodied in import and FDI, this expanding production size necessarily requires more uses of fossil energy without carbon saving. Therefore, policies should be directly targeted at the growing globalization of knowledge to lift technology transfer restrictions erected by technologically advanced countries,<sup>43</sup> so that the intensity of knowledge embodied in foreign trade and investment can increase, creating the *technique effect* that favors domestic carbon savings.

To represent the knowledge globalization policy, our model removes foreign barriers of TD by raising the values of parameters  $\theta^T, \theta^F, \theta^D$  from 0.5 to 1. Results in Fig. 9(a) show that, under the policy shock of knowledge globalization, sector-specific knowledge diffusions are induced to rise by a range of 50-80%, which facilitate creation of more domestic knowledge. As a result, GDP is driven to grow by 8.2% annually from \$2327 to \$16404 billion dollars between 2005-2030 (see Fig. 4(a)). Meanwhile, augmented knowledge capital substitutes for the use of fossil energy, slowing down the emissions growth by 3.4% annually from 5100 to 11305 Mt between 2005-2030 (see Fig. 4(b)). Over the time frame, cumulative emission cuts reach a level of 15.8 gigatons, suggesting that knowledge globalization policy can a *technique effect* that favors domestic carbon saving (Copeland and Taylor, 2003; 2004).

Meanwhile, upon removing foreign barriers of TD, China's indigenous R&D are induced to rise by a range of 20-35% across sectors (see Fig. 9(b)), suggesting that foreign TD in knowledge globalization does not necessarily crowd out indigenous innovation. There is little evidence on China's incentive of free riding on foreign knowledge diffusion without indigenous innovative commitment. That's because indigenous R&D investments are necessary for domestic recipient countries to build indigenous capacity of absorbing foreign diffused knowledge.

In summary, economic globalization policy (trade and FDI liberalization) facilitates a transition to economic integration and production growth, but leading to higher emissions levels without carbon saving (*scale effect*). To acquire the benefits of domestic carbon saving, knowledge globalization policy should be implemented to create the *technique effect*, which depends on: 1) removal of TD barriers by technologically advanced nations; and 2) improvement of knowledge

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<sup>43</sup> While removal of import tariff and FDI tax reflects economic globalization policy adopted by China (technology demand side) to grant foreign access to domestic market in return for technology transfer, a lifting of knowledge transfer limits by foreign advanced countries (technology supply side) can be thought of as a particular type of knowledge globalization policy (UNCTAD, 2010b).



absorptive capacity by host developing countries.

#### 4.4 Climate policy scenario

In last section, knowledge globalization, through facilitating foreign technology flows, indirectly favor domestic carbon savings. While important, it can't stand alone, but rather must be part of policy portfolio to address climate mitigation. In this section, we explicitly consider direct climate regulation and its effect on economic growth, carbon savings, and innovation inducement.

We thus impose the policy shock of a carbon tax of \$20 dollars per ton of carbon dioxide from the year 2012 onward. Simulation results in Fig. 4(b) show that the carbon tax creates a noticeable effect to stabilize emissions growth trend, driving down from 5100 to 9795 Mt between 2005- 2030 (2.2% annual growth rate). Over the time period, carbon tax generates carbon savings of about 26.7 gigatons, translating into 12% cuts relative to emission levels without taxation. The sectoral composition of cumulative carbon abatement is given in Fig. 10(a), coal sector has the highest levels of emission cuts (50%), followed by oil and natural gas sectors (20-30%), with a modest level of abatement (10-20%) occurring in non-energy sectors.<sup>44</sup>

It comes as no surprise that, with higher energy input costs imposed by carbon tax, carbon savings benefits are at the economic cost of deadweight losses. As Fig. 4(a) shows, GDP is likely to grow at a lesser rate by 7.2% annually from \$2327 to \$13309 billion dollars between 2005-2030, with a present-value cumulative output losses of \$9763 billion (an equivalent of 2.4% loss relative to the output levels without carbon tax). The sectoral composition of cumulative output losses is displayed in Fig. 10(b). Most non-energy sectors experience output reductions of less than 5%. Carbon-intensive fossil fuel sectors suffer precipitous output declines of roughly 10-20%.<sup>45</sup>

To demonstrate how innovation helps lower climate compliance costs, we simulate the deadweight loss incurred by carbon taxation in the reference (no-innovation) scenario, where endogenous-TC is absent in private firms' response to energy price shock. Results show that carbon tax is likely to drive down GDP growth at a lesser rate (5.8% annually) from \$2327 to

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<sup>44</sup> An interesting point it that, electricity sector, as compared to non-energy sectors, is carbon-intensive that heavily relies on fossil fuels inputs to generate power. Putting a carbon price on fossil fuels thus incentivize electricity sector to lower fossil fuels uses, hence having a proportionally higher level in carbon emissions.

<sup>45</sup> As compared to primary energy sectors (coal, natural gas, oil), electricity sector (secondary energy sector) is R&D-intensive. Carbon taxation thus induces electricity sector to create and apply low-carbon energy technologies (e.g., wind, solar) to generate power, which partially offsets output loss of coal-fired electricity incurred by carbon tax. Hence, electricity sector has a proportionally lower level of output losses.

\$9357 billion dollars between 2005-2030, with a present-value cumulative output losses of \$23410 billion dollars. It implies that endogenous TC helps partially mitigate economic costs of \$13647 (23410-9763) billion dollars, of which foreign TD (one source of endogenous TC) helps mitigate a deadweight loss of \$3713 billion dollars. Therefore, while climate regulation has a negative effect on economic production, the innovative response of private firm can help partially mitigate the climate compliance costs.

For insights into the effect of climate policy on innovation inducement, we examine the effect of the carbon tax on R&D intensity at sector level. As Fig. 10(c) shows, although higher inputs cost incurred by carbon tax would diminish the absolute levels of production output and hence indigenous R&D spending, R&D intensity (R&D to output ratio) does not necessarily drop across sectors. Decline in cumulative R&D exceeds the fall in cumulative outputs in fossil fuel sectors, but falls short of those in non-fossil fuel sectors. Consequently, R&D intensity increase slightly across a range of non-fossil fuel sectors, suggesting that indigenous R&D are induced by climate policy in these sectors.

Moreover, as Fig. 10(d) shows, decline in cumulative foreign TD also exceeds the fall in cumulative outputs in fossil fuel sectors, but falls short of those in non-fossil fuel sectors. As a result, input share of foreign diffused knowledge in domestic production increase slightly across non-fossil fuel sectors, which indicates that domestic climate regulations also stimulate external knowledge inflows to help increase knowledge uses in domestic production technology.<sup>46</sup> This finding thus broadens the scope of existing studies on “*induced innovation hypothesis*” for a single closed economy (Newell et al., 1999; Popp, 2002; Goulder and Schneider, 1999; Sue Wing, 2003).

In summary, under stringent climate regulation, individual sectors are induced to create new knowledge through indigenous R&D and foreign TD. From an economy-wide perspective, once new knowledge is applied in economic system, the contribution of knowledge-intensive sectors would expand, with that of carbon-intensive sectors contracting. Hence, such a shift in composition/structure of the aggregate economy suggests a *composition effect*.<sup>47</sup>

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<sup>46</sup> This can be explained from a perspective of technology push/market pull. Foreign developed countries have the “first mover advantage” to develop low-carbon technologies (technology push). Meanwhile, China’s climate regulation create a carbon market, where demands for low-carbon technologies can draw in foreign advanced knowledge and best practices (market pull) (Lovely and Popp, 2011; Popp, 2011).

<sup>47</sup> From a sector-specific perspective, this can also be thought of as a *technique effect*, because climate policy induces restructuring of sector-specific technology from a carbon-intensive into a knowledge-based one.

## 4.5 Sensitivity analysis

Tab. 3 lists the results of sensitivity analysis (SA) for key technology parameters used in our model. The SA is implemented by lowering and raising these exogenous parameters by 25% relative to their original values (as shown in Tabs. 1-2). We then compare new simulation results (parameters take new values) with regular simulation results (parameters take original values), and report the SA results as the percentage change between them. As Tab. 3 shows, the results of SA suggest that the basic findings from Sections 4.1-4.4 are robust to changes in exogenous technology parameters. (1) Foreign TD complements indigenous R&D to help cut domestic carbon emissions; (2) Economic globalization generates the *scale effect* that is adverse to domestic carbon savings; (3) Knowledge globalization creates the *technique effect* that favors domestic carbon savings; (4) Climate policy creates the *composition effect* by inducing foreign knowledge inflows to help mitigate climate compliance costs.

Turning to technology parameters specific to China, in the case of lowering  $\sigma^Q$  by 25%, a lower possibility of knowledge substitution translates into a lower incentive to undertake indigenous R&D and absorb foreign TD for knowledge creation.<sup>48</sup> As a result, the *scale effect* in economic globalization is stronger in new simulation, and the *technique effect* in knowledge globalization is weaker. In the meantime, lower knowledge substitution also weakens the effect of carbon tax to induce indigenous innovation, suggesting the *composition effect* becomes weaker. The opposite holds if the parameter  $\sigma^Q$  is raised by 25%.

Turning to technology parameters specific to foreign countries, in the case of lowering  $\sigma^Q$  by 25%, lower possibilities of knowledge substitutions in the foreign countries translates into their lower incentives of R&D investment. As foreign R&D levels decline, the potential of foreign knowledge diffusion into China become small. As a result, *scale effect* in economic globalization is stronger in new simulation, and the *technique effect* of knowledge globalization is weaker. Less foreign TD also suggests a weaker *composition effect*. The opposite holds if these parameters  $\sigma^Q$  are raised by 25%.

## 5 Conclusion and outlook

Building on a multi-country framework, this study models both indigenous R&D and foreign TD

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<sup>48</sup> The following analysis also applies to the case of raising  $\delta_H$  and lowering  $\alpha, \beta, \eta$ , because it also translate into a lower incentive of knowledge creation, with less knowledge substitution for fossil fuels.

as two sources of endogenous TC for domestic carbon savings. We specify foreign TD through three diffusion channels of trade, FDI and disembodied spillovers, with an elaborate treatment on knowledge absorptive capacity.

Simulation results show that 1) foreign TD contributes to 20%-25% of carbon emission cuts by endogenous TC. In the short run, 60-70% of foreign knowledge diffusion occurs via the channel of disembodied spillover. In the long run, the leading diffusion channels become embodied knowledge diffusion via import and FDI which account for almost 80% of total foreign TD; 2) Trade and FDI liberalization facilitates economic growth, creating an additional GDP growth rate of about 0.5% annually over time. But this is at the cost of more carbon emissions, raising emissions growth rate by about 0.3% annually. So economic globalization policy may not create the benefit of domestic carbon saving (*scale effect*); 3) Removal of foreign technology transfers barriers facilitates domestic knowledge creation and productivity growth, generating an additional GDP growth rate of about 0.1% annually. It also brings down carbon emission growth rate by roughly 0.4% annually. So knowledge globalization policy creates the benefit of domestic carbon savings (*technique effect*); 4) Domestic climate policies induce both indigenous R&D (R&D intensity increase by about 2-5%) and foreign TD (input share of foreign diffused knowledge rise by about 5-8%). As a result, both types of innovation inducement would help shift the composition of domestic production techniques (*composition effect*), which eventually lowers climate compliance cost (output losses incurred by carbon taxation) by about 15-20%.

Needless to say, a number of model refinements and extensions are required in future work: (1) Current works focus on modeling unidirectional knowledge diffusion from technologically advanced countries to China, without factoring into multidirectional technology interaction. As China is increasingly integrated into the global innovation landscape, it is possible for technology incumbents in advanced countries to learn the ideas created by the new entrants in the emerging markets. Hence, future work should study the mechanism of cross-country multidirectional knowledge diffusion, based on which the issue of international technology coordination can be addressed; (2) Our current study adopts the traditional *ad hoc* SA method to examine the model robustness to variations in exogenous parameters, which is however far from sufficient to reflect randomness (probability distribution) of these exogenous parameters. Future works hereby need to use systematic SA approaches (e.g., Monte Carlo analysis, Gaussian Quadrature) to examine model robustness.

## Appendix A: Country composition of regions

Region Number	Region Name	Region Description
1	CHN	China
2	USA	United States of America
3	JPN	Japan
4	EUW	Western Europe
5	RIN	Rest of the Industrialized Countries
6	ROW	Rest of the World

### Western Europe:

Austria, Belgium, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Luxembourg, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom

### Rest of the Industrialized Countries:

Canada, Australia, New Zealand, Korea, Singapore, Hong Kong, Taiwan

### Rest of the World:

All countries not included in other region groups

## Appendix B: Model sectoral classification and mapping by reference to the GTAP and OECE ANBERD

Sector number/name in our mode	GTAP sector numbers	OECD ANBERD sector number
1. Electric utilities	43	40
2. Gas utilities	44	41
3. Petroleum refining	32	23
4. Coal mining	15	10
5. Crude oil & gas extraction	16-17	11
6. Mineral mining	18	12-14
7. Agriculture	01-12, 14	01, 03-05
8. Forestry & wood products	13, 30	02, 20
9. Durable manufacturing	34-42	26-37
10. Nondurable manufacturing	19-29, 31, 33	15-19, 21-22, 24-25
11. Transportation	48-50	60-64
12. Services	45-47, 51-57	45, 50-59, 70-99

## Appendix C: 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. 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  $\Omega$  is 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, we estimate the intangible knowledge flows embodied in the intermediate transaction as:

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

where  $x_{ji}$  is the  $(j,i)$  cell of the intermediate transaction matrix  $x$  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.

As mentioned previously, innovations in foreign technologically advanced countries are driven by their indigenous R&D, but TC in China benefits from both indigenous R&D and international knowledge diffusions. Hence, a distinction is made in knowledge accounting between foreign technologically advanced economies and China. For the former, sector-specific R&D investment ( $R_j$ ) is equal to indigenous R&D expenditure, of which the sector-level data can be collected from OECD ANBERD dataset. China's R&D investment, in comparison, amounts to a sum of indigenous R&D and international knowledge diffusion. China's indigenous R&D expenditure data is also available from OECD ANBERD dataset.

International knowledge diffusions through the three channels (trade, FDI and disembodied spillovers) are calculated using the formula presented in the manuscript Sections 2.4.1-2.4.3. The shares of product sales to other sectors in intermediate transaction ( $x_{ji}/X_j$ ) are calculated from the stylized IO table. We then use Eq. (\*) to estimate the intangible knowledge flows embodied in the intermediate production.

Generally, the knowledge accounting by using Eq. (\*) is equivalent to a horizontal mapping of the column of sector-specific R&D investment expenditure into each cell in the intangible knowledge flow matrix. Then, the knowledge flow matrix is vertically aggregated to create an additional row of knowledge input in the primary factor use matrix  $\mathbf{v}$ , with each element being the value of knowledge input into production sector  $i$ ,  $H_i = \sum_j \omega_{ji}$ . Finally, the elements of intermediate production matrix  $\tilde{\mathbf{X}}$  are purged of the intangible knowledge flows to represent the value of pure physical flows.

The residual elements of intermediate transaction matrix ( $\tilde{x}_{ji} = x_{ji} - \omega_{ji}$ ) is subject to the non-negativity constraint. Once the column and row balance hold in the stylized IO table, the matrix balance still holds for the modified IO table with explicit knowledge accounting:  $\sum_j \tilde{x}_{jk} + \sum_f v_{fk} + v_{Hk} = \sum_i \tilde{x}_{ki} + \sum_f \tilde{g}_{kf} + g_{kR}$ . This procedure hereby constructs a modified IO dataset with an explicit representation of R&D investments and knowledge inputs, based on which the CGE model with endogenous TC can be calibrated.

## Appendix D: Policy shocks in economic globalization scenario

### (1) Removal of import tariffs

	China's import tariff rate	Economy globalization
1 ELEC	5%	0%
2 GAS	5%	0%
3 PETROLEUM	5%	0%
4 COAL	8%	0%
5 OIL_GAS	5%	0%
6 MINING	8%	0%
7 AGRIC	20%	0%
8 FORES	5%	0%
9 DURABLE	12%	0%
10 NONDURABLE	15%	0%
11 TRANSPORT	5%	0%
12 SERVICE	5%	0%

### (2) Removal of FDI barriers

China's domestic corporate income tax is 25%, and the preferable tax rate offered to the operation of MNCs is a half of that domestic tax rate. The FDI tax rate is thus equivalent to  $25\% * 50\% = 12.5\%$ . The policy shock of economy globalization cut this FDI tax rate from 12.5% to 0%.

Source: [WTO \(2010\)](#), [UNCTAD \(2010a,b\)](#).



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Table 1 Substitution elasticity

	$\sigma^Q$	$\sigma^Z$	$\sigma^E$	$\sigma^M$	$\sigma^T$	$\sigma^{TT}$	$\sigma^F$	$\sigma^{FF}$
Production sectors								
Electric utility	1.0	0.8	0.2	1.0	2.8	5.6	4.0	2.0
Gas utilities	1.0	0.8	0.9	0.2	2.8	5.6	4.0	2.0
Petro refining	1.0	0.5	0.2	0.2	2.1	4.2	4.0	2.0
Coal mining	1.0	1.7	0.2	0.5	3.0	6.1	4.0	2.0
Crude oil & gas	1.0	0.5	0.1	0.2	7.6	14.4	4.0	2.0
Mineral mining	1.0	1.0	1.1	2.8	0.9	1.8	4.0	2.0
Agriculture	1.0	1.3	0.6	1.7	2.4	4.8	4.0	2.0
Forestry	1.0	0.9	0.9	0.2	3.2	6.7	4.0	2.0
Durable	1.0	0.4	0.8	0.2	3.7	7.6	4.0	2.0
Non-durable	1.0	1.0	1.0	0.1	3.0	6.4	4.0	2.0
Transportation	1.0	0.5	0.2	0.2	1.9	3.8	4.0	2.0
Services	1.0	0.3	0.3	3.0	1.9	3.8	4.0	2.0

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

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

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

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

$\sigma^T$ : Armington elasticity of substitution between domestically-produced and imported intermediate input varieties.

$\sigma^{TT}$ : CES elasticity of substitution for regional allocation of import bundles.

$\sigma^F$ : CES elasticity of substitution between domestic- and foreign-invested capital goods.

$\sigma^{FF}$ : CES elasticity of substitution for regional allocation of FDI.

Notes: Physical capital goods invested in individual industrial sectors are assumed to have a substantial degree of homogeneity, we hereby impose the restriction that substitution elasticities of physical capital investment are equal across sectors. We also impose the restriction that substitution elasticities within individual production sectors are equal across world regions. This specification does not mean, however, that the elasticities are the same across industrial sectors within a world region.

Source: [Goulder and Schneider \(1999\)](#), [McKibbin and Wilcoxon \(1999\)](#), [Sue Wing \(2001; 2003\)](#), [Löschel and Otto \(2009\)](#), [Narayanan and Walmsley \(2008\)](#), [Springer \(1998\)](#), [Lejour et al. \(2008\)](#).

Table 2 Parameters

	CHN	USA	EUW	JPN	RIN	ROW
$\tau_Q$	0.25	0.40	0.30	0.40	0.30	0.15
$\tau_I$	0.20	0.12	0.15	0.20	0.15	0.20
$\tau_R$	0.10	0.06	0.08	0.15	0.10	0.10
$\alpha$	0.18	0.18	0.18	0.18	0.18	0.18
$\beta$	0.53	0.53	0.53	0.53	0.53	0.53
$\eta$	0.02	0.02	0.02	0.02	0.02	0.02
$r$	0.01	0.03	0.03	0.04	0.05	0.05
$\delta_K$	0.05	0.05	0.05	0.05	0.05	0.05
$\delta_H$	0.1	0.1	0.1	0.1	0.1	0.1
$\Psi$	4	4	4	4	4	4

$\tau_Q$ : Corporate income tax rate

$\tau_I$ : Investment tax credit

$\tau_R$ : R&D tax credit

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

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

$\eta$ : Sectoral efficiency of knowledge creation

$r$ : Real interest rate

$\delta_K$ : Depreciation rate of physical capital

$\delta_H$ : Depreciation rate of knowledge capital

$\Psi$ : Investment adjustment cost coefficient

Source: [Goulder and Schneider \(1999\)](#), [McKibbin and Wilcoxon \(1999\)](#), [Popp \(2004\)](#), [Bosetti et al. \(2008\)](#), [OECD \(2010\)](#).



Table 3 Results of sensitivity analysis

		Endogenous TC <sup>a</sup>		Emission cuts <sup>b</sup>		Scale effect <sup>c</sup>	Technique effect <sup>d</sup>	Composition effect		
		Indigenous R&D	Foreign TD	Indigenous R&D	Foreign TD			R&D intensity <sup>e</sup>	Share of foreign knowledge <sup>f</sup>	Cost savings <sup>g</sup>
China										
$\sigma^Q$	Low <sup>h</sup>	-3.52%	-2.61%	6.47%	2.33%	3.85%	2.23%	-2.84%	-0.57%	-1.02%
	High	3.64%	2.85%	6.92%	2.46%	-3.47%	-2.08%	2.65%	0.48%	0.93%
$\delta_H$	Low	2.76%	2.53%	6.89%	2.46%	-2.12%	-0.87%	1.72%	0.36%	0.64%
	High	-2.48%	-2.15%	6.51%	2.34%	1.86%	0.74%	-1.96%	-0.33%	-0.76%
$\alpha, \beta, \eta$	Low	-5.46%	-4.27%	6.35%	2.29%	6.12%	5.20%	-4.15%	-0.91%	-1.45%
	High	6.27%	4.89%	7.12%	2.51%	-5.46%	-4.70%	3.72%	0.64%	1.53%
Foreign										
$\sigma^Q$	Low	-1.26%	-3.85%	6.62%	2.26%	1.58%	1.07%	-0.98%	-3.76%	-0.56%
	High	1.15%	3.67%	6.77%	2.53%	-1.46%	-0.95%	1.11%	3.82%	0.46%
$\delta_H$	Low	0.75%	2.28%	6.76%	2.49%	-0.91%	-0.43%	0.66%	2.34%	0.30%
	High	-0.93%	-2.57%	6.64%	2.31%	0.82%	0.37%	-0.57%	-2.19%	-0.24%
$\alpha, \beta, \eta$	Low	-1.39%	-5.72%	6.62%	2.22%	2.51%	2.13%	-1.72%	-5.92%	-0.95%
	High	1.12%	5.48%	6.79%	2.58%	-2.46%	-2.04%	1.78%	5.75%	0.69%

$\sigma^Q$ : Elasticity of substitution between knowledge and physical input.  $\delta_H$ : Depreciation rate of knowledge capital stock

$\alpha$ : Elasticity of knowledge creation to R&D investment.  $\beta$ : Elasticity of knowledge creation to existing knowledge stock.  $\eta$ : Efficiency of knowledge creation

<sup>a</sup> Percentage change of China's cumulative indigenous R&D investment and cumulative international TD (two sources of endogenous TC) in new simulation relative to that in regular simulation.

<sup>b</sup> China's cumulative emission cuts driven by indigenous R&D and international TD in new simulations. (in regular simulation, cumulative emission cuts driven by indigenous R&D and international TD equal to 6.7% and 2.4%, respectively)

<sup>c</sup> Percentage change of China's cumulative carbon emissions under economic globalization scenario in new simulation relative to that in regular simulation.

<sup>d</sup> Percentage change of China's cumulative carbon emissions under knowledge globalization scenario in new simulation relative to that in regular simulation..

<sup>e</sup> Percentage change of the average levels (among China's eight non-fossil fuel sectors) of R&D intensity (ratio of indigenous R&D investment to output) in new simulation relative to that in regular simulation.

<sup>f</sup> Percentage change of the average levels (among China's eight non-fossil fuel sectors) of input share of foreign diffused knowledge (ratio of foreign diffused knowledge to output) in new simulation relative to that in regular simulation.

<sup>g</sup> Percentage change of China's climate compliance cost savings (mitigation of the deadweight losses incurred by carbon tax) by endogenous TC in new simulation relative to that in regular simulation.

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

	Industries $i$							Final Demand $d$					Total Output
		1	.	.	$i$	.	12	$C$	$I$	$G$	$R$	$X$	
Commodities $j$	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		$Y_1$	.	.	$Y_i$	.	$Y_{12}$						

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)

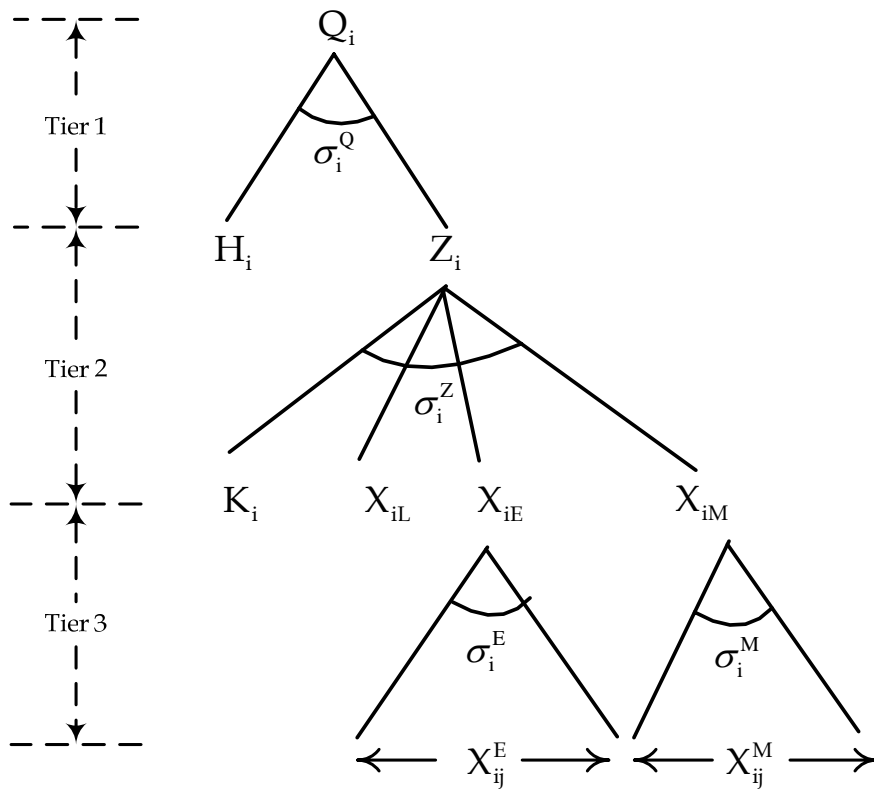


Figure 2: KLEM-H three-tier nested CES technology in twelve production sectors

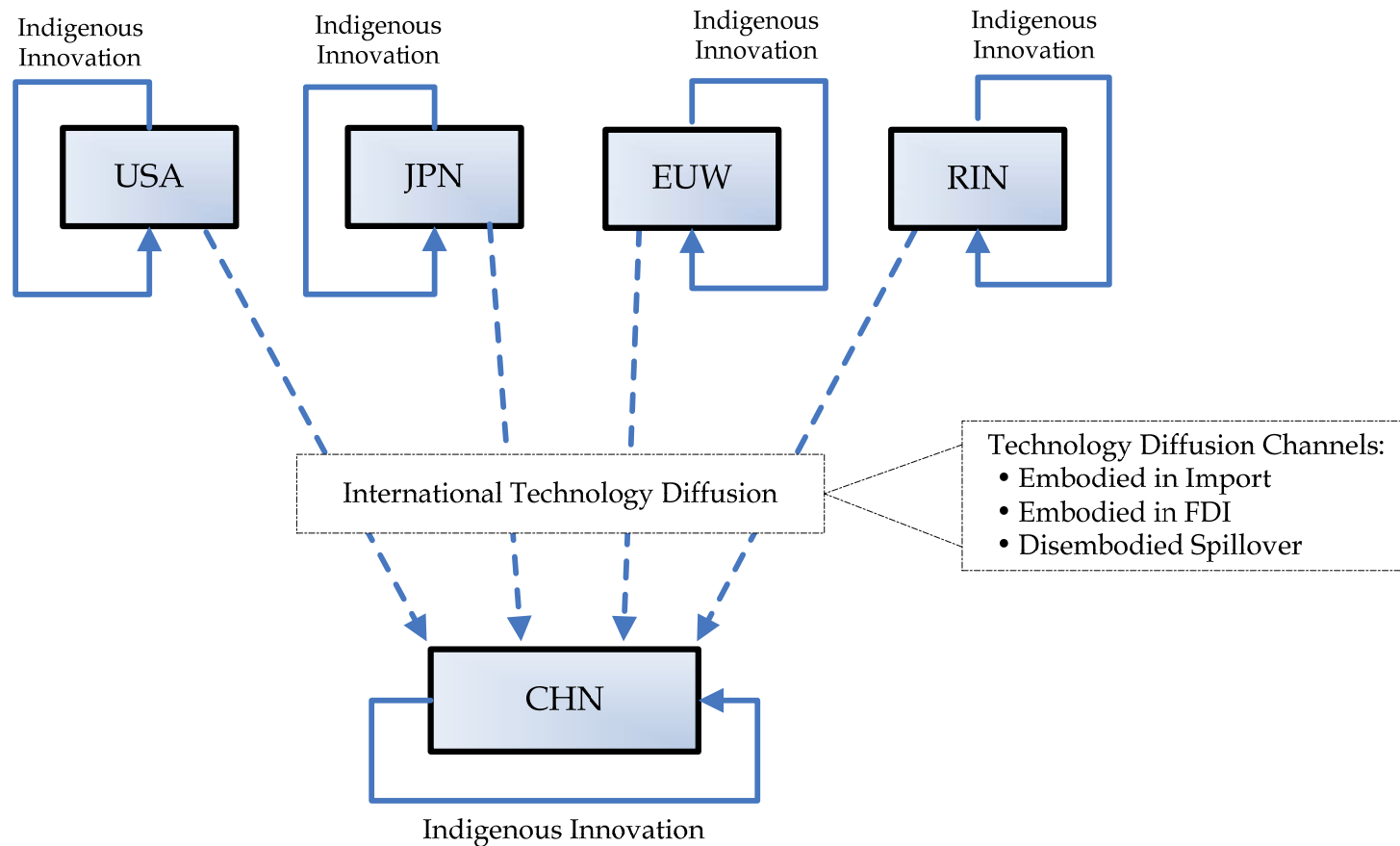


Figure 3: Pattern of international technology diffusion: Unidirectional knowledge diffusion from technologically advanced foreign countries (USA, JPN, EUW, RIN) to China through three knowledge diffusion channels (trade, FDI, disembodied spillover)

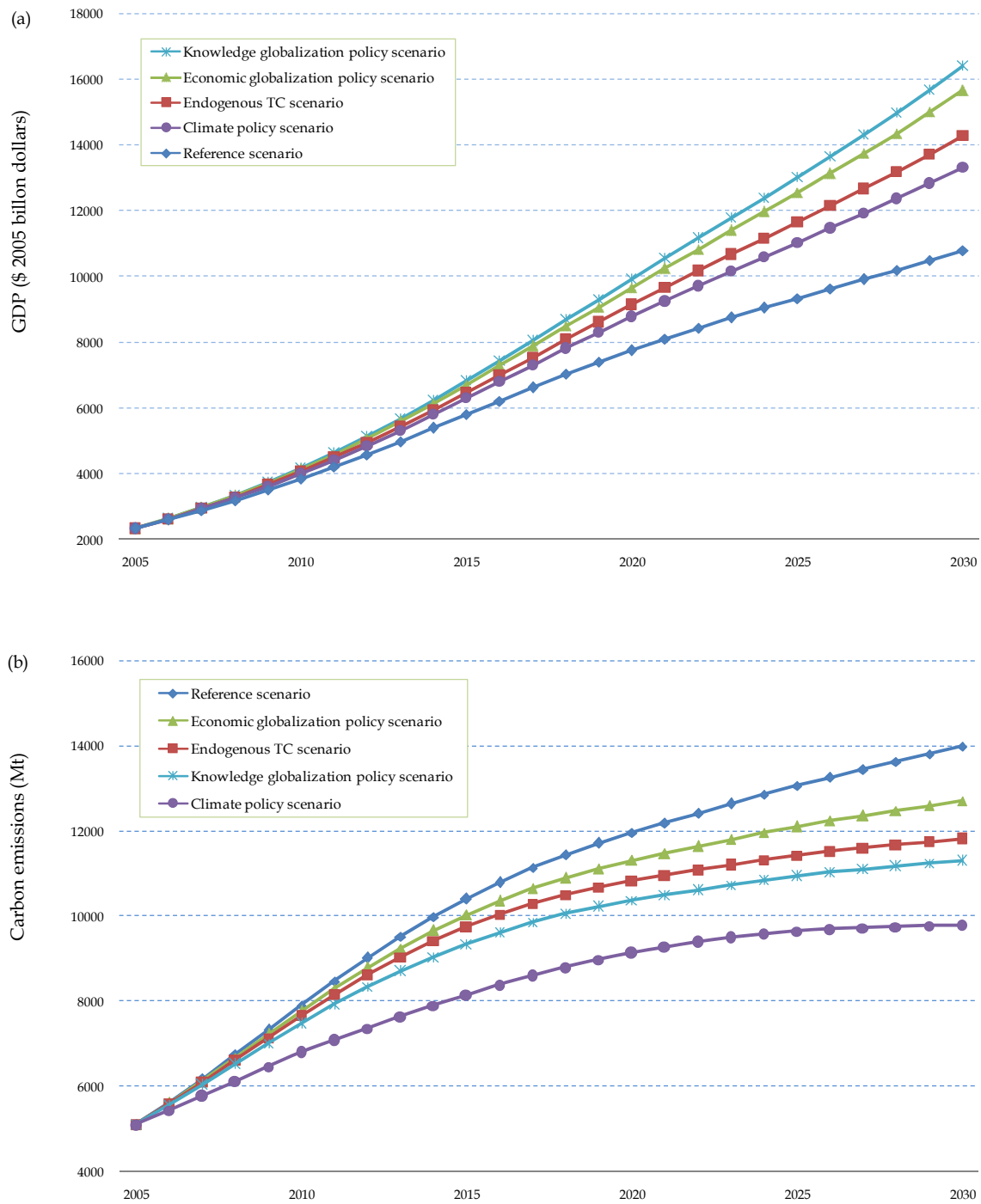


Figure 4: GDP and carbon emission growth paths under various scenarios

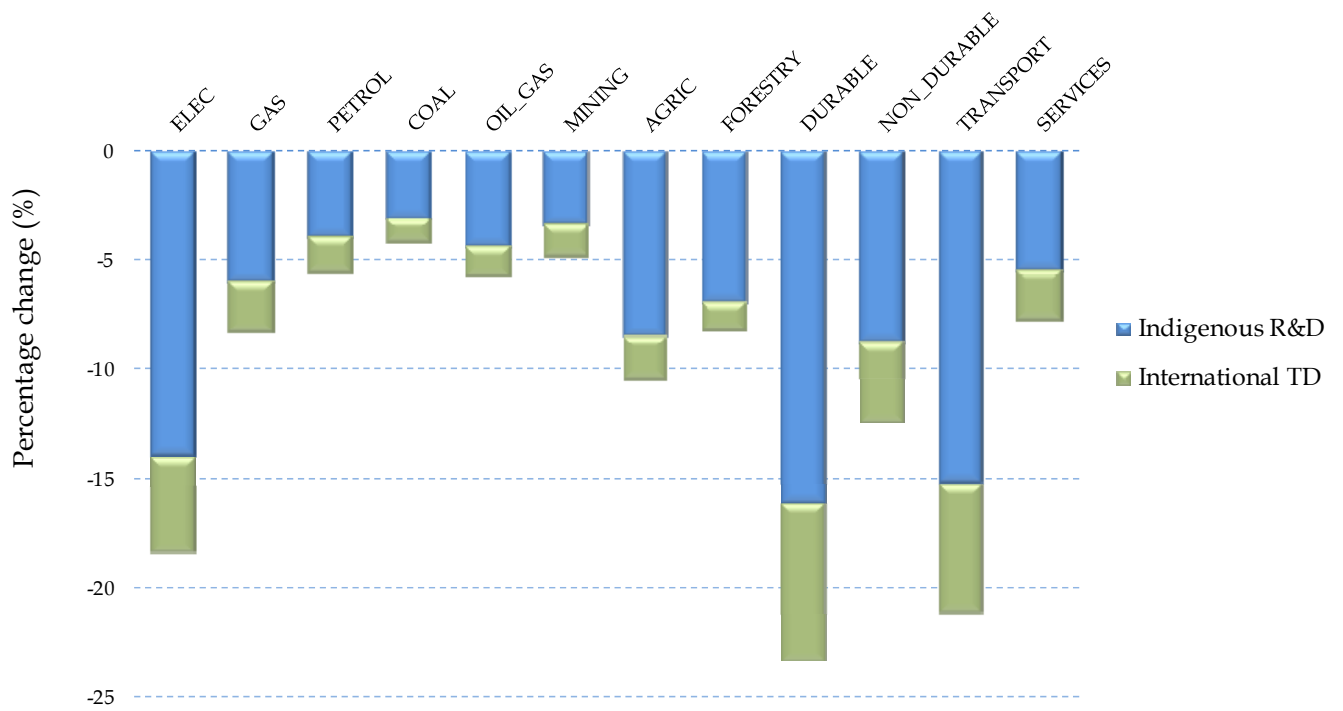


Figure 5: Effect of indigenous R&D and international TD (the two sources of endogenous TC) on the sector-level cumulative emission cuts, measured in terms of percentage changes relative to the cumulative emissions levels in the reference scenario.

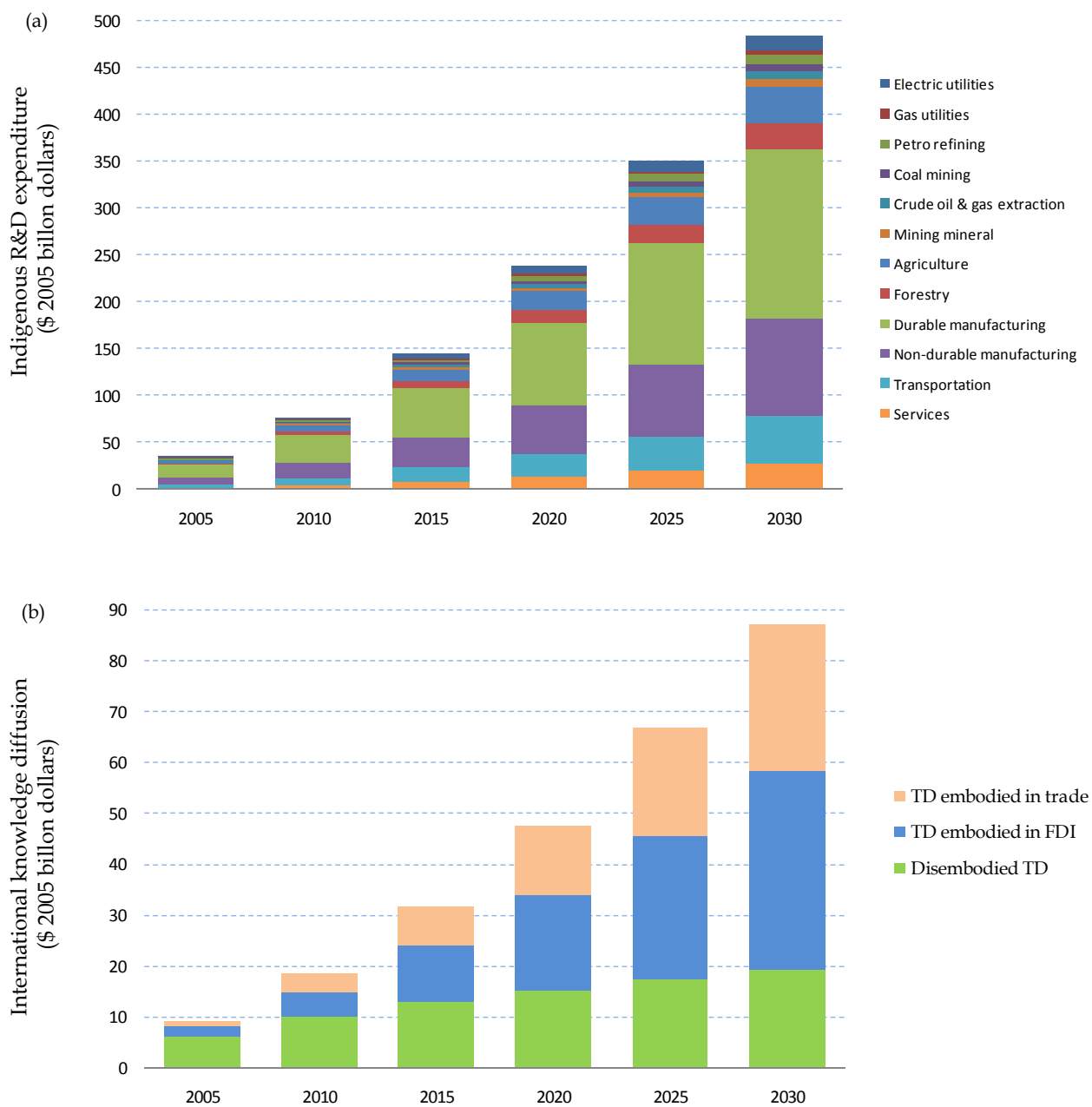


Figure 6: (a) Growth trend of indigenous R&D investment expenditure and its sectoral composition; (b) Growth trend of international knowledge diffusion and its composition among three diffusion channels

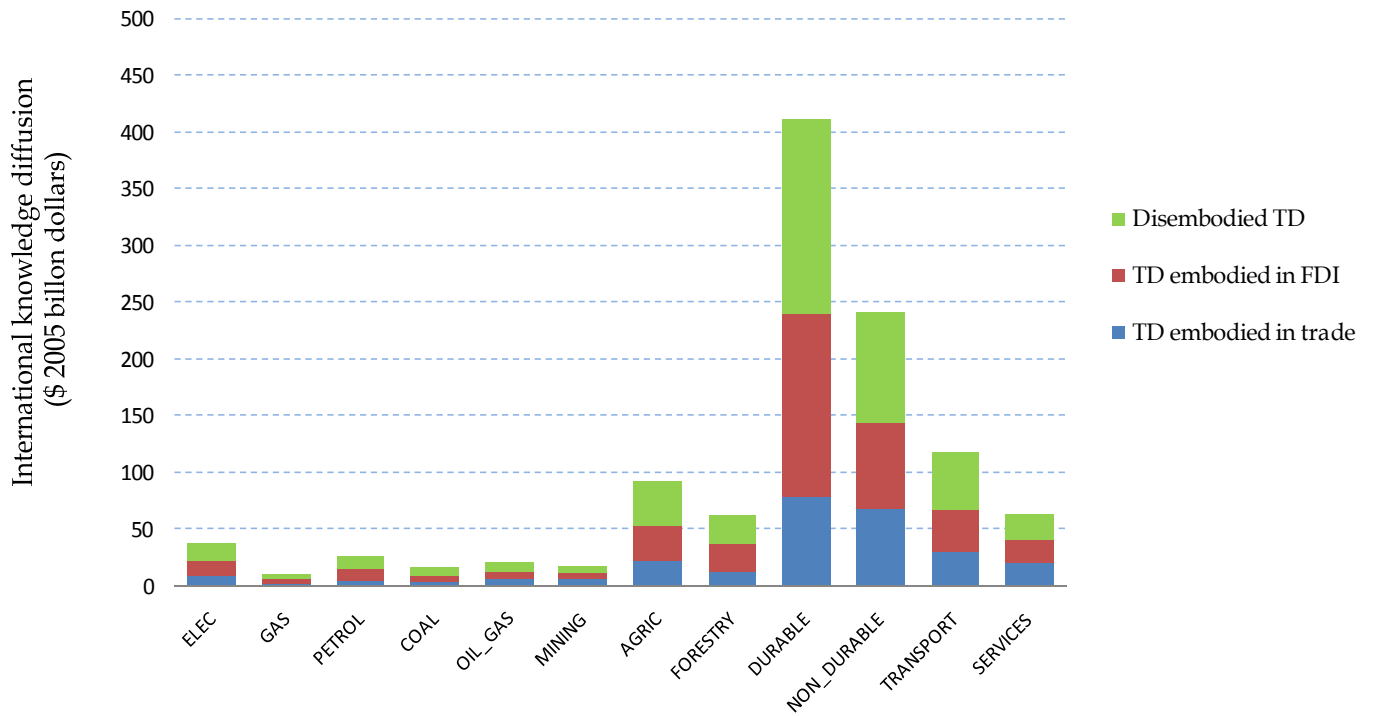


Figure 7: The cumulative amount of international knowledge diffusion into each individual sector and its composition among three knowledge diffusion channels



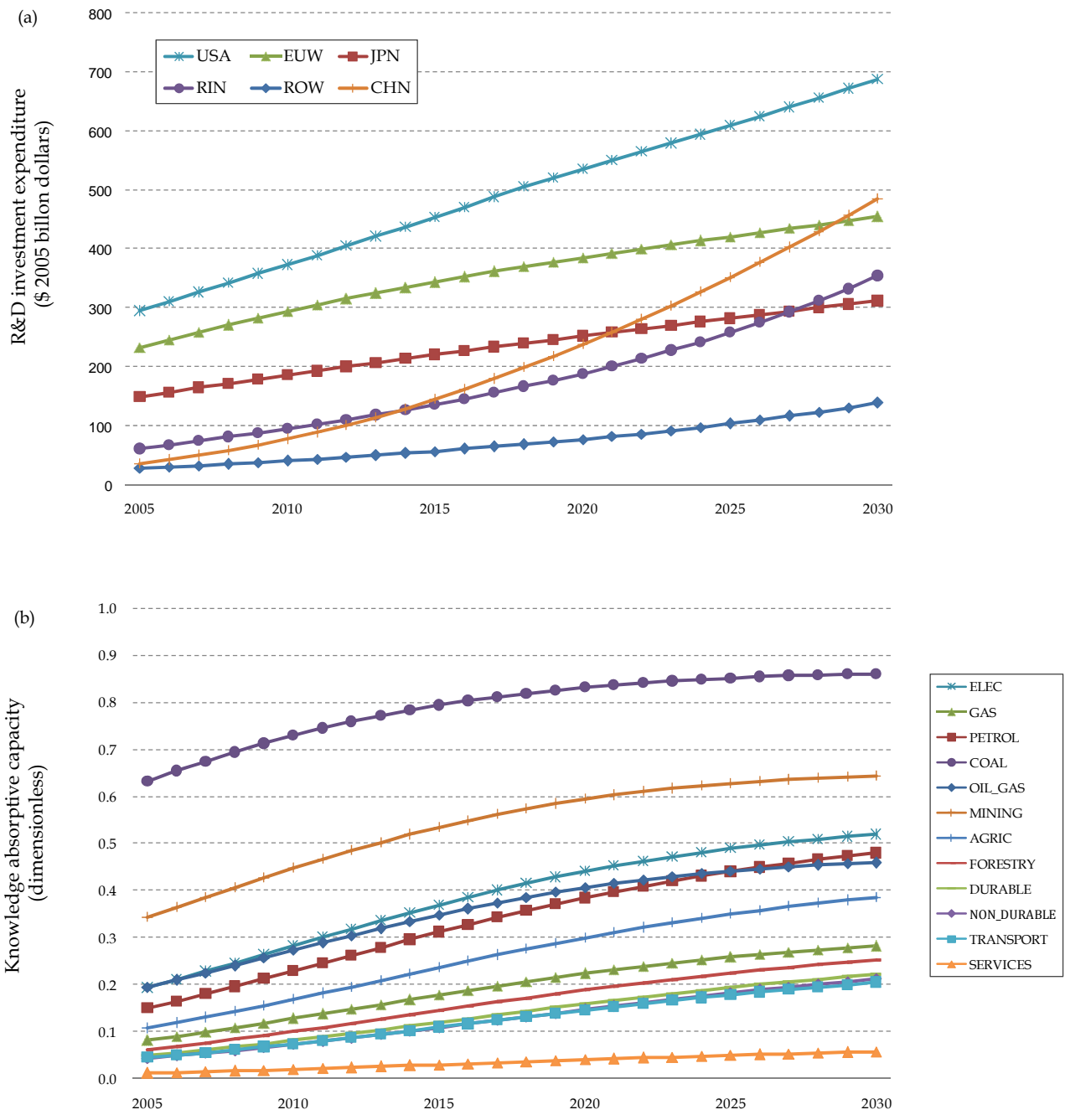


Figure 8: (a) Changing trend of R&D investment expenditure across world countries/regions; (b) Changing trend of China's knowledge absorptive capacity specific to individual production sector.

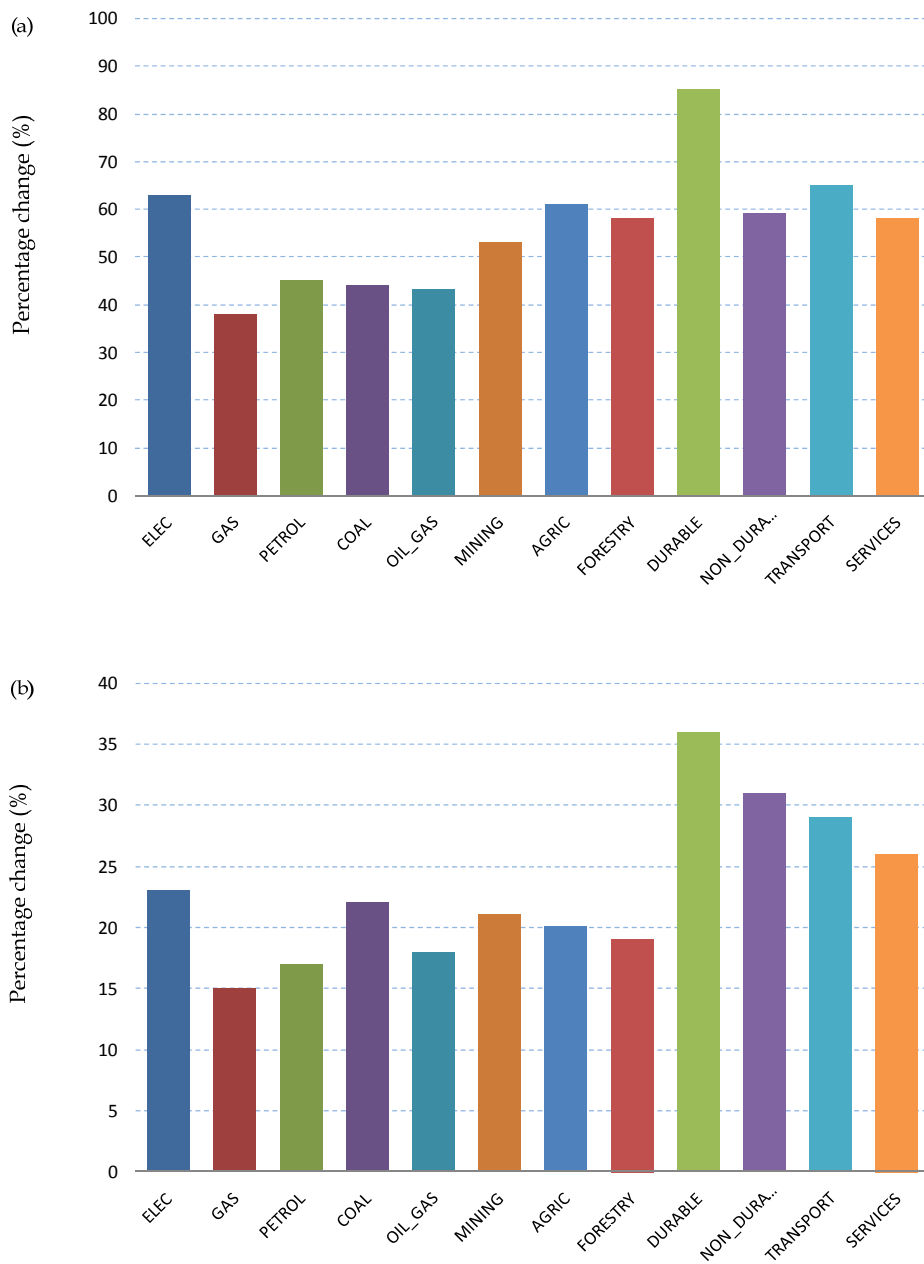


Figure 9: (a) Effect of knowledge globalization policy on sector-level international knowledge diffusion; (b) Effect of knowledge globalization policy on sector-level indigenous R&D investment. Both measured as percentage change relative to the levels without policy intervention;

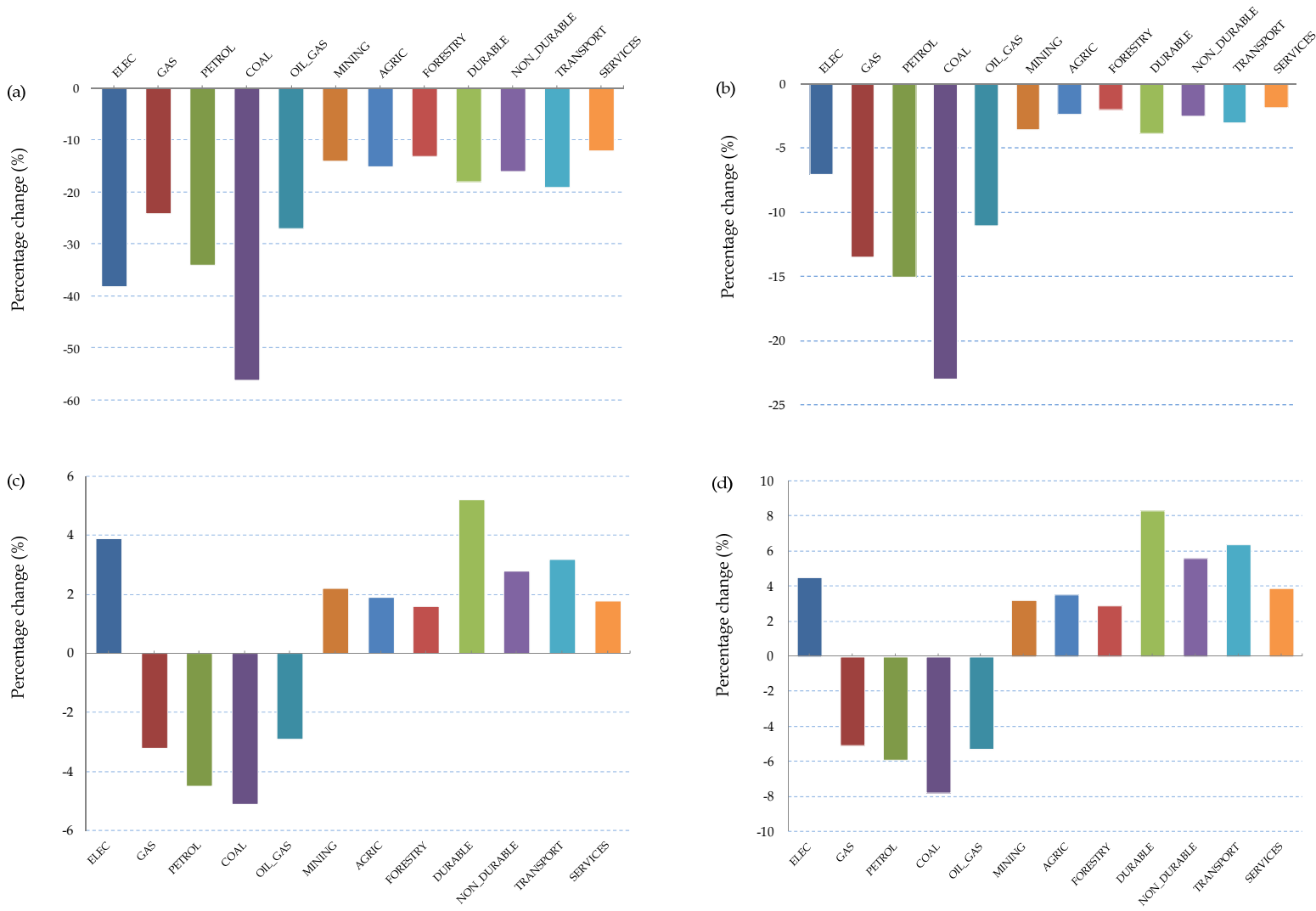


Figure 10: (a) Effect of carbon tax on the sector-level cumulative emission cuts; (b) Effect of carbon tax on the sector-level cumulative output losses; (c) Effect of carbon tax on the sector-level R&D intensity; (d) Effect of carbon tax on the sector-level input share of foreign diffused knowledge. All measured in terms of percentage changes relative to the corresponding cases without carbon taxation.